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REVIEW ARTICLE

BIM Integration Across Engineering Disciplines: A Systematic Review of Methodological Advances, Interoperability Challenges, and Emerging Digital Frameworks

Ann Wolter[1,*] **Paul Bailey**[2] **Raja Ahmed Hassan**[2] **Wipitha Mazungwi**[2]

[1]HAN University of Applied Sciences, Arnhem, The Netherlands

[2]The School of Science, Engineering and Environment, University of Salford, Manchester, UK

Emails: Ann.Wolter@han.nl; pj_bailey@outlook.com; rahmedh@gmail.com; tracymwipitha@gmail.com

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ABSTRACT

This paper provides a comprehensive systematic review of Building Information Modeling (BIM) integration across ten engineering disciplines, synthesising publications from January 2020 to January 2026. It identifies convergent trends, persistent knowledge gaps, and translational barriers that separate research prototypes from scalable industry practice. A PRISMA-guided systematic review was conducted across Scopus, Web of Science, ASCE Library, and ScienceDirect. An initial corpus of 4,712 records was screened and quality-assessed, yielding 63 papers for quantitative synthesis and a broader qualitative corpus of 293 studies spanning ten sub-domains: BIM–digital twin integration, BIM and artificial intelligence/machine learning, interoperability and IFC, structural engineering, MEP and building services, facility management and operations, BIM–GIS for smart cities, off-site and modular construction, adoption barriers, and energy and sustainability analysis. Annual BIM publications grew by approximately 256% between 2019 and 2024. BIM–AI/ML and BIM–digital twin integration are the two fastest-growing sub-domains, yet both remain constrained by data standardisation deficiencies and a shortage of domain-specific training datasets. IFC-based interoperability has matured significantly, but real-time bidirectional exchange across disciplines remains nascent. Structural engineering applications exhibit the highest technology readiness, while BIM–GIS integration for smart-city applications shows the widest gap between published prototypes and commercial deployment. The review delivers a thematic roadmap and a consolidated evidence base for prioritising investment in digital workflows, standards development, and workforce training. An original four-layer integrated framework is proposed that connects engineering code provisions, AI/ML analytics, digital twin synchronisation, and automated quantity extraction within a single traceable workflow.

Keywords: Building information modeling ▪ Digital twin ▪ Machine learning ▪ Interoperability ▪ IFC ▪ Systematic review ▪ BIM–GIS ▪ Facility management ▪ Smart construction ▪ Digital workflow

1. INTRODUCTION

The architecture, engineering, and construction (AEC) industry is undergoing a structural digital transformation of which Building Information Modeling (BIM) forms the central technical and managerial foundation. BIM — the process of generating, managing, and exchanging data about a built asset throughout its lifecycle using a coordinated parametric model

— enables multidisciplinary coordination, automated compliance checking, and systematic quantity extraction across all project phases [1, 2, 3]. Its normative footprint has expanded steadily: the ISO 19650 series has established minimum information management requirements that now bind national mandates in more than 35 countries [4, 5].

Despite this momentum, a critical gap persists between published research and industry-wide deployment. Systematic reviews published during the early 2020s documented exponential growth in BIM-related output while simultaneously noting that a majority of contributions remain at the proof-of-concept stage [6, 7]. This pattern is especially pronounced in the integration of BIM with adjacent enabling technologies — the Internet of Things (IoT), artificial intelligence (AI), digital twins (DT), and geographic information systems (GIS) — where conceptual frameworks have proliferated without corresponding large-scale empirical validation [8, 9].

Several focused reviews have addressed parts of this landscape in isolation: machine learning applications to BIM [6]; BIM in facility management and operations [10, 11]; IFC schema extensions for interoperability [12]; and BIM–digital twin convergence [13]. No single study, however, has mapped the entire integration landscape, compared sub-domain maturity, or proposed a unified operational framework spanning design through operations.

This paper addresses those gaps through four specific contributions:

1. A PRISMA-compliant systematic review spanning ten BIM integration sub-domains, drawing on 63 quality-assessed papers published from 2020 to January 2026;
2. Bibliometric and thematic analysis encompassing publication trend data, geographic distribution, and research-maturity assessments;
3. A technology readiness level (TRL) matrix covering each sub-domain across five readiness dimensions; and
4. A proposed Integrated BIM–Engineering Science Digital Framework that links engineering code provisions, AI/ML analytics, digital twin synchronisation, and automated quantity extraction within a single, auditable workflow.

