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INTEROPERABILITY IMPERATIVE: A BUILT ENVIRONMENT MATURITY-BARRIER ANALYSIS FOR DIGITAL TWIN CONVERGENCE WITH BIM AND IOT

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Abstract

The built environment faces pressure to improve efficiency and sustainability throughout its lifecycle. Digital twins (DT), leveraging BIM, IoT sensor data, and AI, offer significant potential for proactive and intelligent asset management. However, deployment is hindered by the Interoperability Imperative—the need for heterogeneous systems to exchange and interpret data seamlessly. This paper develops a Maturity–Barrier Logic that frames DT evolution as constrained by interoperability-related barriers. It identifies a persistent implementation gap, with applications stagnating at the Digital Shadow and failing to achieve autonomous Cognitive Twins. A diagnostic framework is proposed to support the transition toward federated, system-of-systems DT.

Introduction

The Architecture, Engineering, Construction, and Operations (AECO) industry is undergoing a significant transformation driven by the digitalisation and integration of cyber-physical systems (CPS) (Boje et al., 2020). Central to this transition is the convergence of Building Information Modelling (BIM), the Internet of Things (IoT), and DT technologies, enabling a shift from static representations to dynamic, data-driven systems capable of real-time monitoring, simulation, and predictive analysis. Despite this potential, the realisation of fully functional DTs remains constrained by the interoperability imperative for heterogeneous systems to exchange, interpret, and utilise data without ambiguity. In this study, a Digital Twin is defined as a virtual representation of a physical asset that is continuously updated through automated, bi-directional data exchange, enabling real-time monitoring, prediction, and optimisation (Rasheed et al., 2020; Grieves and Vickers, 2017). This emphasises the distinction between true DTs and lower levels of digital representation, where limited data integration restricts system functionality (Kritzinger et al., 2018). As DT evolves, Artificial Intelligence (AI) is increasingly playing a critical role in enabling advanced capabilities. While BIM provides semantic structure and IoT enables real-time sensing, AI functions as the computational engine that supports pattern recognition, predictive analytics, and autonomous decision-making. This integration enables the emergence of Cognitive Twins at higher maturity levels that are capable of adaptive and self-learning behaviour (Boje et al., 2020; Madni et al., 2019; Yitmen et al., 2021). These capabilities also further intensify interoperability requirements, particularly in relation to semantic integration, data governance, and trust in algorithmic outputs. Despite extensive research on DT technologies and their associated implementation barriers, a critical limitation persists as existing studies either focus on identifying barriers ranging from technical and data-related challenges to organisational constraints (Opoku et al., 2023; Kineber et al., 2023) or on defining Digital Twin Maturity Models (DTMM) that describe system evolution (Deng et al., 2021; Liu et al., 2024). To address this gap, this paper develops a structured analysis that links interoperability barriers to distinct stages of DT maturity. Several DTMMs have been proposed and a referenced classification by Kritzinger et al. (2018) distinguishes between Digital Models, Digital Shadows, and DTs based on the level of data integration and automation. Studies highlight limitations within existing maturity models and Liu et al. (2024) noted that many DTMMs lack clarity in defining capability progression and fail to provide continuous and measurable development pathways thus resulting in models that effectively describe idealised end states. Interoperability is consistently identified as the most critical technical constraint (Naderi and Shojaei, 2023), and challenges arise at both syntactic and semantic levels, reflecting difficulties in data exchange formats as well as inconsistencies in meaning and interpretation across systems. A key issue is the integration of BIM data, typically structured in Industry Foundation Classes(IFC) schemas, with IoT-generated time-series data, which operates on fundamentally different data models (Boje et al., 2020). Machine-readable knowledge representation and integration such as semantic web technologies and ontologies, such as Brick Schema, SOSA/SSN (Sensor, Observation, Sample, and Actuator/Semantic Sensor Network), and ifcOWL(Web Ontology Language representation of the IFC schema), have been proposed to address these challenges (Petrova and Pauwels, 2020; Farghaly et al., 2023), but their adoption remains limited due to implementation complexity and the absence of unified industry standards. In addition, technical, organisational, and governance barriers further impede DT adoption. Concerns related to data security, privacy, and ownership also complicate collaboration across stakeholders, limiting trust and restricting data sharing (AlBalkhy et al., 2024; Kineber et al., 2023).

