

Review

Digital Twin Empowering Whole-Lifecycle Governance of Urban Infrastructure: A Review of Technological Embedding, Organizational Change, and Institutional Reconstruction

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Abstract

As a frontier direction of engineering informatics, Digital Twin technology offers new technical possibilities for the whole-lifecycle governance of urban infrastructure. However, existing research mostly treats Digital Twin as a pure engineering system optimization tool, neglecting its governance attributes as a “Socio-technical System.” Based on the systematic literature review method, this paper retrieves relevant literature from databases such as Web of Science, Scopus, and CNKI between 2010 and 2025; systematically reviews the application evolution of Digital Twin technology in urban infrastructure across the planning, construction, operation and maintenance, and decommissioning stages from the three dimensions of technological embedding, organizational change, and institutional reconstruction; reveals the transmission mechanism through which technological capabilities are transformed into governance effectiveness via organizational mediation; identifies key existing research limitations in current research regarding data governance, cross-sector collaboration, and institutional adaptation; and proposes an integrative three-dimensional “Technological Embedding—Organizational Change—Institutional Reconstruction” analytical framework. This study finds that the core challenge of Digital Twin governance lies in coordinating the structural tension between technological centralization and governance decentralization; future research needs to transcend technological determinism, situate Digital Twin within a broader socio-technical system context, and achieve the substantive transformation from “technology empowerment” to “governance effectiveness.”

Keywords: Digital Twin; urban infrastructure; whole-lifecycle governance; technological embedding; organizational change; institutional reconstruction; socio-technical system

Academic Editors: Xichen Chen, Stacy Vallis, Xuguang Wang and Dermott McMeel

Received: 5 July 2026

Revised: 28 August 2026

Accepted: 1 September 2026

Published: 20 September 2026

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1. Introduction

1.1. Background and Literature Base

Urban infrastructure encompasses transportation, water networks, energy, and communication systems, and its operational effectiveness is directly related to urban resilience and citizen well-being. However, the superposition of facility aging, rising costs, climate risks, and public health challenges has rendered traditional governance models inadequate. According to the International Monetary Fund, the global infrastructure investment gap will reach USD 15 trillion by 2040. Digital Twin (DT) technology provides a new path for the whole-lifecycle governance of infrastructure through the real-time mapping of physical entities and virtual models. The concept of DT originated from NASA's Apollo program and later evolved in the manufacturing context into a technical framework that achieves bidirectional interaction between physical systems and virtual replicas through real-time data connections [1], gradually transitioning from theory to engineering practice through the extension of the five-dimensional model [2]. As this technology penetrates the urban governance domain, academia has proposed the research agenda of the "DT City," whose core lies in constructing the dynamic mapping of the "Physical-Digital-Social" triadic space to support the real-time perception and intelligent decision-making of urban operations [3] (as shown in Figure 1). However, urban infrastructure systems exhibit significant openness, complexity, and heterogeneity, involving multiple stakeholders, cross-level governmental organizations, and dynamic social contexts, which are fundamentally different from the relatively closed and controllable production systems in manufacturing. Consequently, the application of DT in urban governance faces more severe technical challenges and governance dilemmas.



Figure 1. Title-word Co-occurrence Network of DT-Urban Infrastructure Whole-Lifecycle Governance.

Existing research exhibits obvious disciplinary fragmentation and technological bias: engineering focuses on pure technical optimization such as models, algorithms, and rendering, implicitly assuming that technological upgrades can be automatically converted into governance effectiveness; and public management research remains at the level of conceptual elaboration and policy interpretation, lacking systematic analysis of the internal mechanisms through which technological embedding is integrated into governance. This fragmentation obscures a crucial issue: DT is not a purely technical system but rather a socio-technical system that is deeply embedded in organizational structures and institutional environments. Technology Enactment Theory posits that the governance

effectiveness of information technology is not automatically determined by technical attributes but rather is mediated through organizational cognition, structural adaptation, and institutional arrangements [4]. Therefore, the effectiveness of DT in urban infrastructure not only depends on the maturity of technical elements such as sensors, Internet of Things (IoT), and artificial intelligence (AI) but is also constrained by the collaborative participation, power and responsibility configuration, and value co-creation mechanisms of governance entities. Notably, although existing reviews have examined DT technologies in civil infrastructure (e.g., Boje et al. [5]; Opoku et al. [6]; Cheng and Lu [7]), they predominantly adopt single-dimensional technological perspectives. The present review differs by integrating the three-dimensional “Technological Embedding—Organizational Change—Institutional Reconstruction” lens to examine whole-lifecycle governance from a socio-technical systems perspective. This has expanded the relevant research fields, with the aim of providing theoretical guidance for policy implementation.

This paper, through a systematic literature review of internationally mainstream databases covering the period from 2010 to 2025, aims to examine the integration of DT technology into the whole-lifecycle governance of urban infrastructure. The core research questions are as follows: (1) In what ways is DT embedded across the full lifecycle of urban infrastructure governance? (2) What demands for organizational adaptation and what pressures for institutional restructuring emerge as a result of this technological embedding? (3) Through what interactive dynamics and transmission channels do technology, organization, and institution influence one another within this governance context? By addressing these questions, this study seeks to transcend the constraints of technological determinism, advance the transformation of DT technology from a mere instrument of “technological empowerment” toward tangible “governance effectiveness,” and ultimately offer both theoretical foundations and practical implications for the digital upgrading of urban infrastructure governance.

1.2. Review Design

This study adopted the PRISMA guidelines to ensure transparency and reproducibility. A systematic search was conducted across Web of Science, Scopus, CNKI, and IEEE Xplore using structured search strings combining Digital Twin-related terms (“DT,” “virtual twin”), urban infrastructure-related terms (“urban infrastructure,” “smart city,” “BIM,” “CIM”), and governance-related terms (“governance,” “lifecycle management”). The search was limited to peer-reviewed journal articles published between 2010 and 2025 in English and Chinese. Following a three-stage screening procedure (title/abstract screening, full-text review, and snowball sampling), 150 core papers were selected for qualitative synthesis analysis, which was performed on 423 retrieved records. The methodological quality of the included studies was assessed using a customized framework adapted from CASP and AMSTAR-2 that evaluates five dimensions: research design rigor, theoretical foundation, empirical evidence quality, relevance to socio-technical governance, and disciplinary representativeness. Studies were classified into three quality tiers, with higher weight assigned to high-tier studies during synthesis (inter-rater reliability: Cohen’s kappa = 0.84). Bibliometric analysis further revealed exponential publication growth (34.2% annual growth rate), with China (32.1%), the United States (18.4%), and the United Kingdom (12.7%) as the top contributing countries, and dominant methodologies including case studies (38.2%) and conceptual frameworks (27.5%).

Co-occurrence Analysis Parameters: The network in Figure 1 was generated using VOSviewer (v1.6.20) with the following settings: unit of analysis = author keywords and Keywords Plus; counting method = full counting; minimum occurrence threshold = 5; clustering resolution = 1.0; layout = association strength normalization. The network comprises 87 nodes (keywords) and 312 links, organized into four clusters: Cluster 1 (red)—

DT technical implementation (BIM, IoT, real-time simulation, machine learning); Cluster 2 (green)—urban infrastructure systems (smart city, sustainable infrastructure, water management, energy systems); Cluster 3 (blue)—governance and organizational dimensions (cross-sector collaboration, data governance, stakeholder engagement, public value); and Cluster 4 (yellow)—lifecycle and sustainability (lifecycle assessment, circular economy, decommissioning, environmental impact). The sparse connectivity between Cluster 3 and Cluster 4 visually confirms the disciplinary fragmentation and the heavy front-end, light back-end imbalance identified in the qualitative synthesis.

Based on this, this paper defines DT as the dynamic digital mirror formed by mapping the real-time status of physical infrastructure to virtual space through technologies such as sensor networks, Internet of Things (IoT), and cloud computing, whose core characteristic lies in the real-time bidirectional data flow between physical entities and virtual models; defines whole-lifecycle governance as the collaborative participation and value co-creation of government, market, society, and the public at each stage of infrastructure planning, design, construction, operation and maintenance management, and decommissioning and disposal; and provides a broad definition of urban infrastructure, grounded in established academic and institutional frameworks [e.g., UN-Habitat, World Bank Infrastructure Strategy, Hodgson's socio-technical typology], that includes not only traditional material infrastructure such as road traffic, water supply and drainage, energy supply, sanitation systems, and communication networks but also digital infrastructure such as data centers, communication base stations, and IoT sensing networks, as well as social infrastructure including public health and education facilities, and the complex urban technical systems formed by the deep integration of the two. To clarify the analytical consistency of this review, it is necessary to explicate the logical relationship among the three core concepts and delimit the application scope. The real-time bidirectional data flow of DT is embodied differently across lifecycle stages: in planning, it enables scenario simulation; in construction, real-time monitoring; in O&M, predictive maintenance; and in decommissioning, historical data retrospection. While urban infrastructure is broadly defined, this review primarily focuses on the digital governance of physical infrastructure (transportation, water, energy), treating digital infrastructure as the enabling substrate. This delimitation ensures analytical consistency across the four stages.

2. Technological Embedding: The Evolutionary Trajectory and Whole-Lifecycle Applications of DT Technology

2.1. From BIM to CIM to DT: The Formation and Evolutionary Logic of the Technology Genealogy

The technology genealogy of DT for urban infrastructure has evolved from micro-level engineering modeling to macro-level urban governance mirrors. As shown in Figure 2, BIM, serving as the logical starting point, is a building whole-lifecycle information integration and management method based on digital technology [8], and its implementation is subject to the multi-dimensional constraints of technology, process, and policy [9]. This stage focuses on “how to precisely model.” Although it can reduce design errors and optimize construction progress [10], bottlenecks such as missing historical data, the high costs of reverse modeling, and multi-source data heterogeneity [11] have confined it to a project-level static information management tool, which makes it difficult to support the holistic governance of complex urban systems.