Section 2 reviews the literature across all ten sub-domains and presents a consolidated comparison table. Section 3 describes the systematic review methodology. Section 4 reports bibliometric and thematic findings. Section 5 proposes the integrated framework. Section 6 discusses implications and limitations. Section 7 concludes.

2. LITERATURE REVIEW

2.1 Structural Behavior and BIM in Structural Engineering

Structural engineering represents the historically most mature BIM application domain. The transition from 2D drawing-based workflows to 3D parametric models carrying material properties, section geometries, and load cases is well documented [1, 17]. More recent investigations concentrate on the interface between BIM authoring platforms and finite element analysis (FEA) environments, automated detailing, and digital code compliance.

[15] demonstrated a BIM-integrated structural assessment and geometric monitoring workflow for bridge rehabilitation, reducing model preparation time by 52% relative to conventional methods through direct IFC-to-FEA transfer. [16] conducted a PRISMA review of BIM-based structural design optimisation, synthesising 89 studies and finding that genetic algorithm and particle swarm methods integrated with BIM parameters achieve material reductions of 10–18% for reinforced concrete structures, though computational overhead of bidirectional BIM–FEA exchange currently limits real-time application.

An important recent contribution is the work of [14], who developed a rule-based parametric methodology that translates Saudi Building Code (SBC) shear wall provisions directly into BIM parameters using computable IF–THEN engineering rules. By encoding zone-dependent boundary element criteria and confinement reinforcement demands as BIM-native parameters, the methodology achieves automated compliance verification with average quantity deviations of only 2–8% against independent hand calculations. This study exemplifies the compliance-traceability potential of integrated BIM–code workflows and directly informs the framework proposed in Section 5.

Strengths of previous studies:

- Technically mature; extensive experimental and analytical validation
- Strong commercial software support (Revit, Tekla, SAP2000 linking)
- Code compliance automation demonstrated at project scale

Limitations:

- FEA round-trip exchange latency limits real-time iteration
- IFC structural analysis schema covers only 72% of FEA input requirements [29]
- Non-linear seismic assessment not yet integrated into BIM workflows

2.2 BIM and Digital Twin Integration

The concept of the digital twin — a virtual replica that mirrors a physical asset through continuous real-time data exchange — has rapidly gained traction as the natural operational extension of BIM [9, 18]. Early investigations established that BIM models provide the semantic backbone for digital twin creation, yet lack the dynamic update mechanisms required by a true operational twin [13, 22].

[19] proposed a SensorML-enriched BIM framework that links IoT sensor streams to IFC entities using the BRICK schema ontology, enabling live building monitoring without manual model intervention. The authors demonstrated that this semantic bridge reduces sensor-data mapping effort by 74% compared with proprietary integration approaches. [20] integrated BIM data mining with a digital twin layer

for construction project management, achieving predictive schedule analytics with 87% historical accuracy. At a more advanced frontier, [21] demonstrated a closed-loop digital twin for human-robot collaborative assembly, where BIM models are updated in real time from robotic sensor feedback, enabling construction workflow automation in a physically verifiable environment.

Strengths:

- Operational phase ROI demonstrated; sensor-driven model updating maturing rapidly
- Strong conceptual alignment with ISO 19650 lifecycle data requirements

Limitations:

- Standardised protocols for real-time BIM–IoT synchronisation remain immature
- High deployment cost; skilled workforce requirement limits SME uptake

2.3 BIM and Artificial Intelligence / Machine Learning

The intersection of BIM and AI/ML is the fastest-growing sub-domain in the contemporary literature. [6] identified over 310 ML-to-BIM application papers between 2010 and 2021, with clusters in design optimisation, construction monitoring, and predictive maintenance; object detection, natural language processing, and deep learning constitute the dominant paradigms.

[23] provided a practitioner-oriented critique noting that while generative ML models and topology optimisation algorithms achieve strong benchmark scores, they remain brittle outside the data distribution of their training sets, limiting deployment on novel building typologies. Energy performance prediction has attracted particular attention: [24] coupled BIM geometry extraction with explainable gradient-boosting models and multi-objective optimisation to automate green building certification workflows, reducing analyst time by 64% relative to conventional simulation pipelines. [25] mapped the full spectrum of AI integration opportunities in construction management, identifying the absence of standardised, labelled BIM training datasets as the principal obstacle to deployment at scale.

