SASBE 2025 aims to encourage the international exchange of innovative ideas between researchers from academia and industry. In addition to knowledge dissemination, the conference offers a valuable platform for professional networking, particularly benefiting university professors, graduate students, and postdoctoral researchers.

Research Article

KNIT: Unlocking Built Environment Digital Twin Interoperability with Data Fabrics

Kofi A.B. Asare[1], Rui Liu[2], Chimay J. Anumba[3], Caleb Debrah[4], and Frank Ato Ghansah[5]

[1] Haskell and Irene Lemon Construction Science Division, Gibbs College of Architecture, The University of Oklahoma, Norman, OK, USA; asare@ou.edu
[2] M.E. Rinker, Sr. School of Construction Management, University of Florida, Gainesville, FL, USA; liurui@ufl.edu
[3] College of Design, Construction and Planning, University of Florida, Gainesville, FL, USA; anumba@ufl.edu
[4] Department of Building and Real Estate, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong caleb.debrah@connect.polyu.hk
[5] School of Construction, Property and Surveying; College of Technology and Environment, London South Bank University, London, United Kingdom. frank.ghansah@lsbu.ac.uk
Correspondence: asare@ou.edu

Abstract

Digital Twins (DT) have become increasingly popular as a system-of-systems capable of integrating diverse data sources to support real-time decision-making across the built environment. As DT applications expand in facilities management (FM), energy efficiency, infrastructure monitoring, retrofits, and smart cities, ensuring seamless data integration is critical. Despite significant research on data interoperability, current DT implementation relies on ad hoc solutions due to the proliferation of custom and complex data formats that make integration difficult to scale. For DTs to function reliably at scale, especially across interconnected building systems, a universal and flexible data integration framework is needed. This research explores how data fabric architecture can address interoperability challenges by enabling the flexible, extensible, and accessible connection of heterogeneous data sources in DT environments. The study proposes the novel **Knowledge-Networked Integration for Twins (KNIT),** a data fabric-centered design approach for DTs focused on FM applications in the built environment. The proposed approach, comprising a macro- and a micro-scale implementation framework, establishes the foundations for creating standardized data integration pipelines that can handle multiple data modalities. These pipelines, grounded by data governance principles, promote consistency in DT development while remaining adaptable to evolving technical demands. Researchers and industry professionals evaluated KNIT and reported that it offers a promising path towards universal interoperability in DT systems, opening the frontiers for efficiently scaling DT adoption in FM and beyond for a more connected built environment. The study contributes to the body of knowledge by identifying how interoperability challenges in DT systems can be addressed with data fabrics.

Keywords: Digital Twins; Interoperability; Data Fabric; Facilities Management; Built Environment

Highlights

- Introduces the novel KNIT paradigm, combining knowledge graphs, metadata tagging, and federated data space to achieve broader interoperability in built environment DTs.
- KNIT comprises an ecosystem-level data fabric architecture (El-DaFA) and an instance-oriented data fabric architecture (Io-DaFA) for DT design and implementation.
- Researchers and practitioners rate the proposed hybrid approach and conceptual architecture as credible and valuable for DT implementation.

1 Introduction

Digital Twins (DTs) are fast becoming well-known within the built environment (BE), shaping design, optimizing operations, and transforming facilities management (FM). DTs in BE are designed to mirror physical assets like buildings, infrastructure, and their operational systems through cyber-physical representations (Akanmu et al., 2021). Yet, interoperability remains fragmented. Building Information Models (BIM), Building Automation and Control Systems (BACS), Internet of Things (IoT) sensors, Computerized Maintenance Management Systems (CMMS), and analytical engines often employ disparate schemas and protocols. The integration of heterogeneous data sources represents a critical barrier to achieving semantic and syntactic interoperability in DTs within BE (Khallaf et al., 2022). This prevailing interoperability challenge remains a key obstacle in operationalizing DTs as a system-of-systems concept and hinders the broader implementation of DT solutions in the BE. Data fabric, defined as a data architecture that unifies diverse data silos through standardized models, metadata management, and dynamic pipelines, has emerged as a promising solution to achieving broader interoperability within data-centric systems such as DTs (Martin et al., 2021; Zaidi, 2022). However, little attention has been given to it in DT research in BE. This study addresses this gap by exploring how data fabric architecture can address interoperability challenges in FM, which is one of the most common application contexts of DTs in the built environment.