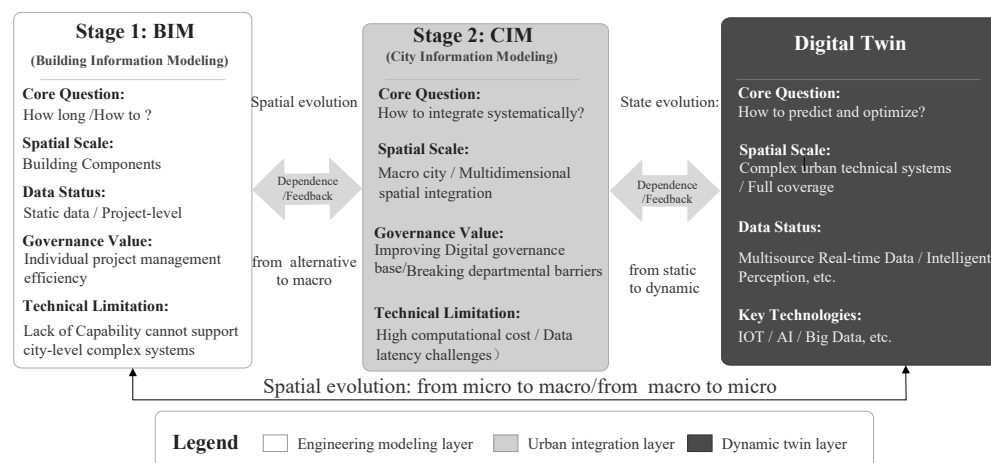


Figure 2. BIM-CIM-DT technology evolution path. This diagram was synthesized from Eastman et al. [8], Succar [9], Xu et al. [12], and Tao et al. [2] and simplified to improve visual clarity.

This limitation drove the evolution toward CIM. CIM integrates Geographic Information System (GIS), building attribute data, and IoT sensing data to construct an urban information complex in a three-dimensional digital space (Xu et al. [12]) and, further, becomes a governance infrastructure supporting integrated planning–construction–management decision-making, whose core function lies in breaking down departmental data silos to achieve cross-domain collaboration [13]. However, CIM still primarily focuses on static data integration and visualization, and its governance effectiveness is constrained by non-unified data standards and insufficient semantic interoperability. It also lacks real-time response capabilities to dynamic changes in the physical world and predictive simulation abilities for future scenarios, which prompted the technology genealogy to leapfrog toward DT. The five-dimensional model of DT establishes the core characteristics of bidirectional virtual–physical mapping, real-time driving, and full-cycle accompaniment [2]; the typological framework provides an analytical basis for technology classification [14]; and the introduction of multi-physics coupling modeling and real-time simulation [3,15] has propelled DT from a “Digital Archive” to a “Living Mirror,” enabling the real-time perception, dynamic simulation, and intelligent decision-making of urban operational states. Certainly, research challenges such as data quality assurance, model verification, and security [16] are particularly prominent in the field of urban infrastructure. In summary, BIM addresses the proposition of “how to precisely model,” CIM addresses the proposition of “how to systematically manage,” and DT answers the proposition of “how to predict and optimize.” Together, the three constitute a complete technology genealogy from micro-level components to macro-level cities, from static data to dynamic mirrors, and from single engineering efficiency to systematic governance capabilities. It should be clarified that BIM, CIM, and DT do not constitute a simple linear substitution but rather a coexistence and nesting relationship. BIM remains the foundational modeling tool for individual assets, CIM serves as the meso-level data integration platform, and DT adds the real-time predictive layer; a mature DT city still relies on BIM for asset-level detail and CIM for district-level integration.

2.2. Planning and Design Stage: Multi-Scenario Simulation, Scenario Simulation, and Public Participation

In the planning and design stage, DT technology has constructed a technical application system encompassing multi-scenario simulation, scenario simulation, and intelligent optimization. However, the full release of its governance potential still faces structural lag (as shown in Figure 3). Specifically, multi-scenario comparison based on virtual

simulation has significantly enhanced the scientific validity of planning decision-making—Boje et al. [5] found that this method can reduce design change costs by more than 30% and shorten the review cycle, while Batty [17] further pointed out from the urban science perspective that DT endows planners with unprecedented “Experimental Capability,” enabling them to test the spatiotemporal impacts of different scenarios in virtual space, thereby effectively reducing trial-and-error costs in the real world. However, existing applications still mainly remain at the level of technical feasibility: Opoku [6] review of DT in the construction industry indicates that although the planning and design stage is its most mature application domain, the practice depth is mostly confined to geometric modeling and performance simulation; although Jiang et al. [18] proposed an intelligent asset management framework integrating DT and BIM and emphasized reserved data interfaces to support whole-lifecycle dynamic updates, Lu et al. [19] systematic review reveals that research in this stage pays notably insufficient attention to governance issues such as public participation, interest coordination, and environmental justice, reflecting the lag in the transformation of DT from a “Technical Tool” to a “Governance Medium.”

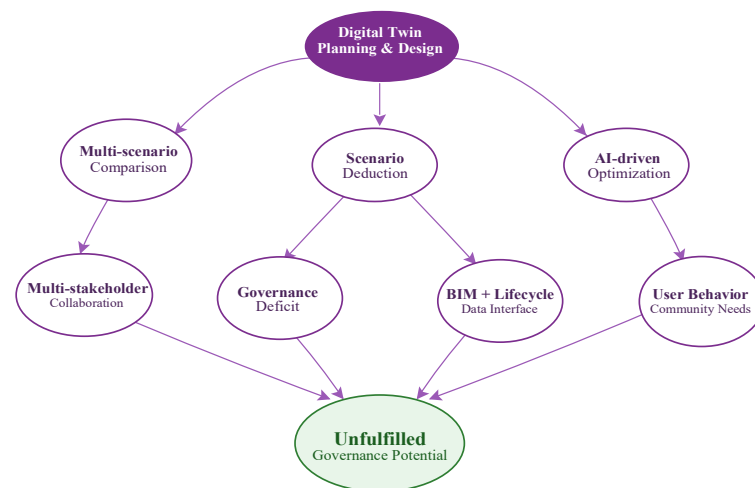


Figure 3. Technological application and governance potential release of DT in the planning and design stage. Conceptualized from planning stage studies, synthesizing Boje et al. [5], Batty [17], and Pan and Zhang [20] with governance critiques from Opoku [6] and Lu et al. [19].

Meanwhile, the integration of artificial intelligence (AI) and DT has opened new pathways for planning optimization—Pan and Zhang [20] pointed out that machine learning algorithms can achieve the automatic optimization of road networks and public transit lines, Lu et al. [21] demonstrated the possibility of multiple stakeholders conducting collaborative planning through shared virtual platforms using smart cities as cases, and Zhao et al. [22] further introduced user behavior simulation into the design frontier of smart buildings. Notably, however, these technology-oriented studies still show limited deep attention to user needs and community demands, and considerations of governance dimensions such as socio-economic impacts, ecological effects, and fairness have not yet been systematically incorporated into the technical framework. Thus, DT applications in the current planning and design stage exhibit a distinct characteristic of “technological capability ahead of governance integration”—although multi-scenario simulation, scenario simulation, and AI-driven optimization have formed a powerful technical support network in virtual space, the lack of an organic connection with democratic consultation, interest coordination, and public wisdom ultimately points to the core bottleneck of “Unreleased Governance Potential.” The planning stage literature reveals a disciplinary divide: engineering studies (Boje et al. [5]; Batty [17]) emphasize cost-efficiency and simulation accuracy, whereas governance scholars (Opoku [6]; Lu et al. [19]) argue that technical

capabilities have not translated into democratic legitimacy or social equity. These conflicting findings suggest that DT planning applications remain trapped in a “technical frontier, governance rear” paradox.

2.3. Construction Implementation Stage: Construction Collaboration, Quality and Safety Monitoring, and Schedule and Resource Management

During the construction implementation phase, DT technology takes construction collaboration, quality and safety monitoring, and schedule and resource management as its core objectives. Through real-time data mapping and virtual simulation, dynamic data such as personnel location, equipment status, environmental parameters, and material consumption on the construction site are linked in real time with the BIM model to construct a “Virtual Construction Site.” Relying on core mechanisms such as 4D BIM simulation, schedule deviation analysis, virtual acceptance, and safety warning, the transparency, precision, and intelligentization of the construction process are achieved (as shown in Figure 4). Research by Jiang et al. [23] indicates that the deep integration of BIM and IoT, combined with Real-Time Location System (RTLS), wearable devices, and computer vision technologies, enables the automatic identification of dangerous areas, real-time warning of personnel trespassing, and post hoc tracing of safety accidents. Ye et al. [24] further proposed a schedule deviation analysis method based on DT, which automatically generates correction suggestions using machine learning algorithms by comparing differences between the planned model and the actual model, significantly improving the response speed and decision accuracy of schedule management. In terms of application value, the critical review by Jiang et al. [18] points out that the core contributions of DT at this stage are manifested in three dimensions: optimizing construction sequence and resource allocation through 4D simulation, reducing risks of quality defects and safety accidents through real-time monitoring and warning, and decreasing on-site rework and change costs through virtual acceptance. Meanwhile, Oztemel and Gursev [25], from the Industry 4.0 perspective, note that the integration of DT with additive manufacturing and collaborative robots holds broad prospects in construction industrialization and modular construction.

