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# BIM–DIGITAL TWIN INTEGRATION FOR CONSTRUCTION SAFETY: MECHANISMS, MATURITY PATHWAYS, AND SOCIO-TECHNICAL PROGRESSION

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***SUMMARY***: *The construction industry continues to experience high rates of serious injury and fatality worldwide, motivating an increasing interest in advanced digitalization strategies that combine building information modeling (BIM) with digital twin (DT) capabilities. By linking static semantic site models with continuous field data, these systems offer a powerful approach to proactive risk management. However, while individual remote sensing and predictive analytics components are well researched, a unified understanding of how these BIM and DT safety systems are integrated remains critically limited. Specifically, there is a clear need to understand how system capabilities evolve across different maturity stages and what underlying factors drive this progression across the construction lifecycle. This paper presents a comprehensive scoping review of BIM and DT integration for construction safety management across the entire project lifecycle. Using a tiered evidence strategy and structured thematic coding, the existing literature is synthesized through three main analytical lenses: integration mechanisms and data exchange patterns, maturity characteristics and capability horizons, and the socio-technical factors that systematically influence maturity transitions. This review clarifies the dominant architectural integration approaches and maps current proof-of-concept efforts against the requirements for more predictive and governance-ready safety twins. The findings indicate that most implementations remain at the interactive monitoring stage, with predictive capability emerging mainly in data-rich contexts and autonomous adaptation not yet realized. Furthermore, it identifies persistent bottlenecks in data interoperability and real-time processing that currently hinder widespread industry adoption. Finally, the study proposes a focused research agenda designed to help transition these intelligent monitoring systems from isolated prototypes to robust, scalable applications suitable for safety-critical construction environments.*

***KEYWORDS***: *Building information modeling, digital twin, construction safety, maturity model, scoping review.*

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# 1. INTRODUCTION

The construction industry continues to record a disproportionate share of global occupational fatalities and serious injuries despite decades of regulatory efforts and procedural controls (International Labor Organization [ILO], 2020; Salzano et al., 2024). In many countries, construction routinely ranks among the top sectors for fatal accident rates, particularly for falls from height and slips, trips, and falls (ILO, 2020). Recent statistics from the United States illustrate this persistent burden. The Bureau of Labor Statistics reported that construction deaths due to falls, slips, and trips increased by 5.9 percent in 2021, even as broader awareness of safety management frameworks has grown (Bureau of Labor Statistics, 2023). These patterns indicate that traditional safety management systems, which rely heavily on procedural compliance, manual inspections, and lagging indicators, are often unable to keep pace with the dynamic, multi-actor, and information-rich nature of contemporary construction projects (Agnusdei et al., 2021; Rashidi et al., 2026).

In response to these challenges, the architecture, engineering, construction, and operations (AECO) sector is experiencing rapid digitalization, characterized by a growing interest in advanced sensing, automation, and data-driven management tools (Okpala et al., 2020; Lan & Awolusi, 2025). Among these technologies, building information modeling (BIM) has emerged as a central information backbone that can integrate geometric, temporal, and semantic data across the project lifecycle (Abdelrahman et al., 2021; Hakiri et al., 2023; Manzoor & Othman, 2021). BIM refers to an object-based model that provides stable geometry and semantics for safety-relevant entities. BIM-based approaches have been used to visualize hazardous workspaces, perform 4D construction simulations, embed safety constraints into design models, support Design for Safety (DfS), and coordinate safety plans among project stakeholders (Manzoor & Othman, 2021; Martínez-Aires et al., 2018). However, systematic reviews indicate that these applications are often episodic and design centric. In many cases, BIM models remain static artifacts that are only loosely connected to real-time site conditions, limiting their utility for operational risk control (Hoeft & Trask, 2022; Hou et al., 2021).

Digital twin (DT) concepts extend this digitalization further by enabling dynamic, bi-directional links between physical assets and virtual representations over time (Agnusdei et al., 2021; Boje et al., 2020). A DT is a representation linked to physical or operational conditions through live or regularly updated data and a codable update pathway. In the built environment, DTs are increasingly understood as evolving, data-enriched models that integrate physical assets, virtual models, and connected data flows to support monitoring, analytics, and decision-making at different spatial and temporal scales (Boje et al., 2020). Within the safety domain, DTs can tightly couple sensor streams, computer vision outputs, and contextual information with simulation or rules-based engines, allowing hazards to be detected, analyzed, and communicated in near real time (Agnusdei et al., 2021; Hou et al., 2021). Implementations have demonstrated capabilities ranging from real-time worker localization and proximity warnings to dynamic risk assessment in smart construction sites (Hou et al., 2021; Jiang Y., 2021; Liu Z. et al., 2020; Zhao et al., 2022).

The term BIM–DT denotes BIM-integrated digital twin systems, in which BIM provides the spatial and semantic reference model, and DT services ingest field data to update state variables and generate safety outputs. For BIM–DT integration to advance safety monitoring and management specifically, rather than digitalization in general, six recurring functional requirements, labelled SR1 to SR6, can be synthesized from this literature. A BIM–DT safety system should (SR1) represent hazards and protective measures in a spatially and semantically anchored form so that field observations can be resolved against model elements; (SR2) maintain an up-to-date representation of safety-relevant site states, with update latency bounded by the dynamics of the hazards addressed; (SR3) support forward-looking estimation of risk over explicit time horizons rather than visualization of current conditions alone; (SR4) deliver outputs that are actionable within existing safety workflows, such as alerts, exclusion-zone controls, and permit decisions; (SR5) preserve safety-relevant information continuity across design, construction, and operations handovers; and (SR6) make accountability for automated or semi-automated interventions explicit (Hou et al., 2021; Jiang W. et al., 2021; Attar et al., 2024; Zhao et al., 2021). These requirements provide the groundwork against which existing reviews and implementations are assessed in this study.

When existing reviews are assessed against these requirements, as Section 2 sets out in detail, the literature could benefit from a coherent, mechanism-level characterization of how BIM and DT components are technically coupled to satisfy these requirements, and of how these couplings relate to capability progression from current-state monitoring (SR2, SR4) toward forward-looking risk estimation (SR3) and accountable automated control (SR6). As a result, it remains unclear how different BIM–DT integration mechanisms align with safety functions

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such as planning, monitoring, prediction, and control, or how these mechanisms vary across maturity levels and project phases.

A coordinated view of BIM–DT safety implementations that integrates technical coupling patterns with maturity characteristics and socio-technical progression constraints is therefore needed. This review addresses this need by synthesizing evidence on how BIM has been integrated with digital twin technologies to support construction safety across the project lifecycle.

The research questions defining this study include:

> **RQ1:** How are BIM and DT components technically coupled in current construction safety applications, and what safety functions do these couplings support across different mechanisms and system architectures?
>
> **RQ2:** How do BIM–DT safety implementations distribute across maturity levels, project phases, and safety capabilities, and what patterns emerge?
>
> **RQ3**: What barriers constrain progression between BIM–DT safety maturity levels, and what strategies or design principles does the literature propose to overcome these barriers?

These questions matter because each targets one of the unmet needs identified above. RQ1 addresses the need for a mechanism-level characterization of BIM–DT coupling; without it, systems that appear similar at the use-case level cannot be distinguished by the safety functions their architectures can actually support (SR1, SR2, and SR4). RQ2 addresses the unknown distribution of implementations across maturity levels and project phases, which determines how far the field currently stands from forward-looking risk estimation and lifecycle continuity (SR3 and SR5). RQ3 addresses the socio-technical constraints on progression, including the accountability arrangements that automated intervention would demand (SR6). Together, the three questions connect how systems are built, what safety capability results, and what impedes progression.

The scope of the review follows from these questions and is twofold. The integration mechanism taxonomy and layered reference architecture that answer RQ1 are derived from a safety-specific corpus but are stated at a level of abstraction that applies to other BIM–DT domains. The safety-specific contribution, developed through RQ2 and RQ3, is the mapping of these mechanisms to safety functions, an empirical maturity baseline for safety capabilities, and a barrier typology explaining why safety twins do or do not progress. Findings are organized so that readers concerned with BIM–DT integration and readers concerned with construction safety can each locate the claims relevant to them, while the questions themselves provide the common structure.

By organizing the literature through these questions, the review seeks to provide a structured maturity view of BIM–DT safety implementations, clarify the role of BIM within digital twin safety ecosystems, and identify priority directions for research and practice. The findings aim to support researchers in positioning future work on BIM-enabled DTs for safety, and to help practitioners understand how to scaffold the evolution of safety-critical digital architectures in construction.

## 2. BACKGROUND

This section positions the review within the existing literature. It first summarizes prior reviews of BIM-based and DT-based safety research and the recognition that BIM and digital twins are complementary layers of a broader cyber-physical ecosystem, then considers the socio-technical conditions that shape deployment, and finally contrasts the major prior reviews with the present study against the criteria that define its contribution.

Several reviews have surveyed digital twin applications for safety across domains and within construction. Agnusdei et al. (2021) conducted a systematic classification of DT uses in the safety domain across multiple industries, spanning topics such as operator risk, anomaly detection, and safety-critical decision support. Hou et al. (2021) provided a focused review of DT applications for construction workforce safety, synthesizing 89 journal articles into clusters covering environment monitoring, worker behavior, and safety awareness. More recently, Attar et al. (2024) analyzed DT applications in construction safety and emphasized the prominence of the Internet of Things and BIM as enabling technologies, while also identifying gaps in design for safety, climate-related hazards, and the safety of non-operators. Collectively, these reviews confirm the expanding role of DTs in safety research but also emphasize that implementations remain heterogeneous and are frequently described at early stages of functional maturity (Agnusdei et al., 2021; Attar et al., 2024; Hou et al., 2021). Other reviews have

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broadened this picture: Luo et al. (2025) organized DT applications for construction safety risk management into five application functions, Wang et al. (2024) mapped the opportunities and threats of DT adoption onto a five-level maturity model, Trask and Linderoth (2023) mapped the evidence base for digital occupational health and safety interventions, and Rashidi et al. (2026) and Wang et al. (2026) provided taxonomic and practice-oriented syntheses of BIM–DT and DT research across the construction industry.

At the same time, there is increasing recognition that BIM and digital twins are complementary layers within a broader cyber-physical ecosystem for smart construction sites (Akanmu et al., 2021; Jiang W. et al., 2021). BIM provides an object-oriented representation of assets and processes, whereas DT approaches emphasize continuous data acquisition, state synchronization, and feedback loops between physical and virtual systems (Moretti et al., 2020; Nguyen & Adhikari, 2023). In practice, many construction safety applications labelled as "digital twins" rely on BIM as the spatial and semantic reference model, enriched through sensor feeds, computer vision outputs, or simulation engines (Attar et al., 2024; Hou et al., 2021). Reported examples include smart site frameworks coupling BIM with cyber-physical sensing for real-time warnings (Jiang W. et al., 2021), DT models for safety risk coupling in prefabricated hoisting (Liu Z. et al., 2021), and BIM-based DT decision-support tools for safety management and occupational health (Torrecilla-García et al., 2021).

In parallel, smart construction and safety risk management research increasingly emphasizes that successful deployment depends not only on technical functionality but also on organizational practices and governance arrangements, including data ownership, interoperability and standards, workforce skills, accountability allocation, and institutional acceptance (Jiang W. et al., 2021; Zhao et al., 2021). Broader reviews of emerging digital technologies in AECO also highlight the rapid diffusion of overlapping tools, including IoT, extended reality, blockchain, and artificial intelligence, creating opportunities for integrated safety analytics but increasing fragmentation risk when technologies and organizational processes are misaligned (Dou et al., 2023).

Table 1 summarizes these major prior reviews, both BIM-focused and DT-focused, and systematically contrasts them with the present study across research scope, BIM–DT integration focus, treatment of integration mechanisms and architectures, maturity assessment, lifecycle coverage, treatment of barriers and enablers, review methodology, and key contribution. The comparison indicates that no existing review couples a mechanism-level analysis of BIM–DT integration with an implementation-level maturity assessment and a transition-oriented barrier analysis for construction safety; this combination defines the positioning of the present study.

Two patterns emerge from this comparison. BIM-focused safety reviews primarily emphasize design-time hazard identification, 4D safety planning, and design for safety, with limited attention to live sensing integration and operational feedback mechanisms (Manzoor et al., 2025; Martínez-Aires et al., 2018). Conversely, DT-focused reviews often treat BIM as one enabling data source among many and prioritize broad DT taxonomies or technology clusters, rather than analyzing BIM–DT couplings as specific integration mechanisms that structure construction safety workflows (Agnusdei et al., 2021; Attar et al., 2024; Hou et al., 2021). Measured against the requirements set out in Section 1, prior reviews address hazard representation (SR1) and current-state monitoring (SR2) but rarely examine forward-looking risk estimation (SR3), lifecycle continuity (SR5), or accountability for automated intervention (SR6) at the level of specific BIM–DT couplings. Neither strand links coupling mechanisms to maturity outcomes or to the socio-technical conditions that govern progression, which is the gap that the research questions stated in Section 1 address.

# 3. METHODOLOGY

## 3.1 Review design

This study adopts a scoping review design to map how BIM and DT technologies are being combined for construction safety across the project lifecycle using the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2018). A scoping review is appropriate because BIM–DT safety integration is an emergent and heterogeneous field, with a mixture of conceptual frameworks, technical prototypes, and contextual studies rather than a consistent body of effect sizes or comparable interventions. The review protocol combines a systematic database search, transparent screening and eligibility procedures, a tiered relevance classification, and structured coding of BIM–DT safety implementations and contextual evidence.

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*Table 1: Systematic comparison of major prior reviews with the present study.*

| Study | Scope and application domain | BIM–DT integration focus | Integration mechanisms/architecture | Maturity assessment | Lifecycle coverage | Barriers and enablers | Review methodology | Key contribution |
|---|---|---|---|---|---|---|---|---|
| Martínez-Aires et al. (2018) | BIM for construction safety management | BIM only; DT not considered | ○ | ○ | (●) Design stage (prevention through design) | ○ | PRISMA systematic review (76) | Five BIM safety application areas |
| Boje et al. (2020) | Construction DTs in general; not safety-specific | BIM as precursor to a semantic construction DT | (●) Three conceptual construction DT generations | (●) Conceptual generations only | ● Full lifecycle, conceptual | (●) Research challenges | Structured narrative review (196) | Semantic construction DT vision and agenda |
| Agnusdei et al. (2021) | DT safety applications, cross-industry | BIM peripheral | ○ | (●) Complexity levels, not twin maturity | ○ | (●) General, cross-industry | Classification-framework review | Cross-industry DT safety classification |
| Hou et al. (2021) | DT for construction workforce safety | BIM one data source among many | (●) Thematic clusters, not couplings | (●) Early maturity noted, not coded | (●) Construction phase | (●) Challenges in future directions | Content-analysis review (89) | Application clusters for workforce safety DTs |
| Trask and Linderoth (2023) | Digital health and safety interventions in construction | BIM tools among interventions; DT not a lens | ○ | (●) Evidence maturity, not technology maturity | (●) Planning, execution, training | (●) Weak outcome evidence | Systematic mapping review (24) | Evidence map for digital health and safety interventions |
| Attar et al. (2024) | DT for construction safety | BIM and IoT as enablers | (●) Technology groupings, not couplings | ○ | (●) Lifecycle stages; DfS gaps | (●) Gap spotting | Scientometric and content analysis | Gap analysis for DT safety research |
| Wang et al. (2024) | DT adoption in construction projects | BIM not a focus | ○ | ● 47 risk factors on a five-level DT maturity model | (●) Project level, not phase-specific | ● 32 opportunities, 15 threats | Scientometric literature review (72) | Risk-to-maturity mapping for DT adoption |
| Luo et al. (2025) | DT for construction safety risk management | DT-centered; BIM not a lens | (●) Five application functions, not couplings | ○ Field described as early-stage | (●) On-site construction | (●) Challenges and trends | Systematic literature review | Application landscape of safety DTs |
| Manzoor et al. (2025) | BIM for construction safety | BIM-centered; live sensing limited | ○ | ○ | (●) Design and construction | (●) Noted briefly; no taxonomy | PRISMA systematic review (125) | BIM's digital potential for safety |

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| Study | Scope and application domain | BIM–DT integration focus | Integration mechanisms/architecture | Maturity assessment | Lifecycle coverage | Barriers and enablers | Review methodology | Key contribution |
|---|---|---|---|---|---|---|---|---|
| Rashidi et al. (2026) | BIM and DT across construction; not safety-specific | BIM-to-DT transition central | (●) Five research clusters | ○ | ● Whole lifecycle; operation phase most studied | (●) Gaps and challenges | Scientometric plus systematic review | Taxonomy of the BIM–DT research landscape |
| Wang et al. (2026) | DT practices across construction | BIM one modeling technology among several | (●) Six-category framework, aggregate level | ○ Identified as a research gap | ● Construction, operation, cross-lifecycle | ● 26 barriers in four domains, with mitigations | Two-stage PRISMA review (122 reviews; 297 studies) | Practice landscape and stakeholder roadmaps |
| This study | BIM-integrated DTs for construction safety, whole lifecycle | BIM–DT coupling is the object; twin status verified per study | ● Mechanism taxonomy M1–M4; layered reference architecture | ● Five-level L0–L4, coded for 27 Tier 1 systems | ● Construction, operations, cross-lifecycle | ● Twelve-barrier typology B1–B12 tied to maturity transitions, with enablers | PRISMA-ScR scoping review, tiered corpus (86) | Integrated mechanism–maturity–barrier framework and maturity baseline |

Note: ● criterion addressed explicitly; (●) addressed partially or indirectly; ○ not addressed. Numbers in parentheses in the Review methodology column are the numbers of studies reviewed.