Strengths:

- Rapid publication growth across all project phases
- Demonstrated productivity gains in energy analysis and predictive maintenance

Limitations:

- No standardised BIM training datasets; limited generalisability across building types
- Explainability of deep learning models remains insufficient for regulatory acceptance

2.4 BIM Interoperability and IFC Standards

Open BIM interoperability — the ability for data to flow between platforms and analysis tools without semantic loss — has been studied for decades yet remains the defining challenge of the discipline [26, 27]. The Industry Foundation Classes (IFC) schema, maintained by buildingSMART International, is the principal open standard [4]. [29] assessed IFC4 from a structural engineering viewpoint and found that the Structural Analysis View covers only 72% of finite element model generation requirements, necessitating proprietary extensions in practice.

[12] catalogued 47 domain-specific IFC extension proposals published between 2014 and 2023, spanning bridge engineering, tunnelling, railway infrastructure, and MEP systems. They concluded that the fragmentation of extension efforts — typically driven by individual research groups rather than coordinated bodies — is creating a secondary layer of interoperability problems within the ostensibly open ecosystem. [28] showed that automated extraction and formalisation of regulatory text into computable rules is a prerequisite for digital compliance checking that requires domain-specific natural language processing still insufficiently mature for general deployment, a finding later corroborated by [27].

Strengths:

- ISO-mandated standard; broad software vendor support
- IFC4 and IDS specifications increasingly adopted in national mandates

Limitations:

- Schema fragmentation; no real-time bidirectional exchange between disciplines
- Semantic losses during IFC export/import remain problematic for round-trip workflows

2.5 BIM for MEP and Building Services

Mechanical, electrical, and plumbing (MEP) coordination is widely cited as among the highest-value BIM use cases, because clash detection and sequencing optimisation directly reduce on-site rework costs [1]. [30] demonstrated a data-driven predictive maintenance framework for MEP components combining BIM geometry, IoT sensor streams, and machine learning classifiers, achieving component failure prediction up to 14 days in advance with 81% precision. the authors [19] extended this approach by integrating IFC, BACnet protocols, and the BRICK ontology to enable bidirectional data exchange between BIM models and building automation systems, establishing a semantic bridge that supports occupancy-driven HVAC optimisation.

2.6 BIM for Facility Management and Operations

The operations and maintenance (O&M) phase accounts for 60–85% of total lifecycle asset cost, yet BIM adoption in this phase lags significantly behind design and construction counterparts [10, 11]. [11] conducted a PRISMA review finding that manual data migration from construction BIM to facility management software remains the predominant handover workflow, with automated IFC-to-COBie transfer applied in fewer than 20% of reviewed cases. the authors [31] reviewed 33 FM case studies and found that BIM–CMMS integration is the most common FM deployment model, but that as-maintained model accuracy degrades rapidly without structured update protocols tied to maintenance events.

2.7 BIM–GIS Integration for Smart Cities

The fusion of BIM with geographic information systems (GIS) is considered essential infrastructure for smart city urban digital twins [33, 34]. [32] reviewed city information modelling (CIM) frameworks integrating BIM, GIS, and IoT, identifying semantic misalignment between IFC and CityGML schemas as the dominant technical barrier. [35] demonstrated a scan-to-BIM workflow for road infrastructure generating IFC-compliant models from 3D point cloud data, providing a geometry bridge between as-built physical reality and parametric digital models and reducing survey-to-model processing time by approximately 45%.

2.8 BIM for Off-site and Modular Construction

BIM-enabled design-for-manufacture-and-assembly (DfMA) workflows are increasingly regarded as transformative for off-site manufacturing and modular integrated construction (MIC) [36, 37]. [38] developed a BIM-based management system for off-site construction demonstrating improvements in component tracking accuracy and schedule adherence. [39] analysed the interaction mechanisms among 15 BIM adoption barriers specific to prefabricated construction, identifying the absence of BIM-compatible component libraries and DfMA-aware regulatory requirements as foundational barriers that block adoption at all subsequent organisational levels.