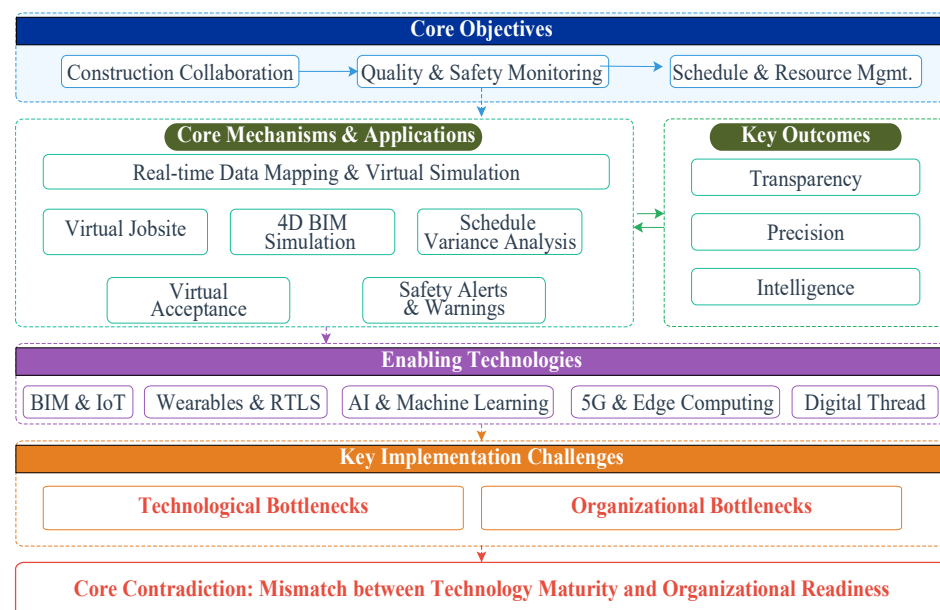


Figure 4. System logic diagram of the construction phase. Synthesized from Jiang et al. [23], Ye et al. [24], and Liu [26], with bottleneck analyses drawn from construction stage studies.

The key infrastructure supporting the implementation of the above applications encompasses BIM and IoT, wearable devices and RTLS, artificial intelligence (AI) and machine learning, 5G and edge computing, and Digital Thread. Liu [26] particularly emphasized that 5G communication, edge computing, and Digital Thread technology are the core enabling conditions for the operation of DT on the construction site. However, as systematically presented in the figure, the promotion of DT in the current construction phase still faces dual bottlenecks: at the technical level, the construction site environment is complex and changeable, sensor deployment is restricted, and data transmission is constrained by network conditions; coupled with the high uncertainty and non-standardized features of construction activities, the construction of precise mathematical models is extremely difficult; at the organizational level, the willingness of various construction participants to share data is weak, information silos and coordination barriers are prominent, and insufficient organizational readiness severely restricts technology implementation. These bottlenecks collectively point to the core contradiction of “mismatch between technology maturity and organizational readiness,” indicating that the application of DT in the construction phase is currently in a critical stage of transition from “pilot demonstration” to “large-scale promotion.” Construction stage studies demonstrate a “proof-of-concept gap.” While Jiang et al. [23] and Ye et al. [24] report promising real-time monitoring capabilities, their evidence derives primarily from single-case pilots. Jiang et al. [18] further acknowledge that the large-scale empirical validation of cost reduction and safety improvement remains scarce. The tension between Oztemel and Gursev’s [25] Industry 4.0 optimism and Liu’s [26] practical constraints regarding 5G deployment highlights the gap between technical potential and organizational readiness.

2.4. Operation and Maintenance Management Stage: Predictive Maintenance, Structural Health Monitoring, and Intelligent Scheduling

The operation and maintenance (O&M) management phase is the domain where the governance value of DT is most significant. Its core lies in achieving a paradigm shift from “passive response” to “proactive prevention” through real-time monitoring and predictive maintenance. This shift is premised on the integration of multi-source sensing technologies: the synergy of accelerometers, strain gauges, and visual measurement technologies provides multi-dimensional data input for structural health monitoring; the development of wireless sensor networks and drone inspection has significantly reduced monitoring costs; and computer vision technology further provides non-contact, high-efficiency data acquisition methods [7,21]. The overall logical coupling relationship of the above DT operation and maintenance system is shown in Figure 5.

On this basis, the “Physical-Data-Knowledge” fusion-driven framework constitutes the core architecture of the DT system. The deep integration of finite element models and real-time monitoring data not only improves structural assessment accuracy by more than 40% but also provides a decision basis for the intelligent scheduling of urban water systems—DT can simulate pipeline hydraulic status, predict pipe burst risks, and optimize scheduling schemes, reducing the leakage rate by 15–30% and shortening emergency response time by more than 50% [7]. It also demonstrates core value in rainstorm waterlogging simulation and overflow prediction in drainage systems. The fusion of hydraulic models and real-time monitoring data is regarded as key support; relevant research systematically evaluated the comprehensive benefits of DT in the water sector and pointed out that it has transcended the attributes of a monitoring tool to become a governance platform supporting long-term asset investment decisions and resource allocation [3].

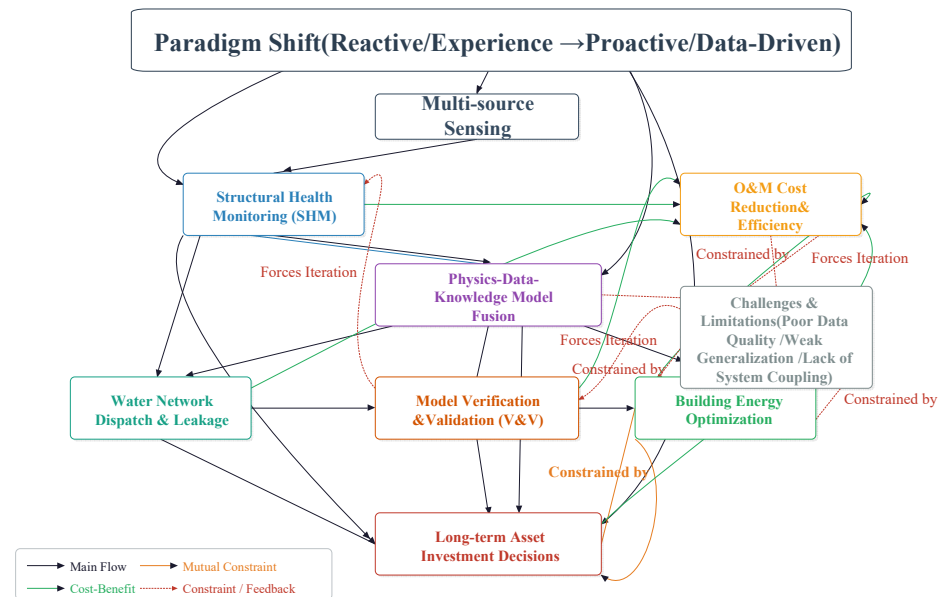


Figure 5. DT logic diagram of the O&M Phase. Synthesized from O&M literature on sensor technologies, hydraulic modeling, and energy infrastructure analyses.

In the energy infrastructure domain, DT can increase equipment fault prediction accuracy to over 85% and reduce maintenance costs by 20–40% [7]. Closed-loop optimization of energy consumption simulation and real-time monitoring is the key path to achieving building energy conservation. However, the key prerequisite for transitioning from research to engineering application lies in the model verification and validation of the system—the consistency between the physical model and measured data directly determines the reliability of the model [15].

When the above technical paths are effectively connected, DT can achieve the governance goals of reducing operation and maintenance costs and improving efficiency. Nevertheless, structural constraints such as uneven data quality, insufficient model generalization capability, and the lack of coupling considerations among urban infrastructure systems still restrict the full release of its value. Although deep learning algorithms demonstrate excellent performance in crack identification and displacement measurement, their generalization capability and adaptability to complex environments still need improvement. The successful implementation of DT in the O&M phase ultimately depends on the trinity of high-quality data, reliable models, and effective governance mechanisms. Breaking through the above bottlenecks remains the core proposition that must be resolved for this field to move from single-point application to system-level intelligent operation and maintenance. O&M research advances unevenly across domains. Water infrastructure studies offer relatively robust longitudinal evidence, whereas energy claims (e.g., 85% fault prediction accuracy) often derive from controlled pilots with questionable scalability. Cross-domain coupling effects remain virtually unexplored, and field studies report a significant performance degradation of computer vision under variable conditions, contradicting laboratory-validated accuracy metrics.

2.5. Decommissioning and Disposal Phase: Environmental Impact Assessment, Resource Recycling, and Sustainable Governance

Compared with the planning, construction, and O&M phases, research on DT in the field of infrastructure decommissioning and disposal exhibits a significant structural imbalance, forming a sharp contrast with the “closed-loop” concept advocated by whole-lifecycle governance. Decommissioning and disposal involve complex issues such as

demolition safety, construction waste resource utilization, soil remediation, and environmental impact assessment, which not only pose prominent technical challenges but also are intertwined with profound ethical considerations and multi-stakeholder games. The current literature mainly focuses on BIM-driven demolition sequence simulation and structural stability analysis, while systematic attention to sustainability issues such as construction waste tracking management, resource utilization, and dynamic assessment of environmental impacts is lacking. From the perspective of whole-lifecycle governance, DT has irreplaceable unique value at this stage: optimizing demolition schemes and resource recovery strategies through historical data retrospection and material composition analysis; assessing the long-term effects of different disposal schemes on surrounding ecosystems and community health through environmental impact simulation; and relying on virtual simulation to identify potential risks such as asbestos exposure and heavy metal pollution before demolition and to formulate emergency plans. However, the realization of these application scenarios faces multiple practical challenges: missing or distorted completion data of historical infrastructure makes it difficult to establish baseline models; high uncertainty in the demolition process causes difficulties in real-time data acquisition and lag in dynamic updates; and organizational barriers and blurred power and responsibility in multi-departmental coordination among environmental protection, safety supervision, and urban management further restrict technology implementation. The value, bottlenecks and future development paths of DT-enabled decommissioning management are summarized in Figure 6.

