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Review

BIM and IoT data fusion: The data process model perspective

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ABSTRACT

Digitalization in the architecture, engineering, and construction (AEC) industry has highlighted the process of gathering and combining data from numerous sources. This paper uses data fusion from information science to investigate how data from information systems like Building Information Modeling (BIM) and the Internet of Things (IoT) could be coupled to enable a data-driven AEC. However, given the large amount of data, the technological diversity, the heterogeneous data schema, and hierarchical data abstraction, BIM and IoT data fusion are not addressed systematically. This study aims to develop a BIM and IoT data fusion framework to facilitate the appropriate data process flow for various applications. To investigate the research topic, an integrative review was conducted. Specifically, a general and tailored four-step data fusion process model was proposed as the review's guiding framework. Critical evaluations were incorporated into a road map to provide a comprehensive perspective of BIM and IoT data fusion. In addition, based on the findings, a two-level and interconnected data fusion framework was proposed, which illustrates the data process flow and differentiates the data abstraction level, data processing technologies and purpose of the fusion. Furthermore, the fusion challenges and future trends are also highlighted.

1. Introduction

Digital transformation in the architecture, engineering, and construction (AEC) industry necessitates novel data analytics strategies [1–3]. The concept of "data fusion", which is described as the overall process of merging data to refine state estimates and prediction estimations [4], has the advantage of creating more consistent, accurate information than any single data source [4]. Data fusion tools have increased the flow of information from raw data to high-level comprehension [5]. Consequently, data fusion has recently made inroads into the literature on construction informatics and management.

The integration of BIM and IoT systems and the creation of digital twin for buildings drive the data fusion problem between BIM and IoT [6–8], which refers to the processes of extracting and incorporating specific data from BIM systems and IoT platforms respectively, for joint use or analysis. Unlike multiple IoT sensors data fusion for smart homes or buildings, this paper focuses on bridging BIM, which serves as a substantial and distinct data source, with various IoT data. In general, static information from BIM and dynamic information from IoT devices can explain the real-time status and operations of a building [9]. By combining BIM with IoT data, it is possible to provide descriptive, diagnostic, predictive, prescriptive, and visual services to diverse stakeholders throughout the building's life cycle [10,11]. In fact, implementing the data fusion of BIM and IoT might not only contribute to the data mining of BIM but also exhibit the translation of low-level data into high-level actionable information (such as decision-making) in the AEC industry [12,13].

The fusion of BIM and IoT data should be systematically investigated. Recent work [12–16] has provided quantitative analysis of the increasing trend and significance of BIM and IoT collaboration in fostering digital transformation and enhancing the efficiency of the AEC industry services. Tang et al. [17] provided an informative and instructive review of the approaches for integrating BIM and IoT systems. From the standpoint of system implementation, integration approaches provide a bridge between BIM and IoT by focusing on architectural and functional design. Nonetheless, the increased value could have been demonstrated more thoroughly from a data standpoint. There is a need to investigate the features of BIM and IoT data and their linkages, which resulted in fusion potential and challenges, as well as how the data was flowed, incorporated, and collaboratively analyzed in an application-specific manner.

However, how to handle the increased complexity that numerous data sets provide has been identified as a critical challenge in the data fusion problem [18], partially for BIM and IoT. BIM and IoT are independent disciplines that place different emphases on data issues. The BIM domain has prioritized data-related themes (such as information modeling, data sharing, data exchange, and model standardization) to

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establish a collaborative environment in the construction industry that significantly boosts productivity and efficiency. In contrast, the IoT domain focuses on collecting data for target objects utilizing a range of sensors and devices and transferring and linking data from multiple sources for monitoring and additional data analysis. The independent development of diverse fields may be one of the most significant hurdles to interdisciplinary data cooperation and interaction. In addition, due to the diverse technological ecosystem, heterogeneous data schema, multiple data scopes, and fragmented application fields for BIM and IoT disciplines, it is difficult to gather the pieces of information and provide a holistic view of the current state of BIM and IoT data fusion. Furthermore, the lack of a common workflow and general architecture to facilitate adequate data flow for diverse objectives and application domains was particularly highlighted in [17]. To overcome these issues, it is essential to explore BIM and IoT data interactions following a general data fusion process.

Data fusion problems can be studied from different perspectives. Previous work in the Information and Communications Technology (ICT) domain has proposed various data fusion models to clarify the elements of particular problems and solutions as well as to facilitate the commonalities without indicating software or physical implementation. These models describe different aspects of data fusion such as desired functionality, processes, relationships, abstraction levels, data architecture, and types of in-and output data [4]. Moreover, data fusion models differ significantly depending on the underlying domain data or applications. For example, Luo et al. [19] presented a four-layer model (signal, pixel, characteristic, and symbol level) focusing on the characteristics of image data in different abstraction layers. However, the majority of these fusion models are domain-specific and attempt to address particular facets of their respective research problems. As a result, the limitation is a weak generalization in handling data and technical challenges in other disciplines due to the differences in data features and the diversity of data fusion problems.

Meanwhile, previous researchers in the AEC industry also attempted to discuss data fusion problems and proposed domain-specific data fusion frameworks from different perspectives. Soibelman et al. [20] proposed a conceptual data fusion process model (four significant components: data source, data extraction, preparation, and operation) for revealing knowledge of construction management. They believe that the critical issue for data fusion in construction is how to represent data efficiently in an analysis-friendly schema for diverse applications; Su et al. [21] pay attention to the fusion schema, which reflects the relationships between different data sources; While Razavi et al. [22] referenced the JDL data fusion framework [23] and incorporated BIM, and IoT sensors as sources to illustrate how construction-related data can be fused at different hierarchical levels. However, the research just mentioned either adopting data fusion models from other domains without considering applicability or proposing a new conceptual framework without adequate proof. Additionally, and most critically, BIM was not studied as a critical data source for data fusion purposes. For instance, how the particular characteristics of BIM data influence the design of a fusion model or framework was not examined. Consequently, a proper perspective is required to investigate this research topic and provide a new fusion framework suited to BIM and IoT data.

In this study, a general-to-specific strategy is taken to investigate the subject issue. We begin by introducing a generic but tailored fusion process model as a reference framework for BIM and IoT data fusion. Then, following the guidelines of the reference framework, an integrative literature study was conducted to incorporate critical insights and present our understanding based on the findings. The objectives of this paper are as follows: (1) describing the current state of BIM and IoT data fusion through the analytic framework; (2) providing an overview of the BIM and IoT data fusion flow; (3) proposing a new conceptual fusion framework for BIM and IoT based on the integrated insights, and (4) offering recommendations for future BIM and IoT data fusion processes. This research could provide valuable insights into the interaction of BIM and IoT data and process flow that resolve practice difficulties in the AEC industry, creating new opportunities and contributing to the future development of a data-enriched built environment.

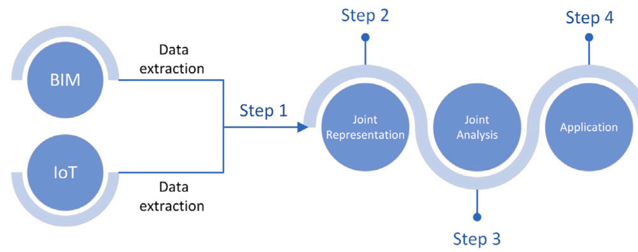


Fig. 1. Data fusion process model.

2. Analytic framework for investigating BIM and IoT data fusion

2.1. A need for analytic framework

A reference model or framework is helpful in investigating BIM and IoT data fusion because it provides a unified perspective to examine the research topic and logically organizes insights. BIM and IoT data fusion is a typical interdisciplinary research issue; a suggested methodology for interdisciplinary research is to reference a theoretical framework, that can be viewed as a tool for identifying theories across disciplines and an orientation that provides guiding perspectives for research and practice [24,25]. When the framework is implemented at the beginning of a research topic, it can serve as a guide for interpreting the literature and as an analytic framework for examining the topic. The advantages of referencing a logical framework are reduced complexity and the ability to integrate and synthesize ideas, methodologies, and discoveries.

2.2. Data process model as a reference framework

However, unlike the previously mentioned data fusion model, a valid reference framework should be not only as general as possible with regard to the essence of the data fusion problem, but also specific to the research topic in terms of BIM and IoT. Therefore, this paper presents a data fusion process reference framework for BIM and IoT as shown in Fig. 1. This framework is a data process model that consists of four major steps that limit the data source to BIM and IoT settings. It illustrates the general data process flow and data interaction for BIM and IoT data from source to application. The description is as follows:

- **Step 1(Data Extraction)**. refers to the process of how to extract information from an existing BIM and IoT environment, respectively.
- **Step 2(Joint Representation)**. refers to the process of coupling extracted BIM and IoT data.
- **Step 3(Joint Analysis)**. refers to the process of analyzing the coupled data by using specific methods.
- **Step 4(Application)**. refers to the field of application to which BIM and IoT data fusion contribute.