2 Literature Review

2.1 Interoperability Challenges in Built Environment Digital Twins

DTs in BE have transcended their product lifecycle management origins to become dynamic living systems that tightly couple physical assets and cyber entities. DTs emphasize bidirectional feedback to orchestrate data between systems (Digital Twin Consortium, 2024). This means they can receive sensor data, process the data into actionable insights, and actuate controls in real time. This provides BE stakeholders with a great tool to monitor asset health, optimize energy use, plan maintenance, and manage smart cities (Moshood et al., 2024; Wang et al., 2022). Bolton et al. (2018) argue that the “realism” of a DT depends equally on data quality, algorithmic fidelity, and visualization efficacy; yet most studies address these dimensions in isolation, with their implementation highlighting the substantial integration overheads, as disparate platform-specific protocols or custom methods must be reconciled. This fragmentation limits the application of DTs within the narrow use cases and frustrates efforts to scale deployments beyond pilot projects. Considering these limitations, resolving broader interoperability emerges as the next frontier. This is because the challenge of unifying heterogeneous data schemas, legacy systems, and vendor-specific interfaces threatens to stall progress or introduce high financial obligations in DTs. The literature highlights interoperability issues inherent in the implementation of DT in the BE. AlBalkhy et al. (2024) characterized many DT initiatives in the BE as isolated ‘data islands’, where DT implementation often stagnates at integrated silos, lacking the architectural blueprint and governance needed for true cross-system synchronization. This highlights two major threads for investigating interoperability relative to DT design and implementation: syntactic and semantic interoperability.

Syntactic interoperability issues arise from the differing file formats and application programming interfaces (APIs). Pan & Zhang (2021) demonstrate a BIM-data mining DT framework for project management that involved aligning IFC-based BIM geometry with proprietary sensor data feeds, requiring the development of extensive bespoke connectors. Such overheads undermine rapid and broader rollout and could introduce larger latency, inconsistent with real-time operation. Similarly, a DT framework for relocatable modular buildings developed by Nguyen et al. (2025) shows the steep integration challenges and associated costs when building DTs with data from diverse BE platforms. Beyond syntax, semantic misalignment presents deeper challenges. **Semantic interoperability** demands a shared understanding of the data exchanged between them. Recent proposals for achieving semantic interoperability include using a reference architecture and domain-specific schemas or ontologies, as well as microservices (i.e., self-contained software components like a time series data handler) to ensure consistent semantic alignment of metadata across models and live sensor feeds (Schlenger et al., 2025). Moreover, semantic web methods such as Resource Description Framework (RDF), Web Ontology Language (OWL) (Tuhaise et al., 2023), and knowledge graphs (Ramonell et al., 2023) have been shown to reconcile the taxonomies of physical entities for automatic inference within DTs, but they require upfront ontology engineering and continuous maintenance to address evolving asset definitions. The foregoing syntactic and semantic issues pose technical challenges that are further magnified by organizational and governance issues (AlBalkhy et al., 2024). Organizational decisions such as vendor lock-ins drive proprietary software implementation and closed architecture systems, whereas contractual and compliance issues hinder open data sharing. Unclear data ownership policies and misaligned stakeholder goals stall cross-organization and cross-system data sharing. In sum, syntactic divergence, semantic misalignment, and organizational inertia collectively impede fully interoperable BE DTs. The next section examines how data fabric-centred approaches can address these challenges.

2.2 Data Fabrics for DT Design

In the context of DT design, data fabrics have the capacity to underpin system-to-system connections and data integration by automating data ingestion, standardization of semantics and syntax, and enforcement of data governance across distributed systems. Four paradigms of data fabrics emerge from the existing literature (Table 1).