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The unit of analysis for the core synthesis is the BIM–DT safety implementation, defined as a system, prototype, or framework that uses BIM and digital twin concepts in an integrated way to support construction safety outcomes. At the same time, the review deliberately incorporates foundational papers on BIM and digital twins, as well as contextual work on enabling technologies and safety management, in order to interpret and explain the patterns observed in the implementation corpus, as seen in the methodology flow in Figure 1.

## 3.2 Data sources and search strategy

The literature search made use of Web of Science and Scopus bibliographic databases, the temporal window spanned research articles from 2018, reflecting the period during which DT concepts became visible in construction research and overlapping with the most recent wave of BIM-based safety and Construction 4.0 studies (Opoku et al., 2021). A single core search string was developed and executed in both databases in 2025. The string combined three conceptual components:

- BIM concepts: (“Building Information Modeling” OR “BIM”).
- Digital twin concepts: (“Digital Twin” OR “Digital Shadow” OR “Virtual Twin”).
- Integration concepts: (“Integrate” OR “Synergy” OR “Coupling” OR “Framework”).

**Combined search string:** ("Building Information Modeling" OR "BIM") AND ("Digital Twin" OR "Digital Shadow" OR "Virtual Twin") AND ("Integrate" OR "Synergy" OR "Coupling" OR "Framework").

These components were combined with Boolean operators so that retrieved papers contained at least one term from each component. Notably, safety-specific terms (e.g., "Safety," "Hazard," "Risk") were deliberately excluded from the initial search string. This broad search strategy was chosen to maximize recall and avoid missing foundational integration papers. In the nascent BIM–DT field, many relevant architectures are framed as "site monitoring" or "real-time tracking" systems that deliver safety outcomes (e.g., collision avoidance) without necessarily featuring safety-specific terminology in the title or keywords. Safety relevance was subsequently assessed during the manual screening and tier classification stages. Searches were limited to peer reviewed journal articles and full conference papers published in English. The combined database searches returned 1,573 records (829 from Web of Science and 744 from Scopus). After deduplication, 1,452 unique records remained for screening.

## 3.3 Screening and eligibility

Screening followed a two-stage procedure. In stage 1, titles and abstracts for the 1,452 unique records were screened to exclude clearly irrelevant studies. Two broad inclusion criteria guided this first pass:

- The paper concerned construction, civil infrastructure, or closely related built environment contexts.
- The paper substantively engaged with BIM and/or digital twin concepts, rather than mentioning them only in passing.

Records were excluded at this stage if they focused exclusively on other sectors with no clear transferability to construction, did not involve BIM or DT concepts at all, were of an inappropriate document type (for example, editorials, commentaries, theses, or conference abstracts without full papers), or were not written in English. Applying these criteria resulted in the exclusion of 1,097 records at the title and abstract stage, leaving 355 papers for full text assessment. A random subset was double screened by a second reviewer to check consistency, and disagreements were resolved through discussion and refinement of the decision rules.

In stage 2, full-text articles were retrieved and assessed against more detailed eligibility criteria and then classified into three tiers of relevance. Papers were excluded at this stage if the full text was unavailable, if the construction context or BIM/DT content proved marginal upon closer reading, or if the study was purely conceptual without any plausible or codable BIM–DT safety pathway. The full screening and eligibility process is summarized in a PRISMA-ScR flow diagram in Figure 1, which reports the number of records at each stage and the final tier distribution.

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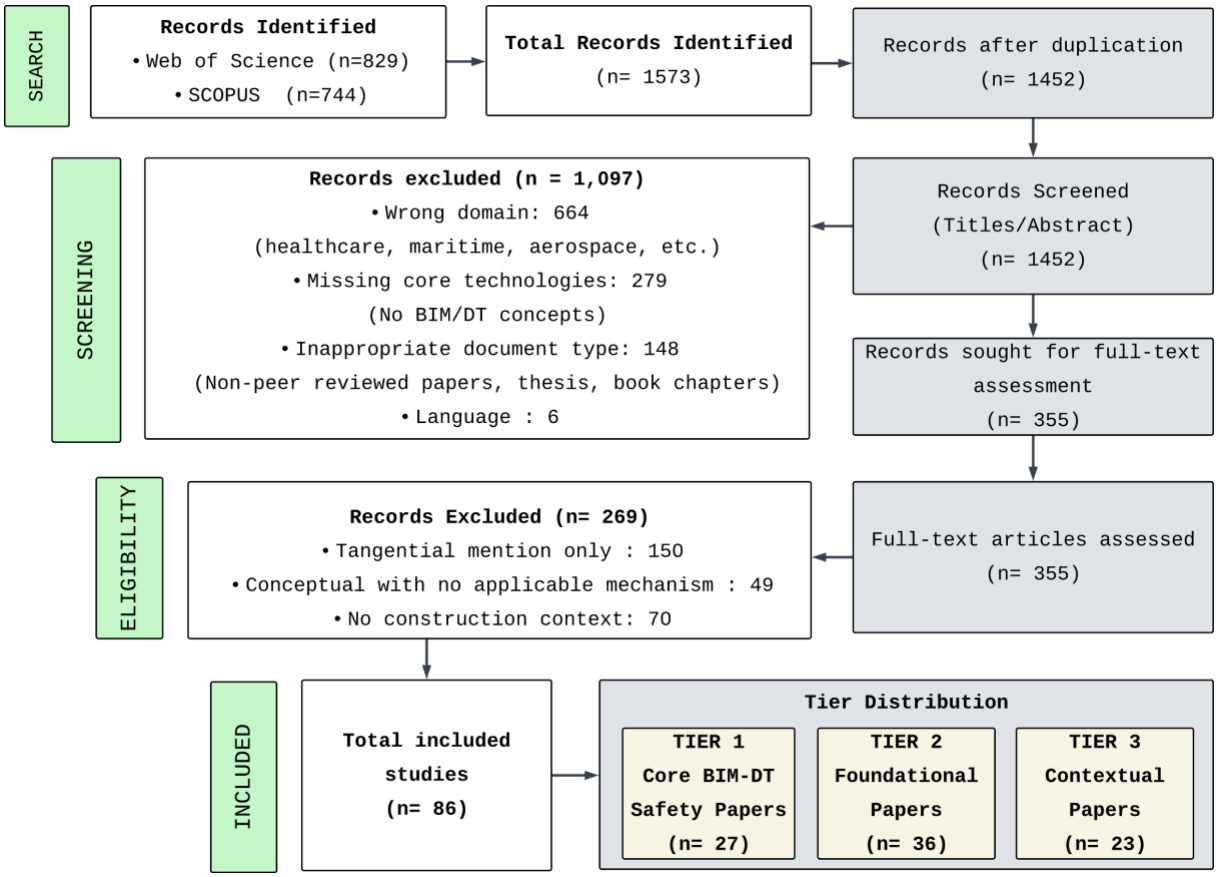



*Figure 1: PRISMA-ScR flow diagram.*

After full-text assessment and tier classification, 86 papers were retained in the final corpus. These were organized into three tiers: 27 Tier 1 core BIM–DT safety implementations, 36 Tier 2 foundational BIM/DT and safety studies, and 23 Tier 3 contextual and barrier-focused studies.

## 3.4 Tiered corpus classification

A simple binary distinction between "included" and "excluded" would either yield a very narrow set of direct BIM–DT safety implementations or an unwieldy corpus that mixes multiple, only loosely related streams. To balance breadth with analytical detail, the retained studies were organized into three tiers of relevance. Tier 1 comprises core BIM–DT safety implementations: studies set in construction or civil infrastructure where safety is a primary focus, BIM and digital twin concepts are integrated within a single safety workflow, and the coupling is described with enough technical specificity to code the integration mechanism and maturity level in a consistent manner.

Operationally, a paper was classified as Tier 1 when it met these conditions and explicitly supported, or was clearly specified to support, construction safety outcomes such as hazard identification, risk mapping, fall or collision prevention, or safety decision support.

Tier 1 includes both implemented systems and strongly specified conceptual systems. For instance, several mechanism M1 studies describe conceptual safety twins at maturity level L0. Although these do not operate on live data, they articulate the BIM–DT coupling, safety functions, and data flows in sufficient detail to be coded consistently; accordingly, they are treated as Tier 1 cases at the lower end of the maturity spectrum.

Tier 2 includes foundational studies that inform the analysis but do not meet all Tier 1 criteria. In practice, Tier 2 captures: (i) single-technology safety studies that use either BIM or DT approaches in depth without integrating both; (ii) BIM–DT integration studies in construction where safety is not the primary focus but where the integration architecture or data flow is transferable to safety applications; and (iii) conceptual BIM–DT safety

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frameworks that describe actors, data sources, and workflows but do not specify integration mechanisms or system operation in sufficient detail to support maturity coding.

Tier 3 consists of contextual literature that does not implement specific BIM–DT safety systems, but provides background needed to interpret adoption and progression. This tier includes studies on digital construction uptake, data infrastructure, IoT and sensing ecosystems, machine learning or vision-based monitoring that could feed twin services, and safety management, regulation, and standards that shape the feasibility of BIM–DT safety twins. Together with Tier 2, these studies support the later barrier-and-enabler synthesis by clarifying the technical, organizational, and institutional conditions under which BIM–DT safety implementations can scale.

This tiered structure ensured that detailed mechanism and maturity coding was applied only to well-specified BIM–DT safety implementations (Tier 1), while Tier 2 and Tier 3 evidence was retained to contextualize patterns and explain constraints observed across the Tier 1 cases.

## 3.5 Data extraction and coding

A structured data extraction template was used to record information from the 86 papers retained after screening. For each study, bibliographic details, project or context type, technologies employed, study methods, and the reported safety or operational outcomes were extracted. For Tier 1 papers, an expanded coding scheme was applied to enable consistent classification of integration mechanisms and maturity characteristics, aligned with the conceptual framework presented in Section 4.

Each Tier 1 implementation was coded for four dimensions. First, the integration mechanism captured how BIM platforms, sensing infrastructure, and digital twin services were coupled, including the pathway by which safety-relevant data were acquired, mapped to BIM objects or locations, and used to update the twin state. Second, maturity level represented the temporal depth and degree of automation of safety functions. Third, safety capability domains were coded to indicate the primary safety functions addressed. Fourth, lifecycle phase coverage captured whether the implementation was situated in design, construction, operations, or spanned multiple phases.

When a paper reported multiple system configurations or application scenarios, the coding scheme was applied separately to each reported implementation. For Tier 2 and Tier 3 papers, extraction and coding emphasized the theoretical framing, reported integration patterns, enabling technologies, and stated barriers and enabling conditions across technical, organizational, and institutional levels. Coding categories were iteratively refined during extraction to improve consistency of interpretation across the corpus. To assess coding reliability, a subset of 8 of the 27 Tier 1 papers (approximately 30 percent) was independently coded by a coauthor acting as a second coder following an initial calibration exercise. Agreement across the four coding dimensions was 87.5 percent (28 of 32 coding decisions), with a mean Cohen's kappa of 0.73 across dimensions, indicating substantial agreement (Landis and Koch, 1977). Discrepancies were discussed and resolved by consensus, and the coding guidance was updated accordingly.

Extracted data and codes were subsequently organized into five analytical dimensions used in the results sections: integration mechanisms (M1–M4), maturity levels (L0–L4), safety capability domains, lifecycle coverage, and socio-technical barrier levels.

## 3.6 Verification of BIM–DT safety twin status

The full-text assessment initially identified more candidate BIM–DT safety studies than the final Tier 1 count (N = 27). To ensure that the integration mechanism and maturity analyses were based on a consistently defined set of cases, an additional verification step was applied to all Tier 1 candidates. This step operationalized the definition of a BIM–DT safety twin using three diagnostic questions.

- Does the proposed framework maintain an operationally meaningful linkage to the physical site or asset through live or regularly updated data, with a clearly specified pathway from data acquisition to model and state update?
- Where predictive capability is claimed, does the study report forward-looking estimation of future states or safety risk over an explicit horizon (for example, probabilistic risk, time-to-threshold exceedance, or trajectory forecasting), rather than classification or visualization of current conditions only?

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- Is the BIM–DT coupling described with sufficient technical specificity to support coding of (i) the integration mechanism, (ii) maturity level, (iii) safety capability domain(s), and (iv) lifecycle phase coverage?

Studies that used digital twin terminology in a purely rhetorical manner, or that presented high-level visions without a codable integration pathway, were reclassified as Tier 2 conceptual foundations. Conceptual M1 safety twins were retained in Tier 1 when they provided sufficiently specified architecture and a safety workflow that supported coding as low-maturity (L0) implementations. After verification and reclassification, Tier 1 comprised 27 core BIM–DT safety implementations used in the mechanism and maturity analyses.

## 3.7 Analytical approach

The analysis combined descriptive statistics with qualitative synthesis. For RQ1, frequency counts and cross-tabulations were used to describe how the Tier 1 implementations (N = 27) were distributed across integration mechanisms and architectural patterns. These results underpin the mechanism taxonomy and layered architecture schematics presented in Section 4.

For RQ2, maturity codes were aggregated to characterize distributions across maturity levels, safety capability domains, and lifecycle phases. Cross-tabulations were used to identify common combinations (for example, the clustering of L2 and L3 implementations within specific domains and phases) and to highlight gaps (for example, the limited representation of higher-maturity safety twins in design or cross-phase settings). These results are reported in the maturity and capability tables and figures in Section 5 and inform the discussion of progression pathways.

For RQ3, qualitative content analysis was applied to reported challenges, limitations, and future-work statements in Tier 1 studies. These statements were inductively coded into barrier themes and grouped into four socio-technical levels: technical and data barriers; analytics and modeling barriers; organizational and human barriers; and institutional, regulatory, and governance barriers. Evidence from Tier 2 and Tier 3 studies was then used to triangulate and elaborate these themes by providing additional examples, explanatory lenses, and proposed strategies. The resulting barrier and enabler clusters are synthesized in Section 6 and inform the design principles proposed for progressing from conceptual models and static visualization toward more interactive and predictive BIM–DT safety twins.

