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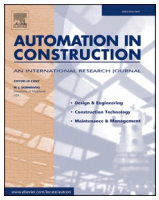

Beyond interoperability: a systematic review of semantic web technologies for BIM-enabled facility management (2019–2025)

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ABSTRACT

The Facility Management (FM) sector faces significant challenges stemming from information fragmentation and the difficulty in accessing accurate, up-to-date building data. Although the integration of Building Information Modeling (BIM) with Semantic Web Technologies (SWTs) offers potential solutions to these barriers, their combined application within the FM context remains underexplored in existing literature. To address these challenges, the study in this paper conducts a systematic literature review of 41 journal articles published between 2019 and 2025, analyzing why, where, and how SWTs are adopted with BIM for FM. The results reveal that the primary application of SWTs is linking across domains, with Information Management emerging as the most targeted FM theme. The findings indicate a mature capability in static data linking, but a deficiency in the bidirectional frameworks necessary for autonomous FM. Suggestions and technological integration for future development are also proposed to benefit the research community and industry practitioners.

1. Introduction

Facility Management (FM) involves the operations, maintenance, and optimization of built infrastructure to sustain its comfort, performance and effectiveness [1]. FM is defined as "a profession dedicated to supporting people, ensuring the functionality, safety, sustainability, and efficiency of the built environment" [2]. It is the longest phase of the building's lifecycle, accounting for over 75% of a project's total lifecycle cost [3]. Researchers have recognized FM as a knowledge-intensive profession, as it requires continuous access to real-time, and historical data to manage built assets [4]. The quality and completeness of this data constitute critical determinants of FM performance, operational efficiency, and long-term asset value.

In practice, however, FM teams deal with information fragmentation, unstructured data, and the absence of effective mechanisms to integrate heterogeneous data sources. These challenges hinder the effective management of asset information [5,6], and limit data reusability, which affects FM decision-support. A key driver of these challenges is the poor handover of information from construction to operations. Studies indicate that approximately 95% of data generated during the design and construction phases is lost or becomes inaccessible during the transition to the FM phase [7,8]. As a result, facility professionals spend an average of 13% of their working hours searching for project information [9], and up to 65% of total maintenance time on resolving documentation inconsistencies or verifying asset locations [10,11]. The economic consequences of information fragmentation are severe as research by the National Institute of Standards and Technology estimated that inadequate interoperability causes $15.8 billion in annual losses in the management of U.S. facilities [12]. Resolving the data integration and interoperability challenge for FM is essential for the financial and functional viability of modern built assets.

In response, existing approaches have attempted to address these challenges with varying degree of success. For instance, Building Information Modeling (BIM) has the potential to centralize FM data, acting as a single structured source of information [13]. However its file-based architecture limits its ability to connect with the heterogeneous data

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streams [14]. Other common integration approaches like pipeline-centric or low-code integration platforms are widely adopted, yet they remain schema-specific and fail to model rich domain knowledge. Alternatively, Digital Twins (DTs) platforms or NoSQL databases offer scalability for integration but rely on proprietary APIs that lock data within a vendor's ecosystem.

In contrast, Semantic Web Technologies (SWTs) emerged as promising tools for linking diverse data sources across knowledge domains [15,16]. They provide a standards-based framework [17] that uses models such as the Resource Description Framework (RDF) and the formal logic of Web Ontology Language (OWL) to create a machine-interpretable semantic layer [18]. Their ability to link disparate data sources and address interoperability [19] makes them suitable for FM due to the presence of cross-domain data. In addition, SWTs extend BIM's capabilities by shifting data management from proprietary file-based systems to an open web-based architectures [20]. It utilizes modular and lightweight ontologies to provide extensible schemas that reduce system complexity [21]. This approach results in a vendor-neutral platform that integrates sensor observations, Building Management Systems (BMS), and BIM models without altering original data sources [22].

SWTs have been shown to improve data exchangeability among project stakeholders [23], supporting better decision-making with complex data [24,25]. This positions SWTs as a technical architecture suitable for FM. Nevertheless, despite this potential, their systematic application with BIM within the FM context remains fragmented in existing literature. This gap is what the present review directly addresses.

1.1. Existing literature

A growing body of reviews has examined SWTs applications in the AEC and FM sectors, as presented in Table 1. However, a critical analysis reveals that current reviews are either (1) too broad, covering the entire AEC domain, or (2) too narrow, focusing on single niche problem, leaving a notable gap to understand the role of SWTs within FM context.

First, several foundational reviews are too broad in scope. The seminal work by Pauwels et al. [19] and a 15-year review by Deng et al. [26] offered comprehensive overviews of SWTs applications across the entire AEC sector. Similarly, Farghaly et al. [27] provided a two-decade analysis with a particular focus on ontology development for DTs and the operational phases. Although these reviews provide valuable foundational analysis, a dedicated examination of SWTs applications within FM remains absent. More recently, Shen et al. [28] analyzed 65 articles and identified a shift from a broad lifecycle-wide perspective towards more concentrated exploration of specific project stages. However, only 12 of 65 articles are explicitly related to FM, indicating that a dedicated examination of FM applications remained outside the scope of the review. Another recent bibliometric study [29] mapped the literature of SWTs in FM but did not include the technological analysis required to understand implementation mechanisms.

Second, a larger body of work is focused on specific theme or niche FM applications. For instance, multiple studies have systematically reviewed semantic BIM enrichment [30,31] with a primary emphasis on Artificial Intelligence (AI), and ontology mapping for design code compliance. Other researchers have explored SWTs for specific uses, such as enhancing energy efficiency [32], construction safety and

Table 1
Comparison of the existing related literature.

References	Primary Domain	BIM	SWTs	FM /O&M	Time Frame	Focus
Bukhari et al. (2025)	FM	✗	✓	✓	Up to mid-2025	A bibliometric analysis mapping the research landscape of Semantic Web technologies in the FM sector.
Jia et al. (2024)	AEC/FM (Broad, IFCOI Focus)	✓	✓	✗	2011–2023	A review of the integration modes, applications, and challenges of IFC (BIM) and Ontology across the entire AEC/FM lifecycle.
Pandithawatta et al. (2024)	Construction Safety	✗	✓	✗	2000–2023	A systematic review of knowledge-driven approaches (Ontologies, KGs, Expert Systems) for construction safety management.
Karabulut et al. (2024)	Cross-domain (DT Focus)	✗	✓	✗	2017–2023	A systematic literature review of how ontologies are utilized within DT architecture across various domains.
Farghaly et al. (2023)	AEC (Broad)	✓	✓	✗	2000–2021	A two-decade systematic review of ontology applications across ten key domains in the AEC sector.
Jiang et al. (2023)	AEC (Broad, BIM + SE Focus)	✓	✓	✗	Up to 2022	A review of the content, methods, and applications of semantic enrichment for BIM across the facility lifecycle.
Dinis et al. (2022)	AECO (Broad)	✓	✓	✗	2010–2020	A semi-systematic review of BIM-based semantic enrichment methods and applications from the last decade.
Deng et al. (2022)	AEC/Construction (KM Focus)	✗	✓	✗	2008–2022	A 15-year review of information and communication technologies (focusing on Ontology and Semantic Network) for knowledge management in the AEC industry.
Bloch (2022)	AEC (BIM + SE Focus)	✓	✓	✗	Up to 2021	A review defining semantic enrichment of BIM and comparing approaches based on the IFC schema versus web ontology.
Xue et al. (2021)	AEC/Urban (BIM vs. CIM SE Focus)	✓	✓	✗	2010–2020	A 10-year review comparing the methods, scopes, and trends of semantic enrichment for Building Information Models vs. City Information Models.
Gilani et al. (2020)	Smart Commissioning	✓	✓	✗	2014–2020	A critical review of ontologies used for Smart and Ongoing Commissioning, categorized by data type, approach, and application.
Ozturk (2020)	AECO/FM (Interoperability Focus)	✓	✗	✗	2004–2019	A scientometric analysis of research trends and gaps in BIM interoperability across the AECO/FM industry.
Pauwels et al. (2017)	AEC (Broad)	✓	✓	✗	Up to 2016	A foundational literature overview of Semantic Web applications in the AEC industry, categorized by three aims: interoperability, linking domains, and reasoning.
Lei et al. (2022)	Road Asset Management	✓	✓	✗	Up to 2019	A systematic review of the development and implementation of ontologies specifically for road asset management.
Lygerakis et al. (2022)	Energy Efficiency	✓	✓	✗	Up to 2022	A review of knowledge grpahs and ontologies used as Decision Support Systems for energy efficiency in buildings.
Donkers et al. (2022)	Indoor Environmental Quality	✓	✓	✗	2009–2021	A review of SWTs for Indoor Environmental Quality to identify patterns for integrating building topology (BIM) and dynamic data.
Shen et al. (2024)	AEC (Broad)	✓	✓	✗	2017–2023	A critical review of recent (2017–2023) Semantic Web Technology applications in the broad AEC sector, focusing on integration with BIM.
This Study	FM	✓	✓	✓	2019–2025	A critical review of recent role of SWTs (2019–2025) in various facility management themes and in-depth discussion of SWTs applications and technology integration.

accident prevention [33], managing indoor environmental quality [34], or enabling smart commissioning [35]. Although these studies are valuable, they remain confined to sub-domains and do not provide an exhaustive picture of SWTs utilizations across the FM literature.

Certain scholarly attention has also been paid to Operations and Maintenance (O&M), which is a subset of FM, in semantic BIM enrichment [31] and in knowledge management [26]. This justifies the need for systematic review focused on FM to identify unexplored areas in semantic BIM applications. The critical analysis presented in Table 1, also confirms a clear gap in the literature: none of the existing reviews provide an assessment of SWTs integration with BIM within the FM context. Therefore, to address this gap, the present study conducts a Systematic Literature Review (SLR) to analyze recent advancements, evaluate existing approaches, and provide structured insights that can guide future research. This study is structured around three research questions.

RQ1: In which FM themes are SWTs applied with BIM, and what functional roles do they support.

RQ2: What methodological frameworks are adopted for integrating SWTs with BIM, and how do technological integrations characterize their applications?

RQ3: What knowledge gaps and future research are required to advance the application of SWTs?

This paper is structured into seven sections. The literature review process, including search terms and screening methods, is presented in Section 2. Section 3 introduces SWTs applications organized around FM themes and Section 4 presents a comprehensive summary of frameworks and implementation methods. Section 5 provides a technological analysis to investigate the integration of SWTs with other technologies. Section 6 highlights research gaps and challenges. Section 7 presents the conclusions and limitations.

1.2. Background

The content of this section is organized around Fig. 1, which illustrates the chronological development of SWTs and their adoption within FM. Fig. 1 is horizontally divided into two tracks: generalized SWTs (upper track) and their integration within AEC/FM sector (lower track). The grey boxes identify key technologies and milestones across the decades. To assist in interpreting the information in Fig. 1, its content is discussed, and further references are provided.

As shown in the upper track, the evolution of the semantic web began long before its formal conceptualization. Its roots trace back to semantic networks developed within AI research in the 1960s and rule-based expert systems such as MYCIN in the 1970s [36]. The concept of machine-readable knowledge was formalized by Sir Tim Berners-Lee, first through his proposal for a hypertext system in the 1980s and subsequently his Semantic Web Road Map in 1998 [37]. The 1990s saw the development of foundational languages like XML, RDF, KIF, and DAML+OIL (a key precursor to OWL) [38]. This work was formalized in the 2000s when the W3C launched its semantic web activity, standardizing the core technology stack: the RDF, OWL and the SPARQL Protocol and RDF Query Language (SPARQL). The 2010s marked an era of large-scale adoption, with the launch of knowledge graph like Wikidata and the standardization of validation languages like Shapes Constraint Language (SHACL). A significant milestone during this period was Google's introduction of the knowledge graph in 2012, improving search capabilities through a better understanding of relationships between real-world entities [39]. This development marked a turning point in the practical deployment of semantic technologies and established the technological foundation for various domain applications.

The integration of SWTs into the FM sector, broadly categorized into three stages, followed a distinct evolutionary trajectory as shown in the lower track of Fig. 1.

