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Development of an ontology-based asset information model for predictive maintenance in building facilities

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Abstract

Purpose – The purpose of this research is to develop a framework of an ontology-based Asset Information Model (AIM) for a Digital Twin (DT) platform and enhance predictive maintenance practices in building facilities that could enable proactive and data-driven decision-making during the Operation and Maintenance (O&M) process.

Design/methodology/approach – A scoping literature review was accomplished to establish the theoretical foundation for the current investigation. A study on developing an ontology-based AIM for predictive maintenance in building facilities was conducted. Semi-structured interviews were conducted with industry professionals to gather qualitative data for ontology-based AIM framework validation and insights.

Findings – The research findings indicate that while the development of ontology faced challenges in defining missing entities and relations in the context of predictive maintenance, insights gained from the interviews enabled the establishment of a comprehensive framework for ontology-based AIM adoption in the Facility Management (FM) sector.

Practical implications – The proposed ontology-based AIM has the potential to enable proactive and data-driven decision-making during the process, optimizing predictive maintenance practices and ultimately enhancing energy efficiency and sustainability in the building industry.

Originality/value – The research contributes to a practical guide for ontology development processes and presents a framework of an Ontology-based AIM for a Digital Twin platform.

Keywords Asset information model, Digital twins, Predictive maintenance, Ontology, Building facility management, Operation and maintenance

Paper type Research paper

1. Introduction

The Architecture, Engineering, Construction, and Facility Management (AEC-FM) industry plays a significant role across the world's energy consumption and greenhouse gas emissions, accounting for more than 40% of the overall energy generated globally and more than 30% of the entire CO2 emission (Himeur *et al.*, 2021). The industry's largest contributor to energy consumption is building installations, particularly heating and cooling systems,

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accounting for around 75% of the energy consumed by building facilities (Frayssinet *et al.*, 2018). In addition, poor energy management practices can result in a 20–30% increase in overall energy consumption and excessive waste production (Bouabdallaoui *et al.*, 2021). A pillar to address this challenge is optimizing building maintenance and management strategies through Information, Communication, and Technology (ICT) tools integration, increasing energy efficiency, reducing costs, streamlining the value chain and enhancing the overall building lifecycle processes (Alonso *et al.*, 2019).

A predictive maintenance approach enhanced by ICT tools can improve the efficiency and reliability of building facilities (Bouabdallaoui *et al.*, 2021) considering predictive maintenance condition-based strategy as an effective method to shift from the traditional fail-and-fix practices to a predict-and-prevent strategy (Tahan *et al.*, 2017). A key technology for predictive maintenance is the Asset Information Model (AIM) (Heaton and Parlikad, 2020), which provides a centralized repository of information about a building facility's components, systems and operations (ISO, 2018). It collects data from multiple sources, including sensors, building management systems and maintenance records, to provide a comprehensive understanding of the facility's performance (Hellenborn *et al.*, 2023). Although it is suitable for data consolidation, the system faces challenges with interoperability (Farghaly and Hagras, 2022). Digital twins (DTs), on the other hand, have been acknowledged as a key technology for information management practice (Götz *et al.*, 2020). A DT is a virtual replica of a physical asset possessing self-evolution characteristics, adapting to real-world circumstances while preserving the contrast between physical and virtual domains, it provides asset managers access to reliable real-time asset data (Zhao *et al.*, 2022). By creating a DT of a building facility, operators can identify potential issues, optimize operations and make informed decisions to improve efficiency (Zhao *et al.*, 2022).

However, DT application development is still in its very early stages (Dai *et al.*, 2021) and its implementation requires the modeling of all the data associated with the asset and its components, as its technical core comprises "a data model that encapsulates physical data and information relationship with its external environment" (Angrish *et al.*, 2017). According to (Yitmen *et al.*, 2023), an essential component of a DT is Ontology, which provides a common understanding of the data and concepts involved in the representation of the building facility. Researchers in the AEC-FM sector are increasingly using ontology methodologies to address the problem of information interoperability (Yang *et al.*, 2019; Yitmen *et al.*, 2023).

Ontologies focus on establishing clearly defined domain concepts in terms of terminologies, definitions and relationships, specifically serving as an enabler of effective knowledge management (Yang *et al.*, 2019). To achieve an accurate depiction of an asset, it is essential to supply the DT platform with an ontology of its components and their relationships (Lei *et al.*, 2021). Hence, to establish a comprehensive and precise representation of the building facility, with a specific focus on predictive maintenance, the utilization of an ontology-based AIM for a digital twin platform is essential (Yitmen *et al.*, 2023). Nonetheless, it is worth noting that building facilities ontologies with a specific focus on predictive maintenance are still developing (Hosamo *et al.*, 2022) and although there are standard building facilities ontologies, such as IFCOwl which provides a Web Ontology Language representation of the Industry Foundation Classes (IFC), the Green Building XML (gbXML), Project Haystack and Smart Applications REFerence (SAREF), good at capturing space-related data, such as zones, rooms and floors and mechanical building systems such as air handling units (AHUs), ducts, flanges and other mechanical components, they focused more on the design and construction stage and lack vocabulary needed for the operational and maintenance (O&M) phase (Balaji *et al.*, 2018; Fierro *et al.*, 2020).

Therefore, this study aims to develop a framework of an Ontology-based Asset Information Model for predictive maintenance in building facilities that could enable proactive and data-driven decision-making during the O&M process.

Based on the purpose of the study, the following three research questions are posed.

RQ1. What are the classes and data hierarchy structures required for the development of an ontology involving condition monitoring in predictive maintenance for Building Facilities?

RQ2. How is data integration and data flow process organized in an AIM to facilitate condition monitoring in predictive maintenance for Building Facilities?

RQ3. How can an ontology-based AIM support predictive maintenance in building facilities management?

In the next section, the theoretical background is outlined, followed by the methodology involving study design, materials and procedures. The fourth section displays an analysis of the collected data, followed by a discussion in the fifth section. Finally, the conclusion is presented together with suggestions for future research.

2. Theoretical background

The use of ontologies in building facility management provides a structured and standardized way of representing and organizing information about assets, systems and processes (Lei *et al.*, 2021). Different maintenance strategies provide a framework for decision-making (Bouabdallaoui *et al.*, 2021). The use of Asset Information Models (AIMs) can enhance the overall management of building facilities by providing real-time data and enabling predictive maintenance (Hellenborn *et al.*, 2023). The integration of an ontology-based Asset Information Model for predictive maintenance in building facilities could enable facility managers to make informed decisions and ensure the optimal performance of building facilities (Heaton and Parlikad, 2020).