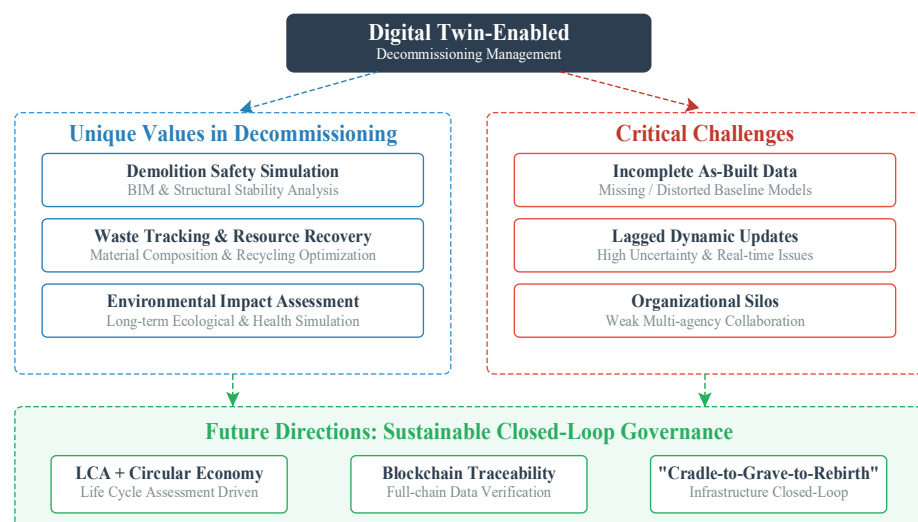


Figure 6. DT logic diagram of the decommissioning and disposal phase. Developed from limited decommissioning literature ($n = 9$ studies) combined with LCA and circular economy principles; simplified for clarity.

Empirical evidence illustrates these bottlenecks concretely. The demolition of the Ruhr region's old industrial plant in Germany was delayed by four months due to incomplete 1960s as-built documentation, forcing costly laser-scanning reconstruction. Conversely, the London Olympic Park's temporary venue demolition achieved 98% waste recycling by integrating BIM as-built models with real-time waste tracking, validating closed-loop governance when baseline data is available. These contrasting cases reveal that decommissioning bottlenecks manifest as tangible cost overruns and schedule delays in specific infrastructure contexts.

It is worth noting that Boje et al. [5], in their research on distributed lifecycle information management, explored the supporting role of blockchain technology in generating trusted evidence with regard to engineering data, providing important technical

inspiration for full-chain traceability in the decommissioning phase, but related applications are still in the proof-of-concept stage. The above existing research limitations profoundly reflect the “heavy front-end, light back-end” structural imbalance in current DT applications and also reveal the deep problem of insufficient attention to sustainable governance issues in engineering informatics. Looking forward, it is urgently necessary to deeply embed lifecycle assessment (LCA) methods and the circular economy concept into the DT technology framework; promote the multi-dimensional integration of blockchain full-chain data verification with historical data, material analysis, and virtual simulation; and ultimately construct a sustainable closed-loop governance system covering infrastructure “from cradle to grave to rebirth.” Decommissioning represents the most pronounced gap, with only 6.3% of reviewed studies addressing this stage. While Boje et al. [5] offer conceptual directions through blockchain traceability, empirical frameworks for demolition optimization and waste tracking remain absent. This structural deficit undermines the whole-lifecycle governance narrative and signals an urgent need for interdisciplinary research.

2.6. Technical Bottlenecks: Data Fusion, Real-Time Mapping, Model Accuracy, and Computational Cost

Although DT technology has demonstrated broad prospects across all stages of the whole lifecycle, technical bottlenecks remain prominent, severely restricting its transition from “proof of concept” to “large-scale application.” Cheng and Lu [7], in their review on DT for civil infrastructure, systematically identified three core technical challenges: the semantic interoperability of multi-source heterogeneous data, temporal consistency between real-time and historical data, and multi-scale modeling of complex urban systems. Specifically, data sources involved in urban infrastructure—including BIM, GIS, IoT sensing, video surveillance, and social media—exhibit significant differences in format, accuracy, temporal granularity, and semantic definition; seamless fusion and semantic alignment of cross-source data remain the primary challenge. Temporal mismatch among sensor sampling frequency, data transmission delay, and model calculation cycle makes it difficult for the virtual model and physical entity to achieve synchronized updates that balance both real-time performance and data quality. Cross-scale information transfer and model coupling from micro-level components to macro-level systems are key to DT’s transition from “single-point application” to “system integration.” On this basis, Rasheed et al. [15] further pointed out from the modeling perspective that existing verification and validation methods mainly target single physical fields and steady-state conditions, with insufficient research on multi-physics coupling, time-varying conditions, and uncertainty quantification; the credibility assurance mechanism for models is still inadequate. Meanwhile, Fuller et al. comprehensively reviewed the interdisciplinary challenges of DT; in addition to the above technical issues, problems such as security and privacy protection, model interpretability, human–computer interaction design, and ecosystem sustainability are equally noteworthy. Qi et al. [27] focused on the integration dilemma at the enabling technology level: although IoT, big data, artificial intelligence, and cloud computing have developed rapidly, issues regarding architecture compatibility, interface standardization, and system reliability remain to be resolved. Furthermore, city-level DT involves real-time rendering of massive 3D models, high-precision simulation of complex physical fields, and parallel processing of multi-source data, placing extremely high demands on computational capability, storage capacity, and network bandwidth. Construction and operation costs remain high, further limiting its promotion and application in small- and medium-sized cities. The hierarchical logical relationship of all core technical bottlenecks restricting large-scale DT application is systematically sorted in Figure 7.

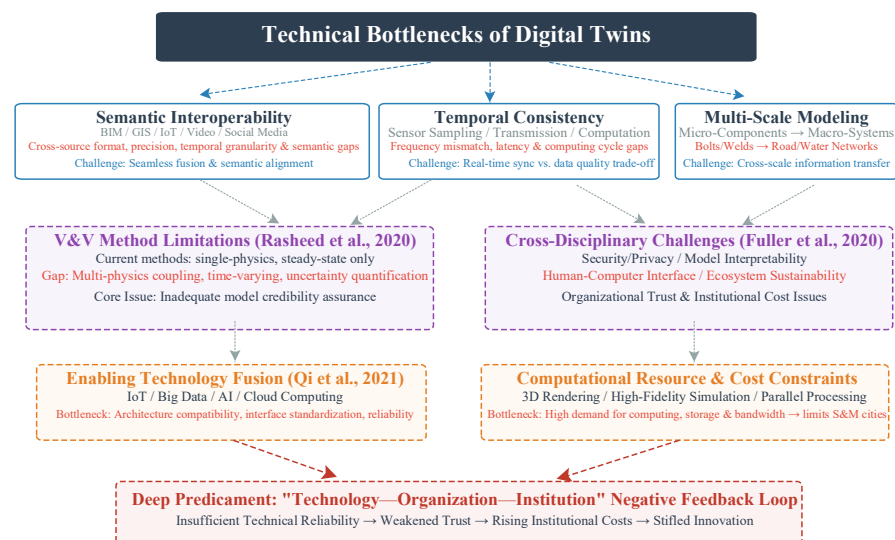


Figure 7. Logic diagram of technical bottlenecks and deep-level impacts. Synthesized from Rasheed et al. [15], Fuller et al. [16], Cheng and Lu [7] and Qi et al. [27], organized by cascading impact logic.

These technical bottlenecks are not merely engineering problems; at a deeper level, they constrain the effectiveness of DT governance—insufficient technical reliability weakens organizational trust, increases institutional costs, and forms a “technology-organization-institution” negative feedback loop. These technical bottlenecks cascade into organizational and institutional governance dilemmas through identifiable causal chains: semantic interoperability deficits trigger data-sovereignty conflicts and departmental information hoarding (Section 3.1); temporal data inconsistency undermines organizational trust and drives decisionmakers back to experience-driven governance (Section 5.3); high computational costs increase institutional risk aversion and conservative procurement (Section 3.4); and security gaps escalate into the data-governance triangular tension (Section 4.1). Thus, technical bottlenecks are endogenous drivers of organizational and institutional change, providing the empirical foundation for the T-O-I framework.

3. Organizational Change: Cross-Sector Collaboration and Governance Process Reengineering Driven by DT

The deep transformation of urban infrastructure governance not only involves technological iteration but also touches on the reconfiguration of organizational architecture and process logic. The fragmentation dilemma under traditional bureaucracy constitutes the primary organizational context for DT application, and whether the technology itself can be transformed into collaborative effectiveness depends on how it is embedded in organizational cognition, institutional arrangements, and power structures.

