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BIM–AI integration in architecture: a workflow-based review

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Abstract:
The integration of Building Information Modeling (BIM) and Artificial Intelligence (AI) has become an important research topic in architecture, engineering, construction, and facility management. However, existing reviews mostly classify related studies according to technical domains or AI techniques, rather than examining how BIM is used within AI-based workflows. This study presents a systematic review of BIM–AI research published between 2015 and 2025. Following a PRISMA-based process, 113 studies were selected from Scopus and Web of Science and analyzed according to five dimensions: (i) the BIM–AI problem addressed, (ii) the specific AI algorithm used, (iii) the broader AI method applied, (iv) BIM's role within the AI workflow, and (v) the validation approach used to evaluate the workflow. The results show that BIM–AI research is mainly concentrated on Scan-to-BIM automation, condition assessment, and energy performance prediction. Deep learning is the most widely used AI method, while machine learning remains common in prediction and management-related studies. The findings also show that BIM is often used as a data source or a visualization environment, whereas semantic BIM integration is less frequent. The reviewed BIM–AI workflows are mostly evaluated through case studies and experimental demonstrations, while benchmark-based evaluation and cross-validation are less frequently used in the reviewed studies. Overall, the review shows that BIM–AI research is rapidly expanding but remains methodologically fragmented. The study contributes by identifying dominant research directions, underexplored areas, and opportunities for further developing BIM–AI workflows, semantic integration, and validation strategies.

Keywords:
Building Information Modeling; Artificial Intelligence; BIM–AI integration; Machine Learning; Deep Learning

1. Introduction

Building Information Modeling (BIM) has become a central approach in the Architecture, Engineering, Construction, and Operations (AECO) sector, enabling building geometry, components, and related information to be represented in a structured way throughout the building lifecycle [1]. Before the recent expansion of BIM–AI research, algorithm-aided BIM studies had already examined how computational methods could support collaboration and optimization in BIM-based project workflows [2–4]. At the same time, Artificial Intelligence (AI), including machine learning (ML), deep learning (DL), and large language models (LLMs), has transformed how complex and large-scale data are analyzed, predicted, and used in decision-making processes. The integration of BIM and AI has therefore emerged as an important research direction, supporting automated model generation, intelligent monitoring, predictive performance evaluation, and data-driven decision-making across design, construction, and operation phases [5,6]. In recent years, BIM–AI integration has been increasingly examined in areas such as Scan-to-BIM automation, energy performance prediction, damage detection, construction management optimization, and digital twin-based operations [7–11].

Alongside this expansion, several studies have attempted to systematize the field. However, most existing reviews classify BIM–AI research according to technical domains, project phases, or AI techniques [5,12–16]. While these studies are valuable, they often treat BIM as a background technology or data container. This limitation is important because BIM can function as more than a data repository. It can also serve as a semantic structure, relational information model, digital twin backbone, or decision-support environment. These different uses influence how AI systems are designed, which algorithms can be applied, and how the resulting systems should be validated. However, current review studies rarely distinguish these roles explicitly.

Therefore, several key questions remain insufficiently addressed: How is BIM used within AI-based workflows? Which AI methods are associated with different types of BIM use? How does the level of BIM–AI integration relate to validation strategies?

To address these questions, this study presents a workflow-focused systematic review of BIM–AI research. Rather than classifying studies only by their technical focus, the review develops a multi-layered analytical framework structured around five dimensions: (i) the BIM–AI problem addressed, (ii) the specific AI algorithm used, (iii) the broader AI method applied, (iv) BIM's role within the AI workflow, and (v) the validation approach used to evaluate the workflow.

2. Materials and methods

2.1. Review methodology and search strategy

This study adopted a systematic literature review methodology to examine how BIM and AI technologies are integrated into computational workflows. The review was conducted in accordance with PRISMA principles to ensure transparency and reproducibility [17]. The literature search was conducted in Scopus and Web of Science (WoS), which were selected for their broad coverage of peer-reviewed journals and conference proceedings in architecture, engineering, construction, and computational sciences. The review process followed a predefined protocol covering identification, screening, eligibility assessment, and inclusion.

According to this protocol, the review was limited to English-language journal articles, conference papers, review articles, and conference proceedings published between 2015 and 2025. Publications in medicine and health-related fields were excluded. The search strategy was designed to identify studies that explicitly address BIM–AI integration. For this purpose, BIM-related terms ("BIM", "Building Information Modeling", "Building Information Modelling", "HBIM") were combined with AI-related terms ("AI", "Artificial Intelligence", "Machine Learning", "ML", "Deep Learning", "Neural Network"). After applying the filters, the search resulted with 86 records from Scopus and 136 records from Web of Science (Table 1). The database search was conducted in January 2026. To ensure reproducibility, the search strings used in Scopus and Web of Science are provided in Table 1.

Retrieved records from both databases were combined, and duplicates were removed. The remaining studies were then evaluated through a two-stage selection process. First, titles and abstracts were screened to exclude studies in which BIM was not central, AI methods were not used, the contribution remained purely conceptual, or BIM and AI were applied separately rather than as an integrated workflow. In the second stage, abstracts or, when necessary, full texts were reviewed to exclude studies in which AI was used only as a statistical tool, BIM was used only for visualization, the BIM–AI workflow was not clearly explained, or no validation approach was reported. At the end of this process, 113 studies were identified as eligible for full review. The PRISMA flow diagram is presented in Fig. 1.

Table 1. Search queries, filters, and retrieved records in the Scopus and Web of Science databases

Database	Query Terms	Results	Filters	Results
Scopus	(TITLE("BIM") OR TITLE("Building Information Modeling") OR TITLE("Building Information Modelling") OR TITLE("HBIM")) AND (TITLE("AI") OR TITLE("Artificial Intelligence") OR TITLE("Machine Learning") OR TITLE("ML") OR TITLE("Deep Learning") OR TITLE("Neural Network")) AND PUBYEAR > 2014 AND PUBYEAR < 2026 AND NOT SUBJAREA(medi)	349	SRCTYPE: Journal (j), Conference Proceeding (p); DOCTYPE: Article (ar), Review (re), Conference Paper (cp); LANGUAGE: English; PUBSTAGE: Final	86
Web of Science (WOS)	TI=(BIM OR "Building Information Modeling" OR "Building Information Modelling" OR HBIM) AND TI=(AI OR "Artificial Intelligence" OR "Machine Learning" OR ML OR "Deep Learning" OR "Neural Network*") AND PY=(2015-2025) NOT (SU=Medicine OR SU="Health Care Sciences & Services")	224	Research Areas: Construction & Building Technology, Engineering Civil, Engineering Multidisciplinary, Engineering Industrial, Computer Science Interdisciplinary Applications, Automation & Control Systems, Engineering; Document Types: Article, Proceedings Paper, Review Article; Early Access: Excluded	136

2.2. Data extraction and analysis strategy

Data extraction was performed using a coding framework developed to reveal both the computational and functional characteristics of BIM–AI integration. A standardized table containing bibliographic information and five analytical dimensions – research focus, AI algorithm, AI method, type of BIM use, and validation method – was completed for each of the 113 studies.