## 3.8 Tier 1 core BIM–DT safety systems and architectures

After eligibility screening and verification, the final corpus comprised 86 papers, including 27 Tier 1 core BIM–DT safety implementations, 36 Tier 2 foundational studies, and 23 Tier 3 contextual studies. Table 2 summarizes the Tier 1 implementations and their coding by project phase, integration mechanism, and maturity level. These cases form the empirical basis for the mechanism and maturity analyses presented in Sections 4 and 5.

*Table 2: Tier 1 core BIM–DT safety systems and architectures (N = 27).*

| ID | Citation | Project Phase | Integration Mechanism | Maturity Level | Implementation Summary |
|---|---|---|---|---|---|
| P01 | Liu Z. et al. (2021) | Construction | M3 | L3 | Predictive hoisting accident risk assessment using IoT-driven data fusion and association rule mining in a lifting digital twin. |
| P02 | Torrecilla-García et al. (2021) | Cross-lifecycle | M1 | L0 | Conceptual BIM to DT framework that structures safety-oriented information flows to support tunneling design review and risk-informed decisions. |
| P03 | Liu D. et al. (2023) | Construction | M2 | L2 | Operational excavation safety twin that fuses multisensor and computer vision-based excavator pose tracking with BIM geometry to monitor clearances and trigger proximity alerts. |
| P04 | Zhou et al. (2019) | Construction | M2 | L2 | Cyber-physical hoisting monitoring system that mirrors crane and load states in BIM and uses |

| ID | Citation | Project Phase | Integration Mechanism | Maturity Level | Implementation Summary |
|---|---|---|---|---|---|
| | | | | | ultrasonic or RFID sensors to detect blind zone incursions and activate alarms. |
| P05 | Teizer et al. (2023) | Cross-lifecycle | M1 | L0 | Digital Twin for Construction Safety conceptual model that embeds safety information and control logic into lifecycle DT architectures for design and planning. |
| P06 | Saif et al. (2024) | Construction | M2 | L2 | Real-time construction safety twin linking 4D BIM with wearables to maintain dynamic hazard zones and push access violation alerts to supervisors and workers. |
| P07 | Eneyew et al. (2022) | Post-construction | M2 | L2 | Smart building digital twin that integrates BIM with IoT sensors for continuous monitoring of indoor environmental and system conditions relevant to occupant safety. |
| P08 | Sacks et al. (2020) | Cross-lifecycle | M1 | L0 | Digital Twin Construction architecture that conceptualizes how safety data, rules, and feedback loops should be represented across BIM-based information systems. |
| P09 | Liu Z. et al. (2020) | Post-construction | M3 | L3 | Indoor safety management twin that classifies danger levels in building spaces using multi-sensor data and support vector machine models mapped onto BIM. |
| P10 | Lai et al. (2022) | Construction | M2 | L2 | Lightweight crane boom digital twin that estimates real-time structural stress responses from sparse sensor inputs using multifidelity surrogate models to support safe lifting operations. |
| P11 | Jiang Y. et al. (2022) | Construction | M3 | L3 | Precast assembly digital twin that links BIM and sensor data with neural network-based prediction of spatial collisions to proactively adjust erection plans. |
| P12 | Hong et al. (2022) | Cross-lifecycle | M3 | L3 | Deep foundation pit monitoring twin that uses measurement and BIM data with machine learning to forecast deformations and stability risks, and issue early warnings. |
| P13 | Hoeft & Trask (2022) | Cross-lifecycle | M1 | L0 | Conceptual exploration of BIM-based platforms for occupational health and safety that identifies opportunities for integrated rule checking and safety by design workflows. |
| P14 | Hu et al. (2024) | Post-construction | M3 | L3 | Structural health monitoring twin that couples BIM with wireless sensing and intelligent diagnostic algorithms to detect damage states and quantify safety margins in real time. |
| P15 | Fang et al. (2024) | Construction | M2 | L2 | Status digital twin for tunneling that compares excavated geometry with BIM to track over- and under excavation and highlight unsafe deviations around support boundaries. |
| P16 | Xu et al. (2023) | Cross-lifecycle | M1 | L0 | Conceptual BIM plus real scene 3D model framework that outlines how to construct structural monitoring twins for safety and condition visualization. |
| P17 | Wang et al. (2022) | Post-construction | M2 | L2 | Semantic built environment twin that enriches BIM with SensorML metadata so facility safety and |

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| ID | Citation | Project Phase | Integration Mechanism | Maturity Level | Implementation Summary |
|---|---|---|---|---|---|
| | | | | | condition sensors can be queried and visualized in a structured way. |
| P18 | Jiang Y. (2021) | Construction | M2 | L2 | Construction management twin that mirrors building progress and selected safety indicators from site data into a BIM-based dashboard to support supervision decisions. |
| P19 | Ellul et al. (2024) | Construction | M2 | L2 | Game engine-based DT environment that streams site and building data into immersive visualizations for combined health, safety, and performance monitoring. |
| P20 | Salzano et al. (2024) | Construction | M2 | L2 | BIM-centered construction risk management platform that updates spatial risk maps and efficiency indicators dynamically from execution data for supervisory control. |
| P21 | Speiser & Teizer (2024) | Construction | M1 | L0 | Data schema and workflow for virtual construction safety training that links BIM and location tracking information to generate realistic hazard scenarios in offline simulations. |
| P22 | Moretti et al. (2020) | Post-construction | M2 | L2 | OpenBIM IoT integration framework that allows continuous monitoring of building assets and conditions so safety and maintenance issues can be detected in near real time. |
| P23 | Badenko et al. (2021) | Post-construction | M2 | L2 | Factory digital twin that integrates BIM and DT to support worker navigation assistance and operational safety insights in industrial facilities. |
| P24 | Messi et al. (2020) | Construction | M3 | L3 | Collision risk digital twin that runs real time fast forward simulations of equipment and worker trajectories to forecast impact hazards and suggest safer alternatives. |
| P25 | Jiang et al. (2021) | Construction | M2 | L2 | Cyber-physical smart construction site twin that mirrors workers and machinery in BIM using location and sensor data to provide live safety monitoring and alerts. |
| P26 | Zhao et al. (2022) | Construction | M3 | L3 | Tunnel construction digital twin that uses time series data with LSTM models to predict ground settlement and trigger early warnings for support and lining safety. |
| P27 | Karlapudi et al. (2023) | Construction | M2 | L2 | IoT-enabled construction twin that fuses equipment and wearable sensor data with BIM to maintain dynamic hazard zones and generate real-time safety notifications. |

## 4. INTEGRATION MECHANISMS AND TECHNICAL ARCHITECTURES (RQ1)

The 27 Tier 1 BIM–DT safety implementations exhibit substantial variation in how data moves between BIM platforms and digital twin engines, how integration is realized technically, and what safety capabilities result. To provide a structured comparison, this section answers RQ1 by examining the technical coupling of BIM and DT components. Section 4.1 analyzes integration mechanisms, defined as the dominant directions and purposes of information flow. Section 4.2 examines the layered technical architectures, middleware patterns, and data flow paradigms that realize these mechanisms in practice.

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## 4.1 Integration mechanisms taxonomy

The Tier 1 corpus identifies four recurring mechanism classes that govern information flow between BIM and DT for safety: M1 unidirectional data sharing, M2 bidirectional synchronization, M3 predictive coupling, and M4 autonomous adaptation. These form an empirical progression in which each mechanism adds feedback, analytics, and automation to the previous one. Each step also changes the safety functions a system can support: M1 aligns with design-time safety planning and hazard communication (SR1), M2 with real-time hazard monitoring and alerting (SR2, SR4), M3 with forward-looking risk estimation (SR3), and M4 with automated intervention (SR4, SR6), tracking the requirements set out in the introduction.

Table 3 summarizes the four mechanisms and their distribution in the Tier 1 studies. Six implementations primarily employ M1, fourteen employ M2, and seven demonstrate M3. While M4 is widely discussed in conceptual literature, it does not yet appear as an implemented mechanism in the Tier 1 corpus. This distribution suggests that contemporary safety-focused twins concentrate around interactive monitoring and selective prediction, with full autonomy remaining a forward-looking ambition.

*Table 3: Integration mechanisms, taxonomy, and distribution across Tier 1 corpus.*

| Mechanism | Description | Data Flow | Synchronization & Automation Level | References |
|---|---|---|---|---|
| M1: Unidirectional data sharing | BIM model is exported as a static geometric and semantic reference to the DT platform, with no feedback loop from the DT to BIM or site control systems. | BIM → DT (one way) | Sync: manual, batch, or one-time export. Automation: none. | (Sacks et al., 2020; Torrecilla-García et al., 2021; Teizer et al., 2023). |
| M2: Bidirectional synchronization | BIM provides spatial constraints and identifiers, while the DT ingests operational data (IoT, wearables, vision, localization) and updates a live digital state to support monitoring, alerts, and supervisory decision support. | BIM ↔ DT (bidirectional) | Sync: near real-time via APIs or brokers. Automation: automated alerts, human-in-the-loop decisions. | (Liu D. et al., 2023; Zhou et al., 2019; Saif et al., 2024; Eneyew et al., 2022; Lai et al., 2022). |
| M3: Predictive coupling | M2-style synchronization is extended with predictive analytics (ML, time-series, simulation, surrogate models) that estimate future risk states or trajectories using live and historical data anchored to BIM semantics. | BIM ↔ DT (state sync) + predictive engine → user/control | Sync: continuous with predictive processing. Automation: automated forecasting, human oversight of intervention | (Liu Z. et al., 2021; Jiang Y. et al., 2022; Hong et al., 2022; Zhao et al., 2022) |
| M4: Autonomous adaptation | Conceptual end state where the twin not only predicts risk but can also trigger bounded interventions through a closed-loop control pathway, subject to explicit governance and assurance constraints | BIM ↔ DT ↔ Control | Sync: closed-loop real-time control. Automation: constrained autonomy under governance constraints. | None observed in Tier 1 corpus; discussed in context as broader DT governance and autonomy literature only as a conceptual target in Tier 2 frameworks. |

Figure 2 visualizes this progression, emphasizing that M1 through M3 can be observed in current safety twins, while M4 remains a conceptual target whose realization would require both technical and organizational changes that most construction and infrastructure organizations currently lack.

### 4.1.1 Mechanism M1: Unidirectional data sharing

M1 represents the foundational mechanism in which BIM models provide a static or periodically updated digital context, while operational data either do not feed back into the model or do so in a manual, low-frequency manner. In these implementations, BIM acts as a geometric and semantic reference for safety planning, hazard visualization, and communication, but the twin itself does not evolve continuously with live field data (Teizer et al., 2023).

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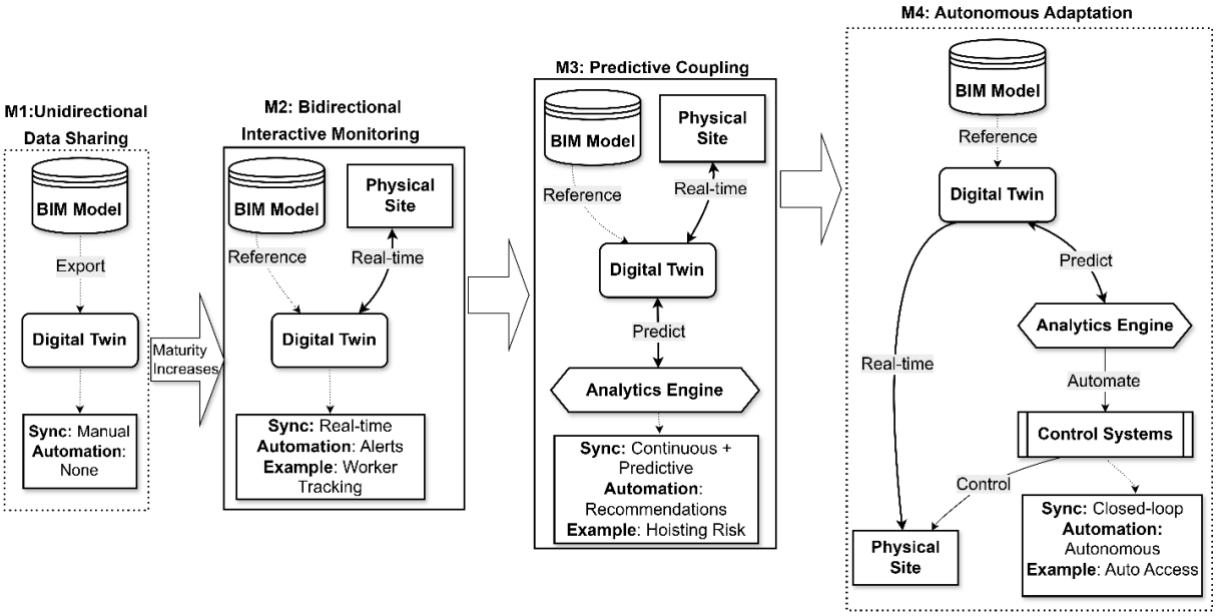



*Figure 2: Mechanism progression.*

Six Tier 1 studies exemplify M1. Common forms include (i) exporting BIM or 4D BIM sequences to simulation or visualization environments for hazard scenario generation and safety training, and (ii) using BIM extracts to populate risk registers, spatial hazard annotations, or design-for-safety reviews that remain decoupled from live sensing. For example, Speiser and Teizer (2024) link BIM and contextual information to generate training scenarios in an offline environment, while Torrecilla-García et al. (2021) use BIM-derived representations to support tunneling safety planning without coupling the model to live monitoring updates. Conceptual architectures that specify BIM–DT safety workflows but do not implement live update pathways also appear within M1 at the low end of the operational spectrum (Teizer et al., 2023; Hoeft & Trask, 2022).

The prevalence of M1 among conceptual frameworks reflects both its accessibility and its limitations. File-based exports require little beyond existing BIM authoring tools, and they align with current design-centric practices in which BIM is primarily a documentation artifact rather than a live operational model (Boje et al., 2020; Opoku et al., 2023). At the same time, M1 cannot support sustained operational monitoring or prediction because state drift is intrinsic. As construction progresses, as-built conditions diverge from design assumptions, and temporary protections change, static exports degrade in safety relevance unless there is an update pathway (Akram et al., 2019). M1 provides no pathway for the DT to correct this drift by feeding discrepancies or new hazards back into the BIM model, which leads to misalignment between the digital representation and site reality (Sepasgozar et al., 2023).

### 4.1.2 Mechanism M2: Bidirectional synchronization

M2 denotes active two-way coupling where BIM provides spatial context, constraints, and identifiers, while DT services ingest operational data to update a live digital state and support monitoring and supervisory decisions. In these systems, BIM typically anchors the semantic mapping between sensed entities and model elements (spaces, objects, work zones), enabling safety functions such as exclusion-zone control, proximity alerting, and threshold-based exposure monitoring.

The Tier 1 corpus shows M2 as the dominant operational mechanism, especially during construction. Representative implementations couple BIM with (i) localization and wearable sensing to detect worker entry into hazard zones and trigger alerts, (ii) cyber-physical sensing for proximity management in equipment operations, and (iii) computer vision pipelines that estimate equipment pose or worker location and map these states into BIM-referenced hazard representations (Zhou et al., 2019; Saif et al., 2024; Liu D. et al., 2023). Facility and industrial contexts also demonstrate M2 coupling through IoT-enabled integration frameworks that update safety-relevant building or asset states in near real time and expose these states through dashboards or services (Moretti et al., 2020; Badenko et al., 2021; Wang T. et al., 2022).

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A key synthesis insight is that M2 systems tend to operationalize safety by leveraging BIM as a stable spatial reference model, then applying rule-based logic to streaming states. This explains why M2 appears frequently in applications where risk can be represented as proximity, zone occupancy, threshold exceedance, or compliance states that are naturally expressed against BIM objects and spaces. However, the same design choice also creates an implicit ceiling: without predictive models and validated temporal reasoning, M2 systems primarily support reactive or near-real-time interventions rather than forward-looking safety planning (Lai et al., 2022; Moretti et al., 2020; Sacks et al., 2020).