1.2.1. Stage 1: foundational (Pre 2015)

The primary focus of this foundational period was on BIM model semanticization, the direct conversion of BIM data, typically from the Industry Foundation Classes (IFC) schema, into a format compatible with web technologies [19]. A landmark exploration was the case study at the Sydney Opera House, which demonstrated one of the first practical applications of SWTs by linking IFC data with various FM data sources using RDF and OWL [40]. Another critical milestone was the development of the ifcOWL ontology [41], developed through a series of

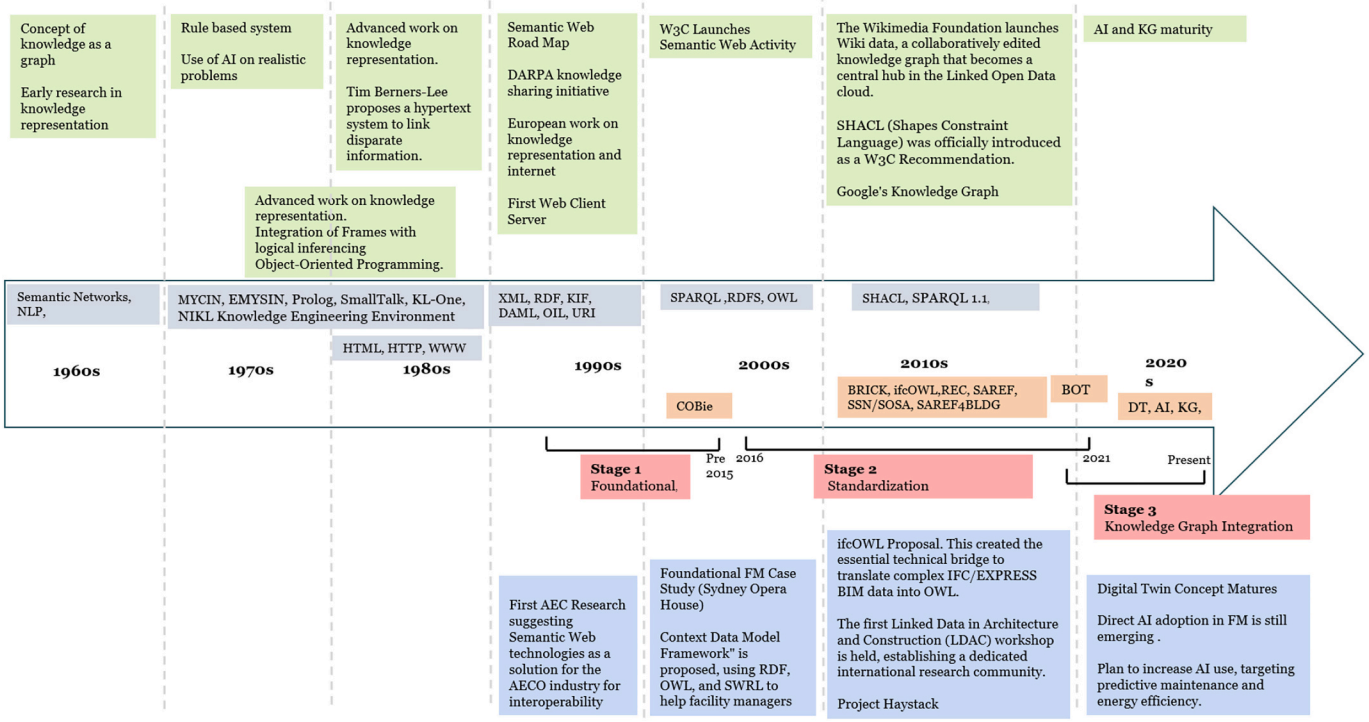

Fig. 1. Timeline for semantic web technologies and their integration in facility management.

conversion proposals from 2009 and with a recommended standard emerging by 2016. This development established the essential technical bridge for translating complex BIM data into a web-native format. Despite these advancements, there were practical constraints such as the monolithic architecture of ifcOWL which produced computationally expensive knowledge graphs that were difficult to query and maintain. The ontology itself faced inherent difficulties in translating the native EXPRESS schema into OWL/RDF, limiting its practical applicability for concrete FM use cases.

1.2.2. Stage 2: standardization (2016–2021)

With a viable approach for representing BIM data, the research focus shifted towards semantic association of multi-source data [31]. This transition was driven primarily by the rapid proliferation of building systems enabled byInternet of Things (IoT), which generated real-time data streams that existing schemas were unable to handle. The goal was no longer simply to convert a BIM model but to link data with real-time streams from heterogenous sources. This resulted in the development of modular ontologies which were easier to maintain, extend, and align with operational environments. Key outputs of this period include Brick Schema [42], the Building Topology Ontology (BOT) [20], the Smart Applications REFerence ontology (SAREF) [43] and the Semantic Sensor Network ontology (SSN/SOSA) [44].

In addition to such core ontologies, other initiatives gained prominence to harmonize data for facility operations. Projects like Haystack [45] provided standardized semantic data models to handle IoT data.

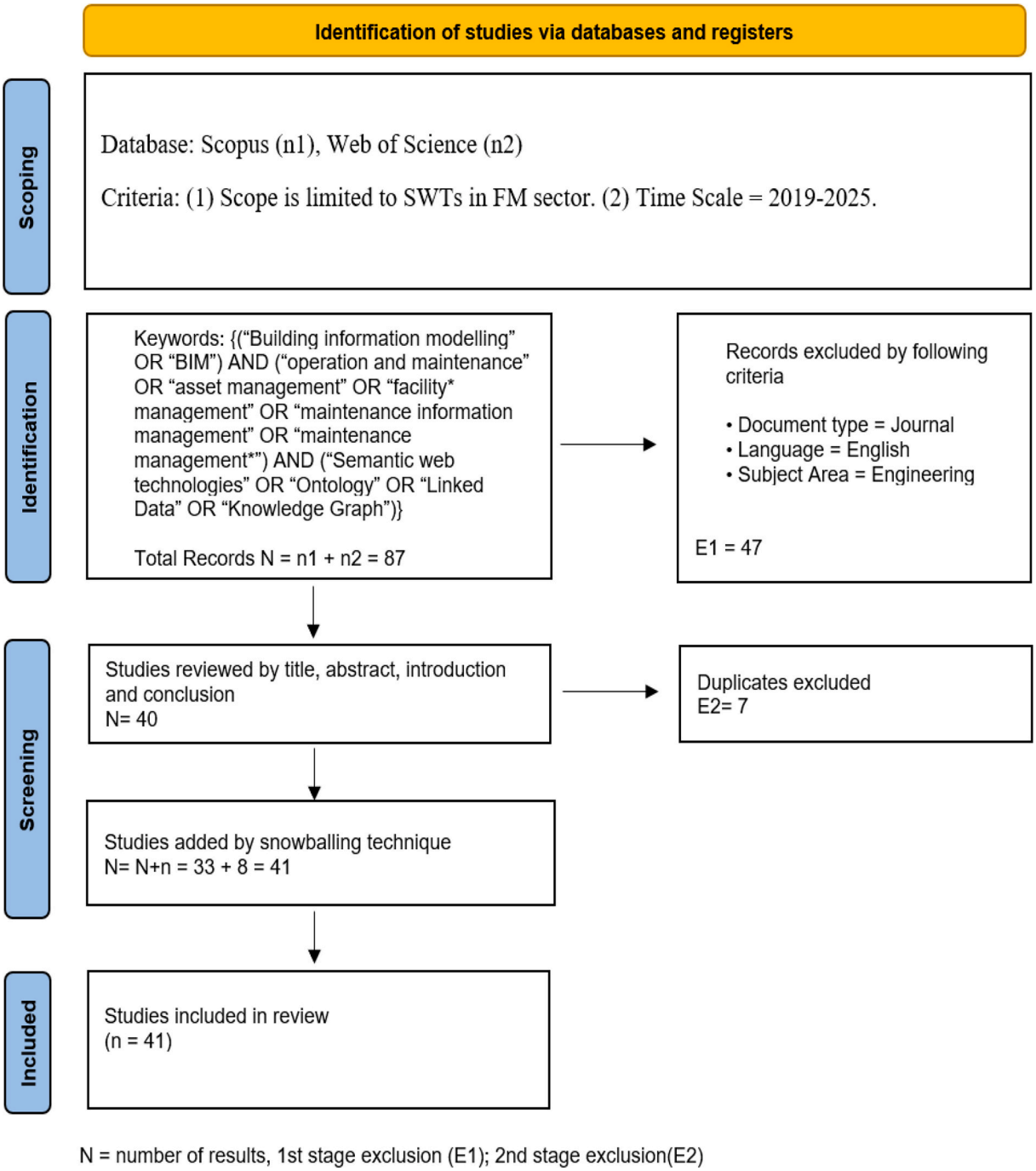

Fig. 2. Article screening for the review process as per PRISMA.

The RealEstateCore (REC) ontology [46] emerged as an open-source model for the real estate domain. In parallel, standards like Construction Operations Building Information Exchange (COBie) [47] addressing the handover of information also gained traction. Together, these developments established the standards necessary for the following stage.

1.2.3. Stage 3: knowledge graph integration (present)

The development of the foundational standards marked a transition to their implementation. This transition was accelerated by rapid adoption of AI, and the deployment of various DTs frameworks. These developments created the demand for semantically rich knowledge bases capable of predictive analytics and automated reasoning, capabilities that knowledge graphs were uniquely positioned to provide [39].

The widespread The widespread deployment of IoT sensors create demand for semantic frameworks capable of contextualizing and reasoning over FM dynamic data streams. This stage was therefore characterized by the construction of knowledge graphs that united static BIM data with IoT streams and maintenance records [38], and the application of semantic reasoning to address challenges including fault diagnosis, energy optimization, and real-time operational awareness [39].

The evolutionary stages described above inform the scope of the present study. The pre-2019 period was defined by foundational work and the proposals for ontologies, while the 2020s current decade serves as a critical inflection point, marking the transition into implementation stage. This study focuses on capturing modern FM applications where foundational standards are being deployed, combined, and evaluated.

2. Research methodology

To address the research questions outlined in the introduction, this study employs a SLR analysis, which provides structured insights into areas where research may be lacking or inconclusive. The methodology adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [48] to ensure a transparent, replicable, and rigorous process. The SLR is structured into three primary stages, as illustrated in the PRISMA flow diagram (Fig. 2): (1) Scoping, (2) Identification, and (3) Screening. The specific inclusion criteria is presented in Table 2.

The scoping stage aims at defininig databases and the time frame for review. The databases used were Scopus (n1) and Web of Science (n2). These two databases were selected for their comprehensive coverage of construction research and their advanced filtering capabilities [28], with a partial non-overlap that justifies their combined use to minimize retrieval bias [49]. Moreover, recent AEC and FM reviews likewise relied on Scopus and Web of Science as primary databases [39,50]. The 2019–2025 timeframe was selected to cover the multiple years of the AEC/FM' industry digital transformation, as described in Section 1.2. The search included articles that were published until the end of 2025 to ensure all relevant publications for the current year were included.

Table 2
Inclusion criteria for the selection of articles.

Parameter	Criteria
Databases	Scopus, Web of Science
Search Logic	(Focus Area 1) AND (Focus Area 2) AND (Focus Area 3)
Focus Area 1 (BIM)	"Building information modeling" OR "BIM" "Operation and maintenance" OR "asset management" OR
Focus Area 2 (FM/ O&M)	"facility* management" OR "maintenance information management" OR "maintenance management*"
Focus Area 3 (SWTs)	"Semantic web technologies" OR "Ontology" OR "Linked data" OR "Knowledge Graph"
Time Frame	Published between 2019 and 2025
Language	Full text written in English
Document Type	Peer-reviewed journal articles
Primary Focus	Must apply SWTs with BIM in the O&M or construction FM phase
Content	Must present empirical results, a case study, or a validated framework (i.e., not purely theoretical papers)

In the identification stage, a comprehensive keyword string was defined match the scope and purpose of this study: {("Building information modeling" OR "BIM" OR "Building information modeling") AND ("operation* and maintenance" OR "asset management" OR "facilit* management" OR "maintenance information management" OR "maintenance management") AND ("Semantic web technolog*" OR "Ontolog*" OR "Linked data" OR "Knowledge Graph")}. In computer science, ontology is defined as "an explicit, formal specification of a shared conceptualization", which is the definition adopted for the present research [51]. The initial results were n1 = 45, and n2 = 42, which were N = n1 + n2 = 87 in total. This search was bounded by several key filters: the subject area was confined to engineering, the publication timeframe was set from 2019 to 2025, the language was restricted to English, and the document type was limited to peer-reviewed journal articles only. After applying these filters, the selection was narrowed down to n1 = 21, and n2 = 19, which were N = n1 + n2 = 40 in total. The limitation to journal articles was a deliberate methodological choice to ensure the findings are based on rigorous peer reviewed articles. This decision is consistent with established review guidance where methodological rigor and replicability are primary concerns [52,53]. Recent major reviews have also restricted their corpus to peer-reviewed journal articles [28,39,54,55].