3.1. Fragmentation Dilemma Under Traditional Bureaucracy and Its Roots

Although the professional division logic of modern bureaucracy has improved single-domain management efficiency, it has created transaction costs for cross-departmental coordination, leading to the phenomenon of “organized irresponsibility.” Infrastructure such as roads, bridges, pipeline networks, and water systems belongs to different functional departments, with planning, construction, and O&M managed by different entities, forming a pattern of “fragmentation of vertical and horizontal sectors.” Research by Angelidou [28] shows that this fragmentation triggers data silos, inconsistent standards, and process fragmentation, which has become the primary organizational obstacle constraining the whole-lifecycle management of infrastructure. Ansell and Gash [29] collaborative governance theory further reveals that when clear common goals, shared resources, and

mutual trust mechanisms are lacking, cross-sector collaboration is highly prone to failure. Bryson et al. [30] systematic study of cross-sector collaboration also confirms that this is the primary reason for public sector collaboration failure. The integrative framework proposed by Emerson et al. [31] points out that collaborative governance must form a positive feedback loop among “principled engagement,” “shared motivation,” and “joint action capacity” to continuously generate effectiveness. O’Leary and Viles [32] review of collaborative public management indicates that although information technology provides technical possibility for cross-sector collaboration, organizational culture, leadership, and institutional incentives are the key factors determining success or failure. Provan and Kenis [33] distinction of network governance modes and Agranoff [34] collaborative experience from a practical perspective both point to the necessity of establishing a common vision, cultivating trust relationships, and clarifying role division. However, traditional information methods such as independent GIS systems and departmental databases essentially superimpose information systems on existing organizational architectures, failing to reshape the deep structure of departmental parochialism and information monopoly. Although DT provides new technical possibilities for breaking organizational barriers, its complexity and the ambiguity of power and responsibility may also intensify rather than dissolve organizational conflicts.

3.2. Collaborative Mechanism of DT as a “Boundary Object”

From the perspective of paths to alleviate the fragmentation dilemma, DT can be regarded as a “boundary object.” The classic research by Star and Griesemer [35] defines it as a technical medium that combines plasticity and stability, capable of establishing a common understanding among different professional fields and organizational departments. Carlile [36] distinction of knowledge boundaries shows that cross-sector collaboration needs to go beyond information transfer at the syntactic level to achieve semantic consensus and pragmatic coordination. Through a unified 3D visualization interface, shared data foundation, and standardized information model, DT provides a common “cognitive anchor” for participants in different stages such as planning, construction, and O&M, significantly reducing cross-professional communication costs. Shi et al. [37] survey based on CIM construction practice in multiple Chinese cities found that DT platforms can reduce cross-departmental communication costs by 30–50%, effectively promoting integrated planning–construction–management collaboration, but its effectiveness highly depends on high-level political support, the coordination capacity of the leading department, and the willingness of participating departments to cooperate. Meanwhile, Boje et al.’s research suggests that the tamper-proof characteristic of blockchain technology can be complementary to the data integration needs of DT, providing trusted technical support for cross-organizational data sharing. What is worth vigilance is that Oslick and Robertson [38] critical reflection on boundary object theory points out that such technical media, while promoting communication, may also solidify power relations—if data standards, access rights, and interpretation rights are monopolized by a dominant department, DT may be alienated from a “digital bridge” to a “digital iron cage,” and, therefore, its governance function must be embedded in democratic mechanisms with multi-stakeholder participation.

3.3. Process Reengineering: From ‘Segmented Management’ to ‘Full-Cycle Collaboration’

At the process level, the DT drives urban infrastructure governance from a linear process to a cyclic feedback loop and from segmented management to full-cycle collaboration. Traditional governance follows a linear process of Planning—Design—Construction—Handover—Operation and Maintenance, in which information is transferred across stages through document handover, which results in significant knowledge loss

and information degradation. The DT achieves continuous information transfer, knowledge accumulation and reuse, and decision closed-loop optimization by constructing a “Digital Thread” that runs through the entire lifecycle. Originating from the aerospace manufacturing industry, this concept has become a data link connecting physical entities and virtual models in the context of the DT, ensuring the integrity and traceability of data at each stage. The practice in Xiongan New Area exemplifies this direction: its CIM platform not only serves the planning and construction stages but also reserves data interfaces for operation and maintenance management, realizing the functional extension from “Digital Blueprint” to “Digital Steward.” However, process reengineering is not merely a technical substitution. Fountain’s [4] Technology Enactment Theory profoundly points out that the actual effect of information technology in the public sector depends on the interaction between “Objective Technology” and “Enacted Technology,” with the latter deeply shaped by organizational cognition, institutional arrangements, and the political environment. This implies that the DT-driven process transformation cannot simply replace governance logic with technical logic; instead, it requires a balance between innovation impulses and institutional stability. The empirical studies of Mergel [39] and Mergel et al. [40] on government digital transformation further demonstrate that successful transformation depends not only on technical capabilities but also on organizational learning capability and institutional adaptation capability and that overly radical changes may trigger organizational rebound. The research by Bannister and Connolly [41] also emphasizes that the application of information technology must be oriented toward public value. Therefore, this paradigm shift should adopt a gradual strategy, achieving deep transformation step by step while maintaining organizational stability through pilot demonstrations, experience diffusion, and institutional embedding.

3.4. Organizational Obstacles: Data Sovereignty, Collaborative Inertia, and Performance Dilemmas

Although the DT possesses the technical potential to facilitate collaboration, organizational-level obstacles remain deeply rooted in the deep structure of bureaucracy. The research by Shi et al. [37] found that “unclear leading departments and unsound collaborative mechanisms” constitute the primary factor restricting the implementation of the DT city. Under the existing administrative system, projects often involve multiple departments, such as housing and construction, transportation, water affairs, and environmental protection, yet lack a statutory leading body, which results in the governance dilemma of “Everyone is Responsible, No One is Accountable.” The maintenance of data sovereignty by each department constitutes the primary obstacle to collaboration—data is regarded as a core resource and power foundation, and sharing means ceding control and influence. The research by Dawes et al. [42] on information integration at the New York State Department of Motor Vehicles profoundly reveals that even if data sharing is technically feasible, the lack of trust and interest conflicts among departments will still substantially hinder collaborative promotion. Furthermore, the avoidance of technical risks aggravates collaborative inertia: the DT involves the centralized storage and real-time transmission of sensitive data, and data leakage, system failures, and algorithmic errors may trigger severe political responsibilities and legal risks, causing departments to tend toward conservative defense rather than active openness. The blurring of responsibility boundaries also constrains collaborative willingness: cross-departmental applications often break down traditional divisions of responsibility, making it difficult to define the attribution of responsibility when problems arise, so departments therefore tend to cling to clear “territories of responsibility.” The dilemma of performance evaluation further weakens participation motivation: the DT has a long investment return cycle, and its benefits are mainly reflected in “implicit benefits” such as long-term operational efficiency improvement and

risk prevention, which are difficult to translate into observable political performance within a single term of office. Linders [43] research on ‘From E-Government to We-Government’ points out that the public sector’s acceptance of open collaboration remains limited; the studies by Nambisan and Wright [44] and Yoo et al. [45] jointly indicate that digital technology is reshaping the organizational boundaries of innovation and giving rise to new organizational forms, yet there exists a fundamental tension between the hierarchical structure and standardized processes of traditional bureaucracy and these new forms. In summary, DT-driven organizational change is a systems engineering effort that transcends a technical perspective and needs to be understood and promoted from multi-dimensional perspectives of organizational behavior, institutional economics, and political science.

3.5. Comparative Analysis of Typical Domestic and International Cases: Differentiated Analysis of Institutional Contexts and Organizational Logic

There is no unified organizational template for DT city governance; the practices of various countries exhibit a path divergence that is deeply embedded in political systems, administrative traditions, and social structures. The Virtual Singapore project adopts a multi-stakeholder governance structure of ‘government-led, enterprise-participated, and citizen-collaborative,’ with coordinated construction through the National Research Foundation, open data interfaces to research institutions and enterprises, and the formation of an industry–university–research–application ecosystem [46]. However, this model relies on a highly centralized political system, efficient administrative execution, and a relatively homogeneous social structure, and its transferability to large democratic countries is rather limited. China’s CIM construction reflects a ‘government-led, top-down’ promotion model: the Ministry of Housing and Urban–Rural Development strongly promotes it by issuing standards, establishing pilot projects, and providing financial support [47]. CIM platforms in cities such as Guangzhou, Shenzhen, Shanghai, and Beijing have initially taken shape, with significant advantages in data integration efficiency and construction speed but insufficient social participation and limited market vitality, with the prominent structural imbalance of ‘government enthusiasm, market coldness, and social indifference.’ European practice exhibits ‘distributed governance’ characteristics. The EU GAIA-X framework emphasizes data sovereignty retention, federated architecture, and privacy protection, reflecting the ‘decentralization’ concept [48]; projects in Germany, the Netherlands, and other countries are led by local governments and industry associations, emphasizing data security and multi-stakeholder governance, but with relatively lower integration efficiency and cross-domain collaboration capabilities [49]. The UK’s ‘National DT Principles’ emphasize open standards, interoperability, and public interest, attempting to establish a unified national-level governance framework [50].

The above comparison indicates that the organizational form of DT governance is deeply constrained by institutional contexts. Smart city governance can be divided into four modes—bureaucratism, marketization, networking and self-organization—each of which adapts to different urban development environments and stages. Meijer and Bolívar [51] further propose the ‘Metagovernance’ framework, emphasizing that the government should play a coordinating, guiding, and supervising role in multi-stakeholder governance rather than simply ‘delegating power’ or ‘centralizing power.’ These theoretical perspectives provide analytical tools for understanding the diverse paths of DT governance and also suggest that local institutional context adaptability must be fully considered when drawing on international experience.