Further analysis reveals a fundamental disconnect between two dominant research streams: the study of DTMM and the identification of implementation barriers. While maturity models define the evolutionary trajectory of DT systems (Deng et al., 2021; Liu et al., 2024), and barrier-focused studies classify implementation challenges (Opoku et al., 2023), there is a lack of integration between these perspectives. Existing research does not systematically examine how particular barriers constrain progress between maturity stages. For example, early-stage DT development is often limited by data acquisition and sensor integration challenges, whereas advanced stages require sophisticated semantic interoperability, data governance, and trust in AI-driven decision-making (AlBalkhy et al., 2024; Boje et al., 2020). This lack of alignment results in a practical limitations where stakeholders are unable to identify which barriers must be addressed to achieve specific maturity transitions, as current frameworks do not provide actionable guidance for implementation or strategic planning (Liu et al., 2024). By synthesising technical, semantic, and organisational challenges identified in the literature, this study proposes a Maturity–Barrier Logic that maps barriers, interoperability challenges to DT maturity stages to address this gap and enable a more systematic understanding of transition constraints and supporting more informed decision-making in DT implementation in the built environment. To guide this investigation, the study addresses the following research questions:

- How do interoperability barriers manifest across different DT maturity stages?
- What specific barriers inhibit progression between these maturity stages?
- How can these barriers be mapped to support DT diagnostic framework development?

Methodology

This study adopts a conceptual synthesis approach to systematically identify and analyse interoperability-related barriers and their relationship to DT maturity stages in the built environment. Guided by PRISMA principles, the review was conducted using Scopus as the primary database. Searches, restricted to English-language publications from 2015 onward, using this terms : Core Concept(Federated DTs); Domain & Context (Built Environment, Construction Industry, Asset Lifecycle, Facility Management (O&M)); Tech & Systems (BIM, IoT, Sensors, Cyber-Physical Systems, Data/System Integration); Interoperability (Semantic & Organisational Standards, IFC, Asset Administration Shell, Ontologies); Performance (Predictive/Proactive Maintenance, Energy Optimisation, IEQ, Occupant Comfort); Governance (Data/DT Governance, Ecosystems, Policy, Stakeholder & Tech Readiness); Implementation (Adoption Barriers (Org/Process), Deployment Challenges, Transformation); Maturity (Digital Twin Maturity Models, Technology & Digital Maturity Levels); Methodology (Systematic Literature Reviews, Bibliometric Analysis). To capture interoperability challenges across the full technological spectrum, keywords included not only “digital twin” but also associated enablers such as BIM and IoT. The search process yielded 1,089 records. Following relevance screening, 180 studies were retained. The analysis covered both technical barriers (data integration, semantic alignment, standards fragmentation, legacy systems) and organisational issues (governance, stakeholder readiness, and workflow alignment). The outcome is a structured Maturity–Barrier Mapping that aligns interoperability challenges with DT maturity progression.

Barrier Taxonomy and Distribution

The systematic analysis of the provided literature reveals that the convergence of BIM, IoT, and DT is hindered by a complex matrix of technical and organisational barriers. These barriers confirm the Interoperability Imperative, in which the primary friction lies not merely in the availability of technology but in the capacity to integrate heterogeneous systems and govern them effectively. The Barrier-to-Maturity Mapping Logic was developed by extracting interoperability-related barriers and grouping them into categories and then mapping them to DT maturity stages. Table 1 illustrates the delineation of these challenges, categorised by their impact on the DT.

Interoperability Barriers:

- **Data Capture and Connectivity:** A fundamental technical barrier is the difficulty in establishing real-time synchronisation between the physical asset and the virtual counterpart (Naderi and Shojaei, 2023).
- **Semantic Alignment:** A critical limitation identified is the semantic gap between BIM that relies on static, hierarchical schemas (e.g., IFC), while IoT generates dynamic, time-series data.
- **Visualisation and Integration:** The integration of diverse software tools and the diversity in source systems create fragmented data silos.

Governance and Organisational Barriers:

- **Organisational Inertia:** This poses challenges that are as great as, or greater than, technical limitations. Overcoming the organisational inertia inhibiting DT adoption requires a shift from voluntary adoption to mandated governance frameworks that support a System-of-Systems approach.
- **Fragmentation and Silos:** The industry is characterised by fragmented supply chains and silos between departments, which obstruct the holistic data sharing required for DTs (AlBalkhy et al., 2024;

Table 1: Taxonomy of Barriers to DT-BIM-IoT Convergence

Category	Barrier Sub-Type	Description & Key Citations
Technical/ Semantic	Semantic Interoperability	Inability of systems to interpret data across BIM (static) and IoT (dynamic) domains; lack of unified ontologies.
	Data Integration/Fusion	Difficulty fusing heterogeneous data formats (e.g., geometric vs. time-series); diversity in source systems.
	Connectivity/Latency	Real-time data transmission, bandwidth, and latency issues that disrupt the physical–virtual link.
	Data Quality	Uncertainties with data quality and reliability, including noisy sensor data and lack of accuracy.
Organisational Governance	Readiness & Skills	Skilled professionals shortage, low level of knowledge, resistance to change, and lack of training.
	Structural/Process	Fragmentation of the industry; silos between departments.
	Economic/Financial	High investment costs, uncertain ROI, and lack of financial incentives.
	Trust & Security	Lack of trust in data security, privacy concerns, and unclear data ownership/intellectual property rights.