Existing ontologies in the AEC-FM industry have been successfully applied in the field of building information modeling (BIM), such as the Building Topology Ontology (BOT) alignment modules (BrickSchema, IFCOwl, Project Haystack, Real Estate Core (REC) and SAREF) (Brick, 2021). However, there is a lack of ontologies specifically designed for predictive maintenance in building facilities (Bouabdallaoui *et al.*, 2021). This lack is a challenge for the adoption and implementation of predictive maintenance in the building industry, as it makes it difficult to standardize and exchange information between different systems (Mahdavi and Taheri, 2017).

2.1 Ontology

The term ontology is typically used in two contexts: as a field of philosophy studying the nature of reality, and as a computational artifact specifying a conceptualization (Gruber, 1995). Ontologies have evolved in computer science, emphasizing the importance of shared conceptualization among stakeholders (Borst *et al.*, 1997). An optimized definition considers ontology as "a formal, explicit specification of a shared conceptualization": "*A 'conceptualization' refers to an abstract model of some phenomenon in the world by having identified the relevant concepts of that phenomenon. 'Explicit' means that the type of concepts used, and the constraints on their use are explicitly defined. 'Formal' refers to the fact that the ontology should be machine-readable, which excludes natural language. 'Shared' reflects the notion that an ontology captures consensual knowledge, that is, it is not private to some individuals, but accepted by a group*" (Studer *et al.*, 1998).

Ontologies establish domain concepts, terminologies and relationships, enabling effective knowledge management. They enhance systems engineering by facilitating an understanding of complex systems and making their nature explicit (Yang *et al.*, 2019).

Ontological knowledge bases use a terminological formalism (T-box) for representation vocabulary and assertional formalism (A-box) for knowledge description. The T-box defines the taxonomy or classification hierarchy within the ontology, while the A-box captures specific facts of individual instances (Brachman *et al.*, 1983; Chandrasekaran *et al.*, 1999). A widely used formal language for ontology representation is OWL (Web Ontology Language), which enhances logical consistency and interoperability (Musen, 2015).

An ontology serves as a common vocabulary for information exchange and integration, providing a framework for organizing and categorizing knowledge (Noy and McGuinness, 2001) facilitating a comprehensive understanding and effective management of interrelated components and systems in building facilities (Mahdavi and Taheri, 2017). Traditional facility management relies on individual practitioners' knowledge and experience, which is challenging to share and hinders the transfer of best practices across projects (Yalcinkaya and Singh, 2014). However, ontology addresses this challenge by offering a structured, machine-readable representation of construction knowledge (Nuñez and Borsato, 2018).

In the context of BIM, ontologies facilitate knowledge exchange by formally defining domain items and their attributes. They enable knowledge and information sharing across BIM applications (Costin and Pauwels, 2022). A common format for transferring information from BIM to FM is the Construction Operations Building Information Exchange (COBie) structure, although it may not represent all information due to incomplete data structure (Wang *et al.*, 2022). Ontologies offer a valuable solution to reducing the gap and achieving data interoperability (Chen, 2019).

2.2 Predictive maintenance

Predictive maintenance is a maintenance strategy that uses data analysis and machine learning algorithms to predict when equipment or machinery is likely to fail, allowing maintenance teams to schedule repairs and replacements before a failure occurs (Yitmen *et al.*, 2023). The goal of predictive maintenance is to minimize downtime, increase equipment life and reduce maintenance costs (Hosamo *et al.*, 2022). It involves collecting and analyzing data from various sources such as sensors, historical maintenance records and machine performance data. This data is used to develop predictive models that can provide real-time monitoring, identify patterns and anomalies and indicate early warnings of potential failures (Tiddens *et al.*, 2022). By detecting potential failures before they occur, maintenance teams can schedule repairs or replacements during planned downtime, rather than in the event of an unplanned failure (Hellenborn *et al.*, 2023). There are several benefits to using predictive maintenance, including reduced equipment downtime, improved equipment reliability, lower maintenance costs and reduced risk of equipment damage. Additionally, predictive maintenance can improve safety by reducing the likelihood of equipment failures that could cause harm to workers or the environment (Bouabdallaoui *et al.*, 2021; Villa *et al.*, 2021).

2.3 Asset information model (AIM)

An Asset Information Model is the compendium of data on physical assets, systems and processes used in the management and maintenance of facilities, providing a centralized repository of information about a building facility's components, systems and operations (Heaton and Parlikad, 2020). The British Standard Institution (BSI, 2014) defines an AIM as "*data and information that relates to assets to a level required to support an organization's asset management system*", complementing the ISO 19650 definition "*an AIM is Information Model relating to the operational phase*" (ISO, 2018).

Furthermore, an Asset Information Model could support the adoption of a Digital Twin, facilitating real-time data about the performance and condition of assets, with the potential to enable predictive maintenance (Heaton and Parlikad, 2020) allowing building facility managers to make informed decisions about asset maintenance and management, reducing the risk of unexpected breakdowns and increasing efficiency of building facilities (Bouabdallaoui *et al.*, 2021). ISO Standard 19650–1:2018 provides guidelines for information management, defining the principles and requirements for the creation and use of AIMs and the processes and responsibilities for creating, maintaining and using these models. The organizational information requirements (OIR) set the asset information requirements (AIR) which specify the contents of an AIM (ISO, 2018). On the other hand, even though asset management contemporary tools enable asset information collection, the data analytics capabilities and integration are poor and unable to manage dynamic data throughout the asset lifecycle (Farghaly and Hagras, 2022; Hellenborn *et al.*, 2023). Therefore, Digital Twin technology is proposed to offer asset managers reliable, real-time records of asset data (Macchi *et al.*, 2018) with the potential of analyzing and predicting the state of the asset, ensuring a healthy building's operation, cutting expenses and saving time during the O&M phase (Ozturk, 2021).