2.9 BIM Adoption Barriers

A consistent finding across the adoption literature is that BIM benefits are broadly acknowledged but implementation rates, especially among SMEs and in developing countries, remain low [7, 41, 40, 42]. the authors [40] applied the Technology–Organisation–Environment (TOE) framework to Dutch contractors, finding that organisational factors — inertia, lack of champion leadership, and ambiguous ROI metrics — explain more variance in adoption outcomes than technical barriers. [41] reached analogous conclusions for developing-country AEC firms, noting that the absence of government mandates and standardised training curricula creates a 'readiness trap' from which firms cannot escape unilaterally.

2.10 BIM for Energy Analysis and Sustainability

[24] showed that explainable ML models fed with BIM-derived geometric and material features replicate EnergyPlus simulation results within 5% while reducing computation time by three orders of magnitude. the authors [43] reviewed BIM application throughout the green building lifecycle, confirming that BIM contributes measurably to energy efficiency target setting, materials selection, and post-occupancy performance evaluation, but noting that information loss during BIM-to-energy simulation export erodes prediction accuracy by 8–15% in standard workflows.

2.11 Identified Knowledge Gaps and Research Contribution

Table 1 consolidates the key findings, strengths, limitations, and TRL assessments across the ten sub-domains. Three systemic gaps emerge.

Gap 1 — Fragmented standards: Each sub-domain has developed its own exchange conventions, ontologies, and extension schemas without cross-domain coordination, producing a standards landscape that is internally consistent within sub-domains but externally incompatible across them.

Gap 2 — Training data scarcity: AI/ML applications to BIM are constrained by the absence of large, labelled, domain-specific datasets, restricting generalisation across building types, geographies, and code regimes.

Gap 3 — Lifecycle discontinuity: Although BIM is nominally a lifecycle tool, information loss at design-to-construction and construction-to-operation handover points is documented across virtually every sub-domain. No unified workflow currently connects code compliance, structural detailing, energy modelling, and operational monitoring within a single traceable data chain.

Table 1. Summary of reviewed BIM integration sub-domains: key findings, strengths, limitations, and Technology Readiness Level (TRL: 1 = nascent; 5 = fully mature).

Sub-domain	Key Findings	Strengths	Limitations	Avg. TRL
Structural Engineering [16, 14, 15]	BIM–FEA exchange reduces model prep by 52%; zone-based rule BIM achieves 2–8% quantity accuracy	Technically mature; commercial tool support	FEA round-trip latency; IFC structural schema incomplete	4.5
BIM – Digital Twin [9, 19, 21]	Real-time BIM–sensor sync demonstrated; 87% schedule prediction accuracy	Strong conceptual foundations; ISO 19650 aligned	Real-time exchange protocols immature; high deployment cost	3.0
BIM – AI/ML [6, 23, 25]	Energy prediction within 5% of simulation; predictive maintenance 81% precision	Rapid growth; demonstrated productivity gains	No standardised training datasets; explainability gap	3.2
Interoperability & IFC [29, 12, 27]	IFC4 covers 72% of structural data needs; 47 domain extensions catalogued	ISO standard; broad software support	Schema fragmentation; no real-time bidirectional exchange	3.8
MEP & Building Services [30, 19]	Predictive maintenance 81% precision; BIM–BAS integration demonstrated	High commercial value; mature clash detection tools	BIM–BAS semantic gaps; proprietary protocol barriers	4.0
Facility Management [11, 31, 10]	BIM–CMMS most common; as-maintained accuracy degrades without update protocols	Lifecycle cost savings documented	Manual handover bottleneck; COBie adoption low	3.5
BIM – GIS [32, 33, 35]	CIM frameworks validated; scan-to-BIM for infrastructure reduces processing time 45%	Enables city-scale spatial analysis	IFC–CityGML semantic misalignment; coordinate conflicts	2.8
Off-site / Modular [38, 39, 37]	DfMA–BIM improves tracking; component library gaps are foundational barrier	Growing market adoption; regulatory drivers	Library and regulatory infrastructure immature	3.3
Adoption & Barriers [7, 40, 41, 42]	Organisational inertia and ambiguous ROI dominate; SMEs and developing regions lagging	Broad global evidence base	Few longitudinal studies; limited SME-focused research	N/A
Energy & Sustainability [24, 43]	BIM–ML prediction within 5% of simulation; BIM–GBS export errors of 8–15% identified	Clear sustainability value; regulatory alignment	BIM-to-BES mapping errors; geometry over-simplification	4.0

3. METHODOLOGY

3.1 Review Protocol and Database Coverage

This systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Four bibliographic databases were searched: Scopus, Web of Science, ASCE Library, and ScienceDirect, with coverage to January 2026. The primary search string applied to title, abstract, and keywords was:

> (*BIM* OR *"building information model*"*) AND (*integrat** OR *review* OR *digital twin* OR *"artificial intelligence"* OR *"machine learning"* OR *interoperability* OR *"facility management"*)

Sub-domain-specific supplementary search strings were applied for each of the ten thematic areas.