The screening stage was conducted in two phases to identify the final dataset. In the first phase, automated methods were used to identify and remove duplicate records ($n = 07$), reducing the initial set to 33 articles. A detailed manual review of these 33 articles was then undertaken, with every title, abstract, introduction, and conclusion was read by the researchers. Articles were excluded based on specific criteria to minimize bias: (1) if the study was purely theoretical without a technical validation or case study, (2) if the primary focus was not on the O&M/FM phase, or (3) if the integration of SWTs was not the core methodology. Although this process followed predefined criteria, selection decisions may involve researcher judgement, and the possibility of bias cannot be entirely eliminated. In the second phase, to ensure comprehensive coverage, a backward snowballing technique was employed, following established guidelines [56]. The articles passing Phase 1 were scanned to identify relevant studies not captured by the keyword search. Each newly identified article was subjected to the exact same inclusion criteria as detailed in Table 2. This iterative process continued until no new relevant publication was found. The snowballing technique proved effective, identifying 8 additional relevant peer-reviewed journal articles, resulting in a final dataset of 41 articles.

The size of the final dataset reflects the deliberately narrow scope of the review, which targets the specific intersection of SWTs integration with BIM within the FM context. Findings should therefore be interpreted as a structured map of published research activity in this area rather than a definitive inventory of SWTs applications. This scope was considered appropriate given that the primary aim of the review is analytical depth rather than breadth.

3. Semantic web technologies in facility management

The analysis presented in this section is based on the corpus of 41 peer-reviewed articles published between 2019 and 2025. To address RQ1, the literature was manually classified into six FM themes and three SWTs applications. This categorization is crucial for understanding the interrelationships between different FM themes and semantic web usage. A comprehensive overview detailing each article's title, authors, corresponding FM themes and semantic web applications is provided in Appendix A.

To visualize the relationship, a Sankey diagram (Fig. 3) was constructed from the data in Appendix A. The diagram includes: (A) author (s) of the publication with the corresponding targets; (B) FM theme; and

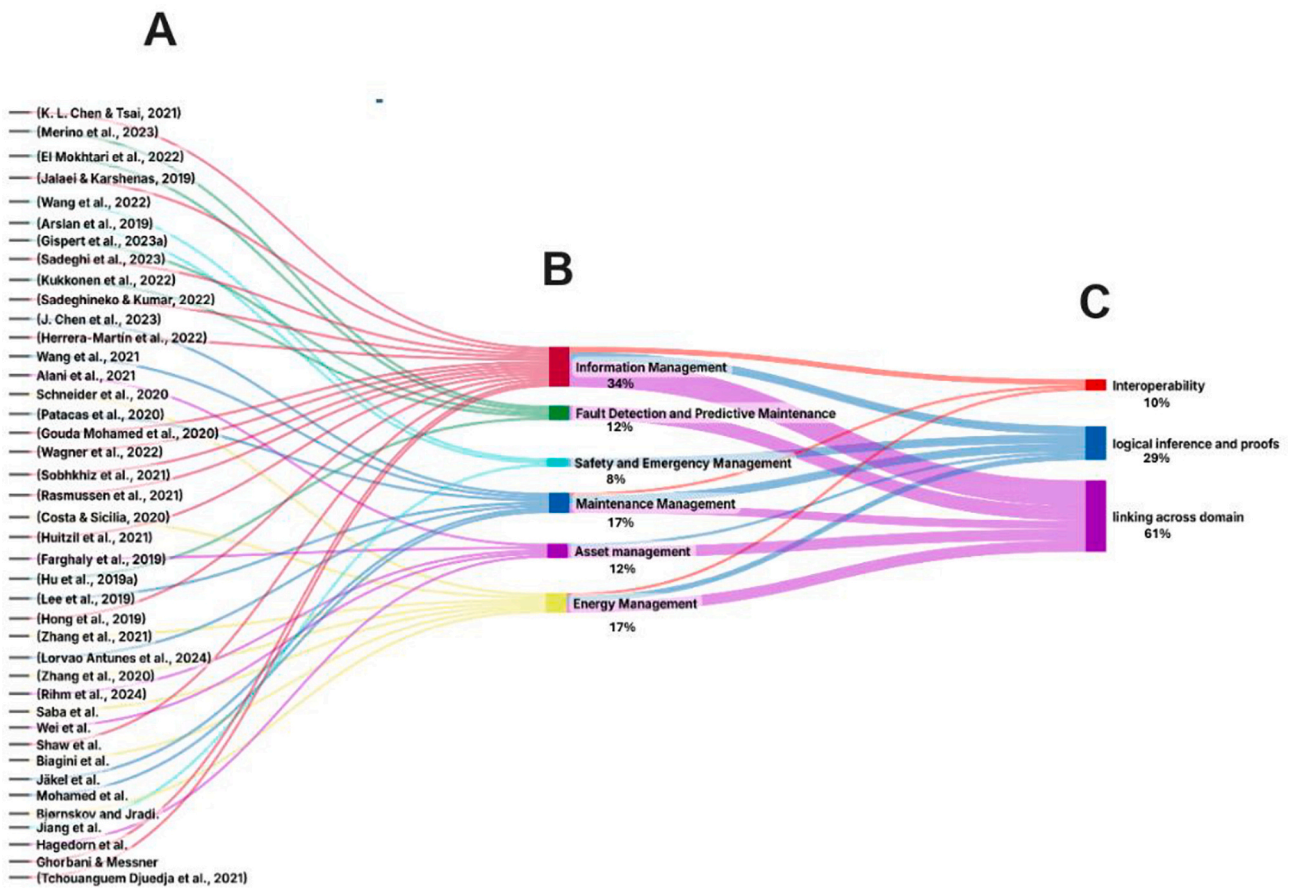

Fig. 3. Sankey analysis for literature, facility management theme, and semantic web technology applications.

(C) specific aim of the semantic web application. To enhance clarity, each FM theme and semantic web application is assigned a distinct color, and every link takes the color of the block it flows into, allowing a study to be traced by color from author to theme to application. This visualization fulfills four functions: (a) identifying specific literature by author; (b) organizing the literature into FM themes; (c) connecting these themes to SWTs applications; and (d) visualizing the relational flow. It is important to note that all links are applied on a one-to-one basis.

The following sections examines SWTs' research trends in FM. Section 3.1 presents an examination of the predominant FM themes through a temporal analysis. Section 3.2 provides an analysis of the SWTs implementation patterns across the corpus. Section 3.3 synthesizes these findings in a detailed cross-analysis directly addressing RQ1.

3.1. Analysis and discussion of facility management themes

In the AEC sector, FM encompasses a range of operational themes within the O&M phase. For this study, six themes were derived from the extant literature [6,57]: Information Management, Fault Detection and Predictive Maintenance, Safety and Emergency Management, Maintenance Management, Energy Management, and Asset Management. This classification was applied systematically to the 41 articles through a formal coding process, whereby each article was manually assigned to its primary FM theme. The operational definitions used for this coding are presented in Appendix B.

First, the most dominant theme identified is Information Management (34%), which represents the largest portion of the corpus. This finding is logical and consistent with the foundational premise of SWTs which are designed to structure and manage information from heterogenous sources [58,59]. The primary application of the semantic web remains focused on mitigating the core challenge of data interoperability and to establish knowledge repositories, as evidenced across multiple studies [60–62]. Second, Energy Management and Maintenance Management each account for 17%, reflecting significant scholarly attention to the tasks in day-to-day operations. Research in Energy Management has concentrated on optimizing building energy consumption through semantic frameworks [63,64], while Maintenance Management have focused on structuring maintenance data through dedicated ontology development [65,66].

Third, Asset Management and Fault Detection and Predictive Maintenance each represent 12% of the corpus. Both themes are defined by large volumes and variety of data, including environmental sensor readings, work orders, asset lifecycle records, making them well-suited to semantic enrichment in support of decision-making. Asset Management highlight the specific challenges associated with creating a unified view of facility components [67,68], while Fault Detection and Predictive Maintenance has applied semantic reasoning for the proactive identification of system failures. Finally, the least represented theme is Safety and Emergency Management (8%), which suggests that research remains concentrated on data-intensive operational tasks rather than safety-oriented applications.

To present a deeper thematic view, a temporal analysis of FM themes is presented in Fig. 4, which classifies the 41 research articles by publication year from 2019 to 2025. The total length of each horizontal bar represents the total number of publications for each theme, with each colored segment indicating the publication count for a specific year. Thus, Fig. 4 captures the evolving research priorities, highlighting both dominant and consistent trends.

Indeed, Information Management shows the most pronounced activity, with a notable peak in 2021 and continued through 2025, confirming its status as both the most studied and most currently active



Fig. 4. Temporal analysis.

research area within the scoped literature. This finding reflects its fundamental importance in FM, as information plays an essential role in operational efficiency. Maintenance Management and Asset Management demonstrate the most consistent publication records, with the former appearing in six of the seven years and the latter across five years. Energy Management was a strong focus back in 2020 and has shown lower-level interest since, while Fault Detection and Predictive Maintenance show clustered activity in 2019, 2022, and 2023, with no publications in recent years. Safety and Emergency Management is the least studied theme, with sporadic publications across the review period.

3.2. Analysis and discussion of semantic web applications

This section examines the distribution of SWTs applications using the three categories proposed by Pauwels et al. [19]: Interoperability, Linking Across Domains, and Logical Inference and Proofs. This classification facilitates the identification of research trends and elucidates how SWTs capabilities are deployed across the six FM themes.

Linking Across Domains emerges as the most prevalent application, accounting for 61% of the corpus. This prevalence is also consistent with the previous findings [19,28]. It indicates that the primary concern is to connect diverse data sources rather than exploiting advanced reasoning capabilities that SWTs offer. Researchers are actively building integrated systems by linking ontologies across different knowledge domains including BIM, Geographic Information System (GIS), and Building Management System (BMS) [69,70]. It also aligns with the foundational vision of linked data: breaking down information into silos and forming a web-like information structure.

Logical Inference and Proofs represents the second most prevalent application at 29%, reflecting a meaningful commitment to exploit the reasoning capabilities of semantic formalisms. It shows that research is moving towards the use of defined rules and axioms to derive implicit knowledge. This shift is actively putting the knowledge graph to support reasoning and automated decision support in FM. For example, fuzzy reasoning has been leveraged for instance retrieval under uncertainty [61].

Interoperability is the least represented application at 10% of the corpus. Such low percentage, may appear counterintuitive given that interoperability is widely considered as a primary motivation for adopting SWTs. However, this finding is consistent with a pattern noted by Pauwels et al. [19], whereby interoperability functions not as an end goal in itself but as a foundational prerequisite upon which higher-level linking and reasoning capabilities can be subsequently built. Accordingly, researchers tend to frame their contributions in terms of data linking functionality, with interoperability serving as an implicit prerequisite rather than an explicit research objective.

3.3. Analysis and discussion of facility management themes across semantic web applications

This section examines the relationship between the six FM themes and the three SWTs applications, as visualized in Fig. 5.

Building on the finding that Information Management is the dominant theme, the cross analysis confirms that its application is focused on Linking Across Domains (64.3%), with Logical Inference and proofs (21.4%) and Interoperability (14.3%) serving as secondary goals. It suggests that Information Management primarily functions to connect siloed data, with logical reasoning representing a less desired objective. A comparable preference for Linking Across domains is also observed in Energy Management (57.1%) and Fault Detection and Predictive Maintenance (100%), indicating that data integration remains their primary technical challenge. Asset Management exhibits a majority focus on Linking Across Domains (80%) followed by Logical Inference and Proofs (20%), with a complete absence of Interoperability. It points towards a two-stage methodology: first establishing semantic links across complex asset data sources and then applying logical reasoning to support asset lifecycle optimization.

Safety and Emergency Management is entirely dedicated to Logical Inference and Proofs (100%), strongly indicating that safety applications prioritize automated reasoning for decision-making. Complementarily, Maintenance Management shows a more balanced approach, with equal emphasis on Linking across domains (42.9%), Logical inference and proofs (42.9%), and a smaller focus on Interoperability (14.2%). This balance reflects the operational complexity of maintenance workflows, which require both the data integration and the application of rule-based reasoning for decision-making.