All the information and data that supports asset management is recorded in an AIM, creating a set of data to aid in decision-making throughout an asset's life cycle. Both organized data (such as databases, timetables and 3D models) and unstructured data (such as sound recordings, video and documentation) are included in the AIM (Hellenborn *et al.*, 2023). Although there exist some standards focused on the implementation of BIM data for the O&M phase, requiring organizations to create an AIM, there are no thorough overall frameworks that support the alignment of strategic, procedural and technological standards (Heaton and Parlikad, 2020). Structuring and standardizing the information and data that shape the AIM is key to its conception and maintenance. A data structure enabled through an ontology-based can ease the integration between AIM and a DT platform, however, its manual creation and maintenance is a challenge. Therefore, the information should be automatically translated through ontology-based knowledge graphs into the AIM (Yitmen *et al.*, 2023).

3. Materials/methods

This section outlines the methodology, strategies and research approach employed in this study. Initially, a scoping literature review was accomplished to establish the theoretical foundation for the current investigation. Subsequently, work on developing an ontology-based AIM for predictive maintenance in building facilities was performed. Thereafter, semi-structured interviews were conducted with industry professionals to gather qualitative data for ontology-based AIM framework validation and insights.

3.1 Scoping review

The concepts underlying the study field, as well as the primary sources and forms of evidence, were mapped using a scoping review (ScR) (Tricco *et al.*, 2016). The ScR was performed to comprehend the theoretical background of the current study, while the Google Scholar (GS) database was chosen over Web of Science (WoS) and Scopus due to its wide scope. According to (Martín-Martín *et al.*, 2018) GS finds nearly all citations found by WoS (95%) and Scopus (92%) across all subject areas, and it also finds a substantial number of unique citations (about 50% more) that are not found in the other databases.

Three different strings were used to reach data from the different relevant fields in the current research.

(1) "Predictive Maintenance" AND "Building Facility" AND "Asset Information Model"

(2) "Predictive Maintenance" AND "Building Facility" AND "Ontology"

(3) "Facility Management" AND "Ontology" AND "Asset Information Model"

The scoping literature review process, guided by PRISMA - ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) (Tricco *et al.*, 2018), initially identified 194 articles through a search on Google Scholar using the mentioned strings. After removing duplicates, 183 unique papers remained. The criteria used during the screening process conduct to include the papers that focus on Asset Information Model(s), digital twins for facility management, data schemas for system/products maintenance, ontology description for building facilities and maintenance and predictive maintenance in building facilities, leading to the exclusion of 116 not relevant articles to the topic at hand, and resulting in 67 full texts for assessment. From the 67 full texts assessed, it was determined that 48 papers were not directly relevant to the topic and were subsequently excluded, resulting in 19 articles for inclusion.

Additionally, eight articles given by an AEC-FM researcher were added, and seven more were identified through cross-reference. Furthermore, nine articles were included to provide concept definitions.

In total, 43 studies were selected for analysis as seen in Figure 1, comprising the initial 19 articles, 8 articles given by the AEC-FM researcher, 7 from cross-references and 9 articles from the concept definitions.

3.2 Ontology development

The ontology development aims to create a structured and standardized knowledge-based AIM for predictive maintenance in building facilities. It will provide a framework for capturing and organizing building systems and equipment knowledge, their interactions and the factors that impact their performance. The development of the ontology is based on the procedure Ontology Development 101 (OD1) (Noy and McGuinness, 2001) as seen in Figure 2.

The OD1 is utilized in this study as it is broadly employed (Gong and Janssen, 2013; Lau *et al.*, 2014; Nuñez and Borsato, 2018; Ren *et al.*, 2019), it has been demonstrated to be highly appropriate for maintenance modeling and has been extensively documented for application in the Protégé environment. Specifically, Protégé is the most dominant ontology publisher

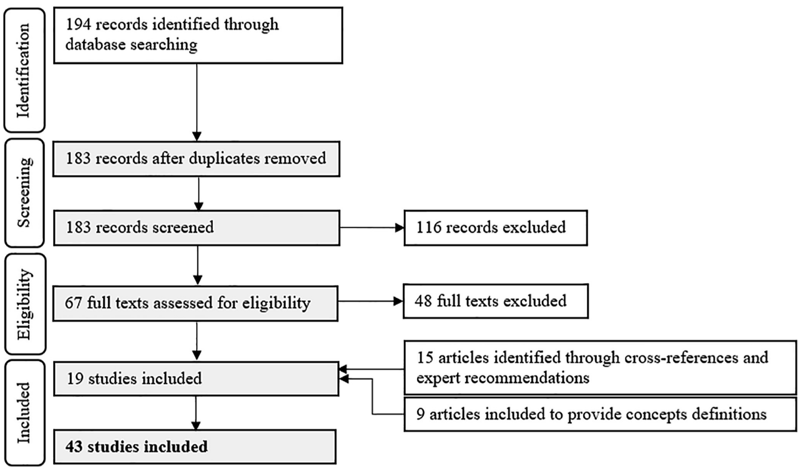

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Figure 1.
PRISMA - ScR flow diagram for studies on ontology-based AIM for predictive maintenance in building facilities

since it is an open platform that offers plug-in extensibility as well as XML Schema, OWL, RDF (S) and Excel support, along with graphic taxonomy, queries in SPARQL Protocol and RDF Query Language (SPARQL), rules in Semantic Web Rule Language (SWRL) and a reasoner (Pellet). Suggested as the preferable Ontology Editor with 66.67% of the experts' recommendation (Siricharoen, 2018).

For this study, a conference room within Pythagoras AB's Office Building in Stockholm served as the case study location. The ontology development utilized the BOT alignment modules, the BrickSchema ontology and REC, notable for their extensive coverage in the AEC-FM industry. Their wide-ranging capabilities include modeling HVAC, lighting, electrical, sensor systems, spatial data, control dynamics, operational relationships and formal definitions (Brick, 2021). The ontology structure is presented in section 4.

3.3 Semi-structured interviews

Semi-structured interviews were conducted as a qualitative research method to collect main themes from eight industry experts (see Table 1) regarding the application of the Ontology-based AIM for predictive maintenance in building facilities. The interviews were conducted online, with a duration of about 40 min, and the questions focused on six main topics.