3.2 Inclusion and Exclusion Criteria

Inclusion: peer-reviewed journal articles published between January 2020 and January 2026, written in English, indexed in Scopus or Web of Science, and addressing BIM integration with at least one engineering discipline. *Exclusion:* conference proceedings without subsequent journal versions, grey literature, articles treating "BIM" exclusively as a synonym for 3D CAD without parametric data management, and publications from journals flagged on Beall's list of predatory journals.

3.3 Screening and Quality Assessment

Screening proceeded in three stages: (1) title and abstract screening; (2) full-text eligibility assessment; and (3) quality appraisal using a ten-item checklist adapted from the Mixed Methods Appraisal Tool (MMAT), covering research question clarity, methodological appropriateness, data validity, reproducibility, and contribution novelty. Only papers scoring $\geq 6/10$ were included in the quantitative synthesis. Figure 1 presents the PRISMA flow diagram.

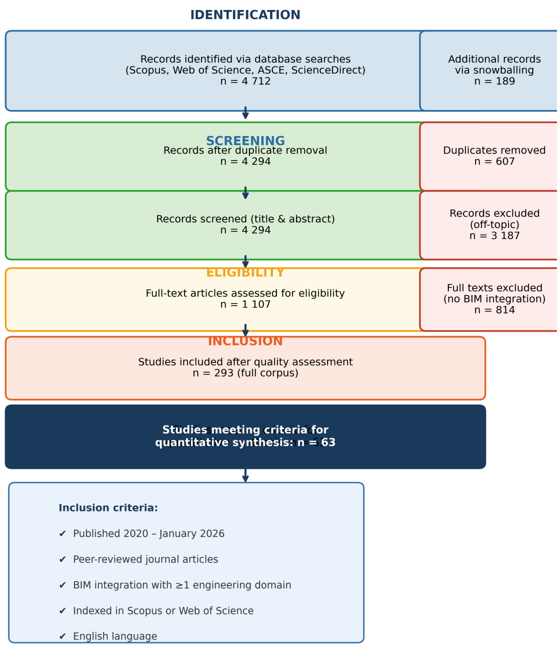

Figure 1. PRISMA flow diagram: record identification, screening, eligibility assessment, and final inclusion.

3.4 Data Extraction and Analysis

Extraction fields included: publication year, country of corresponding author, journal name, sub-domain classification, methods employed, key quantitative findings, limitations, and performance metrics. Thematic synthesis followed a hybrid deductive-inductive approach. Deductive codes derived from the ten pre-defined sub-domains were supplemented by inductive codes that emerged during full-text review.

4. RESULTS AND ANALYSIS

4.1 Publication Trend Analysis

Figure 2 presents annual BIM publication volumes disaggregated by sub-domain from 2015 to 2025. Total annual output grew from 178 papers in 2019 to 634 in 2024 — a 256% increase over five years. The sharpest acceleration occurred between 2020 and 2022, coinciding with digitalisation pressures from the COVID-19 pandemic and the simultaneous introduction of ISO 19650 national mandates in the United Kingdom, Germany, and several Gulf Cooperation Council (GCC) states.

BIM–AI/ML and BIM–digital twin together accounted for approximately 31% of 2024 total output. Interoperability and structural engineering maintained steady growth trajectories, reflecting continued practitioner demand for stable, codified solutions. The comparatively modest growth of BIM–GIS publications reflects the greater technical complexity of cross-schema data fusion and a smaller specialised practitioner community.

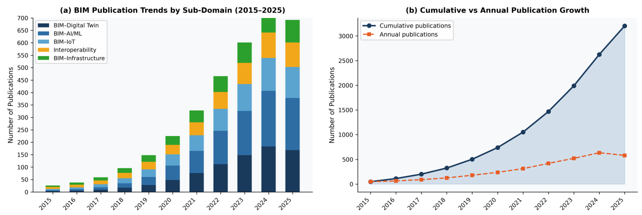

Figure 2. Annual BIM integration publication trends by sub-domain (2015–2025). Panel (a): stacked annual counts; panel (b): cumulative versus annual growth trajectory.