#### 4.1.3 Mechanism M3: Predictive coupling

M3 extends bidirectional synchronization with analytics that produce forward-looking safety estimates from live and historical data anchored to BIM semantics. In M3 systems, the BIM-linked twin maintains a continuously updated state (as in M2) but also hosts predictive components such as time-series forecasting, probabilistic risk models, fast-forward simulation, or surrogate models. These predictive components estimate future hazard likelihood, near-future trajectories, or emerging unsafe conditions over a defined time horizon, enabling earlier and more proactive safety interventions.

The Tier 1 corpus indicates that M3 appears selectively in contexts where (i) hazard consequences are high, (ii) measurable signals are available at sufficient temporal resolution, and (iii) predictive lead time is valuable for operational decision-making. In hoisting and equipment interaction settings, predictive coupling appears through risk forecasting models and simulation-based foresight that estimate collision risk seconds into the future and support rescheduling or trajectory adjustment (Liu Z. et al., 2021; Messi et al., 2020). Geotechnical and structural monitoring applications similarly use predictive analytics layered on synchronized sensing, where time-series models extrapolate displacement, strain, or deformation trends and trigger early warnings when trajectories indicate threshold exceedance within a specified horizon (Zhao et al., 2022; Hong et al., 2022; Hu et al., 2024).

Across these applications, M3 introduces two additional requirements relative to M2. First, it depends on mature data infrastructure for storage, cleaning, fusion, and model lifecycle management, because predictive performance is sensitive to data drift and missingness. Second, it demands tighter organizational coupling between safety, engineering, and operations, because predictive outputs must translate into planned interventions rather than ad hoc reactions, and because model validity must be maintained as site conditions evolve (Hong et al., 2022; Hu et al., 2024).

#### 4.1.4 Mechanism M4: Autonomous adaptation

M4 represents the conceptual frontier in which BIM–DT integration supports closed-loop control, allowing the twin to initiate or execute safety interventions autonomously within predefined limits. In an M4 scenario, the twin is expected to not only predict emerging hazards but also orchestrate system responses, for example, by slowing or halting equipment, locking out access to hazardous zones, or reconfiguring digital work permits without waiting for manual confirmation (Hu et al., 2024). Several Tier 2 and Tier 3 studies in the broader digital twin literature describe such capabilities in smart buildings and critical infrastructure, where digital twins adjust equipment parameters or building systems based on real-time feedback. However, none of the Tier 1 BIM–DT safety implementations reviewed here reach this level in construction infrastructure contexts. Autonomous responses, where they exist, are confined to narrow, pre-scripted actions that remain under close human supervision and are often implemented at the equipment controller level rather than through BIM-linked twins (Liu Z. et al., 2020, 2021; Messi et al., 2020; Zhao et al., 2022; Hu et al., 2024).

These socio-technical constraints suggest that, in the near to medium term, M4 is likely to emerge only in tightly bounded applications where the consequences of incorrect interventions are low and reversible, and where robust governance, liability frameworks, and assurance processes have been established (Opoku et al., 2023; Ghansah & Lu, 2024). In application, the more realistic trajectory involves deepening and scaling M2 and M3 capabilities, while gradually introducing constrained autonomous functions within well-understood envelopes of operation.

### 4.2 Technical architecture patterns

Tier 1 BIM–DT safety implementations span diverse toolchains, sensing modalities, and deployment contexts. However, many consequential design decisions are embedded in the integration infrastructure, including how heterogeneous streams are transmitted, validated, and aligned to BIM entities, and how semantic consistency is

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maintained across software boundaries. This lack of uniformity is not only a reporting issue; it reflects a broader interoperability challenge in construction digital twin ecosystems, where non-uniform interfaces, protocols, and standards continue to hinder robust multi-system integration (Omrany et al., 2023). For safety-oriented twins, these architectural choices condition whether a system can support low-latency monitoring, reliable state updates, auditable traceability, and explainable alerting at the point of work. Figure 3 summarizes the layered reference architecture through which these choices are made.

To make these design choices comparable across the Tier 1 corpus, this section synthesizes the reported mechanisms into: (i) a layered reference architecture that locates where sensing, interoperability, semantics, analytics, and user delivery are implemented, and (ii) a set of recurring technical patterns concentrated in the middleware and semantic layers. Figure 3 presents the layered reference architecture, while Table 4 classifies the principal middleware and semantic patterns used to bridge BIM representations with operational data streams. Sections 4.2.3 and 4.2.4 then relate these patterns to dominant data-flow regimes and deployment scales, clarifying how architectural structure constrains or enables maturity progression.

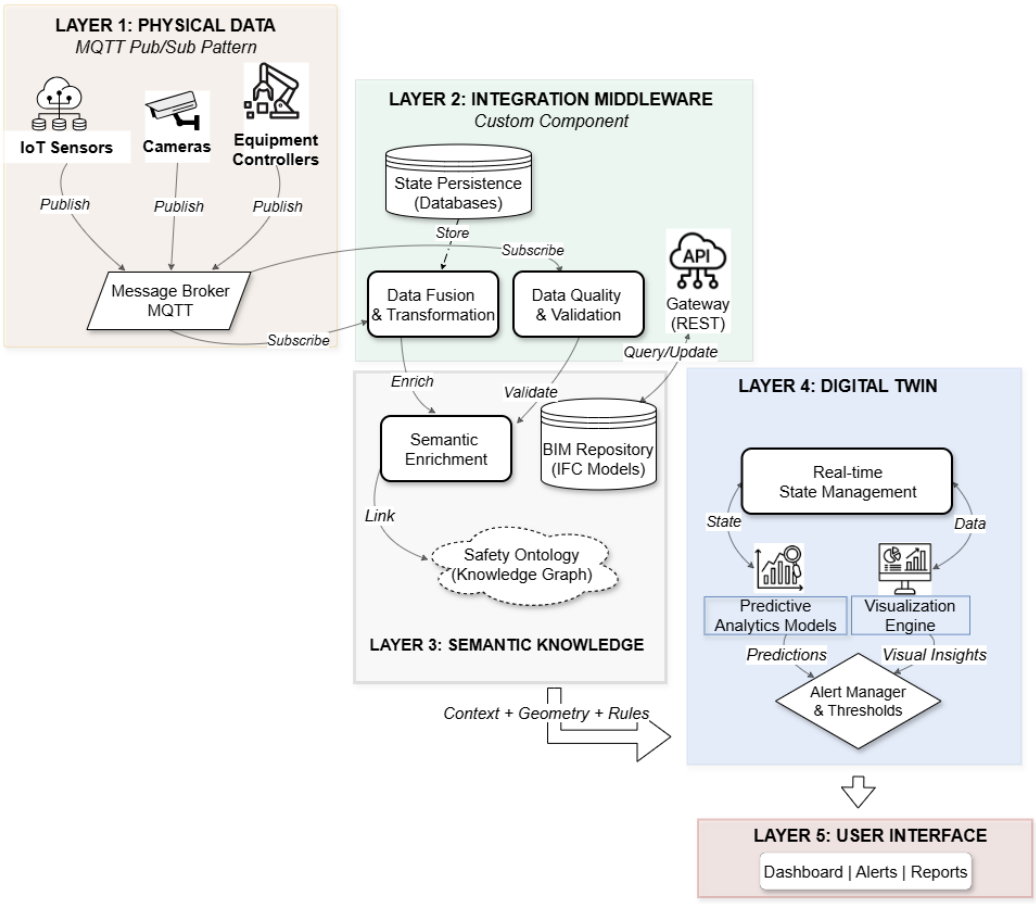



*Figure 3: Layered reference architecture for BIM–DT safety twins.*

### 4.2.1 Layered reference architecture

Figure 3 synthesizes a five-layer reference architecture that recurs across Tier 1 implementations and aligns with construction digital twin reviews that organize enabling technologies around data capture, communication, computation, and visualization, while highlighting persistent integration and interoperability constraints (Akanmu et al., 2021; Jiang W. et al., 2021; Lee et al., 2021; Omrany et al., 2023; Tuhaise et al., 2023; Zhao et al., 2024). The architecture is intended as a reference map rather than a prescriptive blueprint. Its purpose is to make explicit (a) where data are acquired and transported, (b) where BIM alignment and semantic reconciliation occur, (c) where state estimation and prediction are computed, and (d) how outputs are delivered into safety workflows. Although the layer structure is domain-general, its safety instantiation imposes layer-specific constraints, including sensing

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coverage and sampling rates matched to hazard dynamics (SR1, SR2), bounded end-to-end latency between detection and warning delivery (SR2), and outputs that remain interpretable and actionable for site personnel (SR4).

**Layer 1: Physical data.** Layer 1 represents the observed construction or facility environment and the instrumentation used to sense it. Common modalities include radio frequency identification (RFID), inertial measurement units, global navigation satellite systems (GNSS), cameras, and laser scanning, with mobile reality capture (for example, drones and on-worker video) proposed for site-scale perception (Zhao et al., 2024). In Tier 1 safety implementations, Layer 1 ranges from minimal instrumentation (where BIM acts primarily as a static reference) to dense, continuous sensing that supports near-real-time hazard proximity assessment and dynamic zone monitoring (Messi et al., 2020).

**Layer 2: Integration middleware and data services.** Layer 2 ingests streams from Layer 1, persists and routes them, and exposes them to upstream consumers. This layer is typically anchored by data communication and storage services and increasingly relies on application programming interfaces (APIs) and message brokers to exchange data across systems (Saif et al., 2024; Salzano et al., 2024). Because safety monitoring depends on timeliness and reliability, Layer 2 commonly enforces time-stamping, buffering, basic validation, and mediation between event-driven sensor feeds and query-oriented BIM or database services. Interoperability risks concentrate here when interfaces and protocols are not standardized (Omrany et al., 2023).

**Layer 3: Semantic knowledge and BIM alignment.** Layer 3 hosts information structures that allow operational signals to be interpreted in terms of assets, locations, tasks, and hazards. BIM commonly provides the semantically rich substrate for representing sensed and historical data, but meaning must still be reconciled across heterogeneous representations. Consequently, semantic models and ontologies are increasingly used to align data streams and formalize hazard-relevant concepts (Omrany et al., 2023). In safety-oriented twins, Layer 3 enables consistent mapping of detections and trajectories to BIM elements, work zones, and risk rules, supporting auditable interpretation (Liu Z. et al., 2021; Saif et al., 2024).

**Layer 4: Digital twin and analytics.** Layer 4 hosts the twin engine and associated analytics and simulation modules. In M2 implementations, this layer primarily aggregates and visualizes current state data; in M3 implementations, it also runs predictive models, scenario simulations, and optimization routines that estimate future risk states or trajectories using historical and real-time data anchored to BIM semantics (Ellul et al., 2024; Liu Z. et al., 2021).

**Layer 5: User interface and workflow integration.** Layer 5 delivers twin outputs to end users through dashboards, 3D viewers, augmented reality interfaces, alarms, and integration interfaces for external systems. It embeds twin outputs within safety management workflows, for example, by feeding alerts into permit-to-work systems or project management tools (Li et al., 2024; Schiavi et al., 2023).

Interpreted through this reference architecture, lower-maturity implementations often concentrate on BIM-centric representation and user-facing visualization with limited continuous sensing. Higher-maturity implementations activate end-to-end pathways from Layer 1 through Layer 5, including middleware that supports reliable exchange and semantic structures that support consistent mapping and rule-based interpretation. Predictive coupling further intensifies Layer 4 requirements and typically increases dependence on Layer 3 semantic structures to support context-aware reasoning. Section 5.5 revisits how these architectural shifts align with maturity progression across the Tier 1 corpus.

#### 4.2.2 Technical pattern taxonomy

Within this layered architecture, the Tier 1 implementations realize four recurring technical patterns at the semantic and middleware layers. These patterns differ in how they manage data interoperability, extensibility, and coupling between components. Table 4 summarizes these patterns and highlights what is distinctive about each for safety-oriented twins.

*Semantic Web Architectures.*

Semantic web architectures use ontologies, Resource Description Framework (RDF) stores, and SPARQL (SPARQL Protocol and RDF Query Language) endpoints to represent BIM entities, sensor devices, and safety concepts in a unified, queryable form; RDF encodes information as subject–predicate–object triples, and SPARQL

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provides the standard language for querying them. For safety applications, this allows flexible reasoning such as inferring which workers are exposed to a hazard based on semantic relationships, rather than relying on hard coded identifiers (Eneyew et al., 2022). However, the upfront modeling effort and the expertise required to maintain ontologies can be substantial.

*Message broker architectures*

Message broker architectures organize communication between data producers and consumers through publish–subscribe topics. They decouple sensing devices, analytics services, and visualization clients, which is particularly attractive when multiple safety applications must subscribe to overlapping data streams in real time. The tradeoff is that safety logic can become dispersed across services, making global assurance and debugging more challenging (Saif et al., 2024; Liu D. et al., 2023).

*Table 4: Technical architecture patterns at the semantic and middleware layers.*

| Pattern | Core Technologies | Integration Strategy | Strengths | Limitations | Representative References |
|---|---|---|---|---|---|
| Semantic web | Ontology-based mapping (semantic relationships between BIM entities and sensor streams) | Formal semantic alignment between BIM identifiers/objects and operational data to support query and inference | High expressiveness, supports reasoning and inference over hazard relationships and exposure conditions | High modeling effort, potential performance bottlenecks under high-volume data | Eneyew et al. (2022); Jiang et al. (2022) |
| Message broker | Event-driven middleware (publish–subscribe) | Event-driven decoupling of producers (sensors, tracking) and consumers (analytics, dashboards) | Scales to heterogeneous devices, buffering, loose coupling across services | Requires governance of topic schemas, adds infrastructure complexity, logic may disperse across services | (Liu D. et al., 2023; Zhou et al., 2019; Lai et al., 2022; Saif et al., 2024) |
| API-based integration | Web service interfaces (REST/GraphQL) | Components query or exchange state through platform APIs (BIM servers, IoT platforms, twin engines) | Low barrier to integration, leverages existing platform interfaces, supports modular substitution of components | Tight coupling in practice, polling-based designs can bottleneck under high-volume streaming | (Saif et al., 2024; Salzano et al., 2024; Ellul et al., 2024) |
| Custom middleware | Purpose-built connectors and ETL logic | Bespoke integration pipelines tailored to a specific toolchain or testbed | Optimized performance for the target context, fine-grained control of the integration logic | Low portability, high maintenance burden, “glue code” fragility | (Liu Z. et al., 2021; Lai et al., 2022; Hong et al., 2022) |

*Custom middleware architectures.*

Custom middleware architectures implement bespoke integration logic tailored to a specific project or testbed, often combining elements of the patterns above. They can achieve tight integration and low latency for the targeted use case, but their idiosyncratic designs hinder portability and scaling beyond the initial context. Several Tier 1 prototypes fall into this category, particularly early-stage worker tracking and hazard visualization systems (Lai et al., 2022; Hong et al., 2022).

Across the corpus, semantic web and message broker patterns are more common in M2 and M3 implementations that require flexible, real time data fusion, while API based and custom middleware approaches dominate in smaller-scale or proof-of-concept systems.

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### 4.2.3 Data flow and synchronization strategies

The technical patterns above still require explicit data flow and synchronization choices that determine how faithfully digital states track field conditions. Synthesizing Tier 1 descriptions alongside construction DT integration reviews suggests three recurring paradigms: static transfer, event-driven streaming, and continuous fusion (Jiang W. et al., 2021; Omrany et al., 2023). These paradigms reflect increasing temporal coupling and, typically, increasing operations overhead in time alignment, quality control, storage, and computing. Figure 4 summarizes these paradigms schematically. It illustrates the data flow and synchronization paradigms for BIM–DT safety twins, contrasting static transfer, event driven streaming, and continuous fusion in terms of temporal fidelity and infrastructure requirements.