(1) Existing ontologies in Building Facilities which adaptation could be suitable for Predictive Maintenance

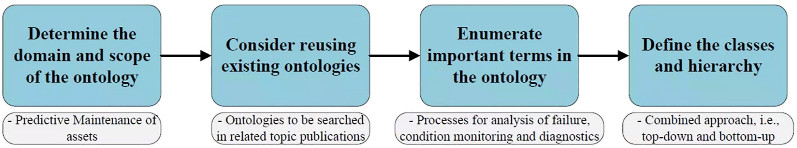
(2) Lack of Common data structures and Ontologies for Predictive Maintenance in Building Facilities

(3) Development of Ontology-based AIM for predictive maintenance

(4) Digital Twin technology adaption for asset management

(5) Ontology Development: Case Study of the office building in Stockholm

(6) Evaluation of Ontology-based AIM for predictive maintenance strategies



Source(s): Figure created by author, adapted from Ontology Development 101

Figure 2. Ontology development methodology

Respondent	Area of expertise	Expertise	Country
R1	Artificial Intelligence (AI), Machine Learning (ML) and Data Analytics	25 Years	Turkey
R2	Process Manager/BIM Coordinator	4 Years	Sweden
R3	Digitization and Sustainability Specialist	10 Years	Sweden
R4	Digital Transformation and Innovation	15 Years	Denmark
R5	Business Development Director - FAIR Data	10 Years	Denmark
R6	Digital Transformation Expert - IoT, Machine Learning, Digital Twins	20 Years	USA
R7	Facility Manager Chief Engineer	32 Years	Mexico
R8	Data Engineer	6 Years	Mexico

Note(s): FAIR data: Findable, accessible, interoperable, reusable
Source(s): Table created by author

Table 1. Interviewees background

The semi-structured format allowed the interviewees to delve into the topics. The interviews were transcribed, data analyzed and categorized into different themes using NVivo. Results are presented in section 4 (Table 2).

4. Results

4.1 Ontology development

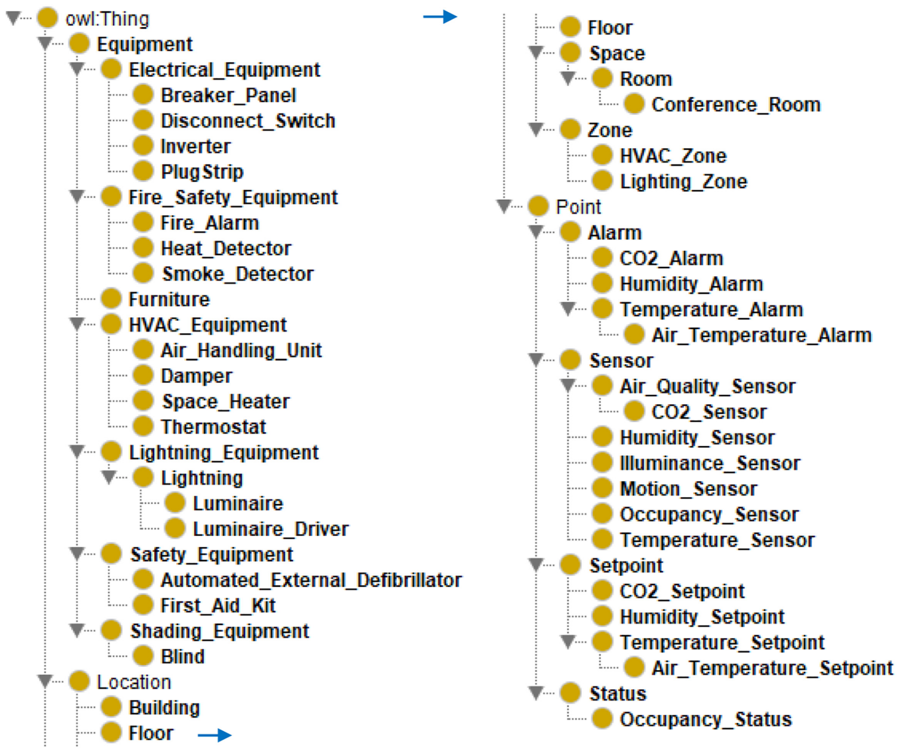
Based on the case study, the Ontology was adapted from BrickSchema and Real Estate Core ontologies, using the methodology of Ontology Development 101 and the software Protégé (Siricharoen, 2018). The development process was achieved through gathering data from Pythagoras AB building and aligning the concepts to the existing classes and subclasses from Brick and REC; new concepts gathered through the interviews (classes, properties and relationships) were added as well to the Ontology in the Protégé environment. The ontology development according to the OD1 Method is presented in Table 2.

The resulting classes of the ontology are presented in Figure 3 visualization on the Web-based Visualization of Ontologies (WebVOWL) is presented in Figure 4. The full Ontology description is located in (Espinosa, 2023).

Step	Results
Determine the domain and scope of the ontology	Domain: Predictive Maintenance in Building Facilities Scope: Ontology-based Asset Information Model for Predictive Maintenance
Consider reusing existing ontologies	From BOT alignment modules: BrickSchema and Real Estate Core (REC)
*Enumerate important terms in the ontology	Conference Room, Occupancy Sensor, Temperature Sensor, Air Quality Sensor, AV Equipment, Window, CO2 Level, Lightning Level, Power Usage
Define the classes and hierarchy	Constructed from BrickSchema and REC Ontologies for Stockholm's conference room case study • Equipment - Electrical Equipment (has 4 subclasses)** - Fire Safety Equipment (has 3 subclasses) - HVAC Equipment (has 4 subclasses) - Lightning Equipment (has 1 subclass with 2 subclasses) - Safety Equipment (has 2 subclasses) - Shading Equipment (has 1 subclass) • Location - Building - Floor - Space (has 1 subclass with 1 subclass) - Zone (has 2 subclasses) • Point - Alarm (has 3 subclasses) - Sensor (has 6 subclasses) - Setpoint (has 3 subclasses) - Status (has 1 subclass) Concepts added, gathered through interviews: Life expectancy, standard condition, assets definition, maintenance task, task interval, task duration, potential costs and staff involved

Note(s): *Terms collected based on Stockholm's conference room case study
**See Figure 3 for the depiction of classes and subclasses
Source(s): Table created by author

Table 2.
Ontology development according to OD1 method



Source(s): Figure created by author

Figure 3. Ontology classes shown in Protégé environment

4.2 Semi-structured interviews

The outcomes gathered from the interviews resulted in Table 3 which is divided into eight different themes.