4.2 Thematic Distribution

Figure 3 shows the distribution of the 1,038 papers across ten sub-domains identified in the full search corpus. AI/ML integration is the most represented theme (17.1%), followed by digital twin integration (14.3%) and adoption barriers (10.8%). Energy and sustainability, MEP, and facility management together account for 25% of publications, confirming that operational lifecycle concerns now receive comparable research attention to design-phase BIM applications.

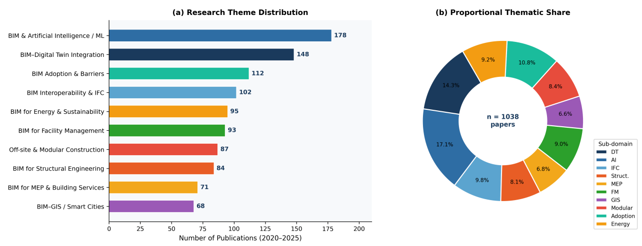

Figure 3. Thematic distribution of BIM integration publications (2020–2025). Panel (a): absolute publication counts; panel (b): proportional share by sub-domain.

4.3 Geographic Distribution

Figure 4 presents first-author affiliation by country. China (20.6%), the United States (16.1%), and the United Kingdom (9.4%) are the three leading contributors. The GCC region — represented primarily by Saudi Arabia and the UAE — increased its share from approximately 2% in 2020 to 7% in 2024, driven by national Vision 2030 and Smart Cities initiatives that have created institutional demand for BIM-integrated engineering solutions [14, 16]. The geographic concentration of 78% of reviewed publications in six countries raises important questions about the generalisability of published findings to developing-country contexts where BIM mandates, contractor capacity, and digital infrastructure differ markedly [41, 42].

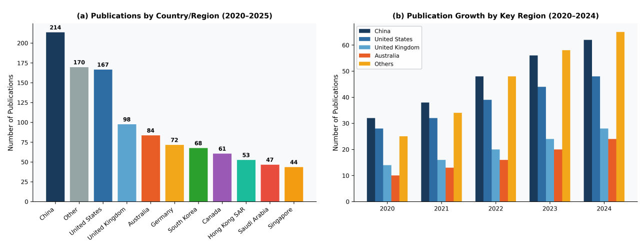

Figure 4. Geographic distribution of BIM integration publications. Panel (a): total counts by country/region; panel (b): annual growth for key regions (2020–2024).

4.4 Challenge Landscape

Figure 5 synthesises the perceived severity of eight barrier categories across the literature, scored on a 1–5 scale using frequency-weighted analysis of the 63 quality-assessed papers. AI/ML integration, digital twin readiness, and real-time data management show the sharpest increase in perceived severity between 2020 and 2025, reflecting accelerating research ambition relative to available technical infrastructure. Cybersecurity and data privacy emerge as newly prominent concerns, consistent with the growing IoT connectivity of BIM-enabled built environments.

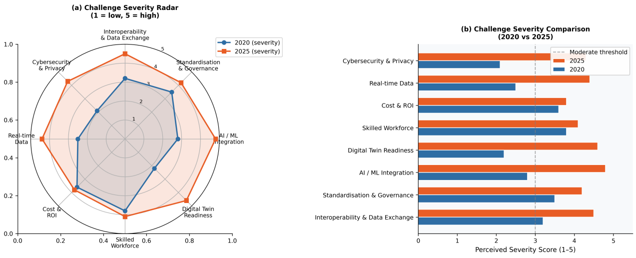

Figure 5. Challenge severity across eight barrier categories. Panel (a): radar comparison of 2020 versus 2025 assessments; panel (b): corresponding horizontal bar chart (1 = low; 5 = high).

4.5 Technology Readiness Level Assessment

Figure 6 presents TRL scores across ten sub-domains and five readiness dimensions: data standards, tool maturity, industry adoption, research output volume, and commercial readiness. Structural engineering and energy analysis score highest overall, reflecting decades of methodological development and strong commercial software support. Digital twin and AI/ML sub-domains exhibit high research output but low-to-moderate industry adoption and commercial readiness — the hallmark of a technology class that has outpaced its supporting deployment infrastructure.