The coding scheme included the following categories:

- Publication_Year: The year in which the study was officially published.
- Journal_Name: The name of the journal or conference proceedings in which the study was published.
- Focus: The main application area or research objective of the study.
- AI_Algorithm: The specific AI algorithm used in the study.
- AI_Method: The broader AI method or learning paradigm used in the study.
- BIM_Use_Type: The role assigned to BIM within the AI workflow.
- Validation_Method: The method used to evaluate the proposed BIM–AI approach.

In the research focus dimension, the main application area or research objective of each study was recorded, such as Scan-to-BIM automation, energy optimization, or design decision support. The AI algorithm category captured the specific computational model used, such as Random Forest, convolutional neural networks, transformers, or reinforcement learning. The AI method category grouped these models under broader learning paradigms, including machine learning, deep learning, NLP/LLM-based methods, and hybrid configurations. The BIM use type category indicated how BIM was positioned within the AI workflow, including roles such as data source, semantic structure, visualization environment, simulation environment, or management framework. The validation method category recorded the evaluation strategy adopted in each study, including case studies, experimental validation, simulation-based tests, comparison datasets, cross-validation, expert assessment, and prototype demonstration. For the cross-analysis, the studies were also grouped according to their level of BIM–AI integration – low, medium, or high – based on the extent to which BIM information and relationships were incorporated into the AI workflow.

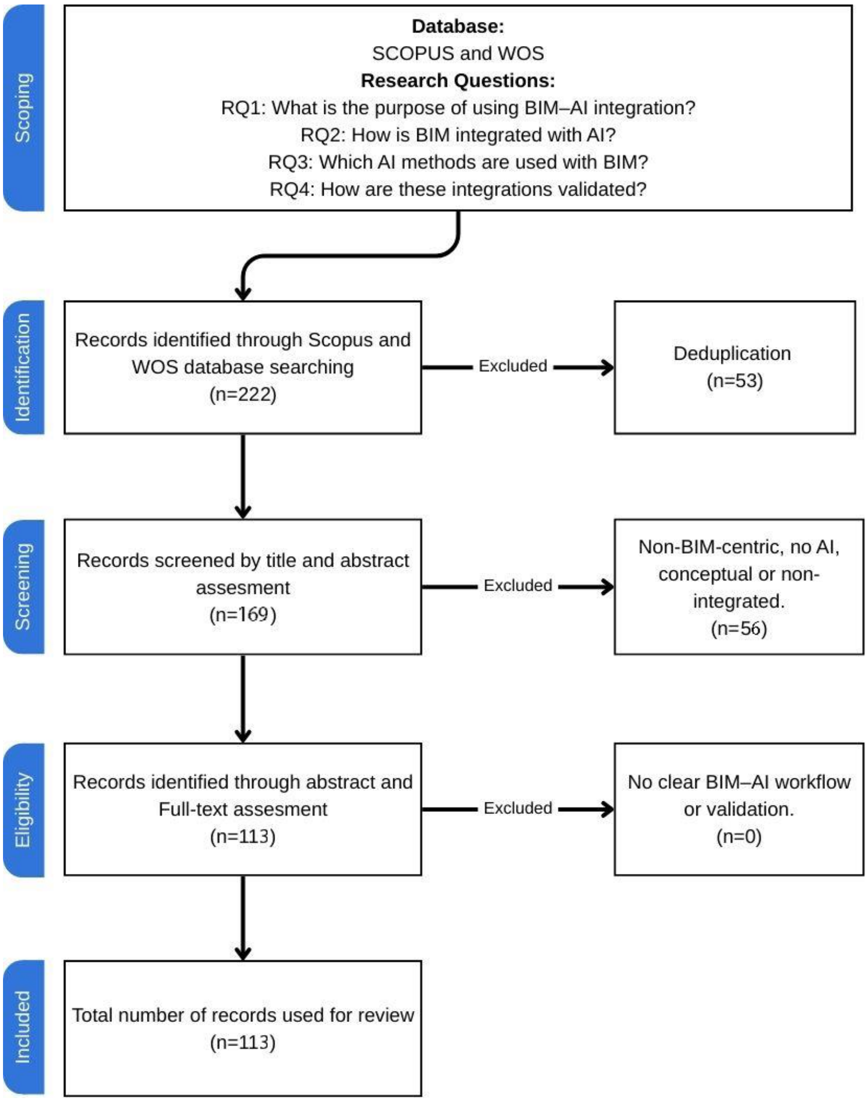

Fig. 1. PRISMA flow diagram of the study selection process

Coding was performed by reviewing abstracts and full texts. When categories were not explicitly stated, they were inferred from the workflow, data structures, and system architecture described in each study. Studies using multiple AI methods or validation strategies were coded according to their primary methodological approach.

The analytical process combined descriptive and relational approaches. Frequency analyses were performed to identify dominant research focuses, BIM use types, AI methods, and validation methods. Subsequently, cross-tabulations were used to examine the relationships between BIM roles and AI methods, as well as between the derived levels of BIM–AI integration and validation strategies. These analyses informed the tables, graphs, and visualizations presented in the Results section, including publication trends, publication outlets, BIM–AI integration objectives, BIM role taxonomy, AI method distributions, and validation–integration relationships.

The screening and coding process was conducted systematically based on predefined criteria. Records were first screened through titles and abstracts; full-text reviews were then conducted when necessary. To ensure comparability, a consistent coding framework was applied across all studies. Although the classification process involved some interpretive judgment, the categories were defined as clearly as possible, and ambiguous cases were resolved by repeatedly cross-checking each study's workflow structure and methodological descriptions.