*Static transfer*

This paradigm involves the periodic or one-off export of BIM geometry, hazard annotations, or temporary works representations to support offline risk assessment, training, or post-hoc analysis. It lacks an automated linkage to live site data. Speiser and Teizer (2024) exemplify this approach in their virtual training workflow, where BIM geometry is exported to a simulation environment to generate static hazard scenarios. Similarly, Torrecilla-García et al. (2021) utilize static BIM extracts to populate risk registers for tunneling design reviews. This paradigm aligns with M1 workflows; while cost-effective for planning, it cannot sustain operational monitoring because state drift is intrinsic and uncorrected.

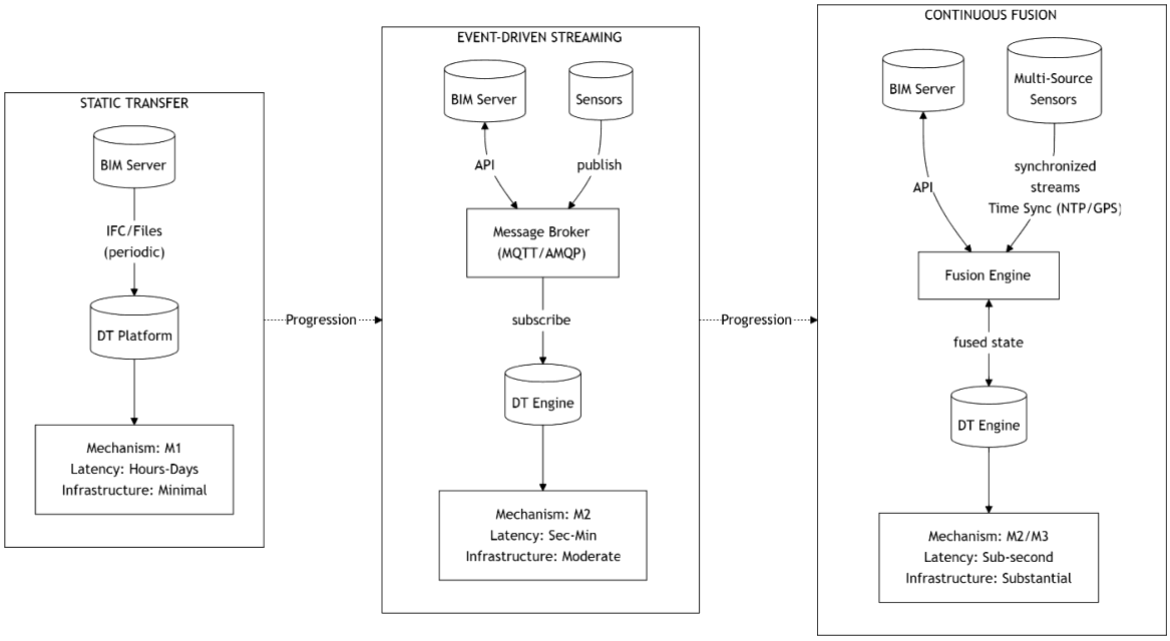



*Figure 4: Data flow and synchronization paradigms for BIM–DT safety twins.*

*Event-driven streaming*

Most operational implementations employ event-driven streaming. Sensor data, tracking events, and status changes are pushed to middleware or twin engines as events, which are then consumed by rule engines, analytics services, or dashboards (Karlapudi et al., 2023; Liu D. et al., 2023). Batch or mini-batch processing is used where full streaming is not required. This paradigm underpins the majority of M2 twins, where the goal is to detect and respond rapidly to emerging hazards, such as workers entering exclusion zones or sensors indicating threshold exceedances.

*Continuous fusion*

The most demanding paradigm, continuous fusion, fuses multiple high-frequency streams (such as dense sensing arrays or continuous analytics outputs) to estimate latent states, predict trends, and update risk indicators with tight temporal coherence. In the Tier 1 corpus, this paradigm is most visible in the predictive monitoring of structural

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and geotechnical safety states. Hong et al. (2022) integrated deep learning models that require synchronized, continuous time-series inputs from multiple inclinometers and strain gauges to forecast foundation pit deformation. Zhao et al. (2022) similarly utilized continuous fusion for tunnel settlement prediction, noting that the LSTM models required strictly time-aligned data frames that event-driven architectures often fail to guarantee. This paradigm shifts effort toward calibration, uncertainty handling, and sustained data management, as prediction quality depends on maintaining rigorous historical and real-time alignment.

In the reviewed literature, synchronization is a design choice that reflects monitoring criticality, tolerance for state drift, and the degree to which predictive performance is required. Static transfer supports planning and learning; event-driven streaming supports operational visibility and alerting; and continuous fusion is justified when the application requires validated prediction and sustained temporal coherence. In the Tier 1 corpus, the transition from static transfer to event-driven streaming is reported more frequently than the move toward continuous fusion, consistent with the dominance of M2 over M3 implementations.

#### 4.2.4 Deployment scale and infrastructure considerations

Beyond data flow, the Tier 1 implementations differ markedly in the scale at which twins are deployed and the scope of assets and processes they cover. Three deployment scales can be distinguished: equipment, site, and facility. These scales interact with the choice of mechanisms and architectures and strongly influence the feasibility of real-time and predictive capabilities (Jiang W. et al., 2021; Omrany et al., 2023).

*Equipment level deployments*

Equipment-focused deployments center on individual machines such as cranes, excavators, or tunnel boring equipment. In these architectures, sensors are mounted directly on the equipment, and data are streamed to a local edge gateway or cloud twin that monitors machine state, operating envelope, and proximity to hazards. Zhou et al. (2019) and Messi et al. (2020) exemplify this approach by instrumenting cranes with ultrasonic sensors and encoders to detect blind zone incursions. By bounding the "twin" to the machine's specific kinematics, these systems achieve high temporal fidelity (M2/M3) with modest infrastructure. Lai et al. (2022) further demonstrated the advantage of this bounded scope; because they only needed to model the physics of a single crane boom, they could employ lightweight surrogate models that run in near real-time. However, the trade-off is situational blindness: these twins effectively manage hazards intrinsic to the machine but remain unaware of systemic site risks not visible to their local sensors.

*Site-level deployments*

Site-level deployments extend coverage to whole construction sites, temporary works, and mobile workfaces. They attempt to integrate diverse sensors, including worker wearables, fixed cameras, and environmental monitors, and map these to BIM-based site models. This scaling introduces significant data fusion challenges. Liu et al. (2023) attempted to track excavator pose relative to the broader site context but reported that maintaining line-of-sight for cameras across a cluttered excavation zone created blind spots that equipment-mounted sensors did not face. Similarly, Saif et al. (2024) integrated wearables with 4D BIM to track workforce exposure. While this provided a holistic view of site safety, it required sophisticated middleware to handle the bandwidth of aggregating hundreds of moving entities. Consequently, site-level twins often operate at a lower refresh rate than equipment twins or require substantial cloud computing resources to maintain synchronization.

*Facility level deployments*

Facility-level deployments operate at the scale of operational plants, infrastructure networks, or large building portfolios (Moretti et al., 2023; Badenko et al., 2021; Bolshakov et al., 2024). Here, BIM and asset information models are integrated with enterprise systems, SCADA data, and long-term monitoring networks. Safety-oriented twins at this scale often focus on structural or process safety, regulatory compliance, and emergency response planning (Moretti et al., 2023). Eneyew et al. (2022) highlighted that success at this scale depends on rigorous semantic mapping to ensure that a temperature reading is correctly associated with a specific BIM space. While these twins offer potential for high-impact interventions in fire safety or structural maintenance, they are often constrained by the rigidity of legacy data schemas.

These deployment scales highlight that moving from equipment to site and facility levels increases integration complexity non-linearly. Scaling from an equipment-level M2 twin to a site-wide M3 twin is not merely a matter

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of adding more sensors; it requires a fundamental shift from edge-centric processing to centralized data fusion and standardized semantics. This complexity cliff helps explain why predictive M3 implementations in the corpus are concentrated in bounded settings, such as individual equipment, stable facilities, or instrumented geotechnical works, while prediction across dynamic, multi-actor site workfaces remains rare.

*Table 5: Taxonomy of BIM–DT maturity levels.*

| Level | Label | Concise Definition | Key Data and Integration Characteristics | Safety Management Capabilities and References |
|---|---|---|---|---|
| **L0** | Conceptual integration | BIM–DT safety integration defined at the level of frameworks, architectures, or workflows without operational deployment. | Static BIM and conceptual DT models only, no live data connection. Data flows and semantics are defined "on paper" or in diagrams, with no continuously updated digital state. | Conceptual hazard identification and risk assessment, mapping of lifecycle risk factors, and design for safety principles, but hazard detection and risk estimation remain manual (Torrecilla-García et al., 2021; Teizer et al., 2023; Sacks et al., 2020; Hoeft & Trask, 2022; Xu et al., 2023; Speiser & Teizer, 2024). |
| **L1** | Static visualization | Conceptual level retained for completeness. BIM visualizations of safety-relevant information, but without continuous data integration or a DT engine maintaining a dynamic state. | Snapshot data or manually refreshed views, no streaming integration, no DT engine maintaining a dynamic state. | No Tier 1 study qualifies as a BIM–DT integration at L1. This level is treated as a conceptual waypoint between L0 frameworks and deployed monitoring twins, and appears implicitly in BIM-based safety planning literature. |
| **L2** | Interactive monitoring | BIM is integrated with real-time or near-real-time data streams so that the DT maintains an up-to-date representation of safety-relevant states. | Continuous or frequent updates from sensors, equipment, and site systems. BIM entities serve as spatial and semantic anchors for data streams from GNSS, ultra-wideband (UWB), RFID, wearables, cameras, and IoT devices. | Automated hazard identification, for example geofenced proximity monitoring, collision and blind zone alerts, and real time environmental monitoring, with dashboards and alarms for supervisors (Liu et al., 2023; Zhou et al., 2019; Saif et al., 2024; Eneyew et al., 2022; Lai et al., 2022; Fang et al., 2024; Wang T. et al., 2022; Jiang W. et al., 2021; Moretti et al., 2020; Ellul et al., 2024; Salzano et al., 2024; Karlapudi et al., 2023). |
| **L3** | Predictive analytics | BIM–DT integration extended with analytical models that estimate future safety states, incident probabilities, or risk trajectories. | Builds on L2 infrastructure plus historical data repositories, predictive models, and calibration routines. Some implementations include explicit model validation and uncertainty handling. | Forward-looking hazard identification, for example, prediction of unsafe hoisting states, geotechnical failures, or unsafe clearances, and proactive risk assessment, such as failure probabilities or time to threshold exceedance (Liu Z. et al., 2021; Liu Z. et al., 2020; Jiang Y. et al., 2022; Hong et al., 2022; Hu et al., 2024; Messi et al., 2020; Zhao et al., 2022). |
| **L4** | Autonomous adaptation | Conceptual end state in which the DT not only predicts risk but also orchestrates safety responses within defined governance constraints. | Would require tight coupling between predictive models, rule-based policies, and actuation systems capable of implementing safety interventions safely and reliably, alongside robust governance and assurance. | Semi or fully automated intervention, for example, autonomous slowdown or lockout of equipment, dynamic access control, or adaptive permit to work logic. Currently appears only in conceptual and governance-oriented DT safety discussions (Sacks et al., 2020; Opoku et al., 2023; Zio & Miqueles, 2024), and no Tier 1 implementation achieves L4. |

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From an RQ1 perspective, Sections 4.1 and 4.2 show that current BIM–DT safety twins are built from a small set of mechanisms, layered architectures, and deployment patterns that cluster around interactive monitoring and selective predictive analytics. The next section uses this integrated view as a starting point to analyze how the 27 Tier 1 implementations distribute across maturity levels, what safety capabilities they deliver at each level, and how these patterns vary across project phases, thereby addressing RQ2.

# 5. MATURITY ANALYSIS OF BIM–DT SAFETY INTEGRATION (RQ2)

Section 4 showed that current BIM–DT safety implementations are built from a small set of mechanisms and technical architectures that concentrate on interactive monitoring and selective predictive analytics. RQ2 shifts the focus from how these systems are technically integrated to how far they have progressed along the maturity trajectory defined in the conceptual framework, and what safety capabilities they deliver at different maturity levels.

This section examines how the Tier 1 implementations distribute across maturity levels, how their safety capabilities differ, and how these patterns vary across project phases. Section 5.1 explains how the maturity framework was operationalized for coding. Section 5.2 reports the distribution of maturity levels in the Tier 1 corpus. Section 5.3 compares safety capabilities across L0, L2, and L3 implementations. Section 5.4 analyzes how maturity levels interact with project phases. Section 5.5 synthesizes these strands to infer progression pathways and to align maturity levels with the integration mechanisms from Section 4.

## 5.1 Operationalizing the maturity framework

The maturity framework used in this review brings together digital twin, BIM, and safety technology literature to distinguish five levels of BIM–DT safety integration, from L0 disconnected models to L4 autonomous adaptation, as summarized in Table 5. For RQ2, the key distinction lies between three empirically observed levels (L0, L2, L3) and two conceptual endpoints (L1, L4) that are useful for structuring gaps.

For coding, each Tier 1 study was assigned an L0 to L4 label based on descriptive evidence about data coupling, temporal behavior, and decision support, as described in Section 3.5. Maturity labels were checked against the Tier 1 coding table, and inter-coder agreement on this dimension was assessed as part of the reliability check reported in Section 3.5, with discrepancies reconciled by discussion. The resulting maturity labels provide the basis for the distribution, capability, phase, and progression analyses in Sections 5.2 to 5.5.

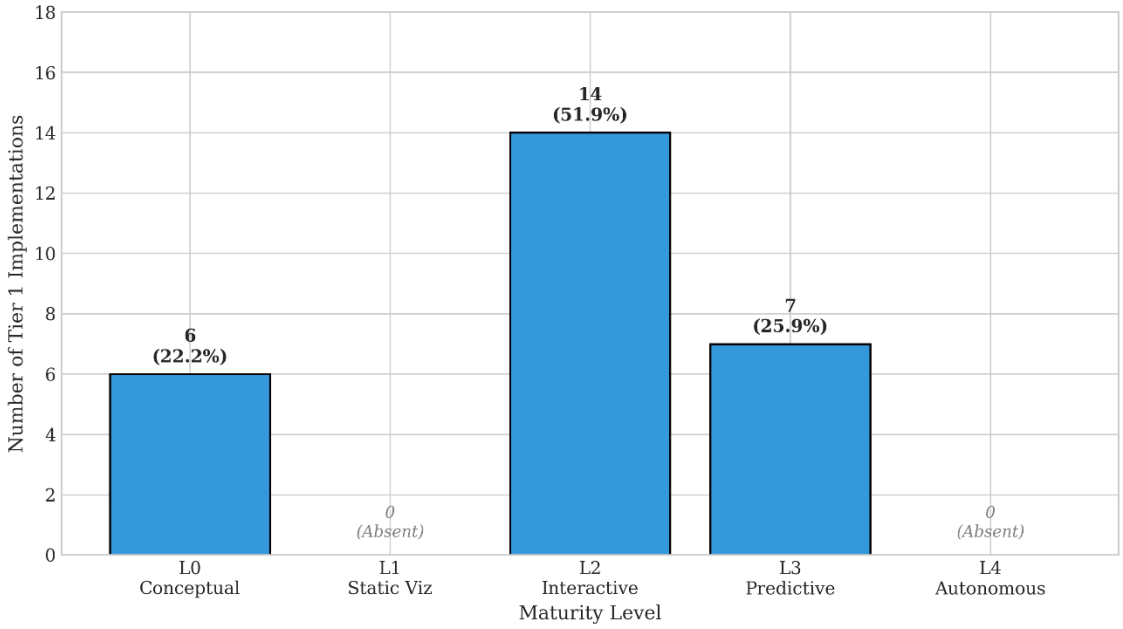



*Figure 5: Maturity level distribution in Tier 1 corpus (N = 27).*

## 5.2 Maturity distribution in the Tier 1 corpus

The 27 Tier 1 implementations populate only three of the five maturity levels. Six studies are coded at L0 conceptual integration, fourteen at L2 interactive monitoring, and seven at L3 predictive analytics. No implementation was classified at L1 static visualization or at L4 autonomous adaptation, and Figure 5 visualizes this distribution.