The first two themes defined different approaches for the creation of an ontology; the traditional (process-based approach), and the innovative (AI-based approach). The AI approach suggests a 3-step process: Define a corpus of data sources (articles, white papers, websites), perform manual annotations of entities and relations and apply automated extraction from the predefined corpus employing Named Entity Recognition (NER) and Relation Extraction (RE).

Theme number 3 explains that "predictive maintenance in building facilities" is still a broad scope and that the study should be narrowed down in order to be able to create specific classes for the ontology, although it still mentions the classes that should be added for predictive maintenance in building facilities at this level of specification. The classes added to the ontology were: Life expectancy, standard condition, assets definition, maintenance task, task interval, task duration, potential costs and staff involved. Sensor's observation, units of measurement, associated zone, data collection frequency and sensor's specific location.

Theme number 4 sets some guidelines for modeling an ontology in this field. Theme number 5 explains the potential values and benefits, while theme 6 describes the challenges of data interoperability. The potential values are the enhancement of standardization and structured handling of large volumes of data, the substitution of repetitive manual tasks,

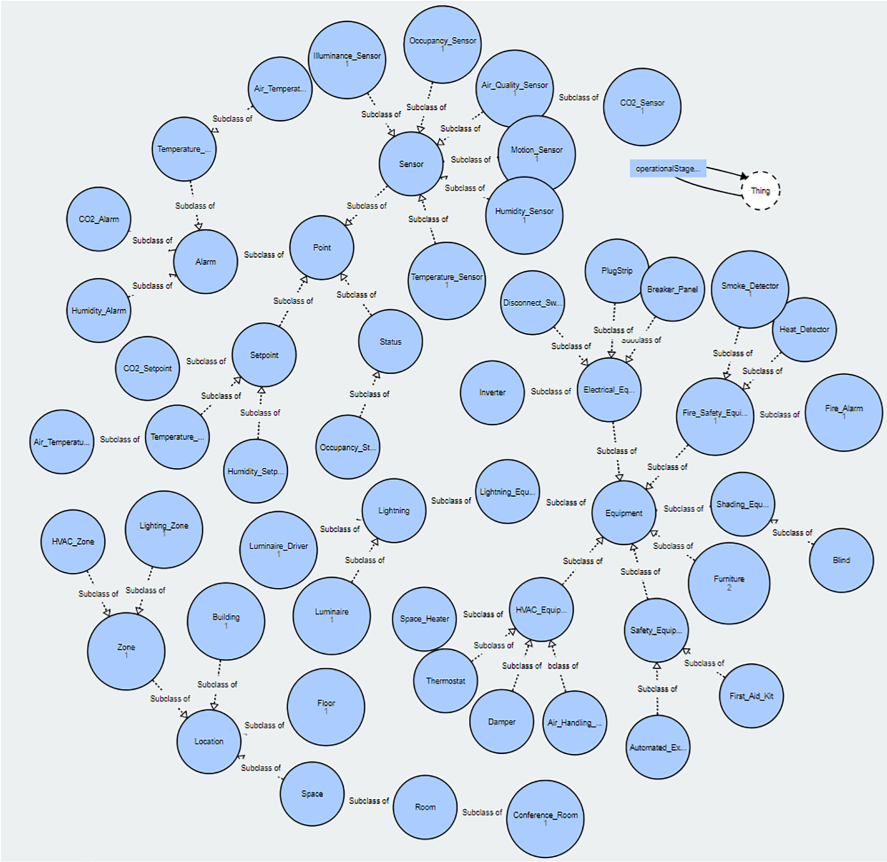


Figure 4.
Ontology representation using WebVOWL

Source(s): Figure created by author

automation of maintenance plan generation, archived data accessibility and data-driven maintenance implementation. A well-defined ontology also minimizes the number of data points needed and it could improve tasks and process automation, improve supervised learning performance and serve as a means of integrating prior knowledge into predictive models. When it comes to the challenges, the sensor data structure incompatibility among different providers stands out, as well as the complexity of the AIM maintenance, data restructuring after refurbishment and the balance between the number of sensors required and the investment in data-point collectors.

Finalizing the interview's outcomes, the last two themes show recommendations on how to assess the data model and an example of an Asset Information Model development respectively.

5. Discussion

5.1 Theoretical contribution

The purpose of this study was to explore a predictive maintenance approach for building facilities. The study outlined a key technology for its implementation named Asset

Theme	Description	Respondent
Process-based Approach	1 Prior to ontology development, define competency questions 2 Reuse existing ontologies, identify and develop the missing pieces of the established context, interview domain experts and prioritize development of modelling guidelines 3 The ontology can be broken down into different cores, such modular approach enables targeting different end users in various contexts	R3-R6
AI-based Approach	*Overview:* Employ NLP algorithms, through NER and RE techniques. Include LLM to ease NER and RE. *Process:* Define corpus of data sources (articles, white papers, websites). Perform manual annotations of entities and relations. Apply automated extraction from the predefined corpus employing NER and RE. *Tool(s):* Open-source platform that encompasses software packages supporting NER, RE and LLM, along with annotation tools (e.g. spaCy IO)	R1
Classes and Data Hierarchy	Hierarchies and classes depend on the context. Predictive maintenance in building facilities still encompasses a broad scope, emphasizing the need for a more specific and well-defined purpose. Nevertheless, modelling guidelines and classes needed for predictive maintenance were identified and are mentioned belowModelling Guidelines - The main classes include Systems, Component/Object Types and Materials - In diagnostics, it is crucial to link sensors to geometry, establish their relationship with BIM models and understand their spatial context and specific measurements. Automation is desirable for efficient implementationClasses gathered through interviews - Product life expectancy, equipment standard condition, defining assets, maintenance tasks, task intervals, task durations, potential costs and staff involved. Sensor's observation, units of measurement, associated zone, data collection frequency and sensor's specific location	R2-R6, R8
Themes for Condition Monitoring	Components must be defined to assess system functionality (e.g. geo coordinates for water level sensors or factors influencing pipe flow for leakage detection). The ontology should be capable of defining the current state of the components, such as dual-purpose elements (e.g. a pipe in a system used for heating and cooling). | It should be capable of defining active and passive components	R3, R5-R8
Potential Values and Benefits	Establish relationships between entities, enhancing predictive capabilities. Enables standardization and structured handling of large volumes of data. Substitution of repetitive manual tasks. Automated maintenance plan generation. Archived data accessibility throughout the building lifecycle. Data-driven maintenance implementation. A well-defined ontology and data model minimize the number of data points needed. Improve tasks and process automation. Improve supervised learning performance. Serves as a valuable means of integrating prior knowledge into predictive models	R1-R8