Opoku et al., 2023).

- **Readiness and Skills:** The pervasive low level of knowledge and lack of competence regarding DT technologies among stakeholders contributes to resistance to change and a preference for traditional workflows (Kineber et al., 2023; Opoku et al., 2023).
- **Cost and Value:** High initial investment costs (CapEx) and an unclear value proposition or unproven Return on Investment (ROI) act as significant deterrents, particularly for Small and Medium Enterprises (SMEs) (AlBalkhy et al., 2024; Kineber et al., 2023).

Exemplars and Benchmarks:

The literature frequently cites specific frameworks as benchmarks for guiding DT implementation:

- **The Gemini Principles:** Proposed by the Centre for Digital Built Britain (CDBB), Purpose, Trust, Function principles are cited as a foundational ethical and functional value-based framework that serves as a benchmark for national-level DT strategy (Al-Sehrawy et al., 2021; Bolton et al., 2018; Chen et al., 2021). It emphasises that a DT must have a clear purpose, must be trustworthy, and must function effectively. Chen et al. (2021) utilised these principles to develop a maturity model for asset management, validating that alignment with these principles correlates with higher DT maturity.
- **Incremental Digital Twin (iDTw) Framework:** A framework, proposed by Calvetti et al. (2025), that breaks down DT implementation into granular levels (Static, Detailed, Sensored, Responsive, Adaptive, Intelligent). It is particularly effective for smart enterprises and construction logistics, offering a phased deployment strategy that lowers the barrier to entry for organisations daunted by the complexity of complete autonomy.
- **BIM-IoT Data Integration (BIM-IoTDI) Architecture:** Developed by Eneyew et al. (2022), this framework explicitly addresses the semantic interoperability gap in smart buildings. By utilising an ontology-based query mediation method, it enables the integration of static BIM data and dynamic IoT data without loss of semantic meaning. It is critical for supporting proactive FM tasks such as predictive maintenance and energy management.
- **CITYSTEPS Maturity Model:** This model assesses governance and technological readiness in urban DTs. It highlights that while many projects achieve visualisation, few progress to real-time decision-making or autonomous stages due to governance and interoperability failures (Masoumi et al., 2023).
- **ISO Standards:** References are made to ISO 19650 for information management and ISO 23247 for automation systems as emerging standards attempting to regulate this space (Calvetti et al., 2025; Palihakkara et al., 2025).

Mapping Maturity Levels and Interoperability Gaps

The analysis identifies a consensus on multi-stage evolutionary pathways for DTs, as presented in Table 2. While terminologies vary, the progression moves from static representation to autonomous interaction. Crucially, specific interoperability gaps act as limitations, preventing progression to higher maturity levels. The strategic roadmap synthesises the technical, semantic, and organisational requirements necessary to navigate the convergence to address the Interoperability Imperative by structuring deployment into maturity phases to overcome specific barrier limitations. To navigate the Interoperability Imperative, stakeholders should adopt a

Table 2: *Maturity Mapping and Levels Gaps*

Maturity Level	Characteristics and Limitation
Level 1: Descriptive (Digital Model)	Static 3D representation (e.g., BIM) with manual data exchange. **Limitation:** Digitisation Gap. The transition to the next level is blocked by the inability to digitise physical assets and processes effectively.
Level 2: Informative (Digital Shadow)	One-way automatic data flow from physical to digital (monitoring)- real-time visualisation. **Limitation:** Connectivity Gap. Progress is restricted by the lack of robust IoT infrastructure and reliable data transmission protocols.
Level 3: Predictive (Adaptive Twin)	Bi-directional data flow or advanced simulation capabilities. Uses historical data and AI to predict future states. **Limitation:** Semantic Gap. Lack of semantic interoperability (ontologies) prevents the DT from contextualising IoT readings within BIM geometry.
Level 4: Comprehensive/ Intelligent (Cognitive Twin)	Autonomous decision-making, self-learning, and prescriptive analytics. The DT can act on the physical world. **Limitation:** Trust and Governance Gap. Stakeholders lack trust in black box AI algorithms and fear security breaches.
Level 5: Federated (System-of-Systems)	Interconnected DTs interacting to optimise broader systems. **Limitation:** Standardisation Gap. The lack of universal data standards prevents disparate DTs from interacting.