4. Institutional Reconstruction: Data Governance, Standards and Specifications, and Power and Responsibility Allocation

4.1. The Triangular Tension in Data Governance Systems

Data is the core resource of DT governance, but the lag in data governance systems constitutes a critical bottleneck. There exists a profound structural tension among the three dimensions of ownership definition, sharing mechanisms, and privacy protection, requiring a dynamic balance to be sought in institutional design. At the ownership level, infrastructure operation data has multi-stakeholder attributes: the government, as the owner or regulator, possesses administrative data; enterprises, as the builders or operators, control technical parameters; and the public, as users, generates behavioral data. However, the existing legal framework lacks a clear division of the ownership, usage rights, and income rights of these three categories of data. The research by Janssen et al. [52] reminds us that data governance is not merely a technical issue but also a political process involving power distribution and interest coordination. Kitchin's [53] critical analysis of smart cities further reveals that the collection and storage of urban data are reshaping the power structure of governance; data advantages may translate into governance advantages, thereby aggravating the Digital Divide and social inequality. In subsequent research, Kitchin [54] also points out that ethical issues such as data ownership, informed consent, and algorithm transparency are particularly prominent in the DT. Regarding sharing mechanisms, although various regions have introduced data openness policies, the phenomenon of "unwilling to share, afraid to share, and unable to share" remains widespread. This is not caused by mere technical incompatibility but rather stems from a lack of organizational trust and insufficient incentives. Gil-Garcia et al.'s [55] comparative study of smart cities in North America, while finding a positive correlation between data openness and citizen participation, also warns of the concomitant effects of privacy leakage and security risks. In the dimension of privacy protection, the fine-grained mapping of urban space by the DT—including building internal structures and personnel flow trajectories—is eroding traditional privacy boundaries [56], while citizens are quietly transforming from traditional "service objects" to "data sources," with their subjectivity and agency being significantly eroded [57]. More fundamentally, technical solutions often serve the interests of capital and the state rather than the needs of ordinary citizens [58], which requires us to maintain democratic supervision and public accountability over smart city technologies [59]. The critical review by Luque-Ayala and Marvin [60] also points out that existing research mostly focuses on technical possibilities while paying insufficient attention to deep issues such as power relations and social justice. In summary, data governance systems must seek a prudent balance between efficiency and equity, openness and security, avoiding the trap of technological utopia.

4.2. Technical Standard Systems: The Fragmentation Dilemma of Model Specifications, Interface Standards, and Interoperability

Technical standards are the institutional foundation for the large-scale promotion of DTs, but the fragmentation of the existing standard system severely constrains interconnection and collaborative governance. Yan [61] emphasize in their review of DTs in road engineering that the lack of unified data exchange standards and model specifications is an important factor restricting industry promotion. Currently, the ISO 19650 series of standards is mainly limited to the information management process of construction projects, with insufficient coverage of city-level infrastructure [62]. Although CityGML provides semantic specifications for urban 3D models, its support for real-time dynamic data integration is limited. The IFC standard, as a de facto standard for BIM data exchange, faces technical bottlenecks in city-level expansion and Internet of Things data integration.

Although the IFC 4.3 version released by BuildingSMART International [63] has added support for the infrastructure domain, and the CityGML 3.0 version released by OGC [64] has introduced dynamic data and temporal dimensions, interoperability issues between the two and their adoption depth in China remain limited. Domestically, although the Ministry of Housing and Urban–Rural Development has preliminarily established a CIM standard system framework, the standard coverage in sub-fields such as underground pipeline networks and utility tunnels is still incomplete, and coordination between local standards and national standards is difficult. From an international comparative perspective, the GAIA-X framework promoted by the European Commission represents a “decentralized” standardization path, emphasizing data sovereignty retention and federated architecture. The National Institute of Standards and Technology [65] defines the reference architecture and interoperability requirements for DTs from a systems engineering perspective. The PAS 1192 series of the British Standards Institution [66] provides process specifications for information management. However, standard fragmentation not only increases technical integration costs but also substantially hinders cross-regional, cross-departmental, and cross-industry collaborative governance. When different cities adopt different CIM standards, data exchange and collaborative management between cities will face enormous obstacles. Therefore, establishing a unified, open, and extensible DT standard system is an indispensable institutional prerequisite for advancing whole-lifecycle governance.

4.3. Power and Responsibility Allocation Systems: The Gray Zones of Regulatory Boundaries, Accountability Mechanisms, and Risk Sharing

The introduction of DT systems profoundly blurs traditional regulatory boundaries, posing severe challenges to existing power and responsibility allocation systems. When algorithmic models make erroneous predictions leading to decision-making errors, the question arises as to whether the responsibility should be borne by the technology provider, data operator, platform manager, or government regulatory department—the algorithmic accountability dilemma. This question has not yet received an adequate response in the existing legal framework. From the perspective of institutional theory, March and Olsen’s [67] assertion that institutions not only constrain behavior but also endow it with meaning and legitimacy suggests that the institutional embedding of DTs needs to undergo a gradual process from cognitive shift to normative adjustment and then to regulatory change. Scott’s [68] three-pillar framework provides a structural analysis tool for this logic, while DiMaggio and Powell’s [69] institutional isomorphism theory explains the universality of the “following the trend” phenomenon in DT construction. North’s [70] distinction between formal and informal institutions further reveals that institutional change is constrained by path dependence, and the transformation of informal institutions is particularly slow.

The analysis of transaction cost economics reveals another dilemma. Williamson [71] points out that the high asset specificity and high uncertainty of DT systems lead governments to prefer vertical integration over market outsourcing, but this may, in turn, result in technology closure and insufficient innovation. Ostrom’s [72] research on common pool resources governance advocates transcending the binary opposition between “government ownership” and “market allocation,” exploring co-governance models with multi-stakeholder participation. In the dimension of digital governance, Hood and Margetts [73] point out that the DT possesses multiple characteristics including nodality, authority, treasury, and organization. Dunleavy et al. [74] emphasize that information technology is driving the government from an efficiency-oriented to an integration-oriented approach. Margetts and Dorobantu [75] further warn that new technologies, if lacking supporting organizational change and institutional innovation, are highly likely to lead to “technology

idling or digital formalism. These theories collectively indicate that the design of the DT's power and responsibility allocation system needs to transcend a simple attribution of responsibility logic and establish a whole-process risk governance system covering prevention, monitoring, response, and recovery.

4.4. Comparison of Institutional Paths: The Differentiated Logic of the EU GAIA-X Data Space and China's CIM Standard System

At the international comparative level, the European Union and China represent two typical paths of DT governance systems, with differences rooted in different political systems, legal traditions, and data governance philosophies. The EU promotes the construction of a distributed data space through the GAIA-X framework, emphasizing data sovereignty retention, federated architecture, and privacy-by-design, reflecting the institutional concept of decentralization [76]. The core architecture of this path includes federated services, data connectors, and a trust framework, aiming to establish an open, transparent, and trustworthy European data infrastructure that enables data owners to achieve sharing and value creation without losing control. It reflects the EU's vigilance against data monopolies by large tech companies and its high regard for individual data rights—as demonstrated by the Right to be Forgotten and Data Portability Right established by the GDPR. In the field of DT cities, the EU's Destination Earth program follows the logic of open science and public interest, opening data access to the global research community. By contrast, China builds a centralized urban data foundation relying on the CIM standard system, emphasizing government coordination, standard unification, and administrative drive, reflecting a top-down, centralized path [77]. Its institutional logic can be summarized as unified planning, step-by-step implementation—the Ministry of Housing and Urban–Rural Development formulates top-level design and standards, local governments are responsible for specific implementation and scenario application, and technology enterprises provide platform support. This path has significant advantages in data integration efficiency, standard unification, and construction speed; CIM platform construction in cities such as Guangzhou, Shenzhen, Shanghai, Beijing, and Xiong'an has already initially taken shape. However, this path also faces criticism regarding data monopolies, innovation suppression, and privacy risks. The two paths reflect different institutional logics: the EU model emphasizes data security, multi-stakeholder governance, and individual rights but has lower integration efficiency and difficulties in cross-domain collaboration; the Chinese model emphasizes integration efficiency, administrative drive, and scale effects but has insufficient social participation and limited market vitality. Future research needs to pay attention to the applicable conditions and integration possibilities of the two paths, exploring a Third Way that can both ensure data security and promote innovation vitality. The Metagovernance framework for smart city governance proposed by Meijer and Boon [76] provides useful insights: the government should play the role of a coordinator rather than a controller among multiple governance actors, promoting active participation from the market, society, and the public by establishing rules, providing platforms, and guiding direction.

Standard differences directly shape governance outcomes through their effects on data flow and organizational collaboration. The EU's federated GAIA-X architecture, while preserving data sovereignty, creates higher transaction costs for cross-domain integration, as evidenced by slower city-level DT rollout in Germany compared to China. Conversely, China's centralized CIM standards enable rapid data aggregation but risk vendor lock-in due to limited interoperability with international standards (IFC 4.3, CityGML 3.0). Thus, standard fragmentation is a governance-shaping force: decentralized standards foster participation at the cost of integration speed, while unified standards accelerate deployment at the risk of innovation suppression.