Table 1. Emerging paradigms of data fabric-oriented DT design

Paradigm and definition	Example	Strength	Weakness
Federated model fabrics: split data ownership but expose a unified semantic interface	Moretti et al. (2023): a federated data model to integrate siloed BIM, IoT, CMMS, and Energy Management System (EMS) data.	Effective in addressing issues of data heterogeneity and interoperability	It may become complicated when multiple federated models are involved.
Knowledge graph fabrics: store metadata and relationships between them in graph databases.	Ramonell et al. (2023): knowledge graph managed by microservices such as GraphDB and Ifc2Graph using IFC, IoT metadata, and operational data.	Enables DT services to issue flexible REST API queries that traverse spatial, temporal, and semantic links for analytics and visualization.	Query latency and memory rise sharply as graph size and schema complexity increase in large application contexts such as regional-scale DTs.
Metadata tagging fabrics: automate the alignment of raw telemetry with standardized schemas.	Mishra et al. (2020): trained supervised classifiers on labelled BAS points and applied unsupervised clustering to detect emerging tag groups.	Ensures that data streams feed directly into relevant DT models. Could unravel rapid annotation of assets and correct mapping of sensor streams to shared ontologies.	Requires availability of high-quality training data and must be retrained as equipment names and network topologies evolve.
Federated data spaces fabrics: extend basic federation by embedding shared governance and policy layers on top of the distributed data silos.	Gil et al. (2024): DT mediators that negotiate access, enforce consent, and translate semantics across municipal, corporate, and vendor domains.	Preserves data sovereignty by keeping raw information under each owner's control while enabling cross-domain/institutional querying and analytics.	Ensuring consistent rules across organizations is difficult.

Across these paradigms, key tensions persist. Federated models safeguard ownership but demand intense semantic engineering and strong governance. Knowledge graphs enable rich connectivity but can bloat as ontologies evolve. Metadata fabrics streamline integration but risk drift without retraining. Federated data space fabrics offer governance, but risk policy overloads. No single approach delivers both scale and flexibility. To bridge these gaps, we propose a hybrid termed the **Knowledge-Networked Integration for Twins (KNIT)**, which combines knowledge graphs, intelligent metadata tagging, and federated governance. The knowledge graph provides the backbone for deep analytics and flexible queries, while the metadata pipelines align ingested data with shared ontologies in real time. Governance aspects are borrowed from the federated data spaces paradigm. Together, they offer a practical path toward universal interoperability and scalable DT deployment in FM and the BE.

3 Methodology

The development and evaluation of the proposed KNIT paradigm for DTs lies within the realm of Design Science Research (DSR). DSR has been widely used in information systems research (Baskerville et al., 2015), typically resulting in socio-technical knowledge contributions such as constructs, methods, models, design principles, technological rules, and instantiations (Gregor & Hevner, 2013). In this respect, this study's investigation of a model to address the interoperability challenges related to DT implementation in BE lends itself to the creation of a conceptual artifact through the lens of DSR, as shown in Figure 1.

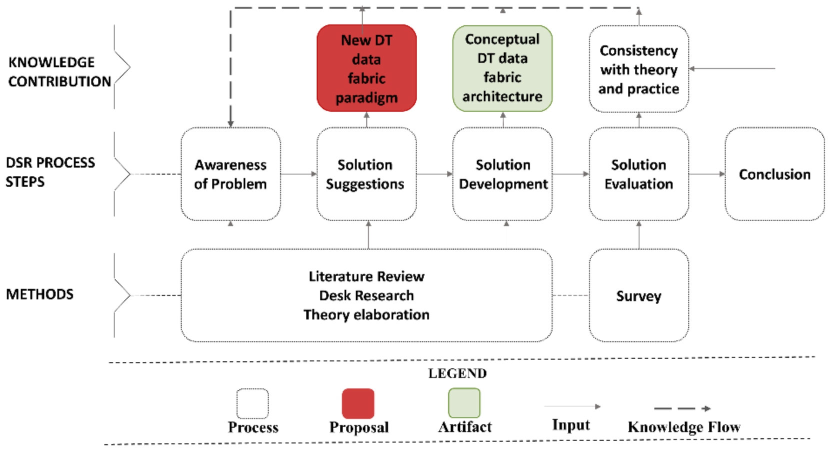

Figure 1. The study's DSR process.

The research methodology was inspired by Vaishnavi et al.'s (2021) DSR cycle. As a start, the study examined secondary sources like peer-reviewed journal articles and conference papers, and other technical literature to clarify the nature of the interoperability problem and the applicability of data fabrics to addressing it. Following this, a new paradigm of data fabric-centred DT design is proposed through a theory elaboration lens. This idea for a hybrid data fabric paradigm to be applied to DT design in BE is then carried forward to the development of an ecosystem-level data fabric (El-DaFA) and a tactical-level conceptual data fabric architecture. The former addresses data fabric-centred DT implementation in BE, while the latter provides a reference architecture for designing DTs for FM that are responsive to the proposed El-DaFA. FM served as the primary domain for developing the instance-oriented data fabric architecture (Io-DaFA) because DT applications are most mature and widely deployed in this area of BE (Opoku et al., 2021). Subsequently, these two artifacts were evaluated through a survey with 33 participants drawn from industry and academia. The proposed hybrid data fabric paradigm, El-DaFA, Io-DaFA, and evaluation results anchor the knowledge contribution of this study as a DSR project.