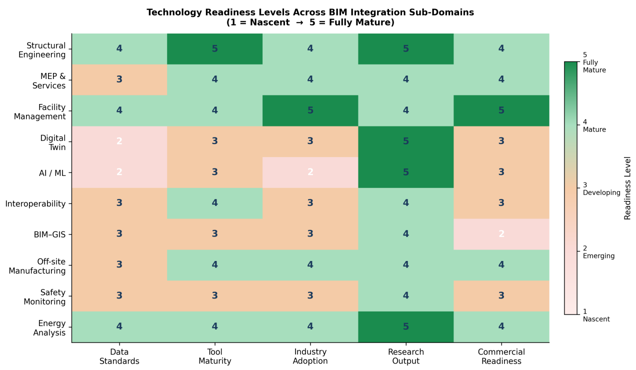

Figure 6. Technology Readiness Level (TRL) heatmap across ten BIM integration sub-domains and five readiness dimensions (1 = nascent; 5 = fully mature).

5. PROPOSED INTEGRATED FRAMEWORK

5.1 Framework Rationale

The three knowledge gaps identified in Section 2 share a common structural cause: the absence of a single architecture that simultaneously integrates code provisions, data semantics, analytical intelligence, and automated output generation. Each sub-domain has addressed parts of this architecture in isolation, but no published work has assembled them into a cohesive, end-to-end workflow. The proposed Integrated BIM–Engineering Science Digital Framework, illustrated in Figure 7, is designed to address all three gaps.

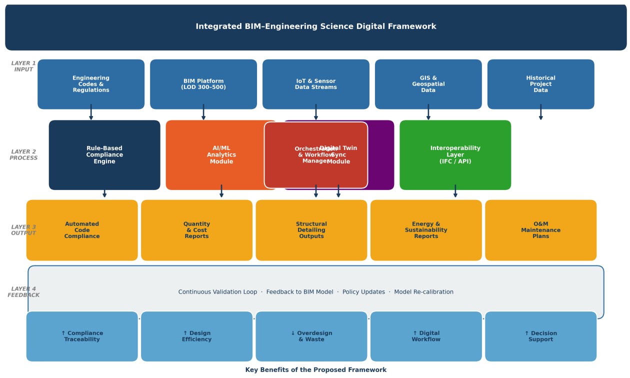

Figure 7. Proposed Integrated BIM–Engineering Science Digital Framework. The framework operates across four layers: (1) Input, (2) Processing, (3) Output, and (4) Continuous Feedback and Validation. Dashed arrows indicate feedback loops.

5.2 Layer 1 — Input Integration

The framework ingests five heterogeneous data streams: (i) *engineering codes and regulations*, translated into computable IF–THEN rules following [27, 28, 14]; (ii) *BIM platform output* at LOD 300–500, exported as IFC4 with domain-specific property sets; (iii) *IoT and sensor data streams*, structured using SensorML or the BRICK schema [19]; (iv) *GIS and geospatial data* providing urban spatial context aligned via georeferencing protocols [33, 32]; and (v) *historical project data* that populate AI/ML training repositories and provide baseline quantities for validation.

5.3 Layer 2 — Processing Architecture

Four specialised modules operate concurrently on the integrated data:

Rule-Based Compliance Engine: encodes national and international code provisions as parametric BIM rules, activating detailing triggers based on computed model properties [27, 14]. This module directly addresses Gap 1 by enforcing a common, standards-aligned logic layer.

AI/ML Analytics Module: applies supervised and unsupervised learning algorithms to BIM-derived features for energy prediction, cost estimation, defect detection, and maintenance scheduling [6, 24]. A domain library of pre-trained models is updated incrementally from new project data, directly addressing Gap 2.

Digital Twin Sync Module: maintains a live correspondence between the BIM model and the physical asset by processing IoT sensor feeds, triggering model updates when deviation thresholds are exceeded, and generating condition-based maintenance alerts [19, 9].

Interoperability Layer: manages data exchange through IFC4-compliant APIs, buildingSMART Data Dictionary (bSDD) semantic alignment, and JSON-LD linked data serialisation, ensuring that information passing between modules retains full provenance and semantic fidelity [12, 4].