The following considerations behind the framework design are applicable:

First, the characteristic problems of the data fusion process include the following three aspects [23]: (1) representing observations or phenomena in conditions of uncertainty; (2) combining non-commensurate information (e.g., the data's distinctive modality); and (3) the method applied to associating and interpreting multi-source observations. In this perspective, the primary considerations for generic data fusion

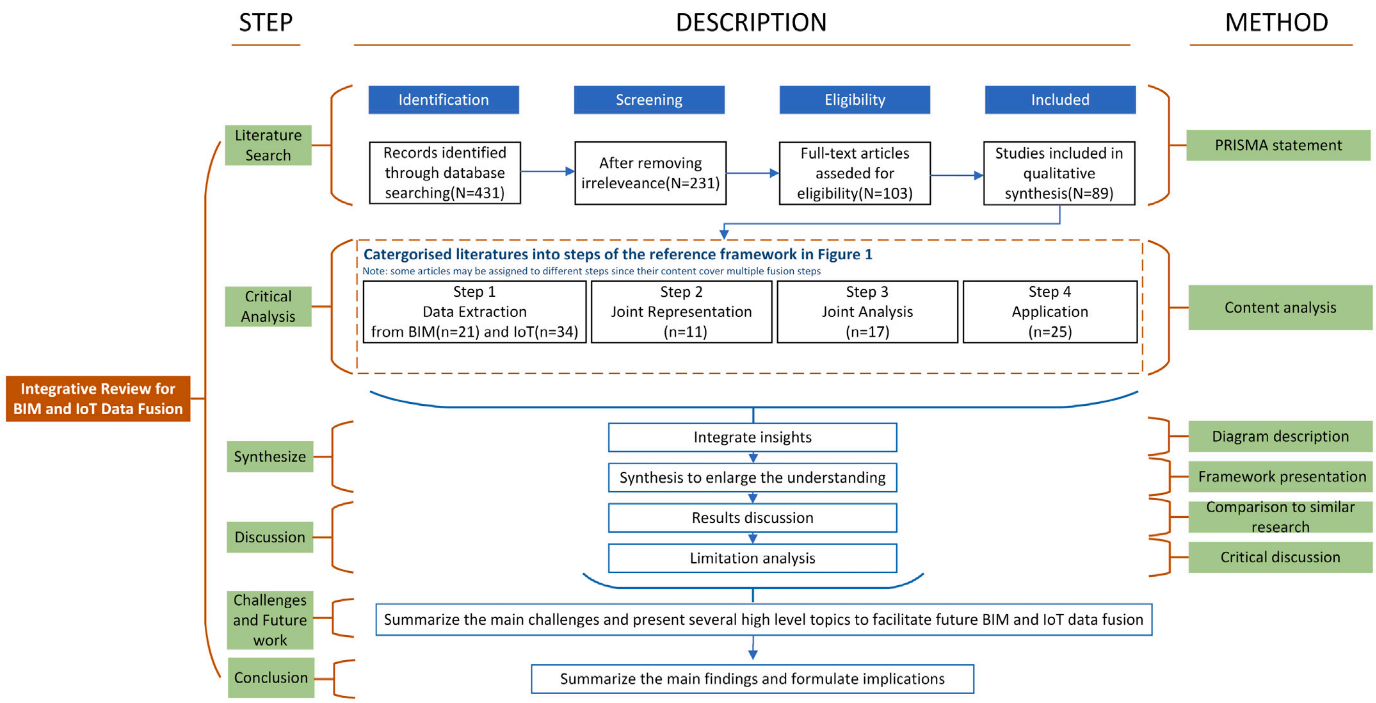


Fig. 2. Graph illustrating the research methodology.

problems should be how to acquire data, how to make data commensurable, and how to analyze the coupled data.

Second, there are numerous theoretical frameworks (with some focusing on methods or paradigms) through which the same problem might be viewed. Function, process, and formal models can be developed to address the issue of data fusion in general. Unlike the function model, which is system-specific, and the formal model, which is algorithm-specific, the process model identifies the fundamental components of an individual fusion process and focuses on the data flow and interaction that meet the needs of this study.

Third, it has been demonstrated that defining the data or information flow is beneficial for investigating and identifying issues and offering a comprehensive and systematic view of data fusion from different systems. The data fusion issues in the BIM and geographic information system (GIS) have been addressed to bridge the data gap caused by the disparity in data schema by critically analyzing the information flow path [26]. As a result of data flow analysis, a standard framework for active information interaction between BIM and robot systems has been proposed in [6]. By evaluating the data links between historical BIM and additional systems, the interdisciplinary data management and interoperability concerns were revealed in [27]. Generally, a data process perspective enables and simplifies the examination of the diverse data interactions between distinct systems.

3. Research methodology

This paper conducted an integrative review in accordance with Toronto's guidebook [28] and utilized the reference framework (Fig. 1) to organize the literature. Unlike a systematic review or a scoping review, an integrative literature review strives to arrive at a holistic understanding of a broad topic from a diverse data source and enables knowledge synthesis from a fragmented field [29,30], in line with the purpose of this study. Moreover, several publications have suggested and employed a reference framework to guide and organize integrative reviews [31,32], as a framework helps to connect the theoretical and practical aspects of a topic so that progress gains in logic and significance [33]. Fig. 2 depicts the overall description of the research methodology. The literature review process was divided into six steps:literature search, critical analysis, synthesis, discussion, challenges and future work, as well as conclusion. For each step, the descriptions and methods (see details in Torraco's guidebook [28]) were given. The following are the specifics:

In the literature searching step, a four-stage (Identification, Screening, Eligibility and Included) paper search strategy called "Preferred Reporting Items for Systematic Reviews and Meta-Analyses(PRISMA)" [34] was applied, specifically:

- **Identification**. The study was carried out by analyzing publications between 2012 and 2022. The keywords "BIM", "IoT", "data fusion", "integration", "digital victory", "smart building", "query", "data schema", "IFC", and "data analysis" were selected for this review. In combination, these keywords were used to search journal articles and conference proceedings for the literature review. Note that we added "integration" as one of the keywords because it was typically discussed in the context of BIM and IoT collaboration, and the terms "data integration" and "data fusion" were detected as being used interchangeably in some publications. Science Direct-Elsevier, IEEE Xplore, American Society of Civil Engineers (ASCE), Web of Science, MDPI, ACM Digital Library, Wiley Online Library, and Springers are the databases used for this investigation. Initially, a database search yielded the identification of 596 documents. After deleting duplicate articles, 431 publications remained.
- **Screening**. At this stage, the titles and abstracts of possibly pertinent literature were assessed, and four critical criteria were evaluated: (1) the title and abstract of the study described BIM, IoT, or building digital twin technology. (2) research focusing on other technologies was omitted. For example, blockchain, Augmented Reality (AR)/Virtual Reality (AR), Geographic Information Systems (GIS), security technology, etc. and (3) papers relevant to IoT data extraction must be limited in the AEC industry. After removing the irrelevant literature, 231 papers remained.
- **Eligibility**. To refine search results, the "Eligibility" step provides insight into the content of the literature. A set of inclusion and exclusion criteria was used to find the most relevant articles: (1) The study must be pertinent to the data fusion process or provide

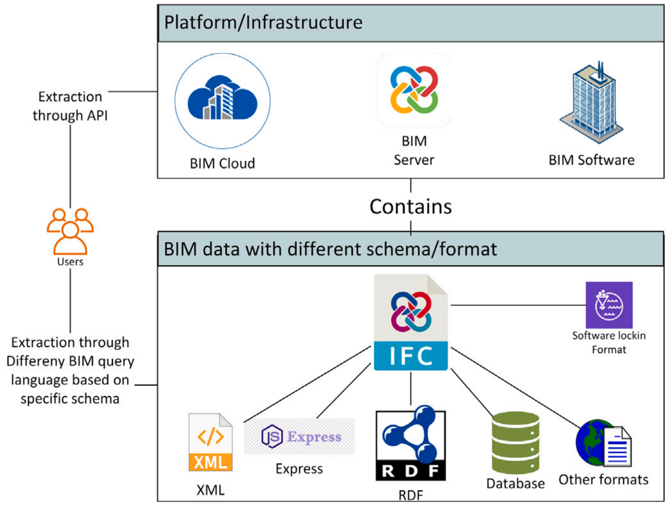


Fig. 3. BIM data extraction methods.

answers to the research question; (2) Studies that only visualize IoT and BIM data are excluded; and (3) Studies that only present a conceptual framework without discussing or implementing it in an actual case of usage are excluded. Following the eligibility evaluation, the number of qualified papers was reduced to 103.

- **Included**. This stage eliminated several publications that, in our opinion, contribute less to the research issue due to their emphasis on the functional design of integrated systems rather than BIM and IoT data and its processing. Finally, 89 papers were accepted.

Relevance-based categorization of the qualified literature into the several steps of the fusion process (BIM data extraction, IoT data extraction, Joint representation, Joint analysis, and Fields of application) was performed at the critical analysis stage. Note that some articles may be assigned to multiple steps according to their relevance. In the synthesis section, the findings from the preceding study were integrated into a linked diagram to provide a holistic view of BIM and IoT data fusion; identifications were synthesized and presented as a framework to enlarge the understanding of the research topic. In addition, the results were discussed and compared to relevent research Furthermore, the challenges were summarized and various high-level topics were explored and presented to assist the future fusion of BIM and IoT data; The conclusion was provided at the end.

4. Critical analysis based on the reference framework

4.1. Step 1: Data extraction from BIM and IoT

This subsection gives a summary of the methods used to extract specific data from the BIM and IoT environments, respectively.