This cross-analysis provides a subtle answer to RQ1. First, the results demonstrate that the research is not uniform across FM themes: some themes prioritize Linking Across Domains, while others show a strong reliance on Logical Inference and Proofs. Second, Interoperability is treated as a prerequisite upon which that makes reasoning capabilities are built. This pattern suggests a growing maturity in the field, where researchers are focused on the semantically driven operational logic built upon a foundation of interoperability. The thematic distribution highlights the application areas of SWTs; however, the functional success depends on the technical architecture. Section 4 therefore shifts focus from what is being achieved to how these semantic frameworks are constructed, implemented and validated.

4. Frameworks of semantic web technologies in facility management

This section addresses the first part of RQ2 by investigating the

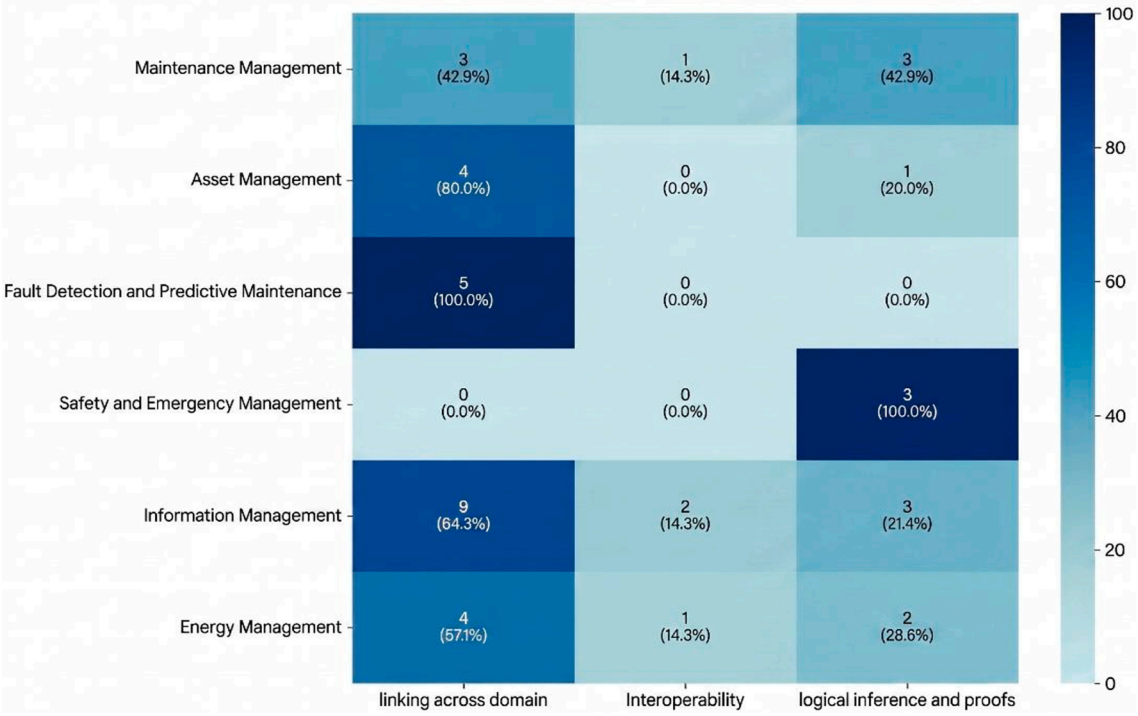

Fig. 5. Relationship analysis.

methods employed to implement SWTs in FM. The study identifies that these methods are fundamentally rooted in Knowledge Management paradigms, which are categorized into two key dimensions: Knowledge Representation and Knowledge Sharing [55]. Examining these dimensions clarifies the methodological approaches and reveals how researchers structure their semantic frameworks.

4.1. Knowledge representation

Knowledge representation involves constructing machine-interpretable structures to capture and organize information for solving complex problems [28]. In FM, ontologies serve as the primary mechanism for this purpose, as they formalize domain knowledge [4] and standardize vast amounts of knowledge-specific data. Two primary strategies for ontology-based knowledge representation are identified in the literature: (a) developing new ontologies for specific domains and (b) extending established schemas to incorporate emerging concepts.

Within the scoped literature, a consistent pattern is identified for developing semantic frameworks. Building on this pattern, the present study synthesizes a comparative workflow drawn from existing studies, organized into three key stages: (i) ontology development, (ii) information querying, and (iii) ontology validation. A summary of these approaches is presented in Appendix C, which details the developed ontology, querying methods, and validation techniques for each study. The subsequent sections provide an in-depth analysis of each stage.

(i) Ontology establishment

In the first stage of the framework, researchers have utilized ontologies to organize domain knowledge and establish semantic relationships between entities [71]. While several methods for establishing ontologies have existed since 1990s [72,73], NeON and Ontology Development 101 (OD101) remain the most prevalent among recent studies [74,75]. The standard approach used in knowledge representation research is to establish an ontology model first. Examples of few established ontologies, within the scoped literature, include the Tunnel Design Ontology for diagnosing tunnel defects [76], an ontology for determining firefighter rescue routes [77], the SIKB ontology for maintenance cost prediction [65], the LCAIM ontology for standardizing life cycle analysis [78], and the UOMO ontology for integrating lifecycle utility O&M data [79].

On the other side of the spectrum, some researchers have leveraged existing ontologies to achieve their objectives. For example, Sobhkhiz et al. [80] augmented BIMSO with their Material Ontology (MATO) to facilitate sustainable material selection and carbon footprint analysis. Ghorbani and Messner [81] extended BIM Use ontology to create their Digital Twin Use ontology. In other examples, Saba et al. [82] extended the OSEIM ontology to improve energy savings, and Bjørnskov and Jradi [83] extended SAREF4BLDG with data-driven models for energy simulation. These examples demonstrate how schema extension leveage established semantic frameworks to address evolving technical challenges.

This study observes a clear methodological split in knowledge representation:17 studies (41.46%) built their own ontology or ontology suite, while 9 studies (21.95%) extended an existing ontology. The finding highlights a strong preference for developing new ontologies rather than extending existing ones. Such a pattern is consistent with previous findings, where pragmatic or proof-of-concept schema definitions have been shown to simplify system development but reduce portability and reuse [39]. Critically, most of these new ontologies lack alignment with foundational standards such as BOT or SAREF, which limits the potential of knowledge reasoning. It creates a central tension because the long-term goal of building an interoperable semantic ecosystem is compromised by the immediate value of solving FM niche problems.

(ii) Information Querying

Once an ontology is constructed, inferencing new knowledge becomes the next step. Information Querying usually refers to the act of deducing or deriving implicit information from existing knowledge. This is one of the core capabilities of SWTs arising from their logical foundation [84]. By applying reasoning rules, it is possible to implement inference processes over the constructed knowledge base [19]. For

querying, a consistent reliance on SPARQL is observed which underscores its maturity for structured data retrieval [17]. SPARQL is frequently paired with a triple store like Apache Jena Fuseki [80] or Stardog graph database [66] to retrieve linked datasets. Then, these datasets drive external use cases such as calculating key performance indicators [85] or extracting parameters for Artificial Neural Network (ANN) models [65].

Beyond SPARQL, research incorporates advanced rule-based and graph-based inference methods. A notable subset of studies utilizes Semantic Web Rule Language (SWRL) to execute reasoning tasks such as evaluating building energy performance [86] or planning fire-rescue routes in long-term care facilities [77]. Moreover, the Jess rule engine has been employed to facilitate uncertainty-based risk reasoning in infrastructure management [68]. BPMN rule models have been integrated to formalize multi-stakeholder workflows and coordinate control sequences across building subsystems. For instance, integration has showed the synchronizing responses between fire alarm and smoke control subsystems within DTs environment [87].

(iii) Ontology Validation

Validation provides an essential feedback on the completeness and correctness of an established ontology. In recent studies, validation methods have matured significantly, moving beyond simple ontology integrity checks towards system-level validation. Three primary categories of ontology validation were identified across the corpus.

The first validation category is stakeholder-driven validation, which employs human-in-the-loop approach to confirm the correctness and practical utility of an ontology. Such human function in validation is commonly implemented through workshops with industry experts [68,77] or against a set of predefined competency questions [78,81]. The second validation category is simulation-based validation where the framework is tested against a real-world application. It involves applying ontology to a real building, such as a 12-storey residential building [80], a historic building from the Qing Dynasty [88], a tunnel project [76], or a pedestrian bridge [66]. In some cases, validation involves simulation engines, such as Fire Dynamics Simulator and Pathfinder [87] or EnergyPlus [83]. The third category is quantitative performance validation that uses statistical metrics to measure the impact. Examples include validating an ANN's predictive accuracy using R-squared values after training on ontology-structured data [65], measuring the percentage of energy saved in a smart home test-cell [82], or confirming the high accuracy of an automated classification system [62]. The study notes that the shift towards multi-faceted validation is a consequence of the field's evolution from standalone ontologies to integrated frameworks. As ontologies become the semantic backbone for simulations and DTs, the research community is responding with the robust, system-level validation required to prove practical viability.

4.2. Knowledge sharing

Knowledge sharing is the process of disseminating and exchanging knowledge [89], and represents a fundamental attribute of semantic web applications. In this study, a paper is classified under knowledge sharing, in which, the researchers integrate, federate, or map two or more ontologies to achieve a particular objective. Knowledge sharing is adopted by 15 studies (36.58%) to develop frameworks that combine the representational strengths of different schemas.

The most prominent strategy is multi-ontology federation, which is mostly used in the development of DTs. This approach is driven by the fundamental need to connect static asset data with dynamic real-time sensing data. A clear methodological consensus emerged which is centered on a stack of foundational modular ontologies. Merino et al. [90] developed a federated data model that acts as a semantic integration layer, combining ifcOWL, BrickSchema, and a custom BOT-based model. Similarly, El Mokhtari et al. [91] combined a Brick-based semantic model with BIM data to create a unified knowledge graph for a smart campus DTs. Likewise, Kukkonen et al. [86] adopted a multi-schema integration approach, creating a FSO ontology by extending SAREF4SYST, SAREF4BLDG, and BOT to model energy flows. This study finds a clear and repeatable strategy: ifcOWL or BOT were used to represent the static information of assets, while Brick or a SAREF modeled the IoT data to enable real-time applications for fault detection and operational monitoring. Another strategy involves repurposing an existing ontology for a new domain, demonstrating the flexibility of former semantic models. For example, Arslan et al. [92] adapted the DNAS ontology to model safety-related behaviors which was originally developed for energy-related occupant behavior.

Despite these advancements, a persistent gap remains between academic innovation and industrial-scale deployment. Although some recent studies have begun to validate frameworks for real-time performance [90,91]; they remain largely proof-of-concept implementations. The general absence of rigorous testing under high-volume data streams risks producing solutions that are academically interesting but not yet industrially or practically viable.

This analysis establishes that SWTs are primarily employed for knowledge management purposes. However, understanding knowledge representation and knowledge sharing alone provides an incomplete picture of how these technologies function in practice. A full understanding of framework development requires examination of how SWTs integrate with other technologies, which is the focus of Section 5.

5. Technology integration

This section addresses the second part of RQ2 by examining the technological integration of SWTs within FM. The technologies identified across the corpus are organized into four groups: Adaptive Digitalization Technologies, Data Infrastructure Technologies, Sensing Technologies, and Semantic Web Technologies, as presented in Table 3.

The Adaptive Digitalization Technologies group includes AI, Digital Twin, and Robotics. Data Infrastructure Technologies consist of BIM, Database Management and Cloud Computing. For this study, an article was classified under Database Management if its implementation explicitly relied on dedicated database systems such as GraphDB, MongoDB, or Neo4j, or involved the development of custom APIs as the primary mechanism for FM data storage, integration, or exchange. BIM is categorized within this group and specifically marked in studies where it functions as a digital repository rather than a modeling tool. The Sensing Technologies group encompasses IoT, Radio Frequency Identification (RFID), and Point Cloud. The Semantic Web Technologies group includes Knowledge Graphs, Linked Data, and Ontologies. These technologies are evaluated through a functional lens: ontologies serve as the formal se- mantic schema, Linked Data functions as the interconnection protocol for linking datasets, and Knowledge Graphs act as the operational instance layer. This functional distinction is important in the FM context where the boundary between schema definition, data linking, and operational deployment is often conflated in the literature [39]. The rationale for examining these four groups lies in the interdependent nature of their FM deployment. The integration of SWTs with other technologies is not incidental but reflects a broader pattern, where semantic technologies achieve their greatest value not in isolation but when combined with data acquisition, processing, and visualization tools [28].