(*continued*)

Table 3.
Interviews results

Theme	Description	Respondent
Challenges of data interoperability	Integrating BIM metadata into FM systems. Numerous suppliers and building automation companies prioritizing closed environments. Sensor data structure incompatibility among different providers. AIM maintenance. Data restructuring after refurbishments. Achieving a balance between the number of sensors required for building performance analysis and the investment in data-point collectors	R2, R4-R6
Assessment of data model	SHACL (Shapes Constraint Language) empowers the assessment of semantic data models, enabling quality evaluation. Tools like PySHACL enable generating data model quality reports using SHACL, facilitating comparisons across projects with consistent ontologies. By establishing a shape to validate model parameters (e.g. requiring occupancy sensors in meeting rooms), benchmarking new buildings against existing ones becomes possible, ensuring consistent standards. Ontology's impact on predictive power can be assessed by comparing predictive performance before and after incorporating it	R1, R3-R6
AIM Development	Automation for relations and pattern identification. Need of linked data and knowledge graph. Methodologies for extracting information from semi-structured data and unstructured documents. IFC data exchange *Sample Process for Existing Assets:* Photogrammetry (of exteriors), LiDAR Scans (of interiors), object classification through algorithms, 3D model build-up, model migration from 3D platform to FM platform (e.g. iTwin), BIM model enrichment with metadata (materials, products), IoT data flow connection (based on installed sensors) *AIM Platform:* A cloud-based FM platform should possess the ability to store and interact with BIM models, photogrammetric models, Point Cloud scanning, CAD drawings and IoT data flows (e.g. iTwin). Additionally, it should automate manual inputs like maintenance documentation, semi-structured data and unstructured documents	R3, R6, R8

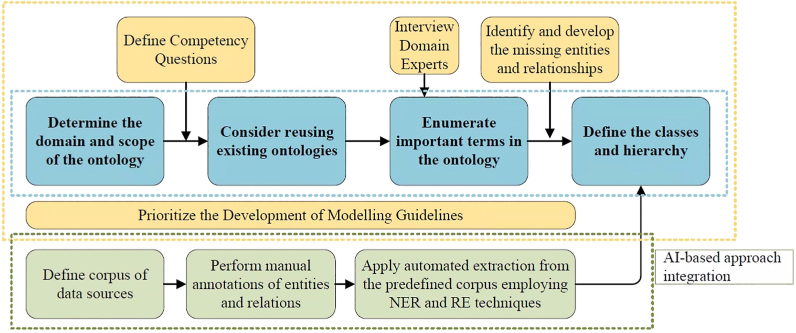
Note(s): AI-based def: NLP: Natural language processing, NER: Nentity recognition, RE: Relation extraction. LLM: Large language models
Source(s): Table created by author

Table 3.

Information Model (AIM) (Heaton and Parlikad, 2020). The AIM provides a centralized repository of information about the building facility's components, systems and operations (ISO, 2018). Nevertheless, it faces interoperability data challenges (Farghaly and Hagras, 2022). Considering that a digital twin is a key technology for information management practices (Götz *et al.*, 2020), and that its core depends on a data model comprised by entities and their relationships (Angrish *et al.*, 2017), an Ontology-based AIM for a digital twin platform is proposed.

Throughout the research, the study branched into two distinct areas of focus: the development of the Ontology itself and the depiction of a framework for implementing the Ontology-based AIM. The first area of focus addressed RQ1, RQ3, and the main research question, while the latter provided insights into addressing RQ2. Subsequently, the results are analyzed through the lenses of the research questions.

To tackle the Main Research Question, which delved into the processes involved in developing an ontology for predictive maintenance, the OD1 framework was adapted based on the findings from the study and the insights gathered through interviews as seen in Figure 5.



Source(s): Figure created by author

Figure 5. OD1 adapted framework

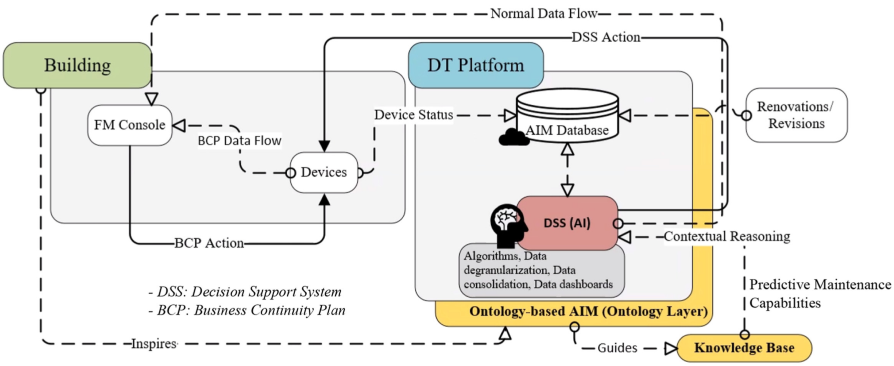
RQ1 inquired on the required classes and data hierarchy for this ontology, and it is approached with Table 2 stating that "predictive maintenance in building facilities still encompasses a broad scope". It emphasizes the need for a more specific and well-defined purpose. This, together with other factors, hindered the ontology development and it is explained under the "limitations" in subsequent paragraphs.

RQ2 explored data integration and data flow processes organized in an AIM to facilitate condition monitoring in predictive maintenance for building facilities. It investigated the Ontology-based AIM framework, and it is addressed by Figure 6 adapted from the Technical architecture of the AI-driven DT framework (Yitmen *et al.*, 2023), along with insights gathered from interviews with data experts.

To conclude, RQ3 studied the potential benefits of an ontology-based AIM approach for predictive maintenance in building facilities. It is addressed by the interview results (Table 2) under the theme "Potential values and benefits". Stating that this approach can enhance predictive capabilities, automate maintenance plan generation, minimize the number of data points needed, enable standard and structured handling of large volumes of data and it could serve as a valuable means of integrating prior knowledge into predictive models.