4.1.1. BIM information extraction

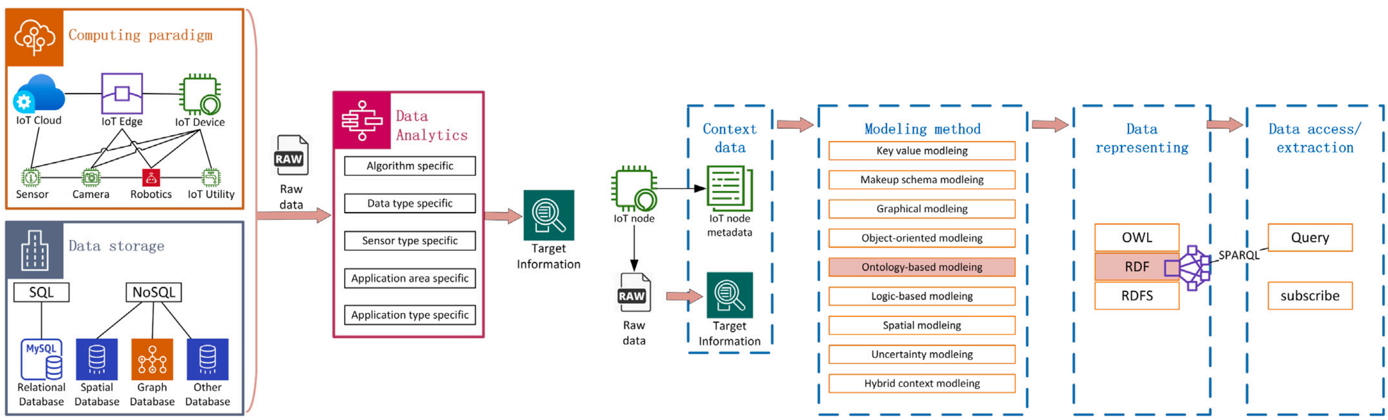
The BIM service infrastructure is associated with the method of accessing data, as Fig. 3 shows. BIM software, BIM Server, and BIM Cloud are current BIM systems that store BIM models and offer model management services. Both BIM Server and BIM Cloud provide remote access capabilities and enable real-time collaboration on BIM models from any Internet-connected location. However, BIM Cloud is significantly more effective, especially for managing a large number of users working on a large number of projects in different locations [35]. BIM data is kept in file systems or certain types of databases with different schemas or formats, and BIM model data is available via the HTTP protocol or API interface to a variety of users. The API interface conceals the internal details of the software system and provides a user-friendly interface for data and command interaction; nonetheless, it is software-dependent and vendor-locked. The pre-defined API protocol restricts the data that can be extracted, and users have less flexibility to export personalized data that is not specified by the API. Therefore it would be desirable to extend the API or any remote access protocol with BIM model query language to enable the more flexible extraction of customized data.

Table 1
Data extraction from BIM.

Method	Format	Functionality
API	Software lockin format	Object and protocol defined query
Borrmann et al. [36]	IFC	Object query, spatial query
Mazairac et al. [37] (BIMQL)	IFC	Object query
Lin et al. [38]	IFC	Submodel query
Preidel et al. [39] (QL4BIM), Daum et al. [40–42]	IFC	Object
Nepal et al. [43,44] (Xquery)	XML/ifcXML	Object
Koonce et al. [45] (EQL)	Express	Object
SPARQL based [46]	RDF	Object, semantic
Zhang et al. [47] (BimSPARQL)	RDF	Object, geometry, spatial, semantic
Solihin et al. [48] (BIMRL)	Star-like schema in data warehouse	Object, geometry, spatial
Alves et al. [49] (BIMSL)	Database	Object
Gao et al. [50]	OWL	Object query
Wang et al. [51]	Hierarchical structure model	Object query
Jiang et al. [52]	IFC BIMserver JSON and Others	Object
Daum et al. [53]	4D BIM model(IFC)	Object, spatial, temporal
Wulfing et al. [54]	5D BIM model(IFC)	Object, spatial, temporal, cost
Tauscher et al. [55]	IFC to Graph	Object
Sattler et al. [56]	IFC	Object
Kang et al. [57]	IFC and LandXML	Object, spatial

Table 1 summarized existing BIM data query or retrieval methods, including BIMQL, QL4BIM, SPARQL, etc. The information that can be derived from BIM is indicated in Column 3 by the query languages' functionality. Current BIM data extraction can extract object information and its properties, geometric and spatial information, temporal and budget information, topological information, etc. Almost all techniques offer object information extraction, but only a few support sophisticated information queries (such as geometry query, spatial query and semantic query), which are required functionalities for a wide range of BIM applications.

According to the data schema, these BIM data query languages can be divided into two types: queries based on IFC and queries based on other schemas or formats. IFC-based query languages are effective in operating directly on data and have wide applicability because of IFC's status as an international building standard format supported by the majority of BIM software. This method, however, demands familiarity with a complicated hierarchical data structure, which poses a technical hurdle for non-technical users. For other query languages, extracting specific types of data requires transforming BIM data into other formats (relational database, ontology-based RDF format, graph structure, etc.).



(a) Time series data extraction (b) Context-aware data extraction

Fig. 4. Graph illustration of IoT data extraction procedure.

However, each format or schema stores data in its own unique way, which is only effective for extracting data of certain types, and there is still some loss of information during the schema transformation process. Database approaches, for instance, are mature solutions that are supported by a wide variety of applications from so many other domains. By representing data in a sequence of linked tables, it is easier for users to search and filter object information in a relational database, but it is difficult to extract spatial data from a relational database [27].

4.1.2. IoT information extraction

The information that can be extracted relates to specific IoT devices, target objects and the context of the application. In different phases of a building's life cycle, a large variety of IoT sensors and devices are utilized to monitor, examine, and detect various target objects [58–63]. However, raw data, such as text information or images, have no meaning without human or machine interpretation. Different types of information require distinct techniques for interpreting raw data to higher level information [64,65]. Generally, the path from raw sensing data to target information and from contextual information to inferenced knowledge adopted different solutions. Fig. 4 gives an overall illustration of the two-stage data or information extraction methods for IoT, the details being given subsequently.

Extracting information from IoT raw sensing data

Extracting meaningful information from raw sensing data is associated with the practical implementation of IoT infrastructure, particularly in terms of data storage systems, computing paradigms, and data analysis techniques, as shown in Fig. 4(a). Data storage is relevant to the way in which data is accessed. The computing paradigm illustrates the architecture of the IoT system and the location where the data is processed, and the data analysis method outlines the techniques used to investigate the data and derive valuable information.

IoT big data is stored in different database frameworks as a consequence of heterogeneous data sources [66]. Numerous database systems were presented and employed to address the issue of big data. These databases could be classified as either SQL or NoSQL, SQL databases are effective at storing structured data with a fixed schema. NoSQL databases, on the other hand, are more appropriate for heterogeneous, non-structured data whose size is continuously growing, while NoSQL systems provide faster data retrieval capabilities in the case of massive data compared to SQL databases [67,68]. Both SQL and NoSQL databases are essential for storing IoT data. Each type of database has its own implementation characteristic distribution strategy and query language [69–71].

Current IoT systems follow a cloud-edge-device continuum hierarchical computing paradigm [72–75]. In the past, the trend to move computing, control and data into the cloud enables comprehensive storage, processing, and management mechanisms for massive IoT systems [76]. Cloud platforms can provide on-demand services anywhere at any time, specifically for the scalable and flexible storing, integrating and advanced processing of massive heterogeneous data generated by IoT. However, a centralized cloud computing platform suffers from specific limitations, including stringent latency requirements, connectivity, network bandwidth constraints, resource-constrained devices, privacy, cyber–physical systems, etc. [77,78]. Facing these issues, the computing paradigm experienced a shift from centralized cloud to distributed edge or fog computing, in which the computational, networking and storage resources can move closer to the physical locations of data sources or end-user applications [79]. In this manner, data is processed in realtime, allowing users to provide fast and context-aware services. In addition, because the computational capability of the cloud, edge, and end devices has increased tremendously, various types of intelligent applications could be developed and implemented in different computing layers, resulting in a distributed data environment [80] and a collaborative intelligence architecture [81–83].

The data analysis technologies utilized to extract information vary significantly in the IoT domain. Plenty of literature discusses the methods of data analysis used in smart building and construction [61]. Typically, IoT data analysis approaches are summarized from a different perspective. The following examples illustrate this:

- Algorithm type: such as the machine learning methods (supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning) in a smart building [58].
- Data type: such as time series data analysis, image data based computer vision analysis [84], speaking processing [85], text-based data analytic methods [86] and spatio-temporal analysis [87].
- Sensor type: such as the frequently used indoor sensors and their relevant data extraction methods [60].
- Application area: such as localization, energy management, facility management, indoor comfort, security and safety [59].
- Application type: descriptive, diagnostic, predictive, and prescriptive analytics [88].

The deployment of IoT methods of data analysis adheres to the IoT computing paradigm, which implies that it could be performed at the device, edge or cloud level, or even by distribution, depending on where the data is stored physically.

Extracting information from IoT context-aware data

As shown in Fig. 4(b), context data is considered to be generated by processing raw sensor data, which is unprocessed and retrieved directly from the sensor [89]. The scope of context information includes not only the information derived from raw data but also the appropriate metadata that has been added. A context model represents the particular information required to comprehend a context. The information contained within a context model varies depending on the device, environment, requirements, and modeling technique. These context models contain extensive semantic information that can be utilized to infer new context data or knowledge, as well as distribute it to customers who are interested in a particular context.

Extracting context information is associated with the modeling methods and practical implementation of context-aware systems. The most widely used methods of context modeling include key–value modeling, markup scheme modeling, graphical modeling, object-oriented modeling, logic-based modeling, ontology-based modeling, spatial modeling, uncertainty modeling, and hybrid context modeling(the details can be found in [90]). Ontology and semantic-based technologies are the most popular solutions due to their ability to facilitate the reasoning of actionable knowledge from multiple heterogeneous information sources and disparate knowledge domains as well as foster interoperability between a number of applications and systems. The context information is represented in RDF, RDFS and OWL formats, which permit language-specific queries. Using a set of semantic reasoning methods, context information can be integrated, aggregated, or fused to generate new context information [91]; this new context information is then remodeled and bound to a specific IoT node. Context consumers can query or subscribe to a specific Iot node or context management system to request and receive context information.

4.2. Step 2: Joint representation

The aim of this step is to combine and organize information extracted from various sources in a coupled format so that hidden relationships within siloed data can be explored by applying joint analytical approaches. However, as stated previously, a set of data can be extracted from BIM and IoT. These data have various types of modalities and are represented in different schema or formats, making data fusion challenging. The crucial issue of joint representation for BIM and IoT data fusion is making extracted data commeasurable. This section summarizes the techniques that addressed the modality and schema representation issues encountered in the existing research, as introduced subsequently.