4.5. Institutional Constraints: The Structural Tension Between Technological Centralization and Governance Decentralization and Its Reconciliation

The inherent logic of DT technology tends toward data centralization, algorithm unification, and platform monopoly, while the practical demands of urban governance require the decentralization of power and responsibility, tailored approaches to local conditions, and multi-stakeholder participation. This structural tension constitutes the core contradiction of DT governance. The logic of technological centralization stems from the technical characteristics of the DT: real-time data mapping requires unified data collection standards and transmission protocols, high-precision simulation requires centralized computing resources and model libraries, and intelligent decision-making requires unified algorithmic frameworks and knowledge graphs. These technical requirements naturally point toward a centralized technical architecture. However, the logic of governance decentralization is rooted in the complexity and diversity of cities: different cities have different natural conditions, development stages, and cultural traditions; different communities have different interest demands and action capacities; and different departments have different statutory responsibilities and resource endowments. This diversity requires governance solutions to have flexibility and adaptability rather than a one-size-fits-all standardized model. Existing literature pays insufficient attention to the tension between technological centralization and governance decentralization, mostly treating institutions as an ‘external environment’ of technology application rather than an ‘endogenous variable,’ implicitly assuming that technical logic can override governance logic. In reality, institutions are not merely constraint conditions but also key forces shaping the direction of technological development; the selection, design, and application of technology are always embedded in specific institutional contexts and profoundly influenced by power relations, interest structures, and value concepts. Tilson et al. [78] research on digital infrastructure points out that digital infrastructure has generative features, and its openness and extensibility can give rise to unforeseen innovative applications, but this generativity requires moderate institutional constraints to prevent abuse and disorder. Henfridsson and Bygstad [79] research on the evolution of digital infrastructure reveals the core role of generative mechanisms in evolution, pointing out that the co-evolution of technology, organization, and institutions is the key to the success of digital infrastructure. These studies indicate that reconciling the tension between technological centralization and governance decentralization requires establishing a ‘layered governance’ institutional architecture: at the data layer, achieving standardization and interconnection to ensure the interoperability of technical systems; at the platform layer, maintaining openness and modularity to support innovative applications for different scenarios; at the application layer, encouraging diversity and adaptability, respecting local knowledge and community wisdom; and at the governance layer, establishing coordination mechanisms and accountability frameworks to safeguard public interests and citizen rights. This layered governance architecture both leverages the scale effects and collaborative advantages of DT technology and preserves the flexibility and inclusiveness of urban governance, representing the institutional path to achieving the organic unity of technology empowerment and governance effectiveness.

5. Three-Dimensional Interaction of ‘Technology—Organization—Institution’: Integrative Analytical Framework and Transmission Mechanisms

5.1. Critique of Technological Determinism and the Introduction of a Governance Perspective

Existing DT research harbors an implicit tendency toward technological determinism, treating technological upgrading as an automatic prerequisite for improved

governance effectiveness while overlooking the social embeddedness and contextual dependence of technological application. This perspective regards DT as a value-neutral tool, presupposing that technological advancement alone can automatically resolve governance challenges, thereby obscuring the “backlash” risks such as the erosion of public trust by algorithmic inexplicability, the threat to privacy posed by the generalization of data surveillance, and the solidification of power structures by platform monopolies. Kitchin’s [53] critical study on big data in smart cities reveals that the collection and application of urban data are deeply influenced by political–economic logic and power relations; Cardullo and Kitchin [57] further note that smart city technologies are redefining citizenship, transforming citizens from “rights-bearing subjects” into “data nodes,” with their political participation and social agency being systematically eroded. The introduction of a governance perspective repositions DT as a “socio-technical system.” The socio-technical systems theory of Trist and Bamforth [80] demonstrates that technical and social systems must be mutually adapted and that the optimization of a single system may lead to a decline in overall effectiveness. Therefore, DT governance research needs to shift from “technical optimization” to “system optimization” and from “instrumental rationality” to “value rationality.”

5.2. Construction of the Integrated ‘Technological Embedding–Organizational Change–Institutional Reconstruction’ Analytical Framework

Based on the above theoretical reflections, this paper proposes the integrated ‘Technological Embedding–Organizational Change–Institutional Reconstruction’ (T-O-I) analytical framework, aiming to transcend the binary opposition between technological determinism and institutional determinism and to reveal the dynamic interaction mechanisms among technology, organization, and institution in DT governance. Technological embedding serves as the starting point of the framework, referring to the way DT technologies alter the information foundation and decision-making processes of governance through data fusion and algorithmic deployment; its depth directly influences the possibility space for subsequent organizational change and institutional reconstruction. Organizational change constitutes the mediating link, encompassing structural adaptation, process reengineering, and capacity building triggered by technological embedding, including both adjustments to formal institutions and the cultivation of cross-sector collaboration networks and sharing cultures. Institutional reconstruction forms the safeguard layer, involving rule-making, standard construction, and power and responsibility configuration oriented toward DT governance needs, thereby providing a legitimacy foundation for technological embedding and organizational change.

These three elements do not proceed in a linear sequence but rather constitute a mutually shaping coupled system. Technological embedding provides both possibilities and constraints for organizational change, organizational change furnishes the practical impetus for institutional reconstruction, and institutional reconstruction offers a normative framework for technological embedding. Conversely, institutional constraints may limit technological choices, and organizational inertia may impede technological diffusion. This implies that DT governance is a complex adaptive system characterized by non-linearity, emergence, and path dependence.

To facilitate future empirical research, the T-O-I framework can be operationalized as follows (refer to Figure 8). The technological embedding variables are as follows: data fusion depth (number of integrated sources), real-time mapping latency, and algorithmic decision scope. The organizational change variables are the structural flatness index, collaborative network density, and Digital Thread coverage across lifecycle stages. Institutional reconstruction variables include data governance completeness (ownership/sharing/privacy regulations), standard system coverage, and accountability clarity for

algorithmic errors. The hypothesized relationships are as follows: (H1) technological embedding positively influences organizational change; (H2) organizational change positively influences institutional reconstruction; (H3) institutional reconstruction moderates the technology–governance effectiveness relationship. These variables and hypotheses can guide future structural equation modeling or qualitative comparative analysis. Finally, it should be noted that the T-O-I framework, while grounded in the systematic synthesis of 150 core papers and established theories (Technology Enactment Theory [4], socio-technical systems theory [80], and collaborative governance theory [29]), remains at the conceptual development stage. Its practical applicability requires future validation through case studies, expert Delphi surveys, or quantitative methods such as structural equation modeling.

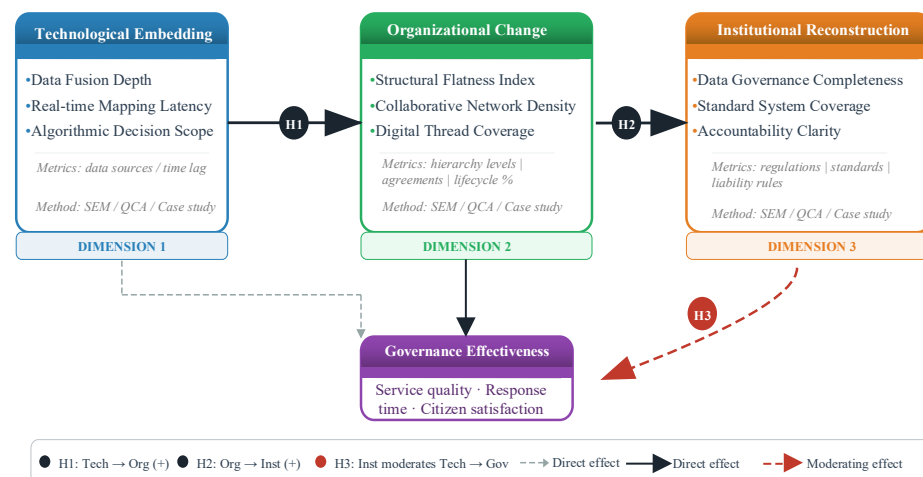


Figure 8. Conceptual Framework: Technology—Organization—Institution.

5.3. Transmission Mechanisms: How Technological Capabilities Are Transformed into Governance Effectiveness Through Organizational Mediation

Drawing on Fountain's [4] Technology Enactment Theory, this paper argues that the governance effectiveness of DT is not a direct output of technical attributes but rather a mediated transformation through organizational cognition, structural adaptation, and institutional arrangement. A significant gap exists between objective technology and enacted technology, and its closure depends on the simultaneous advancement of organizational learning and institutional innovation [81].

Accordingly, three interwoven transmission mechanisms can be identified. The cognitive transmission mechanism drives decision-making to shift from experience-driven to data-driven and from reactive management to predictive governance. The structural transmission mechanism promotes the evolution of organizational structures toward flattening and networking by breaking down information barriers. The institutional transmission mechanism generates new governance demands by exposing defects in existing institutions and propels incremental changes in the institutional system. These three mechanisms operate synergistically: cognitive shifts drive structural changes, structural changes generate institutional demands, and institutional innovation reinforces cognitive shifts. When a positive feedback loop is formed, technological embedding is effectively transformed into governance effectiveness; conversely, if organizational inertia is excessive or institutional constraints are too rigid, technological investments may fall into a “sunk cost” dilemma or even produce negative effects such as “digital formalism” and “technology idling.”

Mergel et al. [40] have empirically validated this transmission logic in their study of digital transformation in the German federal administration, demonstrating that the

degree of synergy among technological capabilities, organizational learning, and institutional innovation is critical to the success or failure of digital transformation. Nambisan et al. [44] note that digital technologies are reshaping the organizational boundaries and institutional logic of innovation, yet the institutional inertia of the public sector constrains the release of its digital innovation potential. Yoo et al. [45] reveal the Generative Features of digital technologies—their modularity and recombability are giving rise to new organizational forms, creating a fundamental tension with traditional bureaucracy. Collectively, these studies indicate that understanding the transmission mechanisms of DT governance requires moving beyond linear input–output thinking and establishing a systematic analytical framework that encompasses multi-dimensional variables of technology, organization, institution, and culture.

To clarify the analytical boundaries: organizational change refers to the reconfiguration of internal governance structures, processes, and collaborative networks triggered by DT adoption—encompassing cross-departmental coordination, process reengineering, and capacity building within existing institutional constraints. Institutional reconstruction, by contrast, refers to the external rule-making, standard setting, and power-responsibility reallocation required to legitimize and sustain DT governance—including data-ownership legislation, technical standards, and accountability frameworks. The two are coupled but analytically distinct: organizational change operates within given institutional parameters, whereas institutional reconstruction alters those parameters themselves.