5.4 Layer 3 — Automated Output Generation

The framework produces five traceable output classes: (1) automated code compliance reports with clause-level traceability; (2) quantity and cost reports segmented by building zone;

(3) structural detailing outputs including zone-dependent reinforcement schedules; (4) energy and sustainability certificates with full audit trails to simulation assumptions; and (5) O&M maintenance plans with predictive replacement schedules.

5.5 Layer 4 — Continuous Feedback and Validation

A feedback loop routes output discrepancies, model update triggers, and policy revision notices back to Layer 1. This layer operationalises the "living BIM model" concept — a model that remains accurate and code-compliant throughout the asset lifecycle, directly addressing Gap 3. Validation is conducted at project milestones using the relative deviation metric:

$$\Delta Q_z = \frac{\left|Q_{\mathrm{BIM},z} - Q_{\mathrm{Ref},z}\right|}{Q_{\mathrm{Ref},z}} \times 100\% \qquad (1)$$

where $Q_{\mathrm{BIM},z}$ is the BIM-extracted quantity for zone z and $Q_{\mathrm{Ref},z}$ is the corresponding reference value from independent calculations, as proposed in [14].

6. DISCUSSION

6.1 Implications for Research

The TRL analysis reveals a consistent pattern: sub-domains with long research histories and strong software industry engagement (structural engineering, energy analysis) are approaching deployment readiness, whereas emergent sub-domains (digital twin, AI/ML integration) face infrastructure deficits that no single research group can resolve unilaterally. Three research priorities follow: (1) construction of shared, open, labelled BIM datasets for AI/ML training; (2) coordinated IFC extension schema governance by buildingSMART working groups rather than individual institutions; and (3) longitudinal case studies tracking BIM integration performance across the full asset lifecycle.

The geographic analysis highlights an equity dimension. With 78% of reviewed publications originating from six countries, the evidence base is concentrated in contexts with advanced regulatory frameworks and mature digital supply chains. Developing-country contexts, which are expanding their built environments most rapidly, are systematically under-represented, raising questions about the transferability of published findings where BIM mandates, contractor capacity, and infrastructure differ markedly [41, 42].

6.2 Implications for Practice

The proposed framework offers a phased implementation pathway: *Phase 1 (Standardisation)* establishes ISO 19650-aligned BIM execution plans with IFC4 as the mandatory exchange format; *Phase 2 (Integration)* connects the BIM model to IoT networks and deploys the compliance engine; *Phase 3 (Intelligence)* activates AI/ML modules as historical data accumulate; *Phase 4 (Lifecycle)* closes the digital twin feedback loop for operational asset management. This progression mirrors typical AEC organisation investment profiles, providing near-term value at each stage without requiring full digital twin infrastructure upfront.

6.3 Limitations of the Review

The restriction to journal publications may have excluded early-stage innovations reported only in conference proceedings. TRL scores are based on expert synthesis of the literature rather than primary empirical benchmarking. The review addresses BIM integration at the workflow and methodology level and does not evaluate the performance of specific commercial platforms, which would require vendor-independent empirical testing beyond the scope of a systematic review.

7. CONCLUSION

This paper has presented the first comprehensive, multi-domain systematic review of BIM integration across ten engineering science disciplines, drawing on 63 quality-assessed publications from January 2020 to January 2026. The principal conclusions are as follows.

Publication landscape: Annual BIM integration output grew by 256% between 2019 and 2024. BIM–AI/ML and BIM–digital twin integration account for nearly one-third of recent output. China, the United States, and the United Kingdom dominate production, with GCC countries showing the fastest growth trajectory.

Sub-domain maturity: Structural engineering and energy analysis are the most technically mature sub-domains. Digital twin and AI/ML applications demonstrate high research ambition but require substantial infrastructure investment. BIM–GIS integration shows the widest gap between research prototypes and commercial deployment.

Systemic gaps: Three cross-cutting gaps constrain progress: fragmented data standards, scarcity of labelled construction datasets, and lifecycle information discontinuity at handover points.

Proposed framework: The Integrated BIM–Engineering Science Digital Framework addresses all three gaps through a four-layer architecture linking code provisions, AI/ML analytics, digital twin synchronisation, and automated quantity extraction within a traceable workflow with a structured phased implementation pathway.

Future work should focus on empirical validation of the proposed framework across diverse building typologies and regulatory environments, development of open BIM training datasets for AI/ML, and longitudinal study designs tracking BIM integration performance from design through multi-decade operations.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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