phased approach, as illustrated in Table 3 case studies for overcoming distinct interoperability challenges at each phase to unlock subsequent maturity levels. For Foundational (Static Twin) where the asset exists as a high-fidelity digital model, the primary hurdle data quality and digitisation is the static nature of building data and the lack of accurate as-built geometric information (Opoku et al., 2023). Without resolving the digitisation gap, the twin remains a passive repository. For digital shadow, the one-way automated data flow from physical sensors to the digital platform affects connectivity and integration. Progression requires overcoming the Connectivity Gap by integrating IoT sensors with legacy systems and ensuring low-latency data transmission (Kang and Mo, 2024; Sepasgozar, 2021). This phase establishes the digital shadow. In Autonomous Cognitive Twin where bi-directional data flow with AI helping drive autonomous decision-making, Semantic Alignment Interoperability is required to move from a shadow to a true twin capable of prediction and control. This involves mapping heterogeneous data streams to unified ontologies (e.g., aligning IFC with SSN/SOSA) to enable automated reasoning and simulation (Boje et al., 2020; Huang and Hsieh, 2026). On the Federated System-of-Systems, trust is the key anchor.

Bridging the Gap: From Connectivity to Cognition

The progression through the roadmap is not linear but rather stepwise; specific barriers serve as limitations that must be overcome to advance.

- **Foundational to Integrative (The Connectivity Limitations):** To move from Level 1 (Static) to Level 2/3 (Dynamic), practitioners must resolve data and/or integration barriers. Specifically, the physical-digital disconnect must be bridged by retrofitting assets with IoT sensors and establishing reliable middleware (e.g., Node-RED) to handle the velocity of real-time data (Biagini et al., 2024; Naderi and Shojaei, 2023).
- **Integrative to Autonomous (The Semantic Limitations):** To move from Level 3 (Monitoring) to Level 4/5 (Prediction/Autonomy), the Semantic/Standards Barrier is the primary obstacle. A DT cannot predict if it does not understand the relationship between a temperature reading and the volume of a specific room. This requires resolving semantic silos by mapping BIM data to ontologies (e.g., Brick, SSN), moving beyond simple data transfer to knowledge graph integration (Boje et al., 2020; Eneyew et al., 2022).
- **Autonomous to Federated (The Trust Limitations):** To achieve a true System-of-Systems (Federated DT), the organisational governance barrier must be resolved. Technical connectivity is insufficient if stakeholders do not trust the data security or the AI's decision-making logic. Overcoming this requires adherence to governance frameworks as these legal structures are essential for resolving data sovereignty issues, enabling stakeholders to share proprietary data within federated ecosystems without compromising control, thereby meeting the governance requirements for Level 5 (AlBalkhy et al., 2024; Jørgensen, 2025). Policy-makers must establish a regulatory environment that incentivises interoperability through three core actions. First, public procurement must mandate open standards to ensure that data remain Findable,

Table 3: Maturity Mapping and Interoperability Gaps: Empirical Case Studies and Barrier Resolution

Maturity Phase	Empirical Case Study Evidence
Phase 1: Foundational (Descriptive Twin)	**The Digitisation Gap:** Overcomes data/integration barriers (AlBalkhy et al., 2024). **Case Study:** Northumbria University City Campus (UK) (Boje et al., 2020; Lu et al., 2020) **Digitisation Barrier:** Case study proves that relying on fragmented legacy documents restricts facility management to manual updates. It demonstrates that establishing a unified, standardised 3D semantic model (ISO 19650) is the foundational requirement to break non-machine-readable data
Phase 2: Integrative (Responsive Twin)	**The Connectivity Gap:** Overcomes established data connectivity barriers. (Boje et al., 2020; Jahangir et al., 2024). **Case Study:** University of Florence & UNF Engineering Building (Biagini et al., 2024; Kang and Mo, 2024) **Connectivity Barrier:** The Florence case proves that a middleware layer (Node-RED) is required to overcome protocol mismatches, while the UNF case shows that custom IFC Property Sets (pSets) anchor dynamic data feeds to static BIM elements, enabling a real-time Digital Shadow.
Phase 3: Autonomous (Cognitive Twin)	**The Semantic Gap:** Overcomes AI reasoning barriers (Boje et al., 2020). **Case Study:** Institute for Manufacturing (West Cambridge, UK) (Eneyew et al., 2022) **Semantic Barrier:** Proves an IFCxBrick pipeline is required for semantic interoperability. Mapping IFC to Brick via RDF/OWL achieves machine-understandable context, making automated tasks like Fault Detection and Diagnosis (FDD) feasible.
Phase 4: Federated (System-of-Systems)	**The Trust Gap:** Overcomes multi-owner data barriers (AlBalkhy et al., 2024). **Case Study:** Smart Dublin / Urban DT (Jørgensen, 2025; Masoumi et al., 2023) **Trust & Governance Barrier:** Proves that formal ‘‘Data Spaces’’ aligned with the Data Governance Act (DGA) are required for trusted exchange. It demonstrates that technical interoperability alone is insufficient without legally compliant open-data frameworks.