Figure 5 visually confirms the strong concentration of implementations at L2 interactive monitoring, followed by clusters at L0 and L3. L0 implementations are dominated by lifecycle frameworks and conceptual safety twins that define how BIM and DT could interact for safety without operational data coupling (Sacks et al., 2020; Torrecilla-García et al., 2021; Teizer et al., 2023; Xu et al., 2023; Speiser & Teizer, 2024). L3 implementations occur mainly in data-intensive, high-risk domains such as hoisting, tunneling, and structural monitoring, where sufficient instrumentation and historical data exist to support predictive modeling (Liu Z. et al., 2021; Liu Z. et al., 2020; Hong et al., 2022; Messi et al., 2020; Zhao et al., 2022; Hu et al., 2024), consistent with the broader shift from static toward dynamic, data-driven risk assessment (Zio, 2018).

The absence of L1 and L4 implementations is notable. Potential L1 cases are folded into L0 when they remain purely conceptual or into L2 when any live data coupling is present. Likewise, although multiple papers discuss potential autonomous or semi-autonomous safety interventions, none of the Tier 1 implementations satisfy the criteria for L4, which would require routine, DT-driven safety actions under explicit governance (Sacks et al., 2020; Opoku et al., 2023; Zio & Miqueles, 2024).

## 5.3 Safety capabilities by maturity level

The maturity levels defined above translate into qualitatively different safety capabilities across four domains: hazard identification, risk assessment, intervention and response, and learning and improvement. Table 6 summarizes how capabilities in these domains change from L0 to L2 to L3, drawing on Tier 1 evidence and interpreting these patterns through Tier 2 digital twin and safety reviews.

*Table 6: Safety capabilities by maturity level.*

| Capability Domain | Maturity Level | Characteristics of BIM–DT Safety Capabilities | References |
|---|---|---|---|
| Hazard identification | L0 conceptual integration | Hazards structured conceptually in BIM–DT frameworks using 4D risk models, lifecycle taxonomies, and scenario-based exposure models. Identification remains manual and design time, for example, through risk checklists and annotated BIM views. | (Sacks et al., 2020; Xu et al., 2023; Teizer et al., 2023; Speiser & Teizer, 2024). |
| Hazard identification | L1 static visualization | Static BIM visualizations of hazard locations or risk scores manually updated or exported from planning tools. No Tier 1 implementation maintains this as a live DT; it is treated as a transitional concept in several L0 frameworks. | No Tier 1 implementations; described as a transitional concept for safety frameworks. |
| Hazard identification | L2 interactive monitoring | Automatic flagging of hazardous states, such as workers entering geofenced exclusion zones, machinery encroaching on blind spots, or environmental conditions exceeding thresholds, using streaming data mapped to BIM spaces and assets. | (Liu D. et al., 2023; Jiang W. et al., 2021; Badenko et al., 2021; Salzano et al., 2024; Saif et al., 2024) |
| Hazard identification | L3 predictive analytics | DT forecasts future hazardous conditions such as support failures, collision risks, or unsafe clearances, based on trends in structural response, equipment trajectories, or operational patterns linked to BIM entities. | (Liu Z. et al., 2021; Zhao et al., 2022; Hong et al., 2022; Hu et al., 2024) |
| Hazard identification | L4 autonomous adaptation | Conceptual stage where DTs would automatically reconfigure work zones, routes, or access states in response to predicted hazards, with human oversight and governance constraints. | None in Tier 1 corpus; discussed in conceptual DT safety governance papers. |
| Risk assessment | L0 conceptual integration | Risk assessment expressed as conceptual mapping between BIM elements, lifecycle stages, and qualitative or semi-quantitative risk ratings in safety frameworks and checklists. | (Torrecilla-García et al., 2021; Teizer et al., 2023). |

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| Capability Domain | Maturity Level | Characteristics of BIM–DT Safety Capabilities | References |
|---|---|---|---|
| Risk assessment | L1 static visualization | Not present as a distinct DT capability in Tier 1. Risk views are static overlays or reports rather than dynamic DT states and thus remain within conceptual BIM-based planning. | Not present as a DT implementation in Tier 1; appears in BIM safety planning literature. |
| Risk assessment | L2 interactive monitoring | Real-time or near-real-time computation of status-based safety indicators, such as distances, load factors, occupancy levels, or support states, visualized through dashboards and traffic light-style indicators. | (Liu D. et al., 2023; Jiang W. et al., 2021; Salzano et al., 2024). |
| Risk assessment | L3 predictive analytics | Probabilistic or scenario-based risk assessment derived from predictive models, including exceedance likelihoods, predicted failure times, or risk indices for alternative plans or sequences. | (Liu Z. et al., 2021; Hong et al., 2022; Zhao et al., 2022; Hu et al., 2024). |
| Risk assessment | L4 autonomous adaptation | Conceptual stage where DTs would continuously adjust control thresholds and risk acceptance criteria based on learned performance while respecting governance constraints. | None in Tier 1 corpus. |
| Intervention and response | L0 conceptual integration | Conceptual recommendations for safer methods, layouts, or protections derived from BIM-based scenario analysis and safety by design workflows, but implemented manually without DT feedback. | (Speiser & Teizer, 2024; Teizer et al., 2023). |
| Intervention and response | L1 static visualization | Conceptual only in the Tier 1 BIM–DT corpus. Static BIM views support communication of safety measures, but do not respond dynamically to live data. | Conceptual only in Tier 1 BIM–DT corpus. |
| Intervention and response | L2 interactive monitoring | DT triggers alarms, notifications, and visual warnings when monitored indicators cross thresholds, supporting supervisors in stopping work, isolating equipment, or evacuating zones. | (Zhou et al., 2019; Saif et al., 2024; Liu D. et al., 2023). |
| Intervention and response | L3 predictive analytics | Suggested interventions are planned ahead based on forecast risk states, for example rescheduling lifts, reinforcing supports, or rerouting traffic before predicted unsafe states occur. | (Messi et al., 2020; Liu Z. et al., 2021; Hong et al., 2022; Hu et al., 2024). |
| Intervention and response | L4 autonomous adaptation | Conceptual stage where DTs would implement semi or fully automated interventions, such as autonomous slowdown or lockout, under strict governance and human override. | None in Tier 1 corpus. |
| Learning and improvement | L0 conceptual integration | Lessons learned are incorporated into evolving BIM–DT safety visions and frameworks, shaping future design for safety and lifecycle strategies, but without continuous operational feedback. | Lifecycle learning is framed conceptually in safety vision papers (Sacks et al., 2020; Speiser & Teizer, 2024). |
| Learning and improvement | L1 static visualization | Historical data may be used to update static risk maps, but there is no DT engine to support continuous learning from operational performance; not implemented in Tier 1. | Not implemented as DTs in Tier 1. |
| Learning and improvement | L2 interactive monitoring | DTs generate logs of alarms, state changes, and operational events that can be analyzed after the fact for training, tuning of geofences and thresholds, and refinement of procedures. | (Jiang W. et al., 2021; Badenko et al., 2021; Saif et al., 2024). |
| Learning and improvement | L3 predictive analytics | DTs incorporate feedback loops in which predictive models are retrained on accumulated data and expert review, improving accuracy and site specificity over time. | (Liu Z. et al., 2020; Hong et al., 2022; Zhao et al., 2022; Hu et al., 2024). |
| Learning and improvement | L4 autonomous adaptation | Conceptual stage where control policies and risk thresholds would be continually adapted by the DT based on observed performance, under explicit governance and audit. | None in Tier 1 corpus. |

In summary, Table 6 shows that progression from L0 through L2 to L3 widens the temporal horizon of safety management and deepens the coupling between sensing, analytics, and decision processes. L1 is absent from the Tier 1 corpus as a distinct DT capability, and L4 remains conceptual. L0 conceptual frameworks define what could be monitored and predicted (Sacks et al., 2020; Torrecilla-García et al., 2021; Teizer et al., 2023; Xu et al., 2023; Speiser & Teizer, 2024). L2 interactive systems monitor what is currently happening and support reactive control

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across multiple hazard types (Zhou et al., 2019; Liu D. et al., 2023; Saif et al., 2024; Eneyew et al., 2022; Badenko et al., 2021). L3 predictive twins estimate what is likely to happen next and enable proactive interventions and learning (Liu Z. et al., 2021; Hong et al., 2022; Messi et al., 2020; Zhao et al., 2022; Hu et al., 2024). Mapped onto the requirements introduced in Section 1, this progression corresponds to the successive satisfaction of SR2 and SR4 at L2, SR3 at L3, and SR6 at L4, while SR1 underpins every level and SR5 depends on continuity across phases rather than on any single level.

## 5.4 Maturity patterns across project phases

Maturity does not develop in a vacuum; it interacts with where in the project lifecycle BIM–DT safety systems are deployed. To explore this interaction, each implementation was coded for its primary lifecycle phase coverage (construction, post-construction/operations, or cross-lifecycle), and phase codes were cross-tabulated with maturity levels. Coding shows that the 27 implementations consist of 15 construction phase systems, 6 post-construction or operations systems, and 6 cross-lifecycle contributions. The phase by maturity cross tabulation indicates that construction accounts for 1 L0, 10 L2, and 4 L3 implementations, post construction for 4 L2 and 2 L3, and cross lifecycle for 5 L0 and 1 L3, yielding the overall 6 L0, 14 L2, and 7 L3 distribution. Figure 6 provides a visual summary of the distribution.

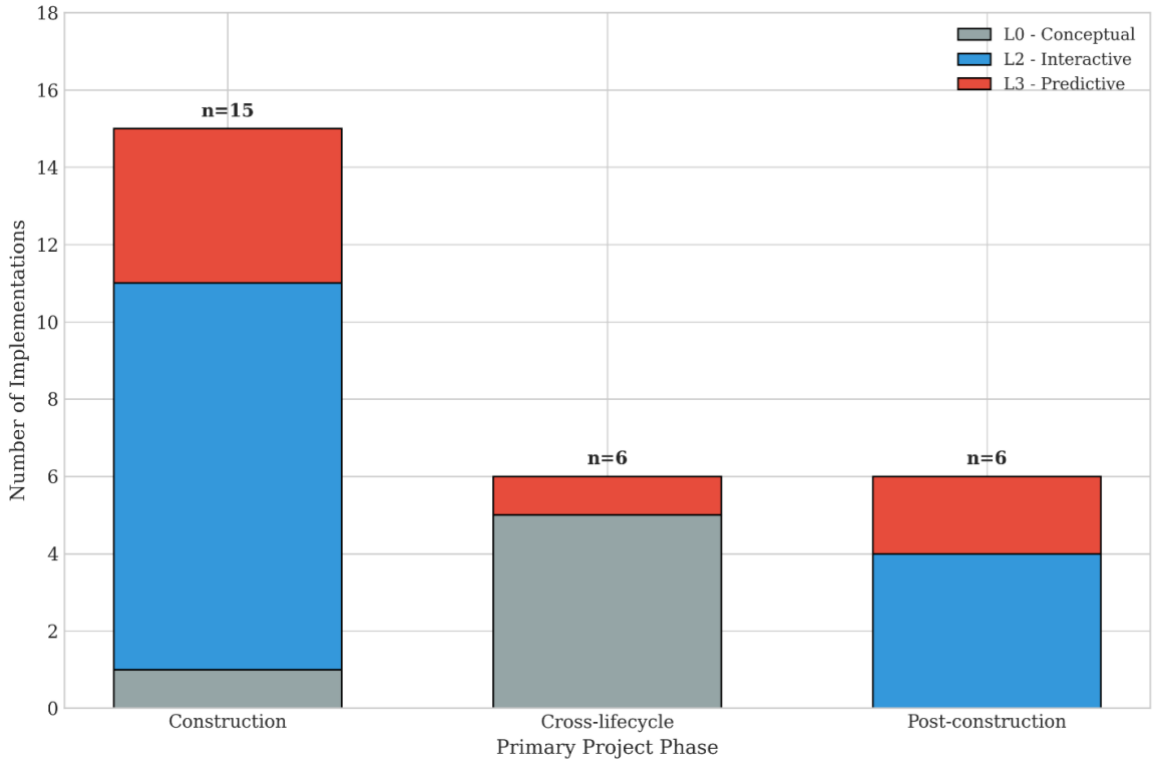



*Figure 6: Distribution of BIM–DT maturity levels across project phases.*

Construction phase implementations form the operational core of the corpus. Within this group, L2 interactive monitoring is dominant: ten systems couple BIM with GNSS, UWB, RFID, wearables, or computer vision to monitor worker and equipment locations, exclusion zones, and environmental conditions in real time (Zhou et al., 2019; Liu D. et al., 2023; Saif et al., 2024; Lai et al., 2022; Fang et al., 2024; Jiang Y., 2021; Ellul et al., 2024; Salzano et al., 2024; Jiang W. et al., 2021; Karlapudi et al., 2023). These implementations emphasize situational awareness on dynamic workfaces and support reactive decision making through alerts and dashboards. Four construction phase implementations are L3 predictive twins that focus on hoisting, tunneling, and excavation, where predictive models of collision risk or structural instability can be justified by the severity of potential failures and the availability of detailed instrumentation (Liu Z. et al., 2021; Jiang Y. et al., 2022; Messi et al., 2020; Zhao et al., 2022).

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Post construction and operations phase implementations, although fewer in number, show a relatively high proportion of predictive twins. Four L2 systems monitor structural or environmental conditions in facilities and infrastructure using BIM-linked IoT architectures, focusing on compliance, comfort, and early detection of abnormal states (Moretti et al., 2020; Badenko et al., 2021; Eneyew et al., 2022; Wang T. et al., 2022). Two L3 twins in this phase extend monitoring into predictive maintenance and long-term safety management by forecasting degradation and risk indicators and optimizing inspection or intervention schedules (Liu Z. et al., 2020; Hu et al., 2024).