6. Research Gap Identification and Future Outlook

6.1. Systematic Identification of Key Existing Research Limitations

Nevertheless, existing research still exhibits several existing structural research limitations worthy of attention. First, there is a lack of an integrated theoretical framework that integrates the three-dimensional interaction of technology–organization–institution. Existing research predominantly adopts a single-dimensional approach: engineering focuses on technical implementation, management on organizational operation, and law on institutional norms, yet the coupling mechanisms and interactive logic among the three dimensions remain insufficiently elucidated. There remains considerable room for theoretical deepening, operationalization, and empirical testing of the T-O-I Framework. Second, the Dark Side of DT governance has received markedly insufficient attention. The existing literature predominantly focuses on the positive effects of technology empowerment while lacking systematic discussion of potential risks such as algorithmic bias, data monopoly, digital exclusion, surveillance generalization, and democratic erosion; assessment indicator systems have also failed to adequately incorporate considerations of negative effects. Third, empirical research exhibits evident limitations in scope and methodology. Most studies concentrate on single cases or specific domains, predominantly focusing on cities in developed countries, with insufficient attention to developing nations; they examine single types of infrastructure, with limited discussion of multi-system coupling effects; and they rely primarily on qualitative description, with relatively scarce large-sample quantitative testing. Fourth, research manifests a structural imbalance of heavy front-end, light back-end. Quantitative analysis of the 150 reviewed papers reveals the following lifecycle stage distribution: planning and design (31.3%, $n = 47$), construction (28.7%, $n = 43$), operation and maintenance (26.0%, $n = 39$), and decommissioning and disposal (6.3%, $n = 9$). The remaining 8.0% ($n = 12$) addressed cross-stage or general lifecycle issues. The existing literature mainly focuses on the planning, construction, and operation and maintenance stages, while issues such as environmental impact assessment, resource recycling, and ecological restoration during the infrastructure decommissioning and disposal stages remain almost entirely unaddressed, and the closed loop of whole-lifecycle

governance has yet to be formed. Fifth, the enabling mechanisms of emerging technologies such as large language models and generative artificial intelligence for DT governance are still in their infancy. Although some studies have preliminarily explored possible pathways for technological convergence, systematic research remains scarce.

These gaps collectively point to a core proposition: DT research urgently needs to shift from ‘‘technology-driven’’ to ‘‘problem-driven’’, from ‘‘single-point breakthrough’’ to ‘‘system integration’’, and from ‘‘efficiency-first’’ to ‘‘effectiveness-oriented’’.

6.2. Multi-Dimensional Expansion of Future Research Directions

The following future directions are organized according to the T-O-I framework and explicitly mapped to the existing research limitations identified in Section 6.1, forming a systematic agenda rather than a disconnected list. Technological embedding directions address existing research limitations 4 and 5; organizational change directions address gap 3; and institutional reconstruction directions address existing research limitations 1 and 2. First, advance integrative theoretical construction. It is necessary to transcend the binary opposition between technological determinism and institutional determinism; further develop the theoretical connotations of the ‘‘technology–organization–institution’’ framework; clarify the mechanisms of action, boundary conditions, and moderating variables among the dimensions; and test its explanatory and predictive power through large-sample empirical research. Theoretical resources such as complex systems theory, evolutionary economics, and the institutional analysis and development framework may be drawn upon to enhance the inclusiveness and explanatory power of the analytical framework. Second, conduct cross-national comparative studies. A systematic cross-national comparative database should be established, covering different countries, cities, and infrastructure types, and methods such as qualitative comparative analysis should be employed to identify the necessary and sufficient conditions for successful DT governance. Particular attention should be paid to the practical explorations of cities in developing countries to avoid a ‘‘Western-centrism’’ bias in their research perspectives. Third, strengthen risk governance research. A multi-level risk assessment framework encompassing technical risks, organizational risks, institutional risks, and social risks should be established while simultaneously advancing algorithmic audit systems, data ethics review mechanisms, and digital inclusiveness index construction to ensure the fairness, transparency, and accountability of DT governance. Fourth, explore pathways for emerging technological convergence. The semantic understanding, knowledge reasoning, and natural interaction capabilities of large language models can be complementary to the spatial computing, real-time simulation, and predictive analysis capabilities of DT. For example, using large language models to parse unstructured engineering documents and citizen feedback, generate natural-language decision reports, and support conversational interactive queries will profoundly reshape the human–computer interaction modes and governance participation patterns of DT. Finally, address the research shortfall in the decommissioning and disposal stage. Lifecycle assessment, the circular economy concept, and ecological restoration technologies should be incorporated into the DT framework to construct a closed-loop governance system covering infrastructure ‘‘From Cradle to Grave to Rebirth’’, with a focus on research issues such as demolition scheme optimization based on DT, construction waste tracking management, material recycling, and soil remediation effectiveness assessment, thereby promoting the shift of DT from ‘‘construction-oriented’’ to ‘‘sustainability-oriented’’ and from ‘‘technical optimization’’ to ‘‘Value Co-creation’’.

7. Conclusions

DT technology provides powerful technology empowerment for the whole-lifecycle governance of urban infrastructure, yet its effectiveness is not automatically realized but rather profoundly constrained by organizational structure and the institutional environment. Through a systematic literature review based on an in-depth analysis of 150 core papers, this paper traces the evolutionary trajectory of DT technologies from BIM to CIM and then to DT; evaluates the progress and technical bottlenecks of their application in the planning, construction, operation and maintenance, and decommissioning stages; reveals the organizational change logic of cross-sector collaboration and governance process reengineering driven by DT; analyzes organizational obstacles such as data sovereignty, departmental barriers, and collaborative inertia; examines the institutional reconstruction needs of data governance, standards and specifications, and power and responsibility configuration; compares the differentiated institutional paths of the European Union's GAIA-X and China's CIM; and proposes a three-dimensional integrated analytical framework of "Technological Embedding–Organizational Change–Institutional Reconstruction," drawing on Technology Enactment Theory to reveal the transmission mechanisms through which technological capabilities are transformed into governance effectiveness via organizational mediation. This study indicates that the core challenge of DT governance lies in coordinating the structural tension between technological centralization and governance decentralization; future research needs to transcend technological determinism and situate DT within a broader socio-technical system context. Specifically, it is necessary to construct integrative theoretical models to elucidate three-dimensional interaction mechanisms, conduct cross-national comparative studies to distill the adaptation conditions of different governance models, attend to risk governance to establish algorithmic audit and digital inclusiveness mechanisms, explore large language model convergence to expand interdisciplinary research frontiers, and strengthen decommissioning and disposal research to perfect the whole-lifecycle governance closed loop. Only by synergistically advancing technological embedding, organizational change, and institutional reconstruction can the substantive transformation from "Technology Empowerment" to "governance effectiveness" be realized, enabling DT to truly become a governance instrument for enhancing the resilience, sustainability, and inclusiveness of urban infrastructure. For municipal governments, we recommend establishing statutory leading agencies for cross-departmental coordination, mandating open data standards (IFC 4.3, CityGML 3.0) in procurement, and incorporating DT metrics into official evaluations. For infrastructure operators, prioritizing data quality assurance and model validation before AI deployment is essential. For policymakers, formulating clear data ownership legislation, establishing algorithmic accountability frameworks, and incentivizing decommissioning stage applications through green procurement preferences would bridge the gap between technological potential and governance effectiveness. The limitations of this study include: the literature retrieval primarily relied on English and Chinese databases, with insufficient coverage of literature in other languages; the literature selection focused mainly on academic journals, with limited inclusion of gray literature (such as government reports and industry white papers); and the T-O-I Framework remains at a conceptual development stage, with its operationalization and empirical testing to be advanced in future research. These limitations also point to directions for improvement in future studies.

Finally, a balanced assessment requires acknowledging the potential negative effects of DT governance. Technological dependence may hollow out experiential governance capabilities; algorithmic bias may exacerbate social inequality if training data underrepresent marginalized communities; high system costs may divert fiscal resources from basic livelihood investments; and surveillance generalization may erode democratic participation. Future governance must therefore incorporate "technological restraint" principles—

human-in-the-loop decision protocols, algorithmic sunset clauses, and distributive justice assessments—to ensure that DT serves inclusive rather than technocratic ends.

Author Contributions: Conceptualization, X.C. and S.L.; methodology, X.C. and S.L.; investigation, X.C., S.L. and C.Z.; resources, S.L.; data curation, X.C. and Y.Z. (Yang Zhao); writing—original draft preparation, X.C.; writing—review and editing, S.L., C.Z. and Y.Z. (Yaping Zhang); supervision, S.L.; project administration, S.L.; funding acquisition, X.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by “China Postdoctoral Science Foundation General Funding” (Approval Number: 2026M790766) and the Development Research Center of Shanghai Municipal People’s Government, (Approval Number: 2025-AZ-17).

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors thank the editor and anonymous reviewers for their numerous constructive comments and encouragement that have improved our paper greatly.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BIM	Building Information Modeling
CIM	City Information Modeling
CNKI	China National Knowledge Infrastructure
E-G	E-Government
EU	European Union
GAIA-X	GAIA-X framework
GDPR	General Data Protection Regulation
GIS	Geographic Information System
IFC	Industry Foundation Classes
IoT	Internet of Things
ISO	International Organization for Standardization
LCA	Lifecycle Assessment
NASA	National Aeronautics and Space Administration
O&M	Operation and Maintenance
OGC	Open Geospatial Consortium
PAS	Publicly Available Specification
RTLS	Real-Time Location System
T-O-I	Technological Embedding–Organizational Change–Institutional Reconstruction
UK	United Kingdom
USD	United States Dollar

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