3. Results

This section presents the results of the systematic analysis of 113 BIM–AI studies. The findings are organized around five analytical dimensions: research focus, AI method, AI algorithm, BIM use type, and validation method. The following sections present the quantitative distributions and cross-analyses derived from these dimensions.

3.1. BIM-AI research trends and distribution

The annual publication trend shows that BIM–AI research began to emerge in the reviewed dataset with two studies published in 2018. This was followed by a gradual increase between 2019 and 2021 (2019: 7; 2020: 5; 2021: 8) and a sharper growth phase after 2021 (2022: 19; 2023: 16; 2024: 27; 2025: 29). Although a slight decline is observed in 2023, the overall trajectory indicates a strong upward trend, with the highest number of publications recorded in 2025. This growth suggests that BIM–AI research has moved beyond an initial exploratory phase and entered a period of rapid expansion and diversification. The cumulative publication curve reaches 113 studies by 2025 and clearly highlights the acceleration after 2021 (Fig. 2; Fig. 3).

Although the BIM–AI literature is distributed across numerous journals and conferences, a significant portion of the publications is concentrated in a small number of core journals. Journals focusing on energy performance, sustainability, and building operations, such as Automation in Construction, Buildings, Advanced Engineering Informatics, and Energy and Buildings, stand out as the main publication outlets for BIM–AI studies. In addition, the dataset shows a long-tail distribution, with many journals represented by only one, two, three, or four articles. This pattern indicates that BIM–AI research is not limited to a single discipline but extends across civil engineering, architecture, computer science, and energy efficiency studies. This fragmented structure also suggests that the field is still undergoing methodological maturation, with core journals shaping the main literature while peripheral outlets address a broader range of BIM–AI problems (Fig. 4).

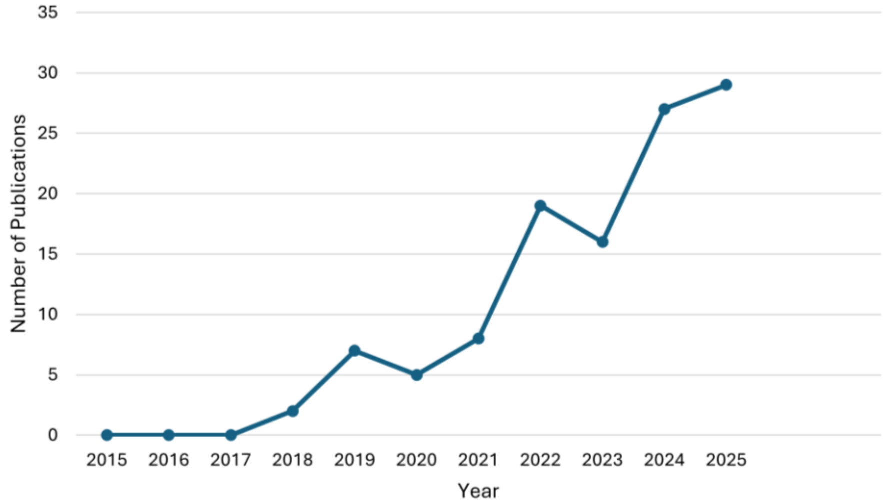

Fig. 2. Annual count of publications in the dataset

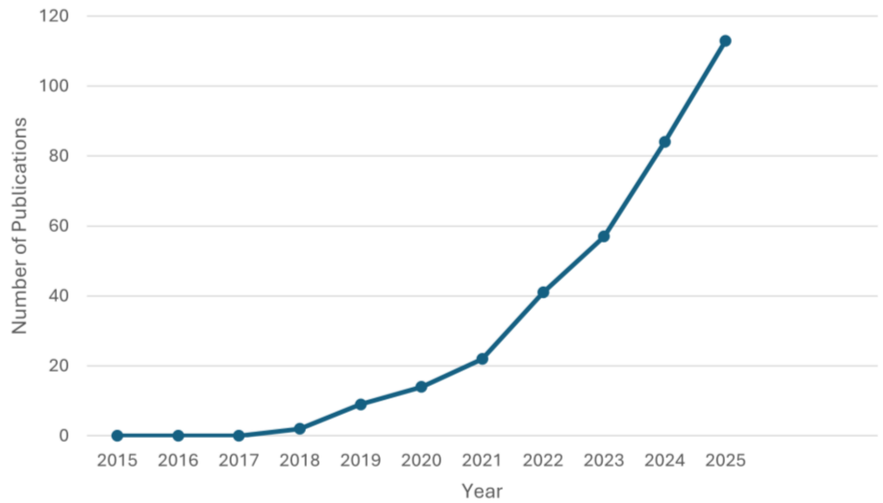

Fig. 3. Cumulative number of publications in the reviewed dataset over time

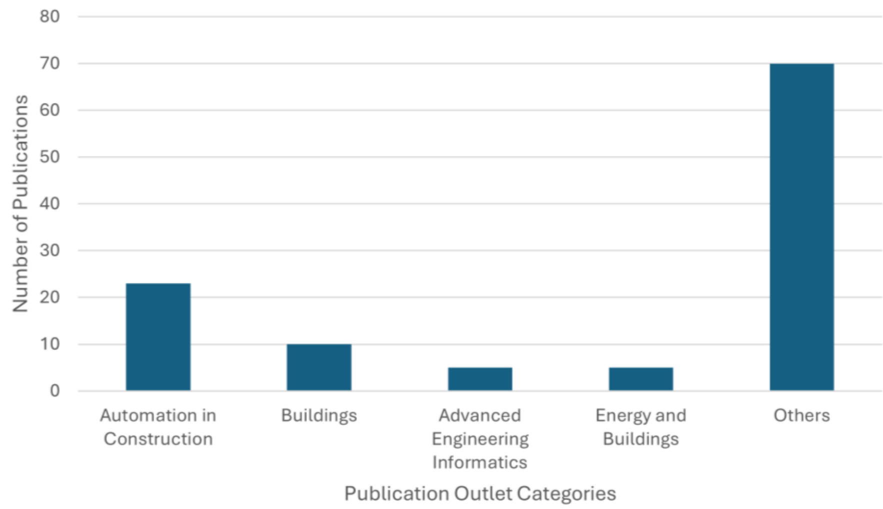

Fig. 4. Distribution of BIM-AI studies according to publication outlets

To further highlight the interdisciplinary nature of BIM–AI research, a keyword co-occurrence network was created based on the keywords extracted from the reviewed studies. The network shows strong connections between BIM, AI, ML, and construction-related topics, while also revealing links with architecture, energy performance, digital twins, and cultural heritage (Fig. 5).