Table 3 presents the adoption of each technology across the 41 articles, with each asterisk indicating the adoption of a technology within a specific study. The results confirm that Ontology, Database Management, BIM, and Linked Data are the most frequently adopted technologies, reflecting their foundational roles in constructing semantic FM architecture. By contrast, Robotics, RFID, and Point Cloud appear infrequently, indicating that physically deployed and sensing technologies remain at the margins of semantic FM.

To explore the co-occurrence relationships between these

Table 3
Different identified technologies in reviewed literature.

Authors	Adaptive Digitalization Technologies			Data Infrastructure Technologies			Sensing Technologies			Semantic Web Technologies		
	AI	Digital Twin	Robotics	BIM	Database Management	Cloud Computing	IOT	RFID	Point Cloud	Ontology	Linked Data	Knowledge Graph
(K. L. Chen & Tsai, 2021)				*	*	*	*			*	*	*
(Merino et al., 2023)	*	*		*	*	*	*			*		*
(El Mokhtari et al., 2022)	*	*		*	*	*	*			*	*	*
(Wang et al., 2022)	*			*	*					*	*	
(Gispert et al., 2023a)	*	*		*			*			*		
(Kukkonen et al., 2022)	*			*						*	*	*
(Sadeghi et al., 2023)				*							*	
(J. Chen et al., 2023)	*		*	*	*		*			*	*	*
(Sadeghineko & Kumar, 2022)				*					*	*	*	*
(Herrera-Martín et al., 2022)				*	*					*	*	*
(Patacas et al., 2020)				*	*	*				*	*	*
(Gouda Mohamed et al., 2020)				*					*	*	*	
(Wagner et al., 2022)					*	*				*	*	
(Sobhkhiz et al., 2021)				*	*				*			
(Rasmussen et al., 2021)				*	*	*	*			*	*	*
(Costa & Sicilia, 2020)				*	*					*	*	*
(Huitzil et al., 2021)					*					*	*	
(Tchouanguem Djuedja et al., 2021)					*					*	*	*
(Zhang et al., 2021)				*	*		*			*	*	*
(Zhang et al., 2020)	*			*	*	*	*			*		
(Lorvao Antunes et al., 2024)				*	*		*			*		*
(Rihm et al., 2024)				*	*		*	*		*		
(Jalaei & Karshenas, 2019)				*	*					*	*	
(Arslan et al., 2019)	*				*		*			*	*	*
(Farghaly et al., 2019)				*	*						*	
(Lee et al., 2019)	*			*	*					*		*
(Hong et al., 2019)				*	*					*		
(Hu et al., 2019a)	*			*	*	*	*			*		
Wang et al., 2021										*	*	*
Alani et al., 2021					*					*		
Schneider et al., 2020	*				*		*			*	*	*
Saba et al.										*		
Wei et al.					*					*		
Shaw et al.				*	*					*		*
Biagini et al.		*		*	*	*	*		*	*		
Jäkel et al.				*	*	*				*	*	*
Mohamed et al.	*				*					*		*
Jiang et al.	*	*		*	*		*			*	*	*
Bjørnskov and Jradi.	*	*			*					*		
Hagedorn et al.				*	*	*				*	*	*
Ghorbani & Messner	*	*		*	*		*			*		
Total	15	7	1	30	34	11	16	1	4	38	24	22

technologies, a chord diagram is constructed and visualized in Fig. 6. In this diagram, each technology is represented as a segment on the outer ring, with its size proportional to its total co-occurrence count. A chord connecting two segments indicates that both technologies are adopted within the same study. Fig. 6 reveals that Ontology (113), Database Management (70), Knowledge Graph (67), Linked Data (64), BIM (62), and IoT (34) form a densely interconnected cluster. It confirms that semantic FM architecture are consistently built around the combination of these technologies. Alternatively, IoT (34) functions as the primary bridge between semantic core and the physical built environment, reflecting an increasing focus on real-time data integration. Robotics (3), RFID (1), and Point Cloud (6) occupy the periphery of the diagram with minimal chord connections. Thus, their integration with SWTs remains isolated and specialized rather than systematic. Such observation is consistent with previous findings, in which the most widely integrated technologies are those operating at the data modeling and integration layer, while physically deployed technologies have remained peripheral to mainstream semantic FM research [28].

5.1. Technological categorization analysis and discussion

This section discusses the four technology groups in detail. Section 5.1.1 examines Adaptive Digitalization Technologies, focusing on the roles of AI and Digital Twin. Section 5.1.2 presents Data Infrastructure Technologies and the trade-off between semantic flexibility and query performance. Section 5.1.3 analyzes Sensing Technologies, with particular attention to IoT data pipelines. Finally, Section 5.1.4 examines the design philosophies adopted for SWTs.

5.1.1. Adaptive digitalization technologies

AI emerges as the most frequently adopted technology followed by Digital Twin. It is crucial to note that the AI use is not monolithic but represents a wide spectrum of techniques, from top-down symbolic reasoning to bottom-up data-driven deep learning. Its widespread adoption can be attributed to its role in enabling autonomous decision-making and predictive analytics. The most common use case identified is pattern recognition with deep learning. To illustrate, El Mokhtari et al.

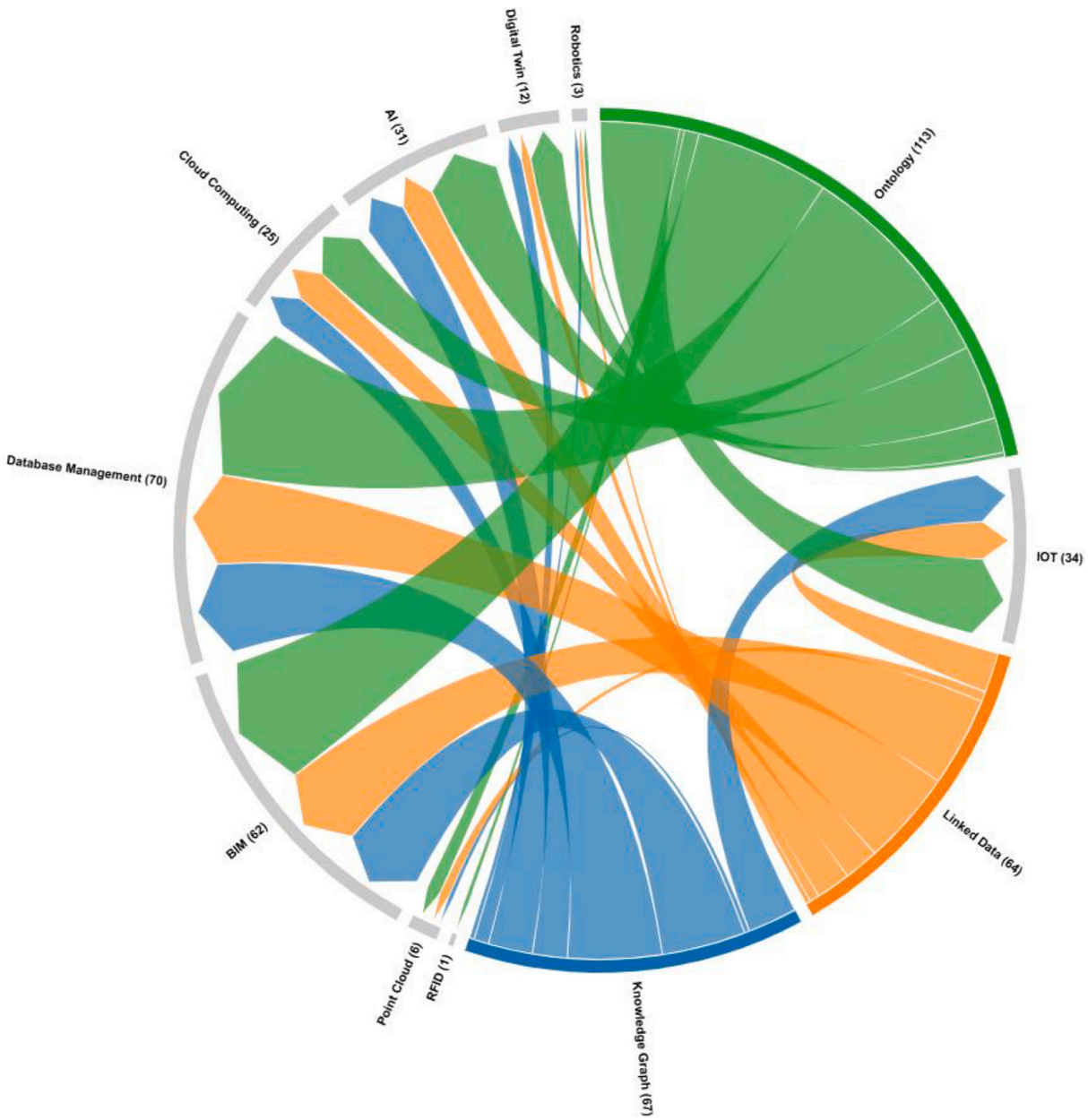

Fig. 6. Relationship analysis of technologies.

[91] applied CNNs, and LSTMs, for fault detection and predictive maintenance. They particularly deployed a CNN-based NLP to read and classify text-based work orders (e. g., Thermal or Acoustic complaints). Mohamed et al. [65] introduced a knowledge-based ANN (SIKB-ANN) framework to predict maintenance costs. In addition, Jiang et al. [87] applied an object detection model to count occupancy during fire emergencies. These approaches are further complemented with probabilistic models. For example, Arslan et al. [92] adopted a hybrid AI approach, using a semantic model (STriDE) to enrich trajectory data, and then feeding that data into a Hidden Markov Model (HMM) to classify occupant movement.

Digital Twin follows as the second most adopted technology, and its integration with SWTs exhibits a consistent architectural pattern. Merino et al. [90] structured their twin around federated data models aligning IFC, BrickSchema, and BOT, allowing the twin to reach siloed subsystem data without displacing ownership. Similarly, El Mokhtari et al. [91] organized their Cognitive Digital Twin around memory, perception, and reasoning, building its data model on the same BOT and Brick foundations and streaming BACnet data from the building automation system into a cloud environment. Neither twin, however, runs on ontologies directly; both hold their semantic models in conventional document or relational databases and keep time-series data in separate stores. SWTs therefore act within these architectures as an alignment schema across BIM, BAS, and IoT sources.

Robotics is the least represented technology, appearing in only one study. Its limited adoption is consistent within the FM literature, and suggests a divergence between current information-centric research and the physical requirements of autonomous navigation and work [39]. The study by Chen et al. [4] represents an exception, combining BIM, robotics, and AI within the iSTA framewor in support for inspection. The status of robotics suggests that while the prerequisites for robotics use cases are being established through ontologies and knowledge graph development, the physical deployment layer remains largely unaddressed.

5.1.2. Data infrastructure technologies

Database Management stands out as the most prevalent data infrastructure technology. There is a clear convergence between Database Management and SWTs, resulting in the creation of semantic databases. These enriched databases prove pivotal for data-intensive tasks in FM by enabling access to interconnected knowledge. It further supports real-time monitoring by providing actionable insights for efficient maintenance, energy management, and decision-making across buildings and facilities.

The widespread adoption of BIM confirms its importance as a digital repository in FM. Its applications have expanded through the integration of SWTs, with a development of ifcOWL ontology that provides the technical bridge for translating BIM data into a web-native format. Merino et al. [90] formalized BIM data by using ontologies to standardize building components, spatial relationships, and IoT sensing metadata. This integration streamlines data handling processes and enables automation within FM systems. Jiang et al. [87] utilized the IfcOpenShell library to extract static geometric and semantic information directly from IFC files to construct a data model. Additionally, Cloud Computing is used to provide the scalability required for DTs and BIM deployments.

It is crucial to note that there is a fundamental technological trade-off between semantic flexibility and query performance. El Mokhtari et al. [91] implemented a hybrid database model on Amazon Web Services (AWS), mapping their ontology into a relational database to optimize query speed. Zhang et al. [69] prioritized scalability through a pure NoSQL (HBase) architecture, which is supplemented by a novel meta-programming workflow that automatically generated the database schema and RESTful APIs from a central XML definition. These divergent strategies illustrate that there is no consensus in architectural design for semantic FM data management because the backend choice is determined by the specific performance, scalability, and interoperability requirements within each context.