4.2.1. Tackling the modality issue

Regardless of the schema of data representation, the modality of fused data may fall into the following categories:

- **Single modality**. Single modality is comparatively simple because data are theoretically compatible in a particular modal space. Data from various sources can easily be integrated if they are represented in a unimodal space and have a unified reference frame. Examples include spatial or geometric data with a coordinate reference; temporal data with a time reference; topology data with a structure reference; and semantically linked data with reference to a unified ontology. Thanks to the unimodal representation of the target data, it is easy to integrate them for further analysis. Notably, the modal space may be any physical, chemical, or user-defined mathematical space in which all elements adhere to the same set of laws.
- **Multi modality**. Multi-modalities as a form of representation refers to the situation in which the extracted data from different sources has different modalities. Different information modalities are inherently incompatible, resulting in difficulties with data processing.

The prerequest of fused data is that they must be correlated so as to solve the problem. Consequently, determining the relationships between data sources is crucial for addressing the modality issue, as shown in Fig. 5. The applicable strategy is to integrate target data according to a given logic and represent target data in a space that

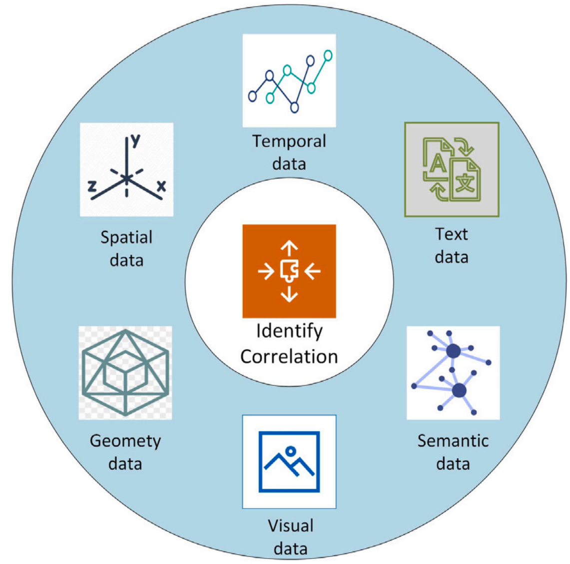


Fig. 5. Correlating different modalities of data.

emphasizes the relationships between data modalities [18]. In addition, data alignment requires specific consideration. The target data should be processed and represented so that it is spatially, temporally, or semantically aligned and, if necessary, normalized into a unit of measure, thus preventing errors and ensuring the quality of the fusion outcomes.

4.2.2. Tackling the schema issue

The schema issue is pertinent to the data modeling dilemma. Schema-related conflicts are the most common obstacles to interdisciplinary collaboration between BIM and the IoT. Integration of data schemas could bridge heterogeneity in source information and enhance schema-level interoperability for both BIM and IoT. Regarding how to deal with the schema difference between BIM and IoT data, the approaches in the public literature are categorized into the following, with examples being given for each type as shown in Fig. 6.

- **Conversion**. This term refers to the process of transforming one schema type into another, for example, exporting BIM data into relational database schema [92], or converting IFC to RDF format [93,94]. The advantage of this method is that it makes one data schema compatible with another, hence facilitating the use of a specific type of data. This approach has the limitation that converting methods require schema mapping, which may result in a loss of information because each schema has its own modeling method (such as IFC, which is an object-relations based modeling schema) that is best suited to solving a specific type of problem.
- **Expansion**. This refers to the case of enhancing the schema of an information model, such as IFC+ [95,96], which extends the BIM model's IFC schema to incorporate IoT-related context information, such as device, deployment, network, and application scenario. The identical treatment of data from both disciplines enables the use of information from one field in software from the other. This method is appropriate for data modeled using the same strategy, such as object-oriented; otherwise, a data conversion procedure is necessary. The limitation of this method is that only a certain amount of data can be in another model since too much data in a single information model may cause difficulties.
- **Linking**: This refers to the circumstance in which an additional link is created to correlate information from several sources. A deep discussion and comparison of the methods used to link

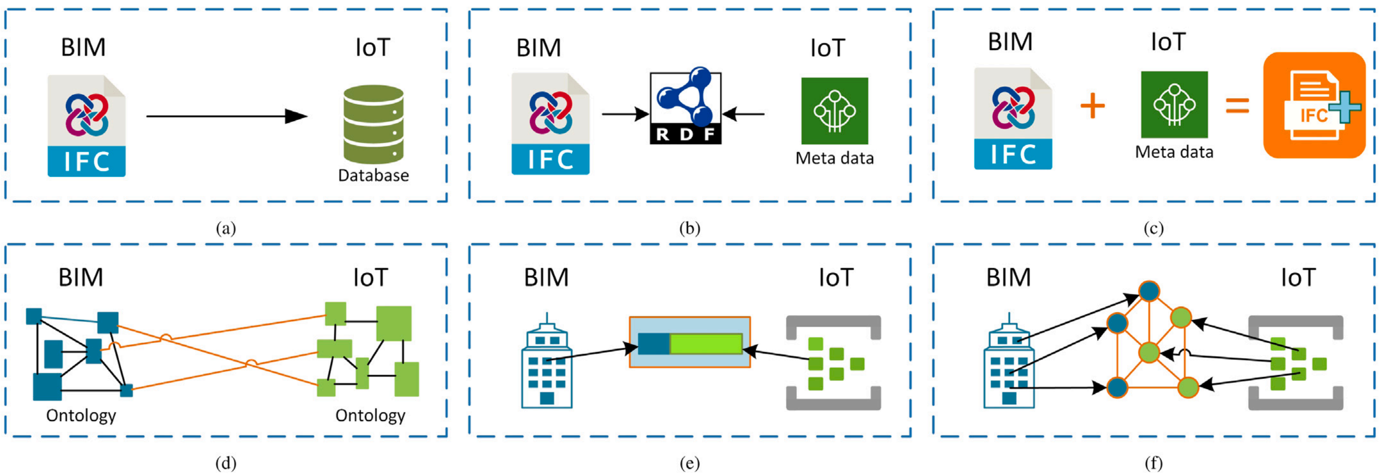


Fig. 6. Graphical example of schema operation: (a) conversion of IFC data schema to database representation; (b) conversion of IFC and IoT metadata into RDF representation; (c) extention of IFC schema with IoT information; (d) linking ontology-based BIM and IoT data representation; (e) merging data from BIM and IoT into a vector or tensor representation; and (f) merging data from BIM and IoT into a graph representation.

BIM and IoT data can be found in [97,98]. The most common approach is the ontology-linked method, which represents BIM and IoT domain information with semantic interoperability. In general, linking approaches provide a common data environment that integrates the data from multiple domains and enables data sharing between various software and stakeholders. The resulting linked data space is extensible and open to new data from many sources and fields. Nonetheless, a consistent ontological creation or name translation operation is necessary, which is complex and time-consuming, especially for large-scale domain collaboration. Moreover, as the linking process needs ontology mapping between BIM and IoT disciplines, avoiding semantic ambiguity and automating such a mapping procedure are difficult.

- **Merging**. This refers to the process of integrating data and transforming it into a different representation appropriate for a particular study. For example, Cheng et al. [99] pick a small number of variables or features from each data source and assign them to a feature vector. While Abdelrahman et al. [100,101] integrate BIM and IoT data(indoor thermal-related spatial–temporal proximity data) into a graph network structure, Ferreira et al. [102] incorporates geometric data from BIM and spatial data from IoT as a graph structure for localization. The merging approach is suitable for small-scale and fragmented data representation for BIM and IoT since merging large-scale data with multiple schemas to create a new schema is evidently difficult: accordingly, this method is usually problem-specific, domain-specific, or algorithm-specific.

Table 2
Joint analysis method for BIM and IoT data fusion.

Method	Advantage	Limitation	Example
Model-based	Highly interpretability	Difficult to model complex problems Lack of accuracy and reliability	Abdelrahman et al. [100] Zahid et al. [103], Teizer et al. [104] Li et al. [105], Choi et al. [106], Kuo et al. [107], Dong et al. [108] Tomasi et al. [109], Cui et al. [110]
Data-based	Do not need explicit knowledge of the system	Limited by data quantity and quality	Cheng et al. [99]
	High accuracy and easy implementation	Lack of Explicability	Pan et al. [111]
Semantic-based	Integrate cross domain data	Lack of time series data analysis capability	Zhong et al. [93]
	Highly interpretable Highly interoperable		Hu et al. [94]
Hybrid	Creating data fusion network Contribute to the flow from data to information and knowledge	Require more effort to deploy	Dong et al. [108], Xiao et al. [112], Vandecasteele et al. [113], Gan et al. [114]

4.3. Step 3: Joint analysis

This subsection summarizes the joint analysis method applied to the represented data introduced in Section 4.2. Four types of approaches were concluded from the reviewed literature. The method's scope and corresponding examples are given for each category, and the advantages and limitations are also presented in Table 2.

4.3.1. Model-based

Model based approaches assume an understanding of physical, functional, mechanical, or other relevant system features and seek to characterize the system's operation using an explicit representation and rules, such as a mathematical function.

For instance, Zahid et al. [103] presented a model for human indoor comfort based on the projected mean vote (PMV), the anticipated proportion of discontent (PPD), and the ISO7730 standard. Due to the fact that human comfort is influenced by numerous factors (such as temperature, air quality, and room size), which may be gathered via BIM and IoT sensors, a dynamic computation model with multiple factors as input parameters might be developed and used to assess the level of comfort.

Model-based methods offer the benefit of formalizing the relationship between dependent and independent variables to characterize the underlying dynamics of a system and allow human professionals to comprehend the results systematically and logically. Consequently, this approach is highly interpretable. In addition, because the data from BIM and IoT devices serve as parameters or conditions, they may be merged into a data model supplied to a specific function for calculation, thereby bypassing the difficulties posed by schema or format incompatibility. Nonetheless, the model-based strategy faces profound challenges, as follows: (1) Building a high-fidelity model is difficult due to the complexity and dynamic nature of systems. Typically, theory-based hypotheses are formulated to simplify the model and make it computationally possible, resulting in disparities between the theoretical model and actual practices; (2) The IoT technology employed has limitations to its theoretical and practical application. For example, the IoT-based distance-detecting method is constrained by the employed wave frequency of the device and is typically influenced by the single-transmission environment, resulting in localization deviation; and (3) The model's input data suffer from quality issues. IoT data may have noise, incompleteness, variants, etc. Additionally, BIM has version control and update issues. Low-quality input data from BIM and IoT sources will result in low-quality outcomes. Overall, due to the aforementioned issues, model-based methods may yield inaccurate and unreliable results, which should be carefully examined in practical situations.