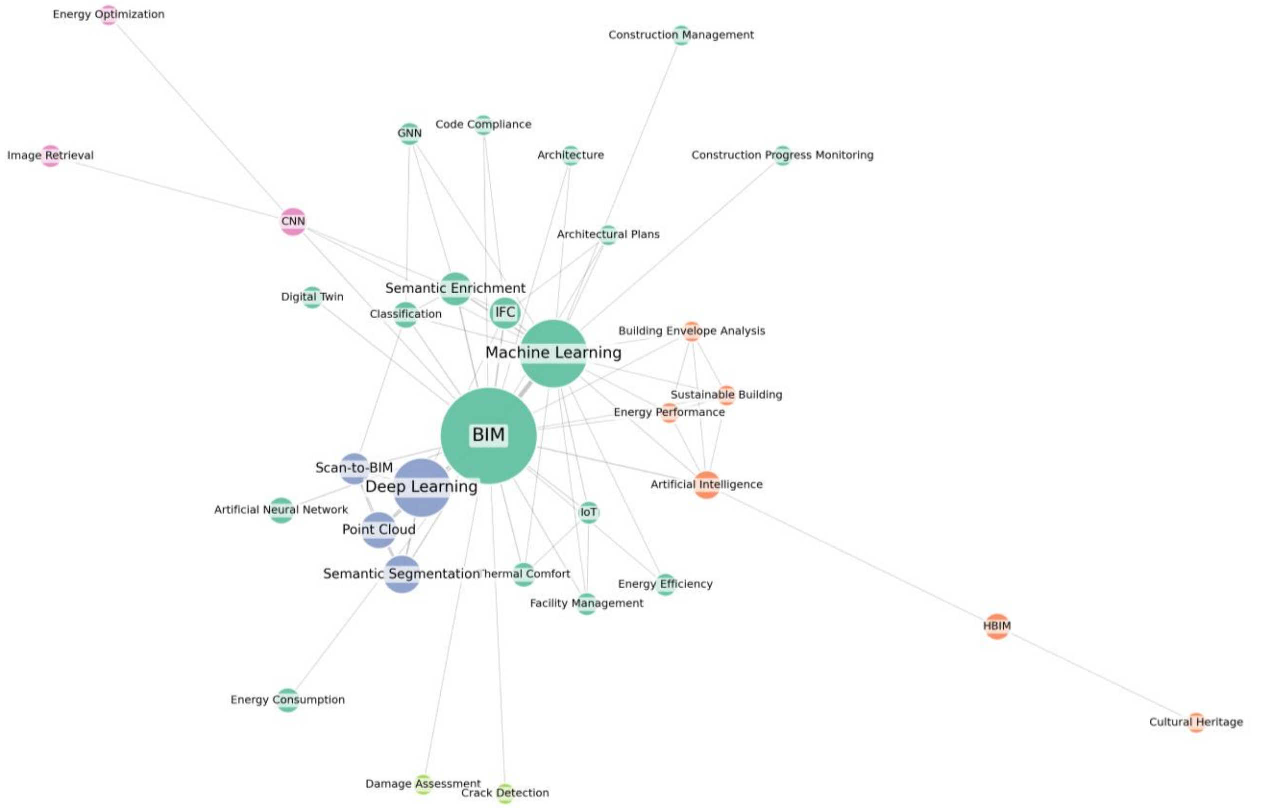

Fig. 5. Keyword co-occurrence network of BIM–AI literature

Another finding shows that BIM–AI research is concentrated in Scan-to-BIM automation, damage detection and condition assessment, and energy performance prediction. These areas constitute a significant portion of the literature, reflecting the dominance of automation-oriented and performance-oriented research agendas. In contrast, design decision support, digital twin-based smart operations, and organizational-level BIM adoption remain relatively limited (Fig. 6).

This distribution indicates that current BIM–AI research primarily addresses issues related to data collection, model enrichment, and operational efficiency. However, the potential of BIM–AI integration to support higher-level design reasoning, strategic decision-making, and continuous digital twin ecosystems remains insufficiently explored.

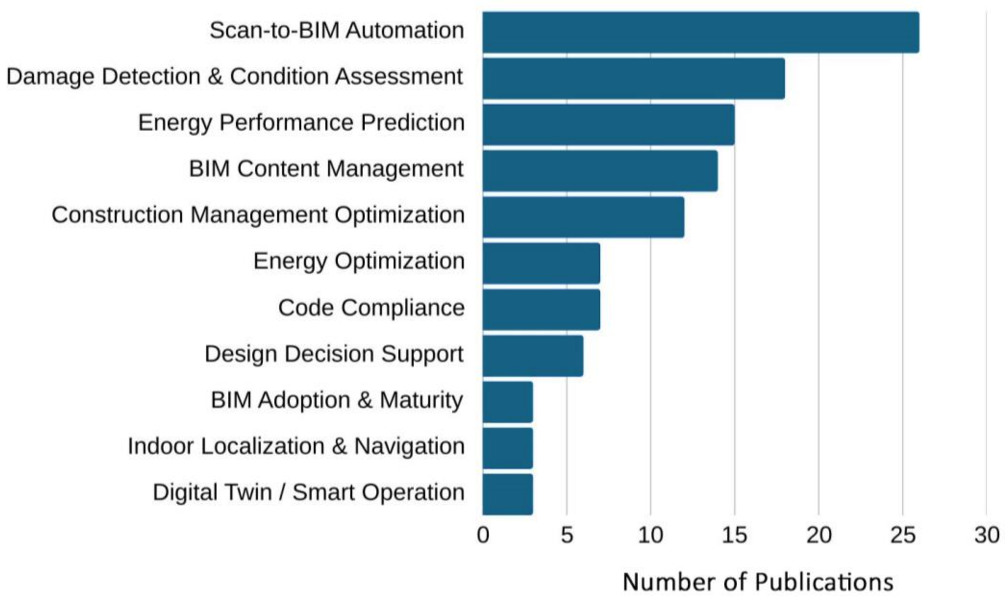

Fig. 6. Research focuses of BIM–AI studies in the reviewed literature

The distribution of AI methods shows a clear dominance of deep learning approaches in BIM–AI research. This pattern can be interpreted in relation to the prevalence of image-based damage detection, While ML and DL learning methods remain relevant, particularly in management-focused and parametric prediction studies, hybrid configurations are still relatively limited. Notably, NLP- and LLM-based approaches are almost absent from the current literature (Fig. 7). These findings indicate that BIM–AI integration is currently driven by perceptual and numerical problem settings, while information-intensive and language-based BIM workflows represent a critical opportunity for future research.