5.1.3. Sensing technologies

IoT is an extensively explored sensing technology, highlighting its pivotal role in connecting physical devices that can enable smart built environments. However, a key challenge was identified: linking sensor data to a changing building context. Arslan et al. [92] addressed this directly through their STriDE model that used Timeslices to historicize changes to a building's geometry. The approach allowed to map occupant trajectories from BLE beacons to the corresponding historical version of the building's layout for behavior analysis. Rihm et al. [93] developed a BIM-integrated system for managing laboratory equipment and chemical storage facilities, leveraging IoT sensors, QR codes, and a mobile application. Beyond applications, the architectural design of the data pipeline emerges as a critical component of IoT integration. A secure two-stage gateway architecture for transferring data from a private BACnet network to the AWS cloud has been implemented to support cognitive DTs development [91]. Also, sensor-to-BIM integration workflows have been demonstrated using DHT22 environmental sensors connected via Node-Red to an open-source data management platform, and LoRaWAN devices transmitting via BACnet to a building management platform [94]. Across both cases, the gateway layer functions served as the primary data normalization mechanism and security enforcement.

Point Cloud appeared as the second most common sensing technology, followed by RFID which appeared in only one study. Although less prevalent, these technologies support specialized applications. For instance, Sadeghineko & Kumar [23] convert point cloud data into 3D BIM models with the help of SWTs to facilitate data verification of maintenance records. The limited adoption of both RFID and Point Cloud indicates that their utility is context-dependent, whereas the prominence of IoT reflects broader trends in the digitization of infrastructure and operational processes.

5.1.4. Semantic web technologies

Ontology is the most adopted technology followed by Linked Data. As detailed in Section 4, SWTs function as the fundamental layer for knowledge representation and sharing. Within the context of technological integration, they serve as the essential semantic backbone that provides standardized data structures.

Ontology adoption spans over a spectrum of competing design philosophies, each with distinct architectural trade-offs. One approach relies on monolithic schemas such as ifcOWL. Hu et al. [76] and Chen et al. [4] adopted this approach to provide an exhaustive semantic foundation for diagnostics. However, such an approach has often been criticized for its inherent difficulties of translating the EXPRESS schema into OWL/RDF, limiting its practical applicability for FM.

In response to these limitations, a shift towards modular Linked Data approaches was observed, in which domain-specific datasets are converted to RDF and linked to BIM rather than encoded within a single comprehensive schema. For instance, Tchouanguem et al. [95] applied linked data principles by converting environmental lifecycle data into RDF graphs and integrating them with BIM software. Gouda et al. [96] mapped COBie spreadsheet data into an OWL-based ontology and integrated it with BIM models, enabling querying to improve building maintenance. A COBie-to-RDF mapping was a key step to create a semantically enriched data repository.

Knowledge graphs have also been employed to integrate instance-level asset and operational data in FM. Jäkel et al. [66], for example, linked digital 3D models of existing bridge structures with a knowledge graph based on an ontology of non-destructive diagnostic methods, using RDF-based data integrating to connect asset data. Such technical advances, however, do not resolve the broader challenges of information management. Practitioner evidence from interviews with facility and data managers suggests that organizational and systemic factors can remain significant barriers to effective information management.

The technological landscape demonstrates a high degree of maturity in the use of SWTs. However, the current integration of SWTs remains largely structural rather than operational. While individual technologies like IoT and AI have been successfully linked to semantic backbones, their collective implementation reveals systemic bottlenecks that hinder the realization of a smart built environments. The following section deconstructs these limitations, identifying scalability, architectural, and standardization gaps.

6. Research gaps and future directions

This section presents critical knowledge gaps and corresponding research directions to guide future studies. It is clear from the reviewed literature that the FM domain can, and in some cases already does benefit from the interoperability and automation that SWTs enable. Yet, realizing its potential requires targeted resolution of the gaps. Addressing such gaps is therefore not merely an academic exercise but a prerequisite for fulfilling the digital transformation goals of Industry 4.0. The rest of this section discusses the research gaps in detail.

6.1. Methodological gaps

FM teams mostly rely on outdated and manual processes for entering and collecting data [91,97] which lead towards inefficiencies and error-prone processes [98]. These shortcomings are compounded by knowledge engineering bottleneck [79], whereby reasoning rules and domain knowledge must be retrieved from historical cases [76] and expert interviews [66,87]. The associated data collection processes are both time-consuming, slow and inefficient. Similarly, mapping datasets, with individual link to connect disparate databases, is another human-dependent process. In the context of user-centered aspects, the current literature does not disclose how FM professionals interact with semantic tools, how they evaluate the trustworthiness of inferred recommendations, and how organizations manage the transition to semantically

enriched and digital workflows. Moreover, existing FM ontologies are manually developed which makes them difficult to scale across multi-asset building portfolios. This methodological deficit is further intensified by a critical shortage of real-world validation. As seen in recent studies [83,87], many frameworks are evaluated only against simulated environments, limiting confidence in their operational reliability.

A promising immediate future direction for addressing knowledge engineering bottleneck is to explore the integration of Natural Language Processing (NLP) to automate the extraction of semantic entities and relationships from unstructured FM sources such as maintenance work orders, safety standards, and regulatory documents. A particular focus within this direction is to explore applications of Large Language Models (LLMs), which offer potential for semantic annotation. As evident in the literature, Boscariol et al. [99] constructed knowledge graphs using LLMs through zero-shot learning, while Jiang et al. [31] show that LLMs can extract structured reasoning rules with limited human intervention. Similarly, Emonet et al. [100] further position LLMs as semantic translators between heterogeneous data formats. These studies demonstrate that LLMs are capable of automating knowledge engineering pipeline that currently rely on manual intervention. Emerging AI paradigms including meta-learning, few-shot learning, and transfer learning should be explored for future studies for automating ontology generation and improving the corresponding accuracy. Another opportunity falls in the real-world deployment of semantic FM frameworks that should be evaluated against operational criteria including the reliability of inferred recommendations, and the capacity to adapt to evolving asset data.

6.2. System design gaps

During semantic FM system development, design choices determine whether acquired knowledge can be shared, extended, and reused across operational contexts. Insights from the review reveal design failures that collectively undermine the interoperability. The goal of interoperability is compromised when new ontologies are constructred. Even, ontology dissemination is limited within the research community, restricting collaboration, and impeding broader adoption. Moreover, there are no comparative benchmarking to guide practitioners towards informed architectural choices for adopting SWTs.

Another design gap concerns the choice of reasoning, which is rarely made explicit as a design decision even though it determines what a system can validate. OWL adopts the open-world assumption, under which an unstated fact is unknown rather than false, so completeness can be asserted only through explicit closure axioms. By contrast, the closed world assumption treats an absent fact as false, which is what completeness checking requires. The practical effect of open-world assumption is also reported by Alani et al. [101], who find open-world assumption as unrealistic for the strict data validation required by the AEC industry. Architectures that admit closed-world validation alongside open-world inference address the problem, yet the trade-off is seldom stated during system design. A further design gap concerns specification: no standardized language exists for defining and communicating DTs use cases in FM.

Another constraint is that large BIM models generate RDF graphs exceeding the processing capacity of reasoning engines. Although partitioning the graph restores tractability, but increases the aggregate cost of inference and risks losing entailments that span partition boundaries. Besides, the high latency in ontology resolution is identified as a barrier against DTs applications. Another concern pertains to data conversion integrity. The transformation of operational data formats into the IFC schema is documented across the literature [66,94]. However, in practice, it results in information loss or semantic errors, undermining the reliability of downstream reasoning and querying.

Future research should prioritize modular ontology development alongside the establishment of the shared foundational layer. The research community would benefit from publicly available benchmark datasets of integrated graphs at building and portfolio scale. The availability of shared evaluation metrics including query latency and ontology coverage, and community-developed references would further promote SWTs for FM use cases. Another research thread should point towards developing hybrid reasoning architectures that can accommodate both open and closed world assumption within a single semantic FM framework.

6.3. Operational gaps

There is an absence of bidirectional, closed-loop semantic architectures which limits physical actions through semantic reasoning. This limitation perpetuates reactive decision-making rather than proactive predictive analytics. Across the corpus, semantic architectures are read-only: reasoning outputs inform decisions but are rarely return to the systems that operate the building. Another concern is the adequacy of existing ontological vocabularies for FM operations. Most reviewed ontologies are lacking the specialized vocabulary required to represent O&M concepts, including maintenance procedures, work orders, service contracts, and inspection protocols. Another gap exists at the intersection of semantic technology and end-user practice. The literature repeatedly identifies it as a high implementation barrier because of complex interfaces and text-only query systems [61].

Future research should target closed-loop frameworks where reasoning outputs should be returned to the systems that operate the building, such as building management and work-order systems. Further, researchers should transition from rule-based to predictive reasoning through neuro-symbolic architectures, in this way, they can address the explainability issues in deep learning algorithms. Another possible direction for future research is to focus on simplifying interfaces via Augmented Reality/ Virtual Reality (AR/VR) and development of user-friendly tools. Also, since Retrieval Augmented Generation (RAG) is utilized to reduce hallucination of LLMs, researchers should target the implementation of Graph-RAG systems for FM data retrieval which can be particularly beneficial in asset-heavy operational contexts where data volume, heterogeneity, and continuous evolution present the greatest challenges.

7. Conclusion

In response to the systematic challenges of information fragmentation within the FM sector, this paper presented a SLR of 41 articles to analyze the evolutionary trajectory of SWTs integrated with BIM in FM. The scope of the study includes consideration of FM themes, methodological frameworks, technological integrations, and research gaps and future research needs. Three RQs were formulated to structure this study, and the search terms were chosen to answer these questions.

The analysis demonstrates a predominant focus on the Information Management theme, which accounted for the largest share of the investigated corpus. The least adopted theme Safety and Emergency Management, signaling an opportunity into safety-critical operational research. Quantitatively, the field prioritizes Linking Across Domains (61%), followed by Logical Inference and Proofs (29%) and Interoperability (10%). This distribution indicates that the research community has moved beyond basic data exchange, focusing instead on multi-domain integration.

Insights from the current review distill three distinct stages in knowledge representation: ontology development, information query, and ontology validation. A critical methodological divergence regarding ontology development is also observed: while 41.46% of studies developed novel, domain-specific ontologies, only 21.95% extended existing schemas. This trend exposes a negative risk of generating semantic silos, which paradoxically undermines the core objective of interoperability. Regarding technological integration, the study found that Ontology, BIM, Data Management, and Linked Data form the primary technological stack, frequently augmented by AI and DTs to facilitate complex operational tasks.

Based on these findings, the study highlights opportunities for future research. There is a pressing need for standardized guidelines for SWTs implementation and hybrid AI models that can enable the transition from reactive rule-based systems to predictive reasoning. Additionally, the reviewed corpus contained no discussions on LLMs, data privacy, or security. Furthermore, several papers highlighted concerns regarding computational scalability, ontology architecture, and the manual bottleneck of knowledge engineering. Such shortcomings indicated s a need for automated knowledge acquisition using LLMs. The scarcity of research on bidirectional read-write data flows remains a significant barrier to achieving fully autonomous, self-optimizing building and.

Finally, the study acknowledges limitations inherent to the adopted SLR methodology. Its conclusions are constrained by the quality and scope of the 41 articles analyzed, thus with potential biases influencing the findings in this paper. The literature was limited to journal articles and the inclusion of conference papers was beyond the scope of this study and thus some emerging concepts may have been missed. Nevertheless, by recognizing these boundaries, this systematic review provides a robust and authoritative foundation for researchers and industry professionals seeking to navigate the contemporary landscape of SWTs and BIM within FM.

CRediT authorship contribution statement

Rafay Ali Bukhari Syed: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Marco D'Orazio:** Writing – review & editing, Validation, Supervision. **Muhammad Jamaluddin Thaheem:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **David Grau:** Writing – review & editing, Supervision, Methodology. **Luigi Mollo:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used different LLMs to check language and improve readability. The authors reviewed and edited all of the content and take full responsibility for it.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.autcon.2026.107265.

Data availability

The data will be made available on request.