5.2 Entity relationships in ontology

In the development of Ontology-based AIM for predictive maintenance in building facilities, the incorporations of relationships and connections between entities are fundamental to



Source(s): Figure created by author, adapted from Yitmen *et al.* (2023)

Figure 6. Ontology-based AIM for predictive maintenance in building facilities framework

understanding how different concepts are interconnected and how data and knowledge are structured. In terms of completeness of the ontology in the context of predictive maintenance, the ontology needs to encompass a wide range of entities, such as building components (e.g. HVAC systems, alarms, sensors), maintenance activities (e.g. inspections, repairs, replacements), environmental conditions (e.g. temperature, humidity, CO2) and sensor data. With reference to the effectiveness of predictive maintenance, without clear and well-defined relationships, it becomes challenging to establish the cause-and-effect connections between different entities (Canito *et al.*, 2022). For instance, if there is a failure in an HVAC system, the ontology should allow for tracing back the possible causes, which could range from environmental factors to previous maintenance activities. If relationships are not well-defined, it becomes difficult to perform root cause analysis and make informed predictions. Regarding interoperability, predictive maintenance systems often rely on data from various sources, including sensors, historical maintenance records and environmental monitoring. Establishing relationships between entities is essential for interoperability between these diverse data sources. The ontology should act as a common language that facilitates the integration of data. Without proper relationships, the data might remain siloed, limiting the system's ability to provide comprehensive insights. In terms of semantic understanding, relationships in an ontology provide a semantic understanding of how different entities are connected. Such understanding is crucial for not only predictive maintenance but also for data interpretation and knowledge extraction (Cao *et al.*, 2020). For instance, knowing that a specific sensor reading is related to a particular component's health status allows for more meaningful analysis. If these relationships are missing or unclear, the data's significance may be lost. When considering scalability, as more data sources and maintenance processes are integrated, a lack of clarity in relationships can lead to confusion and inefficiency. In terms of knowledge transfer, if relationships are ambiguous or undefined, the transfer of knowledge from domain experts to AIM developers or automated systems becomes less effective (Von Enzberg *et al.*, 2020).

5.3 Practical implications and further studies

The findings of this study have important practical implications for the implementation of an ontology-based AIM for predictive maintenance in building facilities. The adapted modeling guideline (Figure 5), together with the themes identified through interviews (Table 2), provides valuable guidance and serves as a solid foundation for constructing an Ontology-based AIM for Predictive Maintenance in Building Facilities. Researchers can use this information as a starting point and customize the ontology to meet their individual needs. Additionally, Figure 6 presents an overview of the processes involved in the ontology-based AIM application.

Future studies should focus on narrowing the scope to a specific domain area, facilitating the definition of precise classes and relationships within that domain. It is also advisable to interview experts from both, the predictive maintenance field and facility management sector. To conclude, it is worth highlighting that by adopting an AI-based approach for ontology development (see Table 2, AI-based approach), the process would gain access to a significantly broader range of data sources compared to manual creation. This expanded access to diverse data sources can greatly enhance the depth and breadth of the ontology's development.

5.4 Limitations

To enhance ontology development, it is recommended to extract relevant data inputs from the literature and gather insights from experts through interviews. The current research focused on investigating modeling guidelines, and interviewing data structure experts to depict how to develop an ontology for building facilities in regard to predictive maintenance. However, due to time constraints, the opportunity to interview predictive maintenance experts and conduct dedicated research on predictive maintenance concepts and relationships was missed. This could have provided valuable insights necessary for the comprehensive development of the ontology. Additionally, it was noted through the interviews that the area of predictive maintenance in building facilities still encompasses a broad scope, consequently hindering the possibility of defining accurate classes and relations.

6. Conclusions

This study has proposed and explored the development of an ontology-based AIM system to enable proactive and data-driven decision-making during the O&M process, and optimize predictive maintenance practices, ultimately enhancing energy efficiency and sustainability in the building industry. Through a comprehensive approach that included a scoping review, ontology development and expert interviews, valuable insights have been gained regarding the processes, data integration and potential benefits of the ontology-based AIM. The findings indicate that despite challenges faced in ontology development, the collaboration between data specialists has resulted in a comprehensive framework for ontology-based AIM adoption in the industry.

This research contributes to the field by providing a practical guide for ontology development processes and presenting a framework of an Ontology-based AIM for a Digital twin platform. These findings underscore the importance of further research and collaboration between different stakeholders to refine and implement ontology-based AIM solutions in real-world contexts. Future studies should focus on further developing the classes and hierarchy that could enable predictive maintenance of an Ontology-based AIM for a digital twin platform. Ultimately, the successful integration of the ontology-based AIM has the potential to revolutionize predictive maintenance practices and contribute to the overall advancement of the building industry.

References

Alonso, R., Borras, M., Koppelaar, R., Lodigiani, A., Loscos, E. and Yöntem, E. (2019), "SPHERE: BIM digital twin platform", *Multidisciplinary Digital Publishing Institute Proceedings*, Vol. 20 No. 1, p. 9, doi: 10.3390/proceedings2019020009.

Angrish, A., Starly, B., Lee, Y. and Cohen, P. (2017), "A flexible data schema and system architecture for the virtualization of manufacturing machines (VMM)", *Journal of Manufacturing Systems*, Vol. 45, pp. 236-247, doi: 10.1016/j.jmsy.2017.10.003.

Balaji, B., Bhattacharya, A., Fierro, G., Gao, J., Gluck, J., Hong, D. and Agarwal, Y. (2018), "Brick: metadata schema for portable smart building applications", *Applied Energy*, Vol. 226, pp. 1273-1292, doi: 10.1016/j.apenergy.2018.02.091.

Borst, P., Akkermans, H. and Top, J. (1997), "Engineering ontologies", *International Journal of Human-Computer Studies*, Vol. 46 Nos 2-3, pp. 365-406, doi: 10.1006/ijhc.1996.0096.

Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L. and Bennadji, B. (2021), "Predictive maintenance in building facilities: a machine learning-based approach", *Sensors*, Vol. 21 No. 4, p. 1044, doi: 10.3390/s21041044.

Brachman, R., Fikes, R. and Levesque, H. (1983), "KRYPTON: a functional approach to knowledge representation", *Computer*, Vol. 16 No. 10, pp. 67-73, doi: 10.1109/MC.1983.1654200.