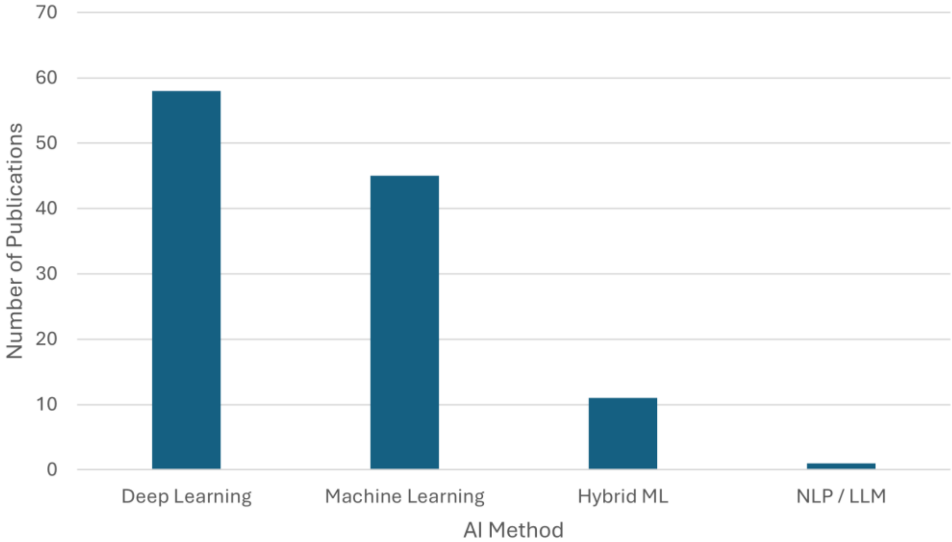

Fig. 7. AI methods used in BIM-AI studies

To further clarify how BIM is positioned within AI workflows, the reviewed studies were analyzed according to their reported types of BIM use. Figure 8 presents this distribution by categorizing BIM as a data source, semantic structure, visualization/context environment, or other/hybrid component.

A significant portion of the reviewed studies fall into the Other/Hybrid category, indicating that BIM's role is often distributed across multiple functions or insufficiently specified. The explicit use of BIM as a semantic structure, including ontology-focused, relational, or graph-based representations, constitutes a smaller but methodologically important subset. Studies that primarily position BIM as a data source or visualization/context environment represent a more limited segment of the literature (Fig. 8).

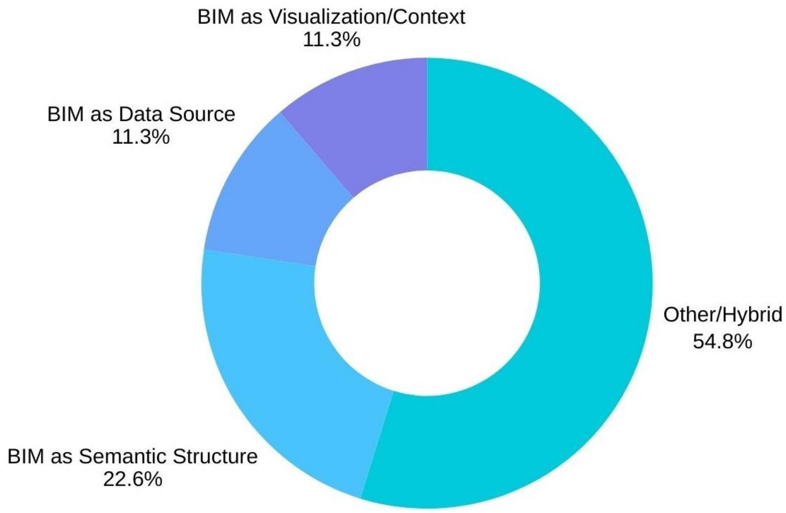

Fig. 8. Roles of BIM within AI workflows in the reviewed studies

To examine the relationship between BIM roles and computational approaches, a cross-analysis was performed between BIM use types and AI methods. The resulting relationships are shown in Fig. 9. These models demonstrate that deeper BIM-AI integrations are not only different in terms of representation, but also compatible with more computationally complex model families. This supports the interpretation that semantic BIM plays a significant role in the development of structurally embedded and learning-intensive BIM-AI systems.

The results reveal a clear relationship between semantic BIM representations and deep learning-based approaches. This indicates that richer BIM structures are predominantly used together with advanced AI techniques. In contrast, studies using traditional machine learning methods are more frequently associated with BIM as a data source or visualization environment. NLP/LLM-based approaches remain marginal in the current BIM–AI literature.

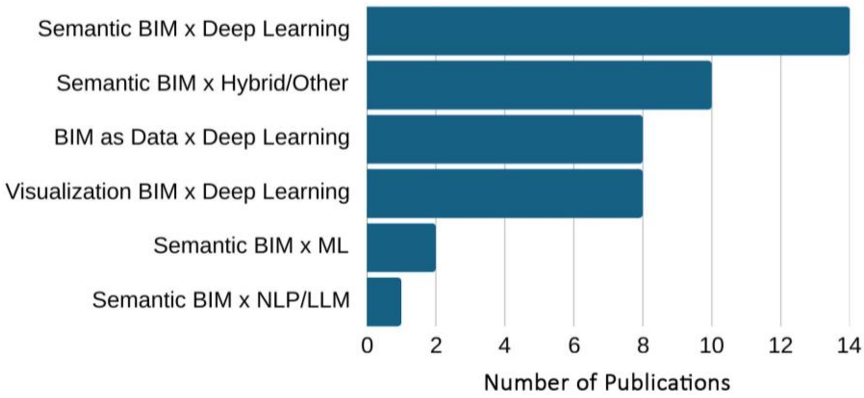

Fig. 9. Relationship between BIM roles within AI workflows and AI methods in the reviewed studies

The relationship between integration depth and validation strategies was analyzed by examining how studies in the low, medium, and high integration categories were empirically evaluated. The results are summarized in Fig. 10. The literature is largely concentrated around medium-depth integrations, which are commonly evaluated through case studies and experimental tests that demonstrate feasibility and operational effectiveness. High-depth integrations remain less frequent; however, these studies more often employ benchmark-based assessments and cross-validation. This pattern suggests that validation practices become more generalizable as the level of BIM–AI integration increases. Low-depth integrations, by contrast, are mostly evaluated through case studies and experimental demonstrations with limited methodological variation.