Accessible, Interoperable, and Reusable (FAIR), thereby preventing vendor lock-in (Klar et al., 2024). Second, the adoption of the Smart Readiness Indicator (SRI) should be promoted as a regulatory benchmark for assessing a building's capacity to adapt to needs and demands, serving as a key performance indicator of DT effectiveness. Finally, governance must align with the Data Governance Act (DGA) and Data Act (DA) to establish secure Data Spaces (Jørgensen, 2025).

Digital Shadow to Cognitive Twin Transition:

The most significant limitation identified in the transition from Level 2 (Digital Shadow) to Level 3/4 (Cognitive Twin) is Semantic Interoperability. To resolve this semantic gap and evolve the DT from a passive visualisation tool into a Cognitive Twin, a Diagnostic Implementation Guide (Figure 1) was developed. By synthesising theoretical concepts, maturity models, and empirical case studies from existing literature, this guide was structured to address specific technical constraints. The involved transforming disparate technical data into a cohesive, step-by-step workflow designed to transition a DT from a stalled state to a cognitive capability. Consequently, Figure 1 serves as a diagnostic framework outlining the technical protocols required to overcome this barrier—a critical distinction, as practitioners frequently conflate mere data connectivity (the transmission of bytes) with true data integration (the synthesis of meaning).

Discussion and Implications

DTs as Socio-Technical Systems: Beyond Technical Maturity: As illustrated in Figure 2, DT progression extends beyond static 3D models to real-time monitoring, predictive analytics, and autonomous decision-making, rather than being solely determined by technological capability (Sacks et al., 2020; Yitmen et al., 2021). Instead, it is inherently socio-technical, requiring alignment between technical infrastructure and organisational practices. The transition across maturity levels is systematically constrained by interoperability-related barriers—digitisation, connectivity, semantic, and governance gaps—which reflect both technical limitations and stakeholder misalignment. The evolution to Cognitive and Federated Twins is not simply a matter of deploying more advanced technologies, but of resolving the human, organisational, and institutional constraints embedded in each transition stage. To bridge and resolve the semantic gap between connectivity and cognition, the diagnostic guide in Figure 1 is useful to aid the transformation of the DTs, a prerequisite for envisioned predictive maintenance and energy optimisation (Boje et al., 2020; Liu et al., 2024).

Stakeholder-Specific Implications: Operationalising the Framework: The Maturity–Barrier Logic provides a structured lens for operationalising stakeholder