4 KNIT: Hybrid Data Fabric Paradigm for Built Environment DT Design

To unlock interoperability bottlenecks in BE DT design, this study proposes KNIT that combines knowledge graph, metadata tagging, and some aspects of federated data spaces. The subsequent sections focus on detailing this nascent architecture with the FM domain as an exemplar. First, the broader El-DaFA, i.e., function/organization-agnostic layer, is conceptually defined. This is followed by an instance-oriented interpretation of El-DaFA at a micro-level (Io-DaFA), with more defined data sources, integration pipelines, governance, and services.

4.1 Ecosystem-Level Data Fabric (El-DaFA)

El-DaFA is a six-layer ecosystem-level data fabric architecture that can be applied to all levels of DT implementation in BE. With reference to Figure 2, the core layers of El-DaFA are:

Layer 1 – Data Governance: Data standards, compliance, and security form the foundational layer for the FM data fabric architecture. This is essential, as having a robust data governance policy ensures that quality, accessible, and usable data is made available (Bolton et al., 2018). In this layer, clear governance structures and policies such as data ownership rights, stakeholder responsibilities, data protection protocols, and compliance regulations must be defined and codified. Codification provides a template that the subsequent layers can be wrapped around as a composite information system.

Layer 2 – Knowledge Base: Layer 1 yields a reliable knowledge base (FM is used as an example in Figure 2) that has efficient methods and tools for data management and information sharing. Layer 2 is foundationally dependent on context engineering to enable machine readability and interpretation of heterogeneous data in subsequent layers. This involves creating a formal representation of each data source or space to facilitate cross-system understanding and exploitation of knowledge (Cao et al., 2022). This study proposes the development of domain ontologies that can be automatically updated to operationalize these knowledge bases. This is because domain ontologies provide better accuracy compared to general ontologies (Hu & Liu, 2020).

Layer 3 – Data Preparation, Delivery, and Integration: This layer defines the variety of data delivery modes the data fabric can support, e.g., extract-load-transform (ETL), data virtualization, streaming, and messaging. Data preparation involves transformation and data cleaning, adhering to governance protocols and quality benchmarks to ensure that only high-quality data enters integration/exchange pipelines. Data delivery must serve a broad spectrum of stakeholders, following the federated data spaces approach (Gil et al., 2024). The data integration pipeline must support both batch and streaming ingestion methods. Batch ingestion suits use cases where data can be read and processed as a group (e.g., bulk equipment ID updates after replacements). Streaming ingestion enables real-time data feeds for analytics (Mezzetta et al., 2022), e.g., sensor data updates.

Layer 4 – Knowledge Graph with Unified Metadata Tagging: An augmented knowledge graph approach is recommended (Mezzetta et al., 2022) to enable advanced intelligence and automated connections between managed entities. This approach combines the knowledge graph and automated metadata tagging fabric paradigms. Syntactic tagging can be achieved through rule-based approaches, as shown by Bhattacharya et al. (2014), whereas semantic tagging can follow methods similar to those advanced by Calbimonte et al. (2012). For higher levels of semantic interoperability, the knowledge graph representation should be overlaid with metadata tagging. This will create an enriched knowledge graph that can support intelligent querying and application of artificial intelligence (AI).

Layer 5 – APIs: This should be an API marketplace with pre-built APIs that have support for data management, ranging from creating, requesting, ingesting, and publishing data. This layer should be tightly connected to the governance layer's policies on data access and consumption.

Layer 6 – Data Orchestration: Data orchestration involves the continuous and timely flow of data. This is critical for DT applications in FM as it drives the delivery of high-quality data to end users (Mezzetta et al., 2022). In large-scale DT implementations, the volume, variety, and velocity of data will increase exponentially. As such, a conductor is needed to control the execution of all automated steps in the data pipeline from end to end. This lends itself to methods such as DataOps (Mainali et al., 2021).