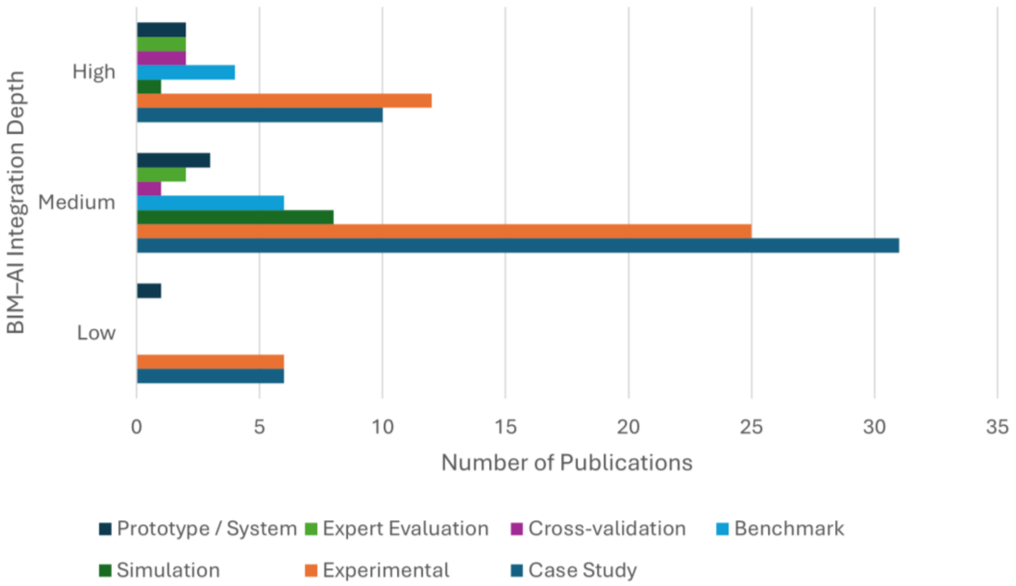

Fig. 10. Distribution of validation strategies across levels of BIM–AI integration

3.2. BIM-AI integration routes and workflows typologies

A review of the literature shows that BIM–AI integration is not a single, homogeneous paradigm. Instead, it consists of different workflow typologies. Understanding these typologies as "integration pathways" is important because they clarify how BIM is positioned within computational processes, how data and semantics are used, and how AI models are connected with building representations. Although a formally established classification system is still lacking in the literature, existing studies provide evidence of diverse BIM–AI workflows [5,15,18]. Based on the analysis of BIM use types, AI methods, and workflow structures, four predominant integration pathways were identified: (i) data-driven BIM–AI pipelines, (ii) semantic and information-rich BIM workflows, (iii) BIM-centered visualization and decision-support systems, and (iv) BIM-based simulation and management frameworks.

3.2.1. BIM as data-driven input for AI models

The integration of BIM into AI workflows often involves the use of BIM as a structured data repository. In this pathway, BIM provides AI models with geometric, material, or performance-related information, thereby supporting model training and prediction. BIM models are typically converted into feature vectors, parametric descriptors, or spatial datasets, which then serve as inputs for machine learning or deep learning algorithms [19–21]. This approach is common in studies on energy performance prediction, construction management optimization, cost estimation, and efficiency analysis [22–26].

In this configuration, BIM data are usually exported from authoring tools or IFC schemas and transformed into tabular, numerical, or voxelized formats before model training [27,28]. These data are then used to predict energy consumption [8,29], identify construction risks [30–32], or optimize schedules and resources [33,34]. Traditional machine learning approaches, such as random forests, support vector machines, and gradient boosting, continue to be widely used in this pathway [7,8,35]. However, deep learning models are increasingly adopted when studies involve image-based, point cloud, or high-dimensional data [36–38].

From a methodological perspective, this pathway emphasizes data availability and predictive performance. However, it often does not preserve the relational and ontological structures of BIM. Therefore, BIM mainly functions as a structured input source and has limited influence on the model architecture or reasoning process. As a result, this pathway is relatively easy to apply and scale, but it provides limited support for high-level reasoning, rule-based interpretation, or semantic decision-making [39,40].

3.2.2. Semantic BIM and knowledge-enriched AI workflows

A smaller but significant group of studies uses BIM not merely as a data container but as a semantic and relational structure that informs AI workflows [41,42]. In this pathway, BIM object hierarchies, spatial relationships, and domain semantics are explicitly used to create information-rich representations, such as ontologies, relational graphs, or rule-enriched datasets [43,44]. These studies generally emerge in contexts where understanding building logic, regulatory constraints, or component interdependencies is central, including code compliance checking, automated model interpretation, and digital twin development [11, 45].

In these workflows, BIM elements are treated not as independent feature vectors, but as interconnected entities embedded within formal schemas. IFC relationships, object classes, and topological connections are preserved or converted into graph-based structures, allowing AI models to operate on relational information [46]. Recent studies also investigate hybrid systems in which data-driven learning is combined with knowledge-based reasoning or semantic enrichment processes [26,39,45]. This pathway represents a shift from predictive modeling toward computational interpretation and knowledge-driven automation.

3.2.3. BIM-centered visualization and decision-support systems

Another important integration pathway positions BIM primarily as an interactive visualization and decision-support environment. In these studies, AI models typically operate outside the BIM platform, while BIM is used to contextualize, visualize, and communicate AI-generated outputs [47–49]. This configuration is common in studies on facility management, construction monitoring, risk visualization, and performance evaluation, where prediction or detection results are fed back into BIM environments to support human decision-making [49,50].

Typical applications include color-coded risk maps, automatic annotation of BIM elements, and dashboard-based BIM interfaces that display AI-derived information. Although this pathway improves interpretability and user interaction, BIM has limited influence on the core AI process, because semantic and relational structures are rarely included in the computation [9,51,52]. Consequently, these workflows are generally characterized by a loose connection between BIM and AI components.