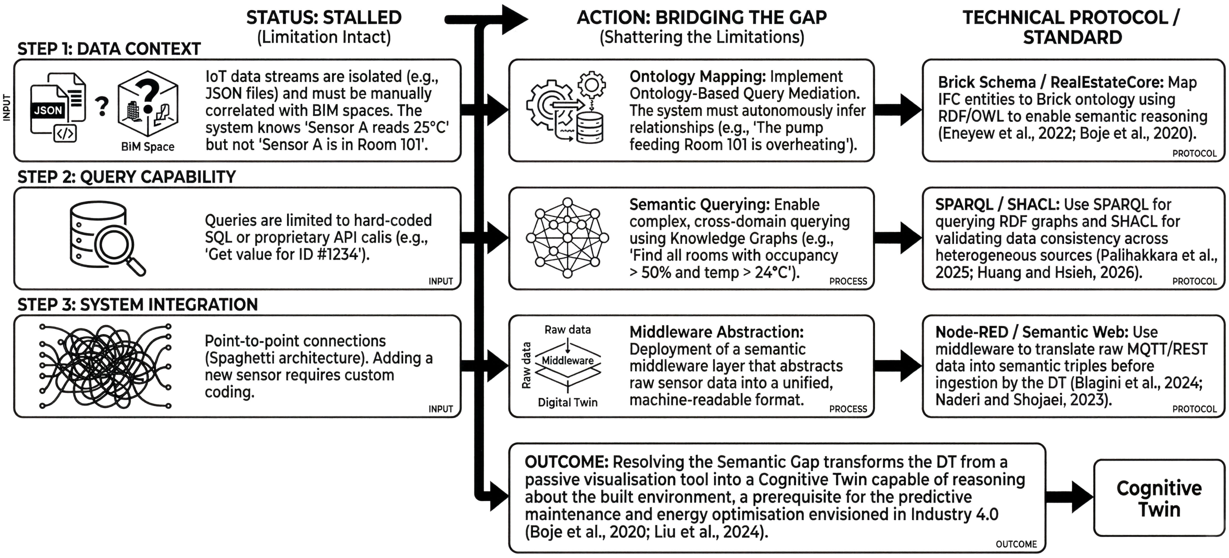

Figure 1: Diagnostic Implementation Guide for Overcoming the Semantic Barrier

responsibilities. Each blockade identified in Figure 2 corresponds to specific actions required by key actors:

- **Asset Owners:** To overcome the barriers at early and intermediate maturity stages of unclear value proposition, asset owners must transition from passive recipients of static BIM deliverables to active drivers of digital continuity. This requires embedding interoperability and semantic data requirements into procurement contracts, ensuring that deliverables support lifecycle integration rather than project completion alone.
- **Technology Providers:** Providers reliance on proprietary systems and closed data architectures inhibits cross-platform integration. To enable progression, providers must adopt open, modular system architectures, supported by middleware solutions (e.g., Node-RED) and semantic technologies (RDF/OWL). Mapping BIM standards such as IFC to ontologies like Brick Schema or RealEstateCore enables machine-readable context, facilitating advanced analytics and automated reasoning capabilities.
- **Policy-Makers and Industry Bodies:** The transition toward higher maturity levels (Levels 4–5) is constrained by trust and governance barriers, where data sharing is limited by legal, ethical, and commercial concerns. Policy-makers need to establish regulatory frameworks and data governance mechanisms to promote secure and standardised data exchange.

Practical and Research Outlook

The proposed Maturity–Barrier Logic serves not only as an analytical model but as a practical diagnostic tool for guiding DT implementation:

- **Industry Practitioners:** Organisations should utilise the framework to assess their current maturity level and identify the specific barriers preventing progression. For firms operating at the Digital Shadow stage, the priority should shift from additional sensor deployment to semantic data integration and architecture development. Implementing ontology-based pipelines (e.g., IFC-to-Brick) and establishing interoperable data environments are critical next steps.
- **Academic Community:** Future research must move beyond conceptual definitions toward empirical validation and implementation strategies. Key priorities should include quantitative evaluation of DT ROI across lifecycle stages, development of automated ontology mapping techniques and investigation of socio-technical governance models addressing data sovereignty, security, and ethics.

Conclusions

This study addressed the challenge of fragmented DT implementation in the AECO industry by developing a structured Maturity–Barrier Logic that links DT evolution to interoperability constraints. A systematic analysis of existing literature, technical standards, and industry practices was conducted to examine the convergence of BIM, IOT, and DT technologies. Through this analysis, DT maturity stages were explicitly mapped against four critical transition barriers—Digitisation, Connectivity, Semantic, and Trust/Governance gaps—thereby reframing DT progression as a sequence of constrained transitions rather than a purely linear technological evolution. The findings reveal a significant disparity between theoretical DT maturity models and real-world implementation. While existing frameworks suggest a clear pathway toward autonomous and federated systems, most practical applications remain constrained at Level 2 (Digital Shadow). This stagnation is primarily driven by a semantic limitation where systems achieve syntactic connectivity but lack the ontology-based interoperability