4.3.2. Data-based

The data-based method relies on analyzing data about a system, in particular finding connections between system state variables (input and output variables) without an explicit understanding of the system's physical behavior [115]. For instance, Cheng et al. [99] proposed ANN and SVM-based prediction models for facility management. Fifteen data types from BIM and IoT sensors are organized into a feature vector for the target facility. The data act as the training dataset for the machine learning model, and the algorithm's output is the facility condition's evaluation indicator.

Data-based approaches are appropriate for complicated systems for which prior information is insufficient to develop a physical model and capture the relationship without knowing the system's details. On the other hand, data-driven approaches rely primarily on data and algorithm design, which presents several relevant challenges: (1) Data collecting is the primary challenge. In theory, the data provided dictate the optimal performance of results, but in practice, adequate high-quality data is typically missing. What types and quantities of data should be collected from BIM and IoT systems are the most pressing issues that must be solved; (2) Data preprocessing is necessary, particularly for heterogeneous and hierarchical BIM and IoT data. Aggregating, transforming, or representing multi-source multi-modality data is needed to make data analysis friendly; (3) Untrustworthiness is caused by data quality issues inherited from BIM and IoT data; (4) Evaluating and verifying data-based approaches is difficult in practice. Without sufficient test data, it is hard to assess and measure the system's performance accurately; and (5) Lack of interpretability. Data-based methods emphasize the relationship between input and output, as opposed to the relationship between dependent and independent variables. Overall, data-driven methods benefit from data but are also limited by it.

4.3.3. Semantic-based

Semantic web technologies can handle data that includes a broad range of concepts with complex linkages, particularly in cross-domain collaborations where data silos are formatted with multiple schemas and representations. By standardizing the conceptualization of things and their relationships, it is feasible to search, compose, and translate information across disciplines. For example, Zhong et al. [93] developed a semantic fusion model that incorporates domain-specific rules for reasoning. Environmental data from sensors and building information are represented in RDF format, and regulatory restrictions in building regulations are transformed into a set of SPARQL rules for anomaly detection in building environments.

However, semantic-based techniques are confronted with several challenges: (1) A semantic-based method requires data format translation for BIM and IoT; (2) Multiple ontologies must be created for complex problems requiring multi-domain knowledge. For example, Zhong et al. [93] presented four ontologies(building information ontology, semantic sensor network ontology, building regulation ontology, and building environment monitoring ontology) for fulfilling the reasoning task; (3) Inference based on large size ontologies is time consuming [27]; (4) The knowledge inference rules design depends on information that can be queried. However, the ontology representation is redundant, and the relationships between objects are limited to semantic data concepts defined in the ontology [98]. This means that a fully integrated semantic dataspace is essential for getting good inference results; (5) Time series data from IoT devices cannot be converted to an RDF file; instead, the information must be independently retrieved from raw time-series data and substantially enable high-level semantic inference; (6) Ontologies may have a poor degree of reusability; Overall, semantic web technology has the advantage of resolving interoperability challenges for BIM and IoT at a semantic level [116] but cannot investigate the value of dynamic time series data for IoT.

4.3.4. Hybrid

Hybrid methods construct a fusion network by integrating the benefits of more than one type of fusion method described above to accomplish complex tasks. For instance, Xiao et al. [112] proposed a framework for building energy management that incorporates data mining and semantic web technologies. BIM and sensor data were integrated into an ontology format and stored in a database. The results of ontology-based semantic inference were input into a data mining program for additional analysis. Other examples of hybrid methods could be found in [113,114] in which machine learning or deep learning methods are combined with simulation model-based methods.

A hybrid approach constructs a fusion network that may overcome the limitations of a single method in addressing practical issues and accomplish more complex tasks. Model-based approaches are suitable for cases where the object system's working principles are well defined (such as simulation), but they are not suited for solving highly complex problems (such as cross-domain analysis). Data-based approaches are appropriate for complicated systems for which there is insufficient prior knowledge to develop a physical model and capture the inner relationships, but they lack interpretation. Semantic-based approaches are effective at integrating silo data from different disciplines, providing opportunities for knowledge inference and providing interpretive assistance, but they are not specialists in time series data mining and analysis. Each method has its appropriate uses, and they can be combined to facilitate the transformation of data into knowledge. For example, semantic-based methods handle data at a high level for knowledge inference, requiring supplemental model-based and data-based approaches to extract insights from raw data.

4.4. Step 4: Fields of application

This subsection outlines the application scenarios for the fusion of BIM and IoT data. The application fields and several items of relevant literature that fall within the scope of our analysis are listed in Table 3.

As indicated by the preceding examples, applications for fusing BIM and IoT data are fragmented at various stages in a building's life cycle. Such characteristics may be inherent in the fragmentation nature of BIM [128] and IoT [129]. These applications either focus on situation awareness or knowledge inference, which demands different types of information needs. Some details are as follows:

- Combining spatial data from BIM with spatial data retrieved from IoT devices could improve localization and navigation [102,118].
- The incorporation of static data from BIM and dynamic data from IoT systems has the potential to facilitate maintenance tasks [99].
- Combining BIM and IoT context data to achieve an accurate or user-friendly assessment of building energy consumption [94,106–108,122].
- Geometry and spatial data extracted from BIM are capable of facilitating network device deployment, simulation, planning and optimization [109,110,123,124].

Table 3
Fields of application.

Fields of application	Related research
Improved localization	Park et al. [117,118], Ferreira et al. [102], Chen et al. [119]
Enhanced health and safety	Liu et al. [120], Liu et al. [121]
Improved energy analysis	Hu et al. [94], Dong et al. [108], Choi et al. [106], Ascione et al. [122], Kuo et al. [107]
Optimized network device deployment	Tomasi et al. [109], Guinard et al. [123], Cui et al. [110], Zhao et al. [124]
Enhanced predictive maintenance	Cheng et al. [99], Ma et al. [125], chen et al. [119]
Others	Pan et al. [111], Zahid et al. [103], Abdelrahman et al. [100], Kim et al. [126], Wang et al. [127], Liu et al. [120], Liu et al. [121]

- Comparing interpreted geometric data from visual devices with component information from BIM for in assessing building quality [126,127].
- Combing geometric information from BIM and visual inspection data from BIM for safety inspection purposes [120,121].
- Other application domains, such as process-mining [111] and indoor thermal comfort optimization [100,103].

In addition, several common findings were identified from the literature, which are critical for BIM and IoT data fusion applications.

- Object relevant and geometric information is BIM's most frequently used data, while IoT disciplines show more "diversity".
- The scope of fused data varies from the component level to the construction site level, which presents requirements for efficient data extraction.
- Continuous, updated, high-quality data requirements are proposed for most applications. This issue heavily affects the performance and trustworthiness of the fused results.
- The cases of application showed limited BIM and IoT data reusability and weak scalability to new applications. As a result, there are difficulties in integrating diverse technologies from BIM and IoT disciplines.

5. Integration and synthesis

5.1. Integration insights and findings

Based on the critical analysis in Section 4, this section integrates the findings and provides a holistic view of the BIM and IoT data fusion process following the data fusion process reference framework in Fig. 1. As shown in Fig. 7, the technologies and methods that are relevant to each step were present and were linked to depict the data process flow. Note that the reviewed literature may stress specific study issues covered by the process model (such as BIM data query) due to the limited research scope and focus. Nevertheless, connecting them makes it feasible to provide a comprehensive perspective on the approaches, processes, and applications that are pertinent to BIM and IoT data fusion and to determine the current trend.

Two key technical routes, the relational data route and the semantic data route, were identified for fusing data from BIM and IoT environments. The data type, fusion level and other features presented in Table 4 distinguish these methods.

Table 4
Two distinct data fusion routes.

Feature/Route	Relational data route	Semantic route
Data type	IoT sensing data and discrete BIM data	IoT context information and integrated BIM model
Fusion level	Data	Information
Association method	Correlation and merging	Conversion, extending, linking
Data relationships	Various causal relationships: spatial-spatial, spatial geometric, object-temporal, etc.	Semantic link
Purpose	Context sensitivity and situational awareness	Semantic enrichment and information inference

5.1.1. Relational data fusion route

The route connected by the blue arrow in Fig. 7 corresponds to the relational data route. The relational data route focuses on extracting discrete data from an integrated BIM environment and combining it with data from an IoT node. For further analysis, the fused data are correlated and merged into a specific format. Model-based and data-based methods are the most frequently employed joint analysis techniques, and this methodology path was recognized as enabling almost all types of fusion applications.

The relational data fusion approach is more specialized in concrete data processing and focuses on the compatibility of associated data. During the design phase, the BIM discipline adopts an integrated data model due to the necessity for data management, sharing and collaboration. However, as the integrated model is not directly useable by specific applications, it is necessary to extract user-required data in order to satisfy various information requirements. Meanwhile, the IoT discipline employs multiple devices and generates dynamic and multi-format raw data, which need further interpretation. Data diversity and heterogeneity are significant factors that contribute to the complexity of data fusion for discrete BIM data and IoT sensor data. On the other hand, the fragmented and diverse applications propose the requirements of multi-domain, multi-scope and multi-detail information needs, which increase and amplify the challenge. Consequently, the goal of the relational data route is to bridge the gap between the existing BIM and IoT data ecosystems and diverse applications. Relational data routes require efficiency in extracting heterogeneous, fragmented and application-specific data from BIM and IoT infrastructure and representing it in an analysis-friendly format to support numerous data analytics.