3.2.4. BIM-based simulation and management frameworks

A significant portion of the literature proposes integrated management frameworks that bring together multiple digital components within BIM-based simulation environments [11,34,53]. These studies generally describe platforms, toolchains, or conceptual systems that integrate BIM with AI, IoT, or simulation tools to support construction management, operational monitoring, or digital twin scenarios [53–55].

3.2.5. Comparative implications of BIM–AI integration pathways

The comparison of BIM–AI integration pathways shows a clear shift from loosely connected, data-driven pipelines toward more structurally embedded and semantically rich workflows. Data-driven pathways mainly treat BIM as a quantitative input source, prioritizing predictive performance while often overlooking relational and spatial structures [56,57]. Visualization and decision-support systems occupy an intermediate position, where BIM improves interpretability but rarely contributes to the internal logic of AI models [58,59]. In contrast, semantic BIM workflows incorporate object relationships and formal schemas into computational pipelines, enabling more advanced interpretation and knowledge-based automation [60,61].

This progression is also reflected in methodological choices and validation strategies. Semantically enriched workflows are more frequently associated with deep learning or hybrid approaches that can operate on structured data [31], while loosely connected pathways predominantly rely on traditional machine learning architectures [6,53,58,59]. Similarly, higher integration depth tends to coincide with more rigorous validation strategies, including benchmark-based evaluation and cross-validation, whereas loosely coupled workflows are mostly evaluated through case studies and proof-of-concept experiments [37,64,65].

3.3. AI methods and validation patterns

In addition to integration pathways, the reviewed studies reveal clear methodological trends in the types of AI approaches used and the rigor of validation strategies. These patterns indicate the current level of methodological maturity in BIM–AI research and clarify the distinction between exploratory workflows and more structurally embedded systems. In this context, “depth of integration” refers to the extent to which BIM is embedded within AI workflows, ranging from loosely connected data exchange to semantically integrated and feedback-driven systems. “Semantic BIM” refers to the use of BIM not merely as a geometric model or data repository, but as a relational and information-rich structure that supports computational interpretation.

3.3.1. Distribution of AI methods

The distribution of AI methods demonstrates a clear dominance of deep learning approaches in BIM–AI studies. This reflects the prevalence of perception-focused tasks such as damage detection, Scan-to-BIM automation, and visual condition assessment, where convolutional and representation learning models are particularly effective. Traditional machine learning techniques, including random forests and support vector machines, continue to be widely used in management-focused and performance prediction studies that rely on structured BIM-derived features for regression and classification tasks [66–69].

Hybrid methodologies that integrate data-driven learning with domain expertise, rule-based frameworks, or semantic enhancement remain relatively limited, but they are methodologically important [26,39]. Notably, NLP- and LLM-based methods are largely absent from the reviewed literature, indicating that text-based BIM artifacts, including specifications, regulatory documents, and IFC schemas, remain underexplored in BIM–AI research.

3.3.2. Validation strategies and levels of BIM–AI integration

Validation analysis indicates that BIM–AI studies are predominantly evaluated through case studies and experimental demonstrations, with a primary focus on feasibility and proof-of-concept performance [70–72]. However, a smaller subset of studies employs more rigorous validation practices, such as comparative evaluation, cross-validation, and comparative performance assessment [65,73,74].

Cross-referencing validation methods with BIM integration depth reveals a systematic relationship between integration depth and evaluation rigor. Semantically enriched and structurally embedded BIM–AI workflows are associated with more frequent use of comparative datasets and cross-validation procedures [37,64], whereas loosely coupled pipelines, where BIM primarily serves as a data source or visualization environment, are mostly evaluated through single-project case studies or pilot applications [63,75–77]. This pattern demonstrates that deeper BIM integration coincides with a transition from demonstrative validation toward performance-focused validation.

3.4. Feedback-driven BIM–AI ecosystems

Although many reviewed studies demonstrate the potential of BIM–AI integration, fully closed-loop, feedback-driven BIM ecosystems remain relatively limited. Only a small number of studies treat BIM as a continuously updated digital twin, where perception, interpretation, learning, and model updating are performed within an integrated computational cycle [53,78]. Most current studies still adopt unidirectional workflows, in which data are processed by AI models and the results are then fed back into BIM environments [60,77,79].

This observation indicates a structural gap between current BIM–AI applications and the vision of smart building systems. The scarcity of semantic BIM cores, hybrid reasoning-learning frameworks, and real-time feedback integration suggests that BIM–AI research still largely focuses on task-specific automation rather than adaptable, system-level intelligence [39,48,66].

3.5. Synthesis of key findings

To provide a comprehensive overview of the findings, the main bibliographic patterns identified across the five analytical dimensions are summarized in Table 2. This synthesis reveals that studies are concentrated in automation- and performance-focused areas, that deep learning approaches are dominant, and that BIM is widely used within AI workflows either as a hybrid or loosely defined component. Additionally, validation strategies largely rely on case studies and experimental setups, while comparative evaluation and benchmarking are used only to a limited extent.

Overall, the reviewed studies consistently indicate that BIM–AI research is rapidly expanding but remains methodologically fragmented. Collectively, the reviewed literature highlights complementary developments in automation, semantic modeling, digital twins, energy analysis, infrastructure management, heritage applications, and intelligent decision-support systems, while also revealing substantial opportunities for semantic integration, hybrid AI methodologies, and more rigorous validation frameworks [80–127].

Table 2. Synthesis of key findings across analytical dimensions

Dimension	Dominant Patterns	Secondary Trends	Identified Gaps	Methodological Implications
Research Focus	Scan-to-BIM, damage detection, energy prediction dominate	Construction management, BIM content management	Design decision support, digital twin systems underrepresented	Shift needed toward design-phase and system-level intelligence
AI Algorithm	CNNs and deep neural networks widely used	Random Forest, SVM, Gradient Boosting common in structured tasks	Limited use of graph-based models, reinforcement learning, transformers	Opportunity for advanced architectures aligned with relational BIM
AI Method	Deep learning dominates	Machine learning still active in structured prediction	NLP/LLM approaches largely absent	Opportunity for text-based BIM reasoning
BIM Use Type	Hybrid/undefined BIM use most common	Data-source usage frequent	Semantic BIM relatively limited	Need for explicit semantic modeling
Validation Method	Case study & experimental validation dominant	Simulation-based validation increasing	Benchmark & cross-validation limited	Weak validation culture in low-integration studies

4. Discussion

This study goes beyond application-based classifications of BIM–AI research by examining how BIM and AI are integrated into computational workflows. In this context, the four integration pathways identified in Section 3.2 – namely, data-driven BIM–AI pipelines, semantic and information-rich BIM workflows, BIM-centric visualization and decision-support systems, and BIM-based simulation and management frameworks – provide a structured foundation for interpreting the heterogeneity observed in the literature. This classification explicitly links types of BIM use with AI methodologies and validation strategies, thereby supporting the proposed integration-centered taxonomy. Furthermore, it facilitates a clearer understanding of how different levels of integration – ranging from loosely coupled data processing pipelines to more advanced, knowledge-based, and feedback-driven BIM–AI systems – influence system capabilities.