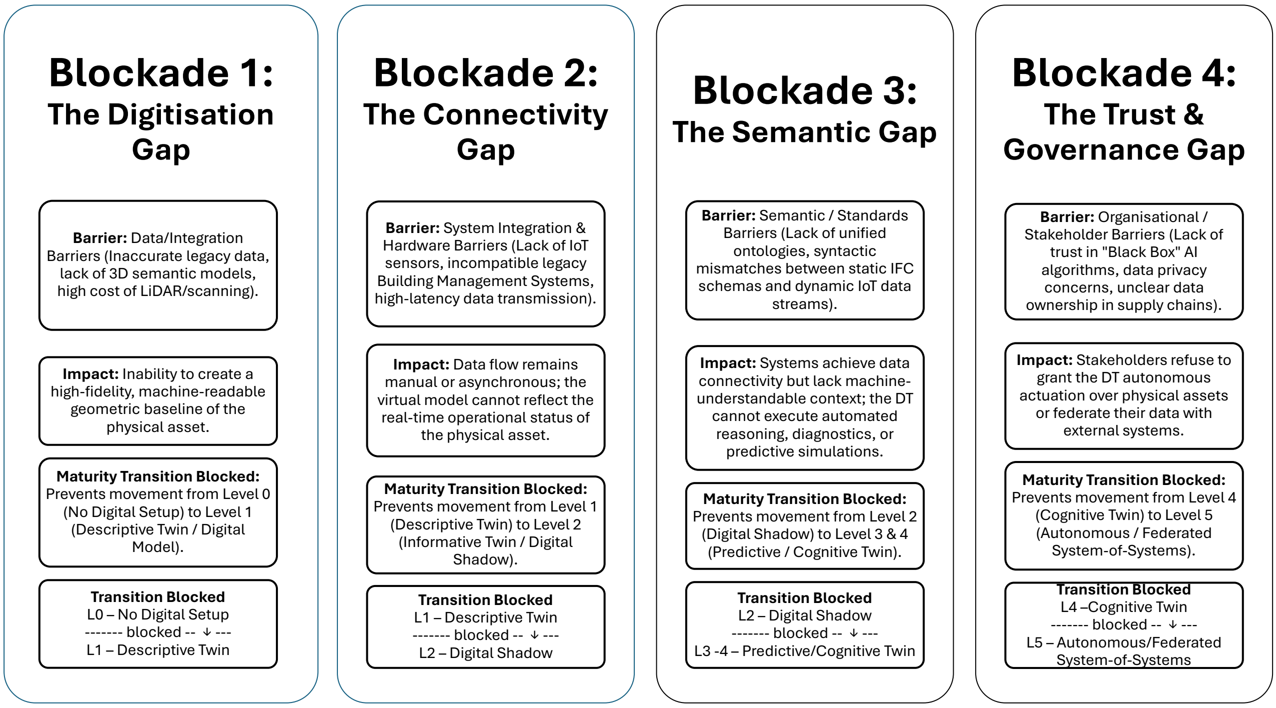

Figure 2: Barrier → Impact → Maturity Transition Diagram

required for machine understanding and AI-driven reasoning. Furthermore, progression to higher maturity levels is inhibited by a trust and governance gap, where organisational, legal, and ethical concerns surrounding data sharing and algorithmic transparency limit the adoption of fully autonomous and federated DT systems. These findings establish interoperability not as a secondary technical issue, but as the central enabling condition for DT maturity. Advancing DTs is less about deploying additional sensing technologies and more about enabling machine-readable, semantically aligned, and governable data ecosystems. Without addressing these barriers, the industry risks remaining confined to isolated, low-value digital implementations. This paper presents diagnostic and decision-support logic for practitioners and researchers alike. This review repositions the future of DTs as an interoperability-driven transformation, where the successful alignment of technology, data, and stakeholders determines the pathway from isolated digital models to fully integrated, intelligent DTs. Achieving this vision requires systematic resolution of the interoperability barriers identified in this study. By addressing these constraints, the industry can transition from fragmented digital implementations to cohesive, intelligent ecosystems that support global sustainability objectives, including Sustainable Development Goal 11.

References

Al-Sehrawy, R., Kumar, B., and Watson, R. (2021). A digital twin uses classification system for urban planning & city infrastructure management. Journal of Information Technology in Construction (ITcon), 26:832–862.

AlBalkhy, W., Karmaoui, D., Ducoulombier, L., Lafhaj, Z., and Linner, T. (2024). Digital twins in the built environment: Definition, applications, and challenges. Automation in Construction, 162:105368.

Biagini, C., Bongini, A., and Marzi, L. (2024). From bim to digital twin: Iot data integration in asset management platform. Journal of Information Technology in Construction (ITcon), 29:1103–1127.

Boje, C., Guerriero, A., Kubicki, S., and Rezgui, Y. (2020). Towards a semantic construction digital twin: Directions for future research. Automation in Construction, 114:103179.

Bolton, A., Butler, L., Dabson, I., Enzer, M., Evans, M., Fenemore, T., Harradence, F., Keaney, E., Kemp, A., and Luck, A. (2018). The Gemini Principles. Centre for Digital Built Britain, Cambridge.

Calvetti, D., Mêda, P., Hjelseth, E., and de Sousa, H. (2025). Incremental digital twin framework: A design science research approach for practical deployment. Automation in Construction, 170:105954.