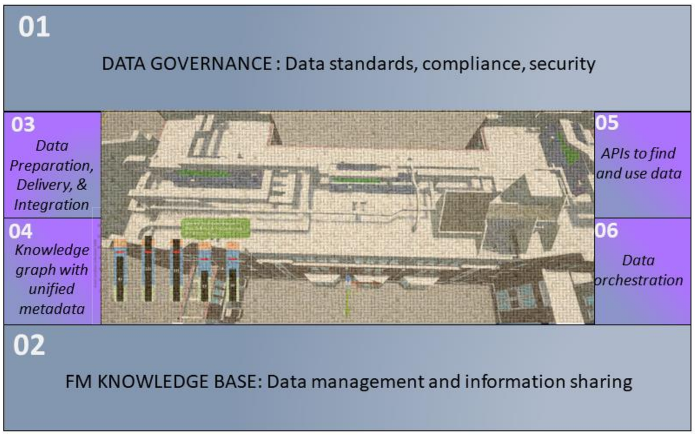

Figure 2. Ecosystem-level data fabric architecture (El-DaFA) layers.

4.2 Conceptual Operationalization of Data Fabric Architecture for DTs in FM

To demonstrate how the proposed El-DaFA can be implemented, a conceptual instance-oriented data fabric architecture (Io-DaFA) for DTs is presented in this section with reference to **Error! Reference source not found.**. This conceptual architecture is presented as a reference architecture that can support the actual instantiation of a data fabric-powered DT.

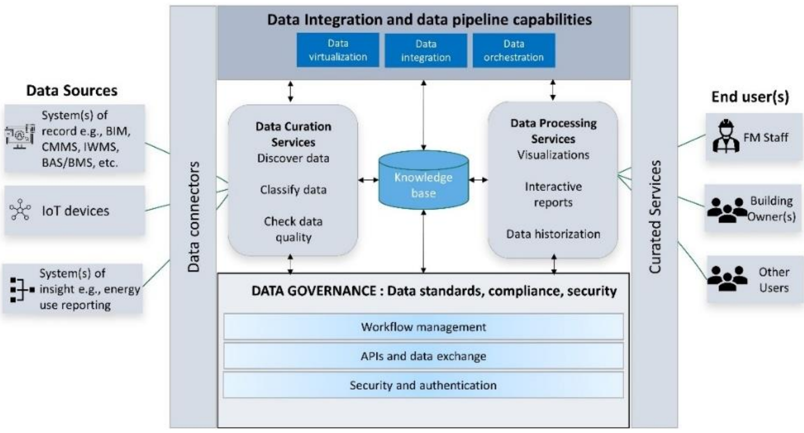

Figure 3. Conceptual instance-oriented data fabric architecture (Io-DaFA) for DT implementation in FM.

Consider an environment where data sources span systems of record like BIM, CMMS, BAS, or even Integrated Workplace Management Systems (IWMS), IoT devices, and systems of insight like energy consumption dashboards. The data within these containers will be governed by shared data standards defined in Layer 1, covering workflows, API management, security, and authentication. At the core, a domain-specific knowledge base built on a knowledge graph enriched with a semantic and syntactic metadata tagging module anchors data preparation, delivery, integration, and data orchestration. Tailored or self-service end-user services are then curated through fit-for-purpose API interactions.

4.3 Evaluation of Ecosystem-Level Data Fabric (El-DaFA)

4.3.1 Evaluation Design

Guided by a human risk and effectiveness strategy for evaluating DSR outputs (Venable et al., 2016), a formative evaluation of the proposed KNIT paradigm's El-DaFA and Io-DaFA was conducted to assess the consistency of the proposed artifact with theory and practice. This metric for the evaluation was defined to help establish the acceptability and usability of the proposed artifacts and is explained as follows:

- **Theoretical consistency:** The degree to which El-DaFA's conceptual foundations align with established theory on interoperability and DTs.
- **Practical consistency:** The extent to which El-DaFA and Io-DaFA correspond to real-world needs and workflows. A practical solution is deemed as one that could be universally implemented without or with minimal customization.

Specifically, the evaluation had the following objectives:

- **Objective 1:** To establish the degree to which the El-DaFA's conceptual foundations align with established theory on DTs capable of seamless system-to-system connections in the built environment.
- **Objective 2:** To ascertain the extent to which the proposed El-DaFA meets real-world DT implementation needs and workflows.
- **Objective 3:** To examine the usefulness of the proposed Io-DaFA for DT implementation in FM.