5.1.2. Semantic fusion route

The route connected by the red arrow in Fig. 7 corresponds to the semantic route. The semantic route emphasizes obtaining context data from an IoT environment and fusing it with an integrated BIM model. Typically, schema operations such as conversion, extension, and linking are employed to make the data commensurable, and semantic-based methods are used to infer information in certain applications.

The semantic route is less precise but more focused on delivering a relevant overview of well-defined building-related data (product and process, static and dynamic). Since IoT context data and the BIM model are represented at the semantic level using vocabularies or ontologies and modeled using a similar approach, cross-domain data from a different source is naturally commensurable, making it possible to create an integrated model for building. In addition, this technology route stresses establishing a "linked data space" to leverage the potential of a unified data environment for data sharing, management, and knowledge inference, irrespective of the diversity and heterogeneity of the data. The objective is to efficiently create a homogeneous presentation model for managing the extended dynamic context information from IoT devices and enabling semantic-level interoperability across disciplines. However, the vast volume, scope, and hierarchy of semantics are significant challenges that result in a complicated network of interconnected data silos for BIM and IoT collaboration [116].

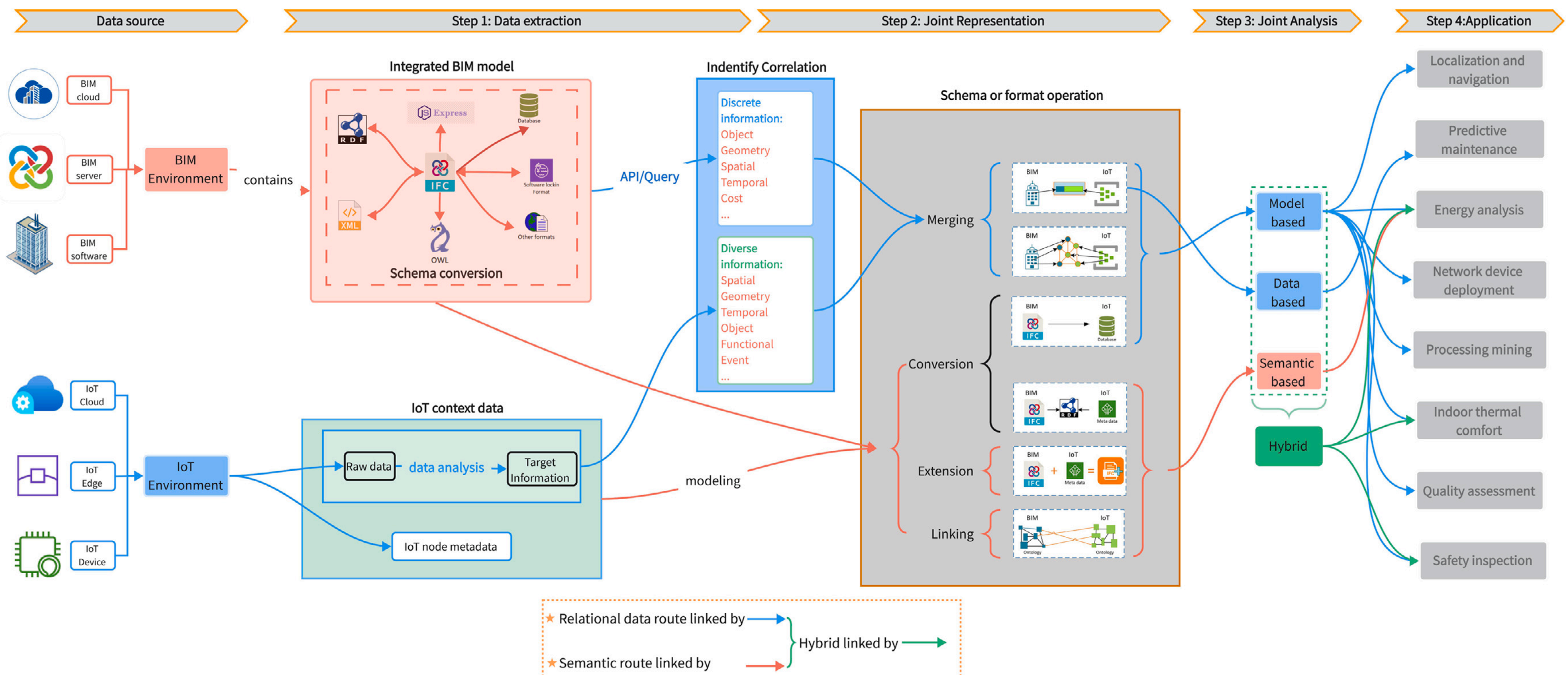


Fig. 7. Holistic view of BIM and IoT data fusion process.

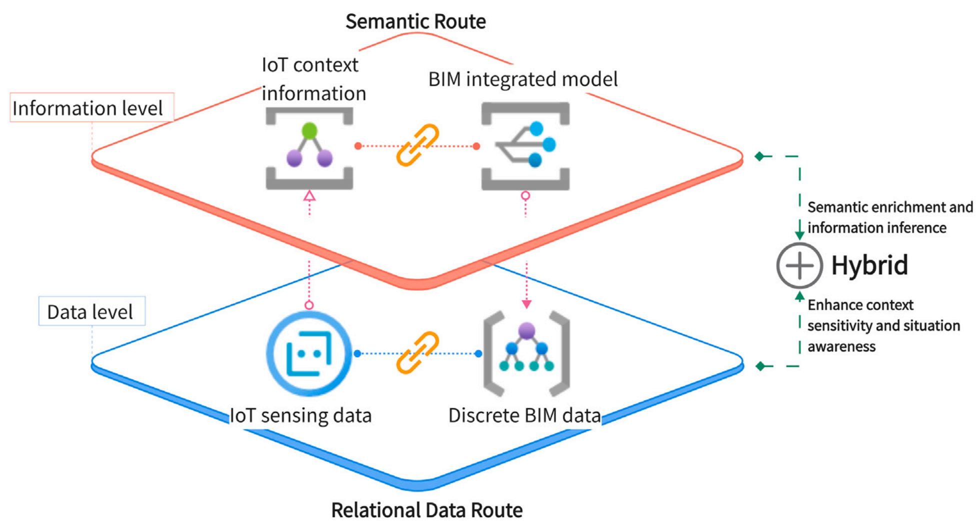


Fig. 8. BIM and IoT data fusion framework.

5.2. Synthesis: BIM and IoT data fusion framework

In general, relational and semantic data routes process data at distinct levels. The former fuses data at a specific data level, whereas the latter fuses data at a higher information level. In practical implementations, however, these two-level data processes are closely related. The output of the analysis of raw sensing data contributes to the IoT context information that is fused with BIM. On the other hand, the discrete BIM data must be retrieved from the integrated BIM model to be fused with IoT sensing data. Such data flow procedures are, in fact, commonly identified in the reviewed literature. Consequently, the relational data route and the semantic route are interconnected. Regarding the significance of these two technology routes, relational data improves the context sensitivity and situational awareness capabilities for the built environment, primarily due to the IoT's sensing capabilities. The semantic route enhances the built environment's semantics by expanding and incorporating dynamic context information from the IoT. The two technology routes both seek to explore the value of data for decision-making purposes.

The primary purpose of this research was to synthesize the literature on BIM and IoT data fusion and to develop a framework to facilitate the appropriate data process flow for various applications. As depicted in Fig. 8, based on the aforementioned identifications, we provide the new framework from a data perspective to depict the overall data flow of BIM and IoT data fusion. The framework consists of two interconnected layers. The lower layer corresponds to the relational data route, which fuses at the data level in an effort to improve context sensitivity and situational awareness. The higher layer corresponds to the semantic route, which operates at the information level and aims to enhance semantics and infer information. These two layers can be combined to construct data fusion networks and contribute to the flow of data, information and knowledge.

6. Discussion

To justify the results, this paper employs the methodologies described in [28] and compares the results to the background literature, the reference framework presented as Fig. 1, and similar research. In addition, the current status of BIM and IoT data fusion was compared with research in other fields, such as BIM/GIS data integration and multisensor data fusion, in order to capture the key similarities and differences resulting from the different types of input data.

6.1. Comparison with background literature

The framework comprises two distinct layers(data and information), which are consistent with the hierarchical nature of BIM and IoT data. The data hierarchy of IoT data has been addressed at two distinct levels [64], data abstraction and semantic abstraction, which were defined as the derivation from raw sensory data to semantically represented information. Whereas in the BIM discipline, from a data consumer's perspective, the need to extract data from the integrated, hierarchical BIM model for purposes of efficient use and fusion was addressed in [92]. Even though the hierarchy of BIM and IoT data is embodied in different aspects(data scope for BIM and data abstraction for IoT), the similarity and association in data still enable the potential of fusion.

The disparity in the two technical routes is consistent with the differences and similarities identified from the BIM and IoT data. BIM and IoT are intrinsically compatible with a semantic approach since they both represent context data similarly, presenting an opportunity to fuse at a semantic level and facilitate interoperability [116]. On the other hand, differences in data content, structure, and format are inherently non-comparable. Still, they are associated with specific applications, fostering diverse methods to investigate the relationship between various data modalities and thus achieve data compatibility [130], resulting in the relational data route.

6.2. Comparison with relevant research

The paper's results led to similar conclusions as several other studies.

The two technology routes we identified are similar to the findings reported by Cursi et al. [27], who investigated the incorporation of external knowledge into heritage BIM. The approaches outlined are separated as the "relational approach" and the "ontology approach". The former entails transferring BIM data to an external database for additional processing, arising from the need to extract the data present in the models for specific requirements and processes to evaluate the feasibility and design for system integration. This conclusion corresponds to the relational data route, which requires the extraction of discrete data from BIM for fusion with IoT sensing data for varied applications. The difference is that this paper has identified numerous data schema conversions for BIM instead of merely a relational database. In addition, the latter utilizes an ontology to connect BIM to other settings to facilitate cooperation among professionals, thus offering a unified model for managing the extended information. This method refers to the semantic route, which expands the BIM model with IoT context information. The difference is that the aim also encompasses knowledge inference in the case of BIM and IoT data fusion. Note that the above comparison does not imply that the results reported in this paper are more trustworthy than those in any other paper; instead, the difference is due to the approach and scope of the research. Their work proceeds from a BIM perspective and only considers heritage BIM, whereas this research examines the data interaction between BIM and IoT, which results in a greater variety of data concerns. As a specific example of incorporating external knowledge into BIM, this paper's findings could contribute to the theoretical framework of the BIM-centric construction industry.