References

[1] J. Bröchner, T. Haugen, C. Lindkvist, Shaping tomorrow's facilities management, Facilities 37 (7/8) (2019) 366–380, https://doi.org/10.1108/F-10-2018-0126.
[2] What is Facility Management? Benefits & Use Cases, IFMA, 2026. Accessed: Apr. 30, 2026. [Online]. Available, https://www.ifma.org/about/what-is-fm/.
[3] L. Pinti, S. Bonelli, A. Brizzolari, C. Mirarchi, M.C. Dejaco, A. Kiviniemi, Integrated information management for the fm: Building information modelling and database integration for the italian public administration, in: eWork and eBusiness in Architecture, Engineering and Construction - Proceedings of the 12th European Conference on Product and Process Modelling, ECPPM 2018, 2018, pp. 21–28, https://doi.org/10.1201/9780429506215-3.
[4] J. Chen, W. Lu, Y. Fu, Z. Dong, Automated facility inspection using robotics and BIM: a knowledge-driven approach, Adv. Eng. Inform. 55 (2023) 101838, https://doi.org/10.1016/J.AEI.2022.101838.
[5] M.K. Dixit, V. Venkatraj, M. Ostadalimakhmalbaf, F. Pariafsai, S. Lavy, Integration of facility management and building information modeling (BIM), Facilities 37 (7/8) (2019) 455–483, https://doi.org/10.1108/F-03-2018-0043.
[6] S.T. Matarneh, M. Danso-Amoako, S. Al-Bizri, M. Gaterell, R. Matarneh, Building information modeling for facilities management: a literature review and future research directions, J. Build. Eng. (2019), https://doi.org/10.1016/j.jobe.2019.100755.
[7] Data Advantage in Construction, Accessed: Apr. 24, 2026 [Online]. Available, https://construction.autodesk.com/resources/guides/harnessing-data-advantage-in-construction/, 2026.
[8] T. Ritter, S. Clarke, Optimizing Building Management with a Lifecycle Approach, IFMA IT Community and Autodesk, 2024. https://knowledgelibrary.ifma.org/optimizing-building-management-with-a-lifecycle-approach/ (accessed 30 August 2026).
[9] J. Snyder, A. Menard, N. Spare, Big Data = Big Questions for the Engineering and Construction Industry, Accessed: Apr. 24, 2026. [Online]. Available, https://groundbreakcarolinas.com/fmi-releases-whitepaper-big-data-big-questions-for-the-engineering-and-construction-ec-industry/, 2018.
[10] M. Ensafi, W. Thabet, Challenges and Gaps in Facility Maintenance Practices. EPiC Series in Built Environment, 2021, pp. 237–245, https://doi.org/10.29007/1h2j.
[11] Why Wrench Time Can Be A Terrible Metric | Plant Services, Accessed: Apr 24, 2026. [Online]. Available, https://www.plantservices.com/planned-maintenance/planning-and-scheduling/article/11288255/why-wrench-time-can-be-a-terrible-metric, 2026.
[12] M.P. Gallaher, A.C. O'Connor, J.L. Dettbarn, L.T. Gilday, Cost Analysis of Inadequate Interoperability in the U.S. Capital Facilities Industry, 2004, https://doi.org/10.6028/NIST.GCR.04-867.
[13] E. Kamel, A.M. Memari, Review of BIM'S application in energy simulation: tools, issues, and solutions, Autom. Constr. 97 (2019) 164–180, https://doi.org/10.1016/J.AUTCON.2018.11.008.
[14] R. Barbosa Otranto, G. Miceli Junior, P. Cesar Pellanda, BIM-FM integration through openBIM: solutions for interoperability towards efficient operations, J. Inform. Technol. Construct. 30 (2025) 299, https://doi.org/10.36680/j.itcon.2025.012.
[15] P.A. Bonatti, S. Decker, A. Polleres, V. Presutti, Knowledge graphs: new directions for knowledge representation on the semantic web (Dagstuhl seminar 18371), Dagstuhl Rep. 8 (9) (2019) 29–111, https://doi.org/10.4230/DAGREP.8.9.29.
[16] B. Abu-Salih, Domain-specific knowledge graphs: a survey, J. Netw. Comput. Appl. 185 (2021) 103076, https://doi.org/10.1016/J.JNCA.2021.103076.
[17] P. Hitzler, A review of the semantic web field, Commun. ACM 64 (2) (2021) 76–83, https://doi.org/10.1145/3397512.
[18] S. Patel, S. Debnath (Eds.), Semantic Technologies for Intelligent Industry 4.0 Applications, 1st ed, River Publishers, 2022 vol. ISBN: 978-87-7022-782-7.
[19] P. Pauwels, S. Zhang, Y.C. Lee, Semantic web technologies in AEC industry: a literature overview, Autom. Constr. 73 (2017) 145–165, https://doi.org/10.1016/J.AUTCON.2016.10.003.
[20] M.H. Rasmussen, M. Lefrançois, G.F. Schneider, P. Pauwels, BOT: the building topology ontology of the W3C linked building data group, Semantic Web 12 (2020) 143–161, https://doi.org/10.3233/SW-200385.
[21] L. Chamari, E. Petrova, P. Pauwels, A web-based approach to BMS, BIM and IoT integration: a case study, in: Proceedings of CLIMA 2022, the 14th REHVA HVAC World Congress, TU Delft Open, 2022, https://doi.org/10.34641/clima.2022.228.
[22] C. Shaw, F. de Andrade Pereira, C. Hoare, K. Hammar, C. McNally, J. O'Donnell, Digital interoperability for the facilities management domain: a review of semantic web-based approaches, in: Proceedings of the CIB W78 Conference 2021, Luxembourg, 11–15 October, 2021.
[23] F. Sadeghineko, B. Kumar, Application of semantic web ontologies for the improvement of information exchange in existing buildings, Constr. Innov. 22 (3) (2022) 444–464, https://doi.org/10.1108/CI-03-2021-0058.
[24] J. Dao, S.T. Ng, Y. Yang, S. Zhou, F.J. Xu, M. Skitmore, Semantic framework for interdependent infrastructure resilience decision support, Autom. Constr. 130 (2021) 103852, https://doi.org/10.1016/J.AUTCON.2021.103852.
[25] A. Khudhair, H. Li, T. Bower, G. Ren, A theoretical holistic decision-making framework supporting collaborative design based on common data analysis (CDA) method, J. Build. Eng. 46 (2022) 103686, https://doi.org/10.1016/J.JOBE.2021.103686.
[26] H. Deng, Y. Xu, Y. Deng, J. Lin, Transforming knowledge management in the construction industry through information and communications technology: a 15-year review, Autom. Constr. (2022), https://doi.org/10.1016/j.autcon.2022.104530.
[27] K. Farghaly, R.K. Soman, S.A. Zhou, The evolution of ontology in AEC: a two-decade synthesis, application domains, and future directions, J. Ind. Inf. Integr. (2023), https://doi.org/10.1016/j.jii.2023.100519.

[28] X. han Shen, S.M.E. Sepasgozar, M.J. Ostwald, Knowledge-based semantic web technologies in the AEC sector, Autom. Constr. (2024), https://doi.org/10.1016/j.autcon.2024.105686.

[29] R.A.B. Syed, R. Agliata, I. Mecca, L. Mollo, Semantic web technologies in construction facility management: a bibliometric analysis and future directions, Buildings *15* (21) (2025) 3845, https://doi.org/10.3390/BUILDINGS15213845.

[30] F.M. Dinis, J. Poças Martins, A.S. Guimarães, B. Rangel, BIM and semantic enrichment methods and applications: a review of recent developments, Arch. Comput. Methods Eng. (2022), https://doi.org/10.1007/s11831-021-09595-6.

[31] S. Jiang, X. Feng, B. Zhang, J. Shi, Semantic enrichment for BIM: enabling technologies and applications, Adv. Eng. Inform. (2023), https://doi.org/10.1016/j.aei.2023.101961.

[32] F. Lygerakis, N. Kampelis, D. Kolokotsa, Knowledge graphs' ontologies and applications for energy efficiency in buildings: a review, Energies (2022), https://doi.org/10.3390/en15207520.

[33] S. Pandithawatta, S. Ahn, R. Rameezdeen, C.W.K. Chow, N. Gorjian, Systematic literature review on knowledge-driven approaches for construction safety analysis and accident prevention, Buildings 14 (11) (*2024*), https://doi.org/10.3390/BUILDINGS14113403.

[34] A. Donkers, D. Yang, B. de Vries, N. Baken, Semantic web technologies for indoor environmental quality: a review and ontology design, Buildings 12 (10) (2022), https://doi.org/10.3390/buildings12101522.

[35] S. Gilani, C. Quinn, J.J. McArthur, A Review of Ontologies Within the Domain of Smart and Ongoing Commissioning, Elsevier Ltd, 2020, https://doi.org/10.1016/j.buildenv.2020.107099.

[36] B. M. Mohaisen and S. S. Abu-Naser, "Expert System Design and Implementation for Medical Diagnostic Applications", doi:10.13140/RG.2.2.12034.95688.

[37] T. Berners-Lee, J. Hendler, O. Lassila, The semantic web, Sci. Am. 284 (5) (2001) 34–43, https://doi.org/10.1038/scientificamerican0501-34.

[38] G. Panzarella, P. Veltri, S. Alcaro, Using ontologies for life science text-based resource organization, Artif. Intell. Life Sci. 3 (2023) 100059, https://doi.org/10.1016/j.ailsci.2023.100059.

[39] E.N. Bringas, Leveraging knowledge graphs in facilities management: a scoping review, J. Build. Des. Environ. (2024), https://doi.org/10.70401/jbde.2026.0033.

[40] H. Schevers, J. Mitchell, P. Akhurst, D. Marchant, S. Bull, K. McDonald, et al., Towards digital facility modelling for Sydney opera house using IFC and semantic web technology, J. Inform. Technol. Construct. 12 (2007) 347–362. https://www.itcon.org/2007/24.

[41] ifcOWL - buildingSMART Technical, Accessed: Mar. 15, 2025. [Online]. Available, https://technical.buildingsmart.org/standards/ifc/ifc-formats/ifcowl/, 2025.

[42] Introduction | Brick Ontology, Accessed: Oct. 16, 2025, https://brickschema.org/, 2025.

[43] R. García-Castro, M. Lefrançois, M. Poveda-Villalón, L. Daniele, The ETSI SAREF ontology for smart applications: a long path of development and evolution, Energy Smart Appl. Appl. Methodol. Challeng. (2023) 183–215, https://doi.org/10.1002/9781119899457.CH7.

[44] A. Haller, K. Janowicz, S.J.D. Cox, M. Lefrançois, K. Taylor, D. Le Phuoc, et al., The modular SSN ontology: a joint W3C and OGC standard specifying the semantics of sensors, observations, sampling, and actuation, Semant. Web 10 (2019) 9–32, https://doi.org/10.3233/sw-180320.

[45] Home – Project Haystack, Accessed: Nov. 16, 2025 [Online]. Available, https://www.project-haystack.org/, 2025.

[46] K. Hammar, E.O. Wallin, P. Karlberg, D. Hälleberg, "The RealEstateCore Ontology," Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11779 LNCS, 2019, pp. 130–145, https://doi.org/10.1007/978-3-030-30796-7_9.

[47] Construction to Operations Building Information Exchange (COBie) V3 – National Institute of building sciences, Accessed: Nov. 16, 2025 [Online]. Available, https://nibs.org/nbims/v3/cobie/, 2025.

[48] M.J. Page, D. Moher, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, et al., PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews, BMJ 372 (2021), https://doi.org/10.1136/BMJ.N160.

[49] P. Mongeon, A. Paul-Hus, The journal coverage of web of science and Scopus: a comparative analysis, Scientometrics 106 (1) (2015) 213–228, https://doi.org/10.1007/S11192-015-1765-5.

[50] D.K. Abideen, A. Yunusa-Kaltungo, P. Manu, C. Cheung, A systematic review of the extent to which BIM is integrated into operation and maintenance, Sustainability 14 (14) (2022) 8692, https://doi.org/10.3390/SU14148692.

[51] T.R. Gruber, A translation approach to portable ontology specifications, Knowl. Acquis. 5 (2) (1993) 199–220, https://doi.org/10.1006/KNAC.1993.1008.

[52] C. Okoli, A guide to conducting a standalone systematic literature review, Commun. Assoc. Inf. Syst. 37 (2015) 879–910, https://doi.org/10.17705/1CAIS.03743.