A survey was conducted to elicit stakeholders' views on the evaluands (El-DaFA and Io-DaFA). The survey was preceded by a twenty-minute presentation that covered the research outcomes of a broader study on DTs for predictive maintenance (PdM). The evaluation presentations were delivered both in-person and via teleconference, depending on participants' location. The presentation explained the foundational knowledge, abstract concepts, and demonstrated their practical linkages to the design and implementation of DTs in the BE, with emphasis on PdM in the BE. The respondents' opinions were then collected using a five-point Likert scale, using the questions itemized in Table 2. The median score was used as a measure of central tendency since it is more representative of the midpoints of the dataset. To measure the composite opinion of participants on objectives 1 and 2, the mean was used as suggested by Boone Jnr & Boone (2012).

Table 2. Evaluation survey and ranking scale.

Objective	Statement	Scale and range
Objective 1	I think the ecosystem data fabric is consistent and applicable within the current FM practice.	1-Strongly disagree (1.00 - 1.80) 2-Somewhat disagree (1.90 - 2.60)
Objective 2	I would imagine many FM departments adopting this (ecosystem-level fabric architecture).	3- Neither agree nor disagree (2.70 - 3.40) 4-Somewhat agree (3.50 - 4.20)
Objective 3	I think I would like to use this to guide my DT implementation.	5- Strongly agree (4.30 - 5.00)

4.3.2 Participant Selection

Stakeholders in the FM and construction industry constituted the target population (n=33) for this evaluation. The sub-groups within the population are described in Table 3.

Table 3. KNIT Evaluation Participants

Participant Group	Description and Sampling	Selection Rationale
Academic Researchers (AR) (n=22)	Scholars specializing in BIM, DT, and Advanced Construction Technology researchers at an R1 university in the United States (US) were conveniently sampled.	Their deep understanding of the theory and practice of emerging technologies was crucial for rigorous validation of the proposed artifacts.
Industry Professionals (IP) (n=5)	Facility Managers, Facilities Technical Services Executives, DT Software Company Executives, and Owners' agents from various US regions were conveniently sampled.	Their practical experience with maintenance practices and organizational structures was germane to examining the real-world applicability of the proposed artifacts.
Hybrid Researcher-Industry Professionals (hRIP) (n=6)	Individuals with active scholarly engagement, working in industry roles.	Their dual perspective was viewed as a reconciliation medium to balance practical feasibility and academic significance.

4.3.3 Evaluation Process and Results

The evaluation followed the following steps:

1. **Introduction of research:** To ensure that participants were adequately informed to contribute to the evaluation, they were given a thorough background on the research, highlighting the knowledge gaps the study aimed to address, and fundamental information on DTs.
2. **Detailed explanation of the KNIT paradigm's architectures:** The proposed El-DaFA and Io-DaFA were graphically illustrated and explained with emphasis on the details of each of the proposed layers and interfaces between end users and data sources.

The results of the evaluation are presented in Table 4.

Table 4. KNIT Evaluation Results

Stakeholder Group	Objective 1 (O1) (Median Score)	Objective 2 (O2) (Median Score)	Composite Rating (O1 & O2) (Mean Score)	Objective 3 (O3) (Median Score)
AR	4.00	4.00	3.70	4.00
IP	4.00	3.00	4.00	5.00
hRIP	4.00	4.00	4.08	4.00
General Population	**4.00**	**4.00**	**3.80**	**4.00**

5 Discussion and Limitations

The results of the study indicate a moderate agreement with the theoretical and practical consistency of the proposed artifacts across all measures for the three objectives. This provides credence to the study's push for a novel paradigm of data fabric-driven DT implementation in the BE. Whereas there are no comparative studies to benchmark the results against, the results shed subtle light on why the current literature continues to report on interoperability issues within the BE relative to DT implementation. The existing paradigms (Gil et al., 2024; Mishra et al., 2020; Moretti et al., 2023; Ramonell et al., 2023), though not articulated as data fabric paradigms, are limited in addressing broad interoperability in isolation. Until a cross between them, as proposed in this study, is implemented, achieving broad interoperability that enables scalable system-of-systems DT implementation remains a mirage. A future research agenda should pursue how such a hybrid approach can be translated from concept to an instantiation. This study has laid the foundations for such work by proposing the KNIT paradigm and its El-DaFA and the Io-DaFA. This pioneering effort, while evaluated by a small population, has demonstrated significant theoretical and practical usefulness. Despite positive stakeholder feedback, KNIT's implementation may be constrained by the explosion in fragmented data formats and persistent data quality challenges in the built environment.