The results in this paper are pretty close to the research results in Boje et al. [131], which reviewed the state of digital twins in the construction industry. They made suggestions for leveraging the value of diverse data from BIM and IoT by using advanced algorithms(overlapping with the relational data route) and creating knowledge bases by linking various conceptually represented BIM and IoT data(similar to the semantic route) to create a semantic digital twin. The difference is that their work did not address the hierarchical nature of BIM and IoT data and the relationships between the different layers. This is due to the fact that their work focuses on the system cooperation level, whereas this research focuses on the data or information level, in particular the data fusion process. Nonetheless, the findings of this paper can contribute to the theory of digital twins for building as data fusion is a specific form of data interaction approach for digital twins.

6.3. Comparison with BIM/GIS data integration or fusion

Since BIM is the common essential data source, BIM/IoT data fusion revealed several similarities with BIM/GIS data integration and fusion. One of the common challenges is bridging the data gap between BIM and other settings (both for GIS and IoT) caused by their distinct data schemas. According to [26], BIM and GIS data integration may be split into: geometric and semantic integration. Correspondingly, the principal tasks include IFC parsing, geometric data representation conversion and transformation, semantics extraction, mapping, merging, etc. The difficulties, inaccuracies, and inefficiencies of the above data procedures were highlighted due to BIM's unfriendly data schema. Such situations were also identified in BIM and IoT data fusion, both on the relational data route and the semantic data route, necessitating data extraction, schema conversion, and representation transformation for BIM (as described in Section 4, and the path from integrated BIM to discrete BIM data depicted in Fig. 8). Particularly, geometric information from BIM generates significant interest in BIM/GIS and BIM/IoT data fusion. The formal process necessitates the transformation of an implicit BIM model into an explicit model (surface model) that is compatible with GIS geometric data. While the IoT disciplines benefit from the increase in sensing equipment and image processing capabilities, the availability of more geometric data is driving the merging of geometric data in BIM.

Due to the dissimilarities in data schema and representation between GIS and IoT data, their fusion paths with BIM are distinct. Similar to BIM, GIS includes a standard, integrated hierarchical model for storing information, such as the semantic data format CityGML or the non-semantic shape file shapefile, resulting in an information flow that stresses geometry and semantic transmission. While IoT data is more diverse in terms of data formats, dynamic in terms of time series, distinct in terms of data modality, and broad in terms of semantics and number of connected things, this makes the data fusion flow between BIM and IoT significantly more complex, fragmented, and non-standard, especially for relational data fusion.

Both BIM/GIS and BIM/IoT data fusion are essential components of the data-driven AEC industry; the former might contribute to the construction of a digital twin at the city or district level, whereas the latter could contribute to the production of a digital twin at the building or infrastructure level. They are focusing on operating data at separate scales, but they have the potential to be linked up for a more digitalized, data-driven AEC industry [132].

6.4. Comparison with IoT data fusion

IoT data fusion has been extensively studied in fields such as smart homes, smart grids, and smart transportation [133]. Modeling the fusion representations concealed in intermodality and cross-modality data to enhance the performance of diverse applications is one of the most critical tasks. In the urban computing area, for instance, urban data has distinct features of spatial attributes, temporal attributes, or spatial–temporal correlation. How to representing the temporal variation trend and spatial distribution as well as establishing correlation relationships plays a significant role in spatial–temporal data fusion [134]. Various advanced methods, such as probability-based methods (Bayesian inference), evidence reasoning methods (Dempster–Shafer (D–S) theory), and knowledge-based methods (fuzzy rules [135], machine learning [136,137], deep learning [134]), have been applied to a variety of industrial problems.

While data fusion problems vary greatly depending on the underlying domain data or applications. BIM is a multi-domain integrated, multidimensional and layered, semantically rich and standardized information model following an object-relational modeling paradigm, with substantial differences in terms of data characteristics for IoT sensor or device data. This highlights the data fusion problem between BIM and IoT with specific objectives focusing on identifying, collecting, representing, and analyzing data from BIM infrastructure, overcoming data issues such as hierarchy, heterogeneity, diversity, etc. Indeed, the data fusion between BIM and IoT differs from IoT data fusion in terms of data type, fusion level, data association method, data relationship, and fusion objective, as shown in Table 4.

It is important to note that BIM/IoT data fusion is linked up with IoT data fusion. On the one hand, the multisensor and multimodel data fusion of IoT could provide rich contextual sensing information of the building environment (as depicted in Fig. 4 and the path from sensing data to context information in Fig. 8), which can then be fused with BIM data. This will enhance the data ecosystem and contribute significantly to the flow of data to advanced information and knowledge in the AEC industry. On the other hand, BIM and IoT data fusion, which handles BIM as a discrete data source, could serve as a particular case that complements the general data fusion in the IoT field. The new data source has enormous potential to enhance the intelligence and smartness of specialized fields, such as smart houses and buildings.

6.5. Comparison with reference analytic framework

The proposed reference framework depicted in Fig. 1 complements the fusion framework shown in Fig. 8, but is viewed from a different perspective and has different focuses. The reference framework is more general and focuses on the process perspective, illustrating the typical procedure and function steps for fusing BIM and IoT data. The limitation of this fusion process model is that it emphasizes the problem of data fusion without taking into account the characteristics of the fused data and technology. While the final framework is an overall description since it was derived from the road map presented in Fig. 7, the emphasis is on the data perspective, which seeks to differentiate the data abstraction level, data processing technologies, and fusion purposes. The data flow and relationships are prioritized over the data fusion procedure in the final framework. However, analyzing from either data or process perspectives independently may not be sufficient to expose the whole picture of BIM and IoT data fusion; instead, linking the data and process perspectives can result in conformance analysis results [138]. Besides, other perspectives can be employed, such as the function, algorithm, or application perspectives. By investigating and inspecting from a different perspective and combining the results, we can achieve a more comprehensive understanding of BIM and IoT data fusion.

6.6. Research limitations

Several limitations were identified in this integrative review. First, the limitation may come from the integrative review method itself, which might lead to inaccurate interpretations of cumulative evidence [29]. Second, a potential limitation relates to the search strategy. This paper only concerns the published literature and does not involve industry reports and cases. While BIM and IoT have collaborated extensively and are widely deployed in actual cases, this could have led to biased results. Thirdly, the limitation may come from the proposed reference framework, since its objectivity has not been proved in practice. In addition, the causal relationships identified in the relational data route are not systematically presented due to the limited literature and diverse, fragmented applications. Future research can investigate more precise data relationships between IoT sensing data and discrete BIM data. Finally, the two-layer structure is roughly classified according to data type, scope, level, etc. In fact, the fusion purpose could be divided into multiple layers appropriate to the applications, thus resulting in a more advisable fusion framework.

7. Challenges and future work

7.1. Challenges for BIM and IoT data fusion

As described in Sections 4 to 6, the path from raw data to valuable impacts (high-level information or knowledge) is complex and multifaceted. Overall speaking, BIM and IoT data face the usual data issues of large volumes, diversity, heterogeneity, and hierarchy. These data have different schemas, formats, qualities, reference points, and levels of detail. Such features cause difficulties in the identification, querying, processing, and analysis of data. On the other hand, the diversity and fragmentation features of the application side propose the requirements of scalability, reusability and flexibility in data operations. As a result, each step of the BIM and IoT data fusion process may involve different types of data processing, which requires dedicated operation tools, analysis methods, domain-specific services or applications to be carried out. Specifically, the obstacles were outlined in accordance with the reference framework in Fig. 1 as well as other data or application-level issues:

- Availability and accessibility of application-specific data: Both BIM and IoT data generated throughout a building's lifecycle are siloed, with separate data ownership, distributed in various locations, and kept on diverse physical storage media, making data access challenging.
- Efficiency of data extraction: Extraction of various discrete data from BIM is a significant challenge that needs the use of sophisticated query languages or schema transformations. Advanced algorithms are required to interpret multimodel IoT data and model it into sophisticated, higher-level semantic information.
- Representating data in an analysis-friendly way: Associating or linking relevant data from BIM and IoT devices or systems is difficult, particularly when managing data modalities, data alignment, and data transfer into specified representations that match the requirements of data input for further analysis.
- Effective joint analysis methods: Better fusion outcomes require novel fusion approaches, such as a high-fidelity simulation model, advanced data analysis algorithms, and a user- or application-oriented semantic information inference rule.
- Fragmented fields of application: The fragmentation of the fusion application diminished the reusability of fractured data and the scalability of new applications.
- Quality of data: Both BIM and IoT are plagued by severe data quality issues (especially for dynamic IoT time series data). For the relational data route, situations such as errors, imperfections, outliers, spurious data, and conflicts could all lead to biased or incorrect fusion results, especially considering that the majority of the joint analysis methods (both model-based and data-driven) listed in Table 2 are data sensitive. For the semantic route, inconsistency, duplication, and errors in semantics as well as the integrity of connected data may accentuate the data quality issue.
- Hybridization: The hybridization of diverse data fusions may introduce new difficulties for architecture design (such as for BIM and IoT system integration or digital twin for building) in a decentralized and siloed data environment.

7.2. Future work

According to the preceding discussion, the fusion of BIM and IoT data is still in its infancy, and there is still considerable work to be done, notably to remove fragmentation, improve automation, and increase efficiency, hence enhancing the effectiveness and trustworthiness of data fusion for BIM and IoT. To do this, stakeholders in the AEC industry must adopt a data-centric mindset and recognize that data is a valuable asset necessitates creative approaches to governance and management, thereby establishing a valuable connected data ecosystem.