The results indicate that BIM and AI are often only loosely connected. While BIM is largely used as a data source or a visualization environment, AI models operate independently. Such configurations are common in perception-focused tasks, such as damage detection, Scan-to-BIM automation, and infrastructure assessment. In these tasks, deep learning models process images or point clouds and then map the results back to BIM environments. Although these processes support the interpretation and use of AI-generated outputs, they often do not utilize BIM's semantic and relational structures, which limits BIM's influence on the operation of AI systems.

Conversely, less common semantic and information-intensive BIM workflows exhibit a qualitatively different form of integration. These workflows support advanced reasoning, rule-sensitive interpretation, and greater computational transparency by integrating BIM object hierarchies, relationships, and formal schemas into AI pipelines. The association between semantic BIM integration and validation strategies, such as comparative evaluation and cross-validation, suggests that more interconnected architectures influence not only system structure but also the ways in which these systems are evaluated and justified. This pattern suggests that integration depth may serve as an indicator of methodological maturity in BIM–AI research.

The distribution of AI methods also reveals a methodological imbalance in the literature. Deep learning is currently the dominant approach in this field, reflecting its suitability for image-based and data-intensive tasks. However, machine learning remains relevant for performance prediction and management-related applications. In addition, hybrid methodologies that combine learning-based models with domain expertise or semantic reasoning remain rare, and NLP- or LLM-based studies are almost non-existent. Since many BIM artifacts, such as specifications, regulations, and IFC schemas, are rule- and text-based, this situation highlights an important research gap that requires further investigation.

Finally, the limited development of feedback-driven, closed-loop BIM–AI systems points to a more structural gap in the field. The majority of current studies rely on unidirectional workflows that merely visualize or record AI outputs in BIM models, rather than integrating these outputs into continuously updated digital twin environments. To address this gap, future research should consider BIM not only as a representation and documentation layer, but also as a computational and semantic framework that supports perception, learning, reasoning, and decision-making within an integrated feedback loop.

However, the transition from task-specific BIM–AI applications to fully feedback-driven smart BIM ecosystems presents several practical and technical challenges. First, existing BIM–AI workflows rely heavily on static data exchange, where BIM data are transferred to AI processes and the resulting outputs are subsequently reintegrated into BIM environments. This structure limits the development of continuous feedback loops. Second, the underutilization of BIM's semantic and relational structures restricts AI models' ability to perform context-aware reasoning and dynamic model updates. Third, most existing systems rely on loosely coupled architectures in which AI models operate independently of BIM environments, thereby hindering real-time bidirectional interaction. Finally, validation remains a critical challenge because continuously evolving systems require evaluation frameworks capable of assessing performance over time and across different scenarios and data conditions. These limitations demonstrate that achieving feedback-driven BIM–AI ecosystems requires not only technological integration but also methodological advances in semantic modeling, hybrid AI approaches, and tightly interconnected system architectures.

5. Conclusions

This study presents a workflow-focused systematic review that moves beyond application-based classifications to examine how BIM and AI are integrated within computational processes. Based on the analysis of 113 relevant studies across five analytical dimensions, this review offers a structured perspective on not only where BIM–AI systems are applied, but also how they are computationally structured and empirically evaluated.

The results reveal that current BIM–AI research is predominantly characterized by loosely integrated, data-driven and visualization-driven workflows. This is particularly evident in areas such as Scan-to-BIM automation, condition assessment, and performance prediction. In contrast, the smaller group of semantically enriched BIM workflows represents a different form of integration, enabling relational reasoning, knowledge-driven automation, and more transparent system behavior. The relationship between integration depth and validation strategies further suggests that deeper BIM–AI integration is associated with more comparative and performance-focused evaluation approaches.

This review also shows a methodological imbalance in the literature. Although deep learning methods are common, hybrid learning-reasoning frameworks and NLP/LLM-based methods remain limited in the reviewed dataset. This gap is particularly significant because many BIM artifacts are inherently semantic and textual. Moreover, fully feedback-driven BIM–AI ecosystems and operational digital twins remain uncommon, indicating that current research has not yet fully addressed the development of smart, adaptable built environments.

These findings indicate that future BIM–AI research should move from loosely defined integration toward more explicitly structured integration architectures, clearer definitions of BIM's computational role, and validation approaches aligned with the intended level of integration. This direction is necessary for BIM–AI systems to develop beyond task-specific applications and function as interpretable and adaptive components of the building lifecycle.

The findings also have direct implications for industry practice. Loosely coupled, data-driven workflows may provide immediate efficiency gains in specific tasks; however, more integrated decision-support and digital twin applications require richer BIM data structures, standardized data schemas, and interoperable workflows. Practitioners should therefore consider not only the performance of individual AI tools, but also how BIM information is structured, exchanged, and updated within the overall workflow. In addition, more tightly integrated BIM–AI systems require evaluation frameworks that support reliability, transparency, and accountability in real-world decision-making processes. In this respect, emerging digital twin platforms provide a promising environment for moving from isolated AI applications toward adaptive, feedback-driven BIM–AI ecosystems.

Despite its contributions, this review has certain limitations. The analysis is based on a predefined dataset obtained from Scopus and Web of Science, which may have excluded relevant studies from other sources. Furthermore, while the coding process was systematic, it involved interpretive judgments when classifying types of BIM use and integration pathways. The study also focuses on workflow structures rather than quantitatively comparing the performance of individual systems. These limitations suggest directions for future research, including expanding the dataset, developing quantitative metrics to evaluate BIM–AI integration, and conducting empirical studies to validate feedback-driven and semantically enriched BIM–AI systems in real-world contexts.

By highlighting BIM's function within AI workflows and integration depth, this study contributes to an integration-centered taxonomy that can support more transparent system design, more comparable research results, and the development of BIM–AI workflows that are better aligned with their computational purposes and validation requirements.

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