6 Conclusions

In conclusion, isolated approaches like federation, knowledge graphs, and metadata tagging fail to deliver full interoperability for DTs in the BE. This study's proposed unification of knowledge graphs with automated and intelligent metadata pipelines represents a new paradigm. This approach models complex asset relationships while ensuring that batch ingested and streamed data feeds align with shared schemas across heterogeneous sources in a timely fashion. The study has also presented a reference architecture (Io-DaFA) for FM implementation, offering clear guidance on the instantiation of the ecosystem-level data fabric (El-DaFA). Stakeholder feedback confirms KNIT's practical value and potential to unlock broader interoperability. This work signals a paradigm shift. It suggests that researchers and practitioners embrace hybrid approaches to data fabric development if they aim to scale DTs across the BE and to reimagine and explore what this connectivity can achieve.

Data Availability Statement
Some of the data presented in this study is available upon reasonable request.

Conflicts of Interest
The authors declare no conflict of interest.

References

Akanmu, A. A., Anumba, C. J., & Ogunseiju, O. O. (2021). Towards next generation cyber-physical systems and digital twins for construction. *Journal of Information Technology in Construction*, *26*(June), 505–525. https://doi.org/10.36680/j.itcon.2021.027

AlBalkhy, W., Karmaoui, D., Ducoulombier, L., Lafhaj, Z., & Linner, T. (2024). Digital twins in the built environment: Definition, applications, and challenges. *Automation in Construction*, *162*(February), 105368. https://doi.org/10.1016/j.autcon.2024.105368

Baskerville, R. L., Kaul, M., & Storey, V. C. (2015). *Genres of Inquiry in Design-Science Research: Justification and Evaluation of Knowledge Production*. *39*(3), 541–564.

Bhattacharya, A., Culler, D. E., Ortiz, J., Hong, D., Whitehouse, K., & Culler, D. (2014). *Enabling Portable Building Applications through Automated Metadata Transformation* (Technical Report No. UCB/EECS-2014-159). http://www.eecs.berkeley.edu/Pubs/TechRpts/2014/EECS-2014-159.html

Bolton, A., Butler, L., Dabson, I., Enzer, M., Evans, M., Fenemore, T., Harradence, F., Keaney, E., Kemp, A., Luck, A., Pawsey, N., Saville, S., Schooling, J., Sharp, M., Smith, T., Tennison, J., Whyte, J., Wilson, A., & Makri, C. (2018). The Gemini Principles. In *Centre for Digital Built Britain*. https://www.cdbb.cam.ac.uk/system/files/documents/TheGeminiPrinciples.pdf

Boone Jnr, H. N., & Boone, D. (2012). Analyzing Likert Data. *Jorunal of Extension*, *50*(2). https://doi.org/10.34068/joe.50.02.48

Calbimonte, J. P., Yan, Z., Jeung, H., Corcho, O., & Aberer, K. (2012). Deriving semantic sensor metadata from raw measurements. *CEUR Workshop Proceedings*, *904*, 33–48.

Cao, Q., Zanni-Merk, C., Samet, A., Reich, C., Beuvron, F. de B. de, Beckmann, A., & Giannetti, C. (2022). KSPMI: A Knowledge-based System for Predictive Maintenance in Industry 4.0. *Robotics and Computer-Integrated Manufacturing*, *74*(October 2021), 102281. https://doi.org/10.1016/j.rcim.2021.102281

Digital Twin Consortium. (2024). *Defintion of a Digital Twin*. https://www.digitaltwinconsortium.org/initiatives/the-definition-of-a-digital-twin/#:~:text=On December 3%2C 2020%2C to,a specified frequency and fidelity.

Gil, J., Petrova-Antonova, D., & Kemp, G. J. L. (2024). Redefining urban digital twins for the federated data spaces ecosystem: A perspective. *Environment and Planning B: Urban Analytics and City Science*. https://doi.org/10.1177/23998083241302578

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *MIS Quarterly: Management Information Systems*, *37*(2), 337–355. https://doi.org/10.25300/MISQ/2013/37.2.01

Hu, M., & Liu, Y. (2020). E-maintenance platform design for public infrastructure maintenance based on IFC ontology and Semantic Web services. *Concurrency and Computation: Practice and Experience*, *32*(6), 1–15. https://doi.org/10.1002/cpe.5204

Khallaf, R., Khallaf, L., Anumba, C. J., & Madubuike, O. C. (2022). Review of Digital Twins for Constructed Facilities. *Buildings*, *12*(11), 2029. https://doi.org/10.3390/buildings12112029