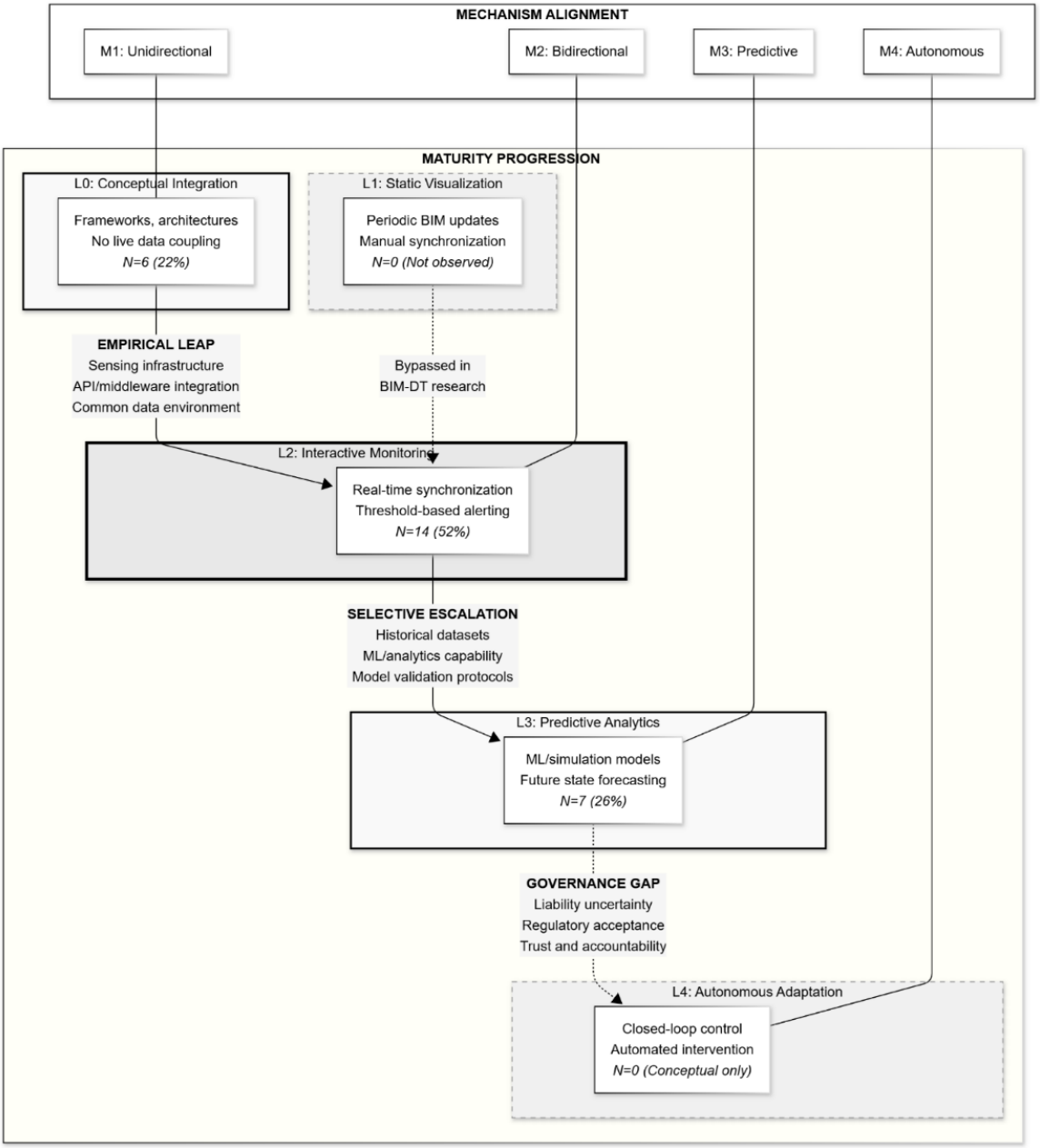



*Figure 7: Maturity progression pathways and mechanism alignment.*

Cross lifecycle studies are predominantly conceptual. Five L0 contributions articulate lifecycle safety twins that would span design, construction, and operation, specifying information flows, actor responsibilities, and feedback loops, but without operational implementations or sustained data continuity (Sacks et al., 2020; Torrecilla-García et al., 2021; Teizer et al., 2023; Hoeft & Trask, 2022; Xu et al., 2023). Only one cross lifecycle implementation

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reaches L3, maintaining a predictive model for a critical asset from late construction into early operation (Hong et al., 2022).

These patterns suggest that construction phase projects currently act as testbeds for operational BIM–DT safety twins, driven by acute risk and evident short-term benefits, while post-construction environments may be well suited to predictive analytics and integration with asset management processes, although the small number of post-construction cases (n = 6) limits this inference. Lifecycle integration remains an attractive but elusive target, constrained by data loss between phases, changing stakeholders, and interoperability issues, as highlighted in several conceptual frameworks (Sacks et al., 2020; Teizer et al., 2023; Xu et al., 2023; Speiser & Teizer, 2024).

## 5.5 Progression pathways and mechanism alignment

The maturity and phase analyses indicate that progression in BIM–DT safety integration is shaped by both technical architecture and broader socio-technical conditions, as summarized in Figure 7.

Figure 7 conceptualizes progression pathways by aligning the maturity levels with the integration mechanisms defined in Section 4. At the lower end of the maturity spectrum, M1 unidirectional data sharing implementations align with L0 conceptual integration, where BIM exports and conceptual DT models support design-time hazard analysis and training but do not maintain a live digital state (Torrecilla-García et al., 2021; Teizer et al., 2023; Sacks et al., 2020; Xu et al., 2023; Speiser & Teizer, 2024). Moving beyond L0 requires organizations to replace file-based workflows with API or cloud-mediated sharing, and to invest in sensing and middleware that support M2 bidirectional synchronization.

The dominant empirical transition observed in the Tier 1 corpus is from L0 conceptual integration to L2 interactive monitoring, an "empirical leap" where conceptual frameworks are turned into live systems that ingest streaming data and provide real-time visibility and alerts (Liu D. et al., 2023; Zhou et al., 2019; Saif et al., 2024; Eneyew et al., 2022; Lai et al., 2022; Badenko et al., 2021; Salzano et al., 2024; Karlapudi et al., 2023). Mechanistically, this leap corresponds to the adoption of M2 bidirectional synchronization architectures, the introduction of site sensing infrastructure, and the implementation of BIM-based semantic mapping, rather than incremental tuning of static BIM-based tools.

A second notable transition is from L2 interactive monitoring to L3 predictive analytics, which involves embedding predictive models in the twin loop. All M3 implementations are coded as L3 and use M3 predictive coupling mechanisms layered on top of M2 synchronization, whether in hoisting, tunneling, excavation, or structural health monitoring (Liu Z. et al., 2021; Liu Z. et al., 2020; Jiang Y. et al., 2022; Hong et al., 2022; Messi et al., 2020; Zhao et al., 2022; Hu et al., 2024). Progression to L3 is therefore associated with additional investments in historical data curation, model development, and validation, and tends to occur selectively in high-risk, data-rich niches rather than as a routine evolution of all L2 systems.

The conceptual transition from L3 to L4 autonomous adaptation, although not observed empirically in the Tier 1 corpus, would require an even tighter coupling between predictive models, rule-based policies, and actuation systems, along with clear governance of autonomy envelopes, liability, and human oversight (Sacks et al., 2020; Opoku et al., 2023; Zio & Miqueles, 2024). Current digital twin safety and governance papers highlight concerns about accountability, regulatory acceptance, and worker trust as reasons why organizations hesitate to delegate safety-critical interventions to autonomous control, even when predictive capability is available.

Overall, the evidence suggests that maturity progression in current BIM–DT safety practice is not a smooth continuum but a sequence of discrete shifts in both mechanisms and socio-technical framing. Moving from L0 to L2 requires an empirical leap to operational monitoring. Moving from L2 to L3 requires selective escalation that embeds predictive analytics under explicit validation. Seemingly, progression beyond L3 toward L4 would depend not only on advanced integration and modeling, but also on governance arrangements that address autonomy and responsibility. Section 6 builds on this interpretation by examining the technical, organizational, and institutional barriers and enablers that shape each of these transitions.

# 6. BARRIERS AND ENABLERS (RQ3)

The maturity patterns documented in Section 5 raise a critical question: what constrains progression between levels? RQ3 addresses this by analyzing barriers and enablers that shape BIM–DT safety twin development. The

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analysis followed an inductive, multi-tier coding strategy. Barrier statements were first extracted from Tier 1 implementation papers wherever authors described limitations, failures, or constraints that kept systems at particular maturity levels. These project-level observations were then complemented with structural barrier analyses from Tier 2 and Tier 3 literature on DT adoption, BIM integration, and safety technology deployment (Sacks et al., 2020; Agnusdei et al., 2021; Boje et al., 2020; Kineber et al., 2023; Omrany et al., 2024).

## 6.1 Barriers to BIM–DT safety twin maturity

Each barrier statement was coded against three dimensions: the socio-technical level, the specific constraint theme, and the maturity transitions primarily affected. This yielded twelve barrier codes (B1-B12) that capture recurring patterns rather than case-specific issues. Throughout, barriers are interpreted as socio-technical patterns that emerge from how implementations combine technology stacks, analytics practices, organizational arrangements, and governance frameworks (Sacks et al., 2020; Omrany et al., 2024). Table 7 presents the complete barrier taxonomy, organized by socio-technical level and mapped to the maturity transitions each barrier primarily constrains. The codes distinguish obstacles that block initial operational deployment (L0 to L2) from those that constrain analytic sophistication (L2 to L3) and those that prevent autonomous capability (conceptual L3 to L4). Each group also identifies the safety requirements it holds back: technical and data barriers (B1 to B4) constrain SR1 and SR2, analytics and modeling barriers (B5 to B7) constrain SR3, fragmented responsibilities (B10) constrain SR5, and regulatory uncertainty (B12) constrains SR6.

*Table 7: Summary of barriers to BIM–DT safety twin maturity.*

| Code | Category | Barrier Label | Description | Primary Transitions Affected | References |
|---|---|---|---|---|---|
| B1 | Technical & Data | Fragmented sensing coverage | Critical work zones or high-risk tasks are only partially instrumented, leaving blind spots in the digital twin representation. | L0 → L2, Scaling within L2 | (Tuhaise et al., 2023; Luo et al., 2024; Omrany et al., 2024) |
| B2 | Technical & Data | Integration complexity | Point-to-point connections between BIM, sensors, and DT engines are brittle under upgrades, making solutions hard to replicate. | L0 → L2, L2 → L3 | Sacks et al., 2020; Boje et al., 2020; Tuhaise et al., 2023 |
| B3 | Technical & Data | Data quality & alignment | BIM models, sensor streams, and DT states drift apart due to inconsistent updating, undermining trust in indicators. | L2 → L3 | Liu Z. et al., 2021; Sacks et al., 2020; Omrany et al., 2024 |
| B4 | Technical & Data | Computational cost & latency | High-fidelity simulations are too computationally expensive to run within the time frames required for operational safety decisions. | L2 → L3, Conceptual L3 → L4 | Zio & Miqueles, 2024; Huang et al., 2022 |
| B5 | Analytics & Modeling | Validation gaps | Safety logic is inherited from coarse risk matrices or code-based rules with limited empirical calibration. | L0 → L2, L2 → L3 | Agnusdei et al., 2021; Zio & Miqueles, 2024 |
| B6 | Analytics & Modeling | Misaligned use cases | Projects focus on visually attractive or easily measurable scenarios rather than systemic, high-consequence risks. | Plateau within L2, Early L3 | Trask & Linderoth, 2023; Luo et al., 2024; Nnaji et al., 2021 |
| B7 | Analytics & Modeling | Lack of reusable patterns | Safety twins are developed as bespoke prototypes with limited modularity, making new implementations costly. | L0 → L2, L2 → L3 | Lai et al., 2022; Boje et al., 2020; Kineber et al., 2023 |

| Code | Category | Barrier Label | Description | Primary Transitions Affected | References |
|---|---|---|---|---|---|
| B8 | Org. & Human | Pilot mentality | Implementations are framed as isolated proofs of concept with limited planning for institutionalization or scaling. | L0 → L2, Scaling within L2 / L3 | Liu et al., 2023; Trask & Linderoth, 2023; Agnusdei et al., 2021 |
| B9 | Org. & Human | Capability & skill gaps | Shortage of hybrid profiles (Safety + BIM + Analytics) constrains design, interpretation, and governance of twins. | L0 → L2, L2 → L3 | Kineber et al., 2023; Tabatabaee et al., 2022; Trask & Linderoth, 2023 |
| B10 | Org. & Institutional | Fragmented responsibilities | Siloed functions (BIM, Safety, Operations) obscure ownership of the safety twin and authority to act on outputs. | L0 → L2, L2 → L3, Conceptual L3 → L4 | Sacks et al., 2020; Omrany et al., 2024; Kineber et al., 2023 |
| B11 | Org. & Human | Privacy & worker acceptance | Concerns about surveillance and data misuse constrain the scaling of worker-centric monitoring approaches. | Entry into L2, Escalation within L3 | Nnaji et al., 2021; Awolusi et al., 2018; Okpala et al., 2022 |
| B12 | Institutional & Regulatory | Regulatory uncertainty | Lack of frameworks for evaluating DT evidence or allocating liability for automated interventions. | Conceptual L3 → L4, Formalization of L2 / L3 | Zio & Miqueles, 2024; Agnusdei et al., 2021; Abdulhamid et al., 2023 |

### 6.1.1 Technical and data constraints (B1–B4)

At the technical level, implementations report persistent challenges that constrain progression beyond L2 interactive monitoring. Fragmented sensing coverage (B1) occurs when systems instrument only specific equipment types or zones rather than providing comprehensive site monitoring. Zhou et al. (2019) documented this in their blind hoisting system, noting that coverage was limited to crane operating zones without broader workface instrumentation. Similarly, Liu D. et al. (2023) reported that their excavation monitoring twin tracked machinery pose but not surrounding workers or temporary infrastructure, creating blind spots in collision risk assessment. While Saif et al. (2024) attempted to address this via wearable tracking, they acknowledged that incomplete adoption among site personnel limited system effectiveness.

Integration complexity (B2) introduces fragility where implementations rely on point-to-point connections between disparate platforms. Lai et al. (2022) noted that their crane monitoring system required custom connectors between structural analysis software, sensor middleware, and visualization tools, offering limited portability. Moretti et al. (2020) reported similar difficulties maintaining an OpenBIM-IoT framework when underlying software versions or sensor configurations changed. Sacks et al. (2020) and Teizer et al. (2023) identify this integration brittleness as a fundamental barrier to scaling beyond controlled pilot contexts.

Data quality and temporal alignment (B3) issues are particularly acute in predictive analytics. Liu et al. (2021) found that hoisting risk models required continuous calibration to address schedule drift, while Hong et al. (2022) reported that inconsistent survey intervals and manual BIM updates created data gaps that undermined deformation forecasts. Furthermore, computational constraints (B4) often necessitate a trade-off between fidelity and speed. Lai et al. (2022) and Zhao et al. (2022) both utilized surrogate models and neural networks (LSTMs) rather than full physics-based analysis to meet the latency requirements of operational safety alerts.

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*Table 8: Enablers and design principles for BIM–DT safety twins, aligned with barrier codes (B1–B12).*

| Cluster | Design Principle | Barriers Addressed | References |
|---|---|---|---|
| Technical & Data | *Targeted Sensing*: Instrument critical risk zones and tasks first using targeted sensors and wearables, then expand coverage gradually as value is verified. | B1, B6 | Tuhaise et al., 2023; Luo et al., 2024; Awolusi et al., 2018 |
| | *Common Data Environment (CDE):* Anchor integrations in a CDE with stable identifiers for assets and locations, avoiding bespoke point-to-point scripts. | B2, B3, B7 | Sacks et al., 2020; Boje et al., 2020; Omrany et al., 2024 |
| | *Hierarchical Modeling:* Use surrogate models so high-fidelity simulations run offline while lighter models drive real-time alerts. | B4, B5 | Zio & Miqueles, 2024; Huang et al., 2022 |
| | *Continuous Governance:* Embed data governance routines to keep digital states aligned with physical conditions (model maintenance & sensor health). | B2, B3 | Sacks et al., 2020; Omrany et al., 2024 |
| Analytics & Modeling | *Co-Designed Analytics*: Design dashboards and thresholds with site teams; validate outputs against incidents, near-misses, and expert judgment. | B5, B6 | Luo et al., 2024; Trask & Linderoth, 2023; Nnaji et al., 2021 |
| | *Ecosystem Integration:* Treat digital twins as part of the broader safety technology ecosystem (planning, inspection) rather than standalone artifacts. | B5, B6, B7 | Agnusdei et al., 2021; Luo et al., 2024 |
| | *Formal V&V Practices:* Establish verification, validation, and uncertainty management, including test cases and explicit communication of limitations. | B5, B6, B12 | Zio & Miqueles, 2024 |
| Org. & Capability | *Explicit Ownership:* Assign product ownership for safety twins; form cross-functional teams (Ops, Safety, BIM, IT) with clear authority to act. | B8, B9, B10 | Sacks et al., 2020; Kineber et al., 2023 |
| | *Hybrid Skill Building:* Build digital literacy through training and partnerships, focusing on safety use cases and analytics interpretation. | B9 | Kineber et al., 2023; Tabatabaee et al., 2022 |
| | *Scaling Playbooks:* Use portfolio roadmaps to select, evaluate, and scale pilots based on clear performance indicators and integration milestones. | B8, B10 | Agnusdei et al., 2021 |
| | *Systemic Framing:* Position BIM-DT tools as part of the safety management system (SMS) and continuous improvement cycles. | B8, B9, B10 | Teizer et al., 2023; Trask & Linderoth, 2023 |
| Human & Regulatory | Privacy-by-Design: Apply data minimization, clear consent processes, and safeguards on secondary use of worker data. | B11, B12 | Nnaji et al., 2021; Okpala et al., 2022; Abdulhamid et al., 2023 |
| | *Early Institutional Engagement:* Engage regulators and insurers early to co-develop standards and liability regimes for DT safety evidence. | B10, B12 | Agnusdei et al., 2021; Zio & Miqueles, 2024 |
| | *Regulatory Sandboxes:* Use sandboxes and V&V protocols to trial DT safety functions under controlled conditions to inform future standards. | B12 | Zio & Miqueles, 2024; Abdulhamid et al., 2023 |

### 6.1.2 Analytics and modeling barriers (B5–B7)

Modeling barriers explain why predictive implementations remain domain-specific. Validation gaps (B5) persist as many systems inherit thresholds from qualitative risk matrices or regulatory minimums rather than empirical calibration (Liu D. et al., 2023; Zhou et al., 2019). Among L3 implementations, only Liu et al. (2021) explicitly validated their model against historical incident data.