[53] B. Kitchenham, S. Charters, "Guidelines for Performing Systematic Literature Reviews in Software Engineering," EBSE Technical Report EBSE-2007-01, Keele University and Durham University, 2007.

[54] A. Celoza, Information management for digital asset development and delivery, Elsevier B.V (2024), https://doi.org/10.1016/j.autcon.2024.105518.

[55] H. Wang, X. Meng, Transformation from IT-based knowledge management into BIM-supported knowledge management: a literature review, Expert Syst. Appl. (2019), https://doi.org/10.1016/j.eswa.2018.12.017.

[56] C. Wohlin, Guidelines for snowballing in systematic literature studies and a replication in software engineering, in: ACM International Conference Proceeding Series, 2014, https://doi.org/10.1145/2601248.2601268.

[57] M. Madroñal-Ortiz, D. Cuartas-Ramirez, C.A. Benavides-Velasco, M. Osorio, Identification and classification of facilities managers functions: a proposal validated by Latin American experts, J. Eng. Res. 10 (3) (2022) 91–107, https://doi.org/10.36909/jer.12139.

[58] M. Uschold, M. Gruninger, Ontologies: principles, methods and applications, Knowl. Eng. Rev. 11 (2) (1996) 93–136, https://doi.org/10.1017/S0269888900007797.

[59] Y. Zheng, S. Törmä, O. Seppänen, A shared ontology suite for digital construction workflow, Autom. Constr. 132 (2021) 103930, https://doi.org/10.1016/J.AUTCON.2021.103930.

[60] M. Sadeghi, J.W. Elliott, M.H. Mehany, Information-augmented exchange objects to inform facilities management BIM guidelines: introducing the level of semantics schema, J. Facil. Manag. 21 (2) (2023) 260–281, https://doi.org/10.1108/JFM-04-2021-0044.

[61] I. Huitzil, M. Molina-Solana, J. Gómez-Romero, F. Bobillo, Minimalistic fuzzy ontology reasoning: an application to building information modeling, Appl. Soft Comput. 103 (2021), https://doi.org/10.1016/j.asoc.2021.107158.

[62] S.H. Hong, S.K. Lee, J.H. Yu, Automated management of green building material information using web crawling and ontology, Autom. Constr. 102 (2019) 230–244, https://doi.org/10.1016/j.autcon.2019.01.015.

[63] G.F. Schneider, G.D. Kontes, H. Qiu, F.J. Silva, M. Bucur, J. Malanik, et al., Design of knowledge-based systems for automated deployment of building management services, Autom. Constr. 119 (2020), https://doi.org/10.1016/j.autcon.2020.103402.

[64] G. Costa, A. Sicilia, Alternatives for facilitating automatic transformation of BIM data using semantic query languages, Autom. Constr. 120 (2020), https://doi.org/10.1016/j.autcon.2020.103384.

[65] A. Gouda Mohamed, J.E. Ghaly, M. Marzouk, Revolutionizing semantic integration of maintenance cost prediction for building systems using artificial neural networks, J. Build. Eng. 96 (2024) 110416, https://doi.org/10.1016/J.JOBE.2024.110416.

[66] J.-I. Jäkel, E. Heinlein, H. Morgenstern, H. Kim, K. Klemt-Albert, System and data-integrated linking of digital 3D models of existing bridge structures with knowledge graphs of non-destructive diagnostic methods, J. Inform. Technol. Construct. 30 (2025) 603–630, https://doi.org/10.36680/j.itcon.2025.025.

[67] P. Hagedorn, L. Liu, M. König, R. Hajdin, T. Blumenfeld, M. Stöckner, et al., BIM-enabled infrastructure asset management using information containers and semantic web, J. Comput. Civ. Eng. 37 (1) (2022) 04022041, https://doi.org/10.1061/(ASCE)CP.1943-5487.0001051.

[68] L. Wei, H. Du, Q. ain Mahesar, K. Al Ammari, D.R. Magee, B. Clarke, et al., A decision support system for urban infrastructure inter-asset management employing domain ontologies and qualitative uncertainty-based reasoning, Expert Syst. Appl. 158 (2020) 113461, https://doi.org/10.1016/J.ESWA.2020.113461.

[69] Y.Y. Zhang, K. Kang, J.R. Lin, J.P. Zhang, Y. Zhang, Building information modeling–based cyber-physical platform for building performance monitoring, Int. J. Distrib. Sens. Netw. 16 (2) (2020), https://doi.org/10.1177/1550147720908170.

[70] A. Kučera, T. Pitner, Semantic BMS: allowing usage of building automation data in facility benchmarking, Adv. Eng. Inform. 35 (2018) 69–84, https://doi.org/10.1016/j.aei.2018.01.002.

[71] J. Zhang, T.E. El-Diraby, Social semantic approach to support communication in AEC, J. Comput. Civ. Eng. 26 (1) (2011) 90–104, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000130.

[72] M. Niknam, S. Karshenas, A shared ontology approach to semantic representation of BIM data, Autom. Constr. 80 (2017) 22–36, https://doi.org/10.1016/j.autcon.2017.03.013.

[73] Z. Zhou, Y.M. Goh, L. Shen, Overview and analysis of ontology studies supporting development of the construction industry, J. Comput. Civ. Eng. 30 (6) (2016), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000594.

[74] A. Lorvão Antunes, J. Barateiro, V. Marecos, J. Petrović, E. Cardoso, Ontology-based BIM-AMS integration in European highways, Intell. Syst. Appl. 22 (2024) 200366, https://doi.org/10.1016/j.iswa.2024.200366.

[75] D.E. Gispert, I. Yitmen, H. Sadri, A. Taheri, Development of an ontology-based asset information model for predictive maintenance in building facilities, Smart Sustain. Built Environ. (2023), https://doi.org/10.1108/SASBE-07-2023-0170.

[76] M. Hu, Y. Liu, V. Sugumaran, B. Liu, J. Du, Automated structural defects diagnosis in underground transportation tunnels using semantic technologies, Autom. Constr. 107 (2019), https://doi.org/10.1016/j.autcon.2019.102929.

[77] R.G. Wang, P.Y. Wu, C.Y. Liu, J.C. Tan, M.L. Chuang, C.C. Chou, Route planning for fire rescue operations in Long-term care facilities using ontology and building information models, Buildings 12 (7) (2022), https://doi.org/10.3390/buildings12071060.

[78] C. Shaw, F. de Andrade Pereira, M. de Riet, C. Hoare, K. Farghaly, J. O'Donnell, Knowledge graph for policy- and practice-aligned life cycle analysis and reporting, Autom. Constr. 176 (2025) 106282, https://doi.org/10.1016/J.AUTCON.2025.106282.

[79] M. Wang, Ontology-based modelling of lifecycle underground utility information to support operation and maintenance, Autom. Constr. 132 (2021), https://doi.org/10.1016/j.autcon.2021.103933.

[80] S. Sobhkhiz, H. Taghaddos, M. Rezvani, A.M. Ramezanianpour, Utilization of semantic web technologies to improve BIM-LCA applications, Autom. Constr. 130 (2021), https://doi.org/10.1016/j.autcon.2021.103842.

[81] Z. Ghorbani, J.I. Messner, An ontology for digital twin operations and maintenance use cases in the AECO industry, J. Inform. Technol. Construct. 30 (2025) 335–351, https://doi.org/10.36680/j.itcon.2025.014.
[82] D. Saba, Y. Sahli, A. Hadidi, An ontology based energy management for smart home, Sustain. Comput. Inform. Syst. 31 (2021) 100591, https://doi.org/10.1016/J.SUSCOM.2021.100591.
[83] J. Bjørnskov, M. Jradi, An ontology-based innovative energy modeling framework for scalable and adaptable building digital twins, Energ. Buildings 292 (2023) 113146, https://doi.org/10.1016/J.ENBUILD.2023.113146.
[84] K. Farghaly, R. Soman, J. Whyte, cSite ontology for production control of construction sites, Autom. Constr. 158 (2024) 105224, https://doi.org/10.1016/J.AUTCON.2023.105224.
[85] Y.Y. Zhang, Z.Z. Hu, J.R. Lin, J.P. Zhang, Linking data model and formula to automate KPI calculation for building performance benchmarking, Energy Rep. 7 (2021) 1326–1337, https://doi.org/10.1016/j.egyr.2021.02.044.
[86] V. Kukkonen, A. Kücükavci, M. Seidenschnur, M.H. Rasmussen, K.M. Smith, C. A. Hviid, An ontology to support flow system descriptions from design to operation of buildings, Autom. Constr. 134 (2022), https://doi.org/10.1016/j.autcon.2021.104067.
[87] L. Jiang, J. Shi, C. Wang, Z. Pan, Intelligent control of building fire protection system using digital twins and semantic web technologies, Autom. Constr. 147 (2023) 104728, https://doi.org/10.1016/J.AUTCON.2022.104728.
[88] P.C. Lee, W. Xie, T.P. Lo, D. Long, X. Tang, A cloud model-based knowledge mapping method for historic building maintenance based on building information modelling and ontology, KSCE J. Civ. Eng. 23 (8) (2019) 3285–3296, https://doi.org/10.1007/s12205-019-2457-0.
[89] M. Alavi, D.E. Leidner, Review: knowledge management and knowledge management systems: conceptual foundations and research issues, MIS Q. 25 (1) (2001) 107–136, https://doi.org/10.2307/3250961.
[90] J. Merino, N. Moretti, X. Xie, J.Y. Chang, A. Parlikad, Data integration for digital twins in the built environment based on federated data models, Proc. Inst. Civ. Eng. Smart Infrastruct. Constr. 176 (4) (2023) 194–211, https://doi.org/10.1680/jsmic.23.00002.
[91] K. El Mokhtari, I. Panushev, J.J. McArthur, Development of a cognitive digital twin for building management and operations, Front. Built Environ. 8 (2022), https://doi.org/10.3389/fbuil.2022.856873.
[92] M. Arslan, C. Cruz, D. Ginhac, Understanding occupant behaviors in dynamic environments using OBiDE framework, Build. Environ. 166 (2019), https://doi.org/10.1016/j.buildenv.2019.106412.
[93] S.D. Rihm, Y.R. Tan, W. Ang, M. Hofmeister, X. Deng, M.T. Laksana, et al., The digital lab manager: automating research support, SLAS Technol. 29 (3) (2024) 100135, https://doi.org/10.1016/j.slast.2024.100135.
[94] C. Biagini, A. Bongini, L. Marzi, From BIM to digital twin. IOT data integration in asset management platform, J. Inform. Technol. Construct. 29 (2024) 1103–1127, https://doi.org/10.36680/j.itcon.2024.049.
[95] J.F. Tchouanguem Djuedja, P. Pauwels, H.A. Fonbeyin, C. Magniont, M.H. Karray, B. Kamsu Foguem, Integration of environmental data in BIM tool & linked building data, in: CEUR Workshop Proceedings Vol 2389, 2019, pp. 78–91 (ISSN 1613-0073).
[96] A. Gouda Mohamed, M.R. Abdallah, M. Marzouk, BIM and semantic web-based maintenance information for existing buildings, Autom. Constr. 116 (2020), https://doi.org/10.1016/j.autcon.2020.103209.
[97] K.L. Chen, M.H. Tsai, Conversation-based information delivery method for facility management, Sensors 21 (14) (2021), https://doi.org/10.3390/s21144771.
[98] M. Niknam, F. Jalaei, S. Karshenas, "Integrating BIM and product manufacturer data using the semantic web technologies," J. Inf. Technol. Constr. 24 (2019) 424–439. Available: https://www.itcon.org/2019/22.
[99] M. Boscariol, S. Meschini, L.C. Tagliabue, Knowledge engineering with LLMs for asset information management in the built environment, Proc. Instit. Civil Eng. Smart Infrastruct. Construct. 18 (2025), https://doi.org/10.1680/JSMIC.24.00035.
[100] V. Emonet, J. Bolleman, S. Duvaud, T.M. de Farias, A.C. Sima, LLM-Based SPARQL Query Generation From Natural Language Over Federated Knowledge Graphs, 2025, https://doi.org/10.48550/arXiv.2410.06062. Accessed: Nov. 17, 2025.
[101] Y. Alani, N. Dawood, J. Patacas, S. Rodriguez, H. Dawood, A semantic common model for product data in the water industry, J. Inform. Technol. Construct. 26 (2021) 566–590, https://doi.org/10.36680/j.itcon.2021.030.