Brick (2021), "Building facilities ontologies", available at: https://docs.brickschema.org/intro.html (accessed 23 March 2023).

BSI (2014), *PAS 1192-3:2014 Specification for Information Management for the Operational Phase of Assets Using Building Information Modelling*, British Standards Institution, London.

Canito, A., Corchado, J. and Marreiros, G. (2022), "A systematic review on time-constrained ontology evolution in predictive maintenance", *Artificial Intelligence Review*, Vol. 55 No. 4, pp. 3183-3211.

Cao, Q., Samet, A., Zanni-Merk, C., de Bertrand de Beuvron, F. and Reich, C. (2020), "Combining chronicle mining and semantics for predictive maintenance in manufacturing processes", *Semantic Web*, Vol. 11 No. 6, pp. 927-948.

Chandrasekaran, B., Josephson, J. and Benjamins, V. (1999), "What are ontologies, and why do we need them?", *IEEE Intelligent Systems and Their Applications*, Vol. 14 No. 1, pp. 20-26, doi: 10.1109/5254.747902.

Chen, W. (2019), *Integration of Building Information Modeling and Internet of Things for Facility Maintenance Management*, Hong Kong University of Science and Technology, Hong Kong.

Costin, A. and Pauwels, P. (2022), "Building information modeling and ontologies: overview of shared representations", in *Research Companion to Building Information Modeling*, pp. 12-34, ISBN 1839105526, 9781839105524.

Dai, S., Zhao, G., Yu, Y., Zheng, P., Bao, Q. and Wang, W. (2021), "Ontology-based information modeling method for digital twin creation of as-fabricated machining parts", *Robotics and Computer-Integrated Manufacturing*, Vol. 72, 102173, doi: 10.1016/j.rcim.2021.102173.

Espinosa, D. (2023), "Ontology-based asset information model", available at: https://github.com/jth-esdi21tq/Ontology-based-AIM/blob/main/1st (accessed 22 May 2023).

Farghaly, K. and Hagras, A. (2022), "BIM and asset management (AM) interoperability towards the adoption of digital twins", *International Journal of Digital Innovation in the Built Environment*, Vol. 11 No. 1, doi: 10.4018/ijdibe.294445.

Fierro, G., Prakash, A., Mosiman, C., Pritoni, M., Raftery, P., Wetter, M. and Culler, D. (2020), "Shepherding metadata through the building lifecycle", *Proceedings of the 7th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, Vol. 7, pp. 70-79, doi: 10.1145/3408308.3427627.

Frayssinet, L., Merlier, L., Kuznik, F., Hubert, J., Milliez, M. and Roux, J. (2018), "Modeling the heating and cooling energy demand of urban buildings at city scale", *Renewable and Sustainable Energy Reviews*, Vol. 81, pp. 2318-2327, doi: 10.1016/j.rser.2017.06.040.

Götz, C.S., Karlsson, P. and Yitmen, I. (2020), "Exploring applicability, interoperability and integrability of Blockchain-based digital twins for asset life cycle management", *Smart and Sustainable Built Environment*, Vol. 11 No. 3, pp. 532-558, doi: 10.1108/SASBE-08-2020-0115.

Gong, Y. and Janssen, M. (2013), "An interoperable architecture and principles for implementing strategy and policy in operational processes", *Computers in Industry*, Vol. 64 No. 8, pp. 912-924, doi: 10.1016/j.compind.2013.06.018.

Gruber, T. (1995), "Toward principles for the design of ontologies used for knowledge sharing?", *International Journal of Human-Computer Studies*, Vol. 43 Nos 5-6, pp. 907-928, doi: 10.1006/ijhc.1995.1081.

Heaton, J. and Parlikad, A. (2020), "Asset information model to support the adoption of a digital twin: West Cambridge case study", *IFAC-PapersOnLine*, Vol. 53 No. 3, pp. 366-371, doi: 10.1016/j.ifacol.2020.11.059.

Hellenborn, B., Eliasson, O., Yitmen, I. and Sadri, H. (2023), "Asset information requirements for blockchain-based digital twins: a data-driven predictive analytics perspective", *Smart and Sustainable Built Environment*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/SASBE-082022-0183.

Himeur, Y., Ghanem, K., Alsalemi, A., Bensaali, F. and Amira, A. (2021), "Artificial intelligence based anomaly detection of energy consumption in buildings: a review, current trends and new perspectives", *Applied Energy*, Vol. 287, 116601, doi: 10.1016/j.apenergy.2021.116601.

Hosamo, H., Svennevig, P., Svidt, K., Han, D. and Nielsen, H. (2022), "A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics", *Energy and Buildings*, Vol. 261, 111988, doi: 10.1016/j.enbuild.2022.111988.

ISO (2018), *19650-1 Organization and Digitization of Information about Buildings and Civil Engineering Works, Including Building Information Modelling (BIM) - Information Management Using Building Information Modelling- Concepts and Principles*, International Organization for Standardization, London.

Lau, R., Li, C. and Liao, S. (2014), "Social analytics: learning fuzzy product ontologies for aspect-oriented sentiment analysis", *Decision Support Systems*, Vol. 65, p. 80, doi: 10.1016/j.dss.2014.05.005.

Lei, X., Wu, P., Zhu, J. and Wang, J. (2021), "Ontology-based information integration: a state-of-the-art review in road asset management", *Archives of Computational Methods in Engineering*, pp. 1-19, doi: 10.1007/s11831-021-09668-6.

Macchi, M., Roda, I., Negri, E. and Fumagalli, L. (2018), "Exploring the role of digital twin for asset lifecycle management", *IFAC-PapersOnLine*, Vol. 51 No. 11, pp. 790-795, doi: 10.1016/j.ifacol.2018.08.415.

Mahdavi, A. and Taheri, M. (2017), "An ontology for building monitoring", *Journal of Building Performance Simulation*, Vol. 10 Nos 5-6, pp. 499-508, doi: 10.1080/19401493.2016.1243730.

Martín-Martín, A., Orduna-Malea, E., Thelwall, M. and López-Cózar, E. (2018), "Google Scholar, Web of Science, and Scopus: a systematic comparison of citations in 252 subject categories", *Journal of Informetrics*, Vol. 12 No. 4, pp. 1160-1177, doi: 10.1016/j.joi.2018.09.002.

Musen, M. (2015