This section broadens the overall understanding of the BIM and IoT data fusion problem as a whole and discusses several relevant higher-level topics (data value chain, interoperability and compatibility, data management and services, digital twin) from a data perspective. The focus is on presenting future research suggestions applicable to the outlined issues addressed in Section 7.1.

7.2.1. Creating data value chain

To explore the value of data from BIM and IoT, it is essential to identify and investigate the data value chains for BIM and IoT data fusion in the AEC industry. A data value chain indicates how data sources are discovered, ingested, processed, stored, analyzed and ultimately exploited by the users to add value [139]. A transparent data value chain for BIM and IoT collaboration describes all the processes of data creation and use, from defining the need for specific data to its end use and possible reuse. It helps identify impediments, demonstrates the high-value steps where more effort is needed, and provides a framework and principles for transforming raw data into actionable information.

Data security and privacy concerns have been significant roadblocks in developing the BIM and IoT data fusion value chain because most construction firms would rather keep productivity-related information private from other parties. This prevents the joint use of data. To facilitate collaborative BIM security, current efforts have adopted an encryption protocol, distributed database technology, cloud security, and blockchain technology [140]. However, these efforts operate on distinct levels (data security, network security, system security level, etc.), and each has its constraints. For instance, blockchain can make data sharing accountable and traceable [141,142], but with limitations considering the large size and complex data model of BIM.

Existing studies that place security and privacy concerns on the BIM and IoT data fusion or system integration are extremely rare. Atazadeh et al. [143] aimed to determine the legal ownership of IoT-generated data using BIM. Still, additional efforts are anticipated to expand large-scale and diversified IoT devices. More security and privacy rules and standards are required to guide the fusion of BIM and IoT data, addressing the multi-owner, distributed data environment. To overcome the aforementioned issues, it is necessary to conduct the following investigations: to what extent it is permissible and ethically sound to capture data in a multi-stakeholder built environment; how to resolve conflicts over data ownership rights; what information is shared with or made available to third parties; what promising technique can be utilized to transmit the fused data securely; and how could security mechanisms be implemented to maintain control over the BIM and IoT data fusion processes?

In addition to the security and privacy issues, creating a comprehensive data fusion value chain for BIM and IoT is difficult since each application of the data value chain may differ from one instance to another, and its complexity increases over time. Future efforts could focus on creating a data value chain from a sub-area or specific perspectives, such as different phases of a building's life cycle, different subdomains, different users, different applications, or even different dimensions of data, thereby reducing the complexity and addressing user requirements more precisely.

7.2.2. Improve interoperability

Interoperability is one of the factors that affect the efficiency of data fusion. As stated previously, the original software or platform from each discipline cannot deal directly with the data from another one, and an integrated new platform is usually presented in the literature to make BIM and IoT components compatible and cooperative. Such efforts are usually technically challenging. In addition, the data fusion process for BIM and IoT data requires data schema operations to make it analysis-friendly. This process is usually time-consuming or error-prone. The lack of interoperability between BIM and IoT environments hinders data value creation.

However, interoperability between BIM and IoT is quite impossible to achieve. Interoperability in the BIM domain is not yet possible, as it primarily pays attention to the exchange of data and its meaning [144] between BIM software. On the other hand, the IoT domain focuses on solving interoperability issues at multiple levels: device, syntactic, semantic and platform [145]. When BIM meets IoT, the aim of interoperability may not be limited to facilitating data sharing or exchange, but the complexity extends to an unprecedented level. Various data formats are tailored to plenty of specific applications, but none of them can cover the full range of different data exchange scenarios or the necessary depth of information [27]. Besides, as the IoT system advances, interoperability is a continuously challenging task. More seriously, there are no agreed definitions, frameworks, automation tools, or practical guidelines for BIM and IoT interdisciplinary interoperability, and achieving interoperability also comes with high costs in terms of time, effort, and money [116]. Therefore, a more reasonable choice is that the interdisciplinary interoperability between BIM and IoT can be attained on smaller scales or in specific domain applications. For example, Tomasi et al. leverage BIM interoperability for UWB-based WSN planning [109], so that the complexity of interoperability can be reduced to a controlled scope, which is more feasible from a technological perspective.

7.2.3. Enhance data management

Fusing BIM and IoT data demands efficient data management to support various applications and users. Data management requirements have been addressed frequently in each discipline. Due to the large amounts of heterogeneous and hierarchical data and the imperfect data and incompatibility formats, data management for BIM and IoT is quite challenging. Data fusion is a data-intensive process that will face various data issues, such as data errors, inconsistency, inaccuracy, low availability, and insecurity arising from BIM and IoT during a building's life-cycle. If data is not managed efficiently, it will lead to wrong decision-making.

Currently, BIM and IoT data management emphasize different domain requirements. This is despite the fact that the BIM data management strategy is not suited to understanding and fulfilling the sophisticated data processing and management requirements of IoT devices and vice versa. Several common issues still have to be addressed from a data perspective, such as data storage, data integrity and data security. Additionally, new challenges arise when managing BIM and IoT data for fusion purposes. The growing emergence of new types of data and information, including human knowledge and contextual information, enables more accurate decisions but results in an increase in the complexity of data fusion systems [146]. There is a need for increased manageability to deal with multi-source, multi-format, multi-scale, multi-phase data.

In particular, data quality is the dominant issue that has been identified for BIM and IoT data fusion. BIM was thought to lack consistency [147]. IoT suffers the quality issues resulting from data discrepancies, duplication, leakage, and multisource data time synchronization [148]. Continuously updated and clean BIM and IoT data are crucial for ensuring and enhancing their trustworthiness, quality and the user experience. Future work should focus on identifying valuable data from BIM and IoT devices, improving its accessibility and usability, and proposing new data management techniques to ensure data consistency, granularity and reusability.

7.2.4. Demand for data service

Data services encapsulate data operations and provide an abstraction layer for data consumers to cope with multiple data sources with less effort. A unified data service layer or platform is capable of abstracting multi-scale data, improving data reusability, aggregating homogeneous and heterogeneous data sources, supporting multiple applications and, most importantly, enabling single-point interaction with data entities for consumers. These capabilities are particularly important when processing silo BIM data and heritage IoT data for fusion purposes, which require consistent, accurate, and useful data representation. BIM and IoT data fusion have to handle data schema issues, data storage differences, multi-data query languages, and so on, while the limitations and challenges are the lack of efficient tools to automate these processes. In fact, there is a shortage of studies investigating how to provide BIM and IoT data services simultaneously to enable more convenient and efficient collaborations.

To overcome the gap, the following items are recommended to satisfy these requirements: (1) supporting multi-data source linkages, such as BIM server, data warehouse, or a variety of IoT devices(static or mobile devices); (2) developing fixed scripts to support the data service API and business API in order to create application-specific data models; (3) supporting computation API to invoke data processing (such as simulation, machine learning, knowledge inference, and so on) and return a result; and (4) supporting a data visualization service for data consumers. It is suggested that researchers design data service platforms according to their needs for information and applications. Future work could focus on creating an agile data service architecture or framework and developing tools (such as a more efficient query language to support scalable and flexible data operations) to deliver data services that continually meet evolving business requirements.

7.2.5. Fusion BIM and IoT towards future digital twin

BIM and IoT data fusion, as a part of data interaction in digital twins for the built environment, are able to collect data generated in the physical world, leverage the value of data in the virtual world, and improve or enhance decision-making in the physical world. It contributes to the data flow from raw data to a high level of information or knowledge leading to a high-fidelity digital twin of building. Nevertheless, the design of a digital twin for a building can be approached from multiple perspectives with respect to different abstraction layers or application domains, such as the semantic construction digital twin [131] and the digital twin for asset monitoring and maintenance [149]. Future trends in digital twins may lead to the development of a composite digital twin system that consists of several other composite digital twins [150]. In this case, data are acquired not only to generate numerous models (such as physical models, simulation models, analytic models, visualization models, or VR/AR models) within a composite digital twin, but also to connect with other twins via multi-service interfaces. Future research is therefore encouraged to combine BIM and IoT to improve the functionality of building digital twins in the context of a multi-twin ecosystem, leveraging the value of diverse data in BIM and IoT through advanced data processing algorithms to increase the intelligence of building digital twins, and adopting more digital techniques(such as 5G, VR/AR, and next-generation computation platforms) to achieve a timely, user-friendly, hierarchical building digital twin.

8. Conclusion

This review has provided a comprehensive understanding of the state of BIM and IoT data fusion through an integrative literature review. A tailored process model was presented as a reference framework to guide the investigation. The literature relevant to each process model's component was collected, categorized, and analyzed critically in sections; identifications and insights from each section were integrated and synthesized to provide a holistic view of BIM and IoT data fusion. The identified insights were gathered together and linked to an overview picture to illustrate the technologies, methodologies, applications, and most importantly, the data process flow, which indicate two distinct technology routes operating at the data and information levels respectively. One is the relational data route, specifically in the fusion of IoT sensing data with discrete BIM data to enhance context sensitivity and situational awareness. The other is the semantic data route, which focuses on fusing IoT context data with a context-based integrated BIM model to achieve semantic enrichment and information inference. These two technological routes are interconnected since IoT sensing data contributes to the IoT context data through data analysis, and discrete BIM data can be retrieved from the integrated BIM model. Consequently, based on their differences and connections, this paper has proposed a new framework for BIM and IoT data fusion, which have two levels but are associated with each other. The new framework illustrates the data and its process flow, contributing to the future design of BIM and IoT data fusion systems. However, this framework offers an overall illustration of BIM and IoT data fusion that is viewed from a data and process perspective. There are more perspectives from which to investigate the research topic; additional material can be contributed, and various partitioning techniques can be utilized to produce a more precise and advisable framework. In addition, this research has addressed a series of high-level topics (data value chain, interoperability, data management and service, digital twin) to facilitate future BIM and IoT data fusion and the development of a data-enriched built environment.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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