Use case alignment (B6) also remains skewed. Reviews indicate that while proximity and zone control applications are technically tractable (Saif et al., 2024; Karlapudi et al., 2023), they often miss systemic or high-consequence injury mechanisms (Trask & Linderoth, 2023). The concentration of predictive models in structural domains (Hong et al., 2022), at the expense of fall prevention or ergonomics, suggests a prioritization of infrastructure integrity

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over human factors. Additionally, the absence of reusable patterns (B7) results in bespoke architectures. Systems by Lai et al. (2022) and Hong et al. (2022) were tailored to specific equipment or geologies, confirming Sacks et al.'s (2020) observation that standardized architectures remain conceptual without demonstrated operational portability.

#### 6.1.3 Organizational and institutional barriers (B8–B12)

Organizational factors often prevent the transition from demonstration to sustained use. Pilot-scale framing (B8) is prevalent, with studies offering limited evidence of deployment beyond initial proof-of-concept (Liu et al., 2023; Zhou et al., 2019). This is compounded by capability gaps (B9); effective deployment requires hybrid expertise in safety, BIM, and data analytics, a profile scarce in typical project teams (Kineber et al., 2023).

Governance issues further impede scaling. Fragmented responsibilities (B10) create ambiguity regarding ownership of the safety twin and authority to act on its outputs (Sacks et al., 2020). Privacy concerns (B11) also limit worker-centric applications; while research settings may secure consent, broader deployment faces significant resistance regarding surveillance and data governance (Nnaji et al., 2021). Finally, regulatory uncertainty (B12) obstructs the move toward L4 autonomy. The lack of frameworks for validating DT-based safety evidence or allocating liability (Zio & Miqueles, 2024) leaves organizations reluctant to delegate safety-critical decisions to algorithmic systems.

### 6.2 Enablers and design principles

The barrier analysis also identifies enabler clusters and design principles that implementations employ to address these constraints. Several implementations demonstrate specific enabler strategies in practice. To address computational constraints (B4), Lai et al. (2022) employed hierarchical modeling, utilizing high-fidelity finite element models offline for design validation while deploying lightweight surrogate models for real-time structural state estimation. Similarly, Messi et al. (2020) leveraged game engine-based fast-forward simulation for collision prediction, effectively trading physics fidelity for the computational speed required by operational time constraints. Regarding validation gaps (B5), Hong et al. (2022) and Zhao et al. (2022) established verification practices for their predictive geotechnical models, utilizing independent sensor measurements and expert review to benchmark performance. While these do not yet meet formal verification and validation (V&V) standards, that is, codified requirements for demonstrating that a model is implemented correctly and reproduces the real system with sufficient fidelity for its intended use, they represent critical steps toward building trust in predictive outputs. Furthermore, Liu Z. et al. (2021) incorporated continuous feedback loops, where prediction performance was reviewed to iteratively refine association rule mining models, demonstrating a practical approach to maintaining model alignment over time.

Table 8 presents a synthesis from successful implementation accounts and best-practice recommendations, organizing principles by the barriers they primarily address. The enablers do not guarantee progression along the maturity spectrum, but they indicate strategies that have supported successful implementation, scaling, or institutionalization in current practice.

## 7. DISCUSSION AND IMPLICATIONS

### 7.1 Integrating the answers to RQ1–RQ3

Taken together, the Tier 1 implementation record indicates that BIM–DT safety integration is progressing, but unevenly. The field currently displays a maturity profile dominated by live situational awareness rather than validated foresight or closed-loop control. Most systems achieve interactive monitoring and alerting (L2), while predictive capability (L3) appears selectively in tightly scoped, data-rich, and high-consequence contexts. Autonomous adaptation (L4) is absent under the review criteria, suggesting that the limiting frontier is assurance and accountability rather than sensing alone (Liu D. et al., 2023; Zhou et al., 2019; Saif et al., 2024; Zio & Miqueles, 2024). In requirement terms, the corpus routinely satisfies spatial anchoring (SR1), state currency (SR2), and actionable output (SR4); satisfies forward-looking risk estimation (SR3) only selectively; and has not satisfied lifecycle continuity (SR5) or explicit accountability for automated intervention (SR6) outside conceptual work. The two unmet requirements are precisely those that depend on organizational and governance arrangements rather than on sensing or analytics.

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### 7.1.1 Mechanism–maturity alignment

A primary synthesis insight is that the dominant BIM–DT safety mechanisms largely capitalize on BIM's role as a spatial and semantic anchor. RQ1 shows that most operational systems couple BIM with sensing and localization, then apply rule-based logic to deliver proximity management, exclusion-zone control, and threshold-based exposure monitoring (Zhou et al., 2019; Saif et al., 2024). In these Bidirectional Synchronization (M2) implementations, BIM geometry and object identity map cleanly to streaming site states. In contrast, mechanisms that explicitly represent behavioral or organizational determinants of safety remain comparatively rare.

RQ2 demonstrates that these mechanism choices correspond to a concentrated maturity profile. The absence of L1 suggests that capability does not typically stabilize at "static visualization" as an operational outcome; once coupling moves beyond conceptual framing (L0), the value proposition is almost always tied to sustained live data flows (L2). Furthermore, in the Tier 1 corpus each mechanism class coincides with a single maturity level, suggesting a practical "maturity ceiling," although this alignment is partly definitional because both codes draw on the presence of live coupling and predictive analytics. Unidirectional workflows (M1) remain conceptual (L0), bidirectional synchronization (M2) aligns with monitoring (L2), and predictive coupling (M3) aligns with predictive maturity (L3). This mapping implies that movement from monitoring to prediction requires architectural reconfiguration, including embedding analytics within the operational data loop, rather than incremental upgrades to an existing monitoring stack.

### 7.1.2 The nature of maturity transitions

RQ3 explains these outcomes by showing that constraints shift by transition rather than accumulating uniformly.

- The Empirical Leap (L0 → L2): The transition from concept to operation is dominated by barriers that determine whether credible monitoring can be sustained. These include fragmented sensing coverage (B1), integration complexity (B2), and data quality issues (B3) that degrade trust in live indicators.
- Analytic Escalation (L2 → L3): Once monitoring is established, the move to prediction is constrained less by hardware and more by analytics-specific requirements. Validation gaps (B5) become the binding constraint, as predictive models require rigorous calibration against historical data, which is often sparse. Consequently, L3 appears first in niches where failure modes are well-specified, and the benefit of early warning justifies the modeling overhead (e.g., hoisting, tunneling settlement).
- The Governance Gap (L3 → L4): The absence of L4 is coherent under this integrated view. While some L3 papers describe actuation pathways, the literature lacks the accountability envelopes, liability allocation, and regulatory frameworks (B12) necessary to delegate safety-critical decisions to algorithmic control. Moving toward autonomy is therefore less about adding algorithms and more about establishing governance structures (B10) that support auditable, certifiable DT-based safety evidence (Sacks et al., 2020; Zio & Miqueles, 2024).

### 7.1.3 Lifecycle continuity

Finally, the lifecycle analysis described in Figure 6 clarifies why construction-phase implementations dominate. Acute risk and immediate supervisory value make L2 monitoring compelling during execution. Post-construction settings, with more stable assets, show a higher propensity toward predictive applications. Cross-lifecycle integration remains predominantly conceptual because it is a stewardship problem as much as a technical one; without sustained data governance and ownership across phase transitions (B10), the "Golden Thread" of safety data breaks.

## 7.2 Contributions relative to existing literature

This review extends existing BIM and DT safety literature through three integrated contributions. First, it introduces an integrated mechanism–maturity–barrier lens. Prior reviews have often treated these dimensions separately, scanning multiple industries (Agnusdei et al., 2021) or focusing on application themes without unpacking the coupling mechanisms (Hou et al., 2021; Attar et al., 2024). Table 1 summarizes this positioning against the major prior reviews. By linking coupling mechanisms (how data moves) to maturity outcomes (what

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capability results) and transition barriers (what impedes progress), this framework is intended to enable more precise positioning of implementations. It clarifies, for instance, why proximity monitoring systems that appear similar at the use-case level may diverge significantly in integration architecture and governance readiness.

Second, the study provides an empirical maturity baseline. Instead of treating "digital twin" as a binary label, the review codes each implementation by mechanism, maturity, phase, and capability. This reveals that the field clusters at interactive monitoring (L2), with predictive capability (L3) remaining a specialized frontier. This baseline supports expectation calibration for practice and enables future replication studies to track field progression quantitatively.

Third, the paper contributes a transition-aligned barrier and enabler typology. Prior work has documented challenges like interoperability and skills (Boje et al., 2020; Kineber et al., 2023), but typically without clarifying which barriers bind at which maturity stage. The B1–B12 typology supports targeted diagnosis: it highlights that the constraints binding operational monitoring (e.g., sensing gaps) differ materially from those binding predictive escalation (e.g., validation gaps) or autonomy (e.g., regulatory uncertainty).

## 7.3 Limitations and directions for future research

This scoping review is subject to several limitations that shape how the findings should be interpreted. First, the search was restricted to Web of Science and Scopus and to English-language peer-reviewed articles; consequently, industry deployments, vendor documentation, and regulatory guidance that may contain operational BIM–DT safety implementations were not captured. Second, the mechanism and maturity coding necessarily relied on what authors reported. In several cases, publications described high-level “digital twin” capabilities while omitting implementational detail (for example, state update pathways, synchronization frequency, or decision rights), which may have led to conservative tiering and maturity assignments. Third, the barrier typology reflects constraints surfaced in academic prototypes and evaluations; commercial systems may encounter additional factors (for example, contractual data access, cybersecurity constraints, and procurement pathways) that are underreported in the scholarly record. These limitations suggest priorities for future research:

1. Cross-phase implementation:

Future research should prioritize longitudinal, multi-stakeholder case studies that follow BIM–DT safety twins from late design through construction and into early operation to directly observe how integration mechanisms and maturity levels evolve, and where continuity fails. Such studies should document how BIM identifiers, hazard ontologies, and sensing configurations are maintained (or re-established) during handovers, and how responsibility for model stewardship and decision authority is negotiated across organizations. This direction is essential for resolving the review’s finding that cross-lifecycle BIM–DT safety remains predominantly conceptual and is constrained by data governance and ownership discontinuities (B10) rather than sensing alone.

2. Decision-grade validation for predictive safety twins:

Given that L3 implementations remain niche and are constrained by validation gaps (B5) and data alignment issues (B3), methodological research is needed to define evidence standards for predictive safety twins. This includes (i) benchmarkable validation designs that account for site change, non-stationarity, and sparse incident labels (for example, evaluation against near-miss proxies, leading indicators, or expert-adjudicated ground truth); (ii) uncertainty quantification and communication formats suitable for supervisory decision-making; and (iii) model monitoring protocols that detect drift and trigger recalibration when work conditions or sensing coverage changes.

3. Reusable BIM–DT integration patterns and portability tests:

To address the review’s observation that many systems rely on custom middleware or fragile point-to-point integrations (B2, B7), future work should develop and openly evaluate reusable integration patterns (for example, reference pipelines for mapping streaming events to BIM entities, topic schema conventions for message brokers, and API contracts for BIM–DT synchronization). Comparative studies should test portability across at least two different sites or asset types to establish which architectural choices generalize, under what assumptions, and at what operational cost. This line of work would directly strengthen the mechanism taxonomy by linking M2/M3 claims to replicable architectural commitments rather than one-off toolchains.

4. Bounded autonomy assurance and accountability frameworks.

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Because the absence of L4 in the Tier 1 corpus appears to be driven by accountability, liability, and regulatory uncertainty (B12) rather than the availability of algorithms, future research should focus on governance and assurance mechanisms for BIM–DT-informed interventions. This includes bounded autonomy; defining what actions can be automated, under which conditions, with which overrides. Also, audit trails that link sensed evidence to BIM-referenced decisions, and assurance arguments that can be inspected by clients, regulators, and insurers. Empirical work in controlled settings (for example, limited-scope access control, lock-out/tag-out integration, or equipment slowdown triggers) would allow evaluation of safety benefits while keeping interventions reversible and governance transparent.

## 8. CONCLUSIONS

This study reviewed how BIM and DT technologies are currently being integrated to support construction safety, and what these integrations imply for capability development and progression. Across the Tier 1 evidence base, most BIM–DT safety twins remain concentrated in descriptive and interactive operation, where the dominant value proposition is near real-time visibility, tracking, and rule-based warning. Predictive coupling is still comparatively uncommon and appears mainly in tightly scoped, data-rich contexts, and no reviewed implementation met the criteria for L4 autonomous adaptation in which safety-critical interventions are delegated to the twin within a clearly bounded accountability and governance envelope.

The principal contribution is an integrated synthesis that links the safety requirements a BIM–DT system should satisfy (SR1–SR6) with (i) how BIM and DT components are coupled (mechanisms M1–M4), (ii) what capabilities those couplings realize (maturity levels L0–L4), and (iii) which barriers bind at each transition (B1–B12). The mechanism taxonomy shows a structured progression from unidirectional BIM exports (M1) through bidirectional synchronization (M2) to predictive coupling (M3), while M4 remains a conceptual target. The maturity analysis further suggests that progression is discontinuous: the shift from L0 to L2 typically requires an "empirical leap" involving sensing coverage, middleware capability, and semantic alignment, whereas the transition from L2 to L3 is limited by validation and model governance rather than by integration alone. The barrier typology makes these binding constraints explicit, thereby supporting more targeted research design and more realistic implementation planning.

For practice, the findings imply that advancement should be planned as discrete, governable transitions rather than treated as a single technology acquisition. Near-term scalable deployments are most likely where the safety objective is clearly bounded, BIM identifiers and data pathways can be maintained with low operational overhead, and data governance responsibilities are explicit. Progress toward predictive capability requires decision-grade evaluation designs, uncertainty communication suitable for supervisory use, and disciplined processes for maintaining BIM–DT alignment as site conditions evolve. More broadly, cross-lifecycle BIM–DT safety remains limited by stewardship and continuity across phase boundaries, suggesting that the ability to sustain ownership, accountability, and information continuity is a necessary condition for moving beyond isolated pilots toward mature safety-twin ecosystems.

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