Chen, L., Xie, X., Lu, Q., Parlikad, A., Pitt, M., and Yang, J. (2021). Gemini principles-based digital twin maturity model for asset management. Sustainability, 13(15):8224.

Deng, M., Menassa, C., and Kamat, V. (2021). From bim to digital twins: A systematic review of the evolution of intelligent building representations in the aec-fm industry. Journal of Information Technology in Construction (ITcon), 26:58–83.

Eneyew, D., Capretz, M., and Bitsuamlak, G. (2022). Toward smart-building digital twins: Bim and iot data integration. IEEE Access, 10:130487–130506.

Farghaly, K., Soman, R. K., and Zhou, S. A. (2023). The evolution of ontology in aec: A two-decade synthesis, application domains, and future directions. Journal of Industrial Information Integration, 36:100519.

Grieves, M. and Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In Transdisciplinary Perspectives on Complex Systems, pages 85–113. Springer, Cham.

Huang, C.-P. and Hsieh, S.-H. (2026). Ontology-driven automation for bim-fm data integration using neo4j, python, and workflow platforms. Advanced Engineering Informatics, 71:104240.

Jahangir, M., Schultz, C., and Kamari, A. (2024). A review of drivers and barriers of digital twin adoption in building project development processes. Journal of Information Technology in Construction (ITcon), 29:141–178.

Jørgensen, B. N. (2025). Digital twins under eu law: a unified compliance framework across smart cities, industry, transportation, and energy systems. Electronics, 14(24):4881.

Kang, T. and Mo, Y. (2024). A comprehensive digital twin framework for building environment monitoring with emphasis on real-time data connectivity and predictability. Developments in the Built Environment, 17:100309.

Kineber, A., Singh, A., Fazeli, A., Mohandes, S., Cheung, C., Arashpour, M., Ejohwomu, O., and Zayed, T. (2023). Modelling the relationship between digital twins implementation barriers and sustainability pillars: Insights from building and construction sector. Sustainable Cities and Society, 99.

Klar, R., Arvidsson, N., and Angelakis, V. (2024). Digital twins' maturity: The need for interoperability. IEEE Systems Journal, 18:713–724.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., and Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 51(11):1016–1022.

Liu, Y., Feng, J., Lu, J., and Zhou, S. (2024). A review of digital twin capabilities, technologies, and applications based on the maturity model. Advanced Engineering Informatics, 62:102592.

Lu, Q., Parlikad, A., Woodall, P., Don Ranasinghe, G., Xie, X., Liang, Z., Konstantinou, E., Heaton, J., and Schooling, J. (2020). Developing a digital twin at building and city levels: Case study of west cambridge campus. Journal of Management in Engineering, 36(3):05020004.

Madni, A., Madni, C., and Lucero, S. (2019). Leveraging digital twin technology in model-based systems engineering. Systems, 7(1):7.

Masoumi, H., Shirowzhan, S., Eskandarpour, P., and Pettit, C. (2023). City digital twins: Their maturity level and differentiation from 3d city models. Big Earth Data, 7(1):1–36.

Naderi, H. and Shojaei, A. (2023). Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects. Automation in Construction, 149:104785.

Opoku, D. G. J., Perera, S., Osei-Kyei, R., Rashidi, M., Bamdad, K., and Famakinwa, T. (2023). Barriers to the adoption of digital twin in the construction industry: a literature review. In Informatics, volume 10, page 14. MDPI.

Palihakkara, A. et al. (2025). Toward cloud-based scalable and interoperable digital twins: Review of the state of the art. Journal of Information Technology in Construction (ITcon), 30:1209.

Petrova, E. and Pauwels, P. (2020). Semantic enrichment of association rules discovered in operational building data. In Proceedings of the 37th CIB W78 Information Technology for Construction Conference (CIB W78), pages 308–326, São Paulo, Brazil.

Rasheed, A., San, O., and Kvamsdal, T. (2020). Digital twin: Values, challenges and enablers from a modeling perspective. IEEE access, 8:202438.

Sacks, R., Brilakis, I., Pikas, E., Xie, H. S., and Girolami, M. (2020). Construction with digital twin information systems. Data-Centric Engineering, 1:e14.

Sepasgozar, S. (2021). Differentiating digital twin from digital shadow: Elucidating a paradigm shift to expedite a smart, sustainable built environment. Buildings, 11(4):151.

Yitmen, I., Alizadehsalehi, S., Akıner, and Akıner, M. E. (2021). An adapted model of cognitive digital twins for building lifecycle management. Applied Sciences, 11(9):4276.