Mainali, K., Ehrlinger, L., Himmelbauer, J., & Matskin, M. (2021). Discovering DataOps: A Comprehensive Review of Definitions, Use Cases, and Tools. *DATA ANALYTICS 2021 : The Tenth International Conference on Data Analytics*, *October*, 61–69. https://www.researchgate.net/profile/Kiran_Mainali2/publication/355107036_Discovering_DataOps_A_Comprehensive_Review_of_Definitions_Use_Cases_and_Tools/links/615dd703fbd5153f47e938a1/Discovering-DataOps-A-Comprehensive-Review-of-Definitions-Use-Cases-and-

Martin, S., Szekely, B., & Allemang, D. (2021). *The Rise of the Knowledge Graph: Toward Modern Data Integration and the Data Fabric Architecture*. O'Reilly Media, Inc.

Mezzetta, S., Sullivan, P. O., Ramos, J., Ackerman, E. A., & Jones, S. W. (2022). *Data Fabric:Its time has come* (Issue ARB-1316).

Mishra, S., Glaws, A., Cutler, D., Frank, S., Azam, M., Mohammadi, F., & Venne, J. S. (2020). Unified architecture for data-driven metadata tagging of building automation systems. *Automation in Construction*, *120*, 1–20. https://doi.org/10.1016/j.autcon.2020.103411

Moretti, N., Ph, D., Xie, X., Ph, D., Garcia, J. M., Ph, D., Chang, J., Parlikad, A. K., & Ph, D. (2023). *Federated Data Modeling for Built Environment Digital Twins*. *37*(4), 1–15. https://doi.org/10.1061/JCCEE5.CPENG-4859

Moshood, T. D., Rotimi, J. O., Shahzad, W., & Bamgbade, J. A. (2024). Infrastructure digital twin technology: A new paradigm for future construction industry. *Technology in Society*, *77*(October 2023), 102519. https://doi.org/10.1016/j.techsoc.2024.102519

Nguyen, T. D. H. N., Ly, D. H., Jang, H., Dinh, H. N. N., & Ahn, Y. (2025). Digital twin framework to enhance facility management for relocatable modular buildings. *Automation in Construction*, *176*(April), 106249. https://doi.org/10.1016/j.autcon.2025.106249

Opoku, D. G. J., Perera, S., Osei-Kyei, R., & Rashidi, M. (2021). Digital twin application in the construction industry: A literature review. *Journal of Building Engineering*, *40*(May), 102726. https://doi.org/10.1016/j.jobe.2021.102726

Pan, Y., & Zhang, L. (2021). A BIM-data mining integrated digital twin framework for advanced project management. *Automation in Construction*, *124*(July 2020), 103564. https://doi.org/10.1016/j.autcon.2021.103564

Ramonell, C., Chacón, R., & Posada, H. (2023). Knowledge graph-based data integration system for digital twins of built assets. *Automation in Construction*, *156*(October). https://doi.org/10.1016/j.autcon.2023.105109

Schlenger, J., Pluta, K., Mathew, A., Yeung, T., Sacks, R., & Borrmann, A. (2025). Reference architecture and ontology framework for digital twin construction. *Automation in Construction*, *174*(July 2024), 106111. https://doi.org/10.1016/j.autcon.2025.106111

Tuhaise, V. V., Tah, J. H. M., & Abanda, F. H. (2023). Technologies for digital twin applications in construction. *Automation in Construction*, *152*(October 2022), 104931. https://doi.org/10.1016/j.autcon.2023.104931

Vaishnavi, V., Kuechler, B., & Petter, S. (2021). *Design Science Research in Information Systems* (pp. 1–62).

Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A Framework for Evaluation in Design Science Research. *Association for Information Systems*, *25*(1), 77–89. https://doi.org/10.1057/ejis.2014.36

Wang, T., Gan, V. J. L., Hu, D., & Liu, H. (2022). Digital twin-enabled built environment sensing and monitoring through semantic enrichment of BIM with SensorML. *Automation in Construction*, *144*(October), 104625. https://doi.org/10.1016/j.autcon.2022.104625

Zaidi, E. (2022). *Understand the Role of Data Fabric - Guides for Effective Business Decision Making*. https://emtemp.gcom.cloud/ngw/globalassets/en/publications/documents/understand_the_role_of_data_fabric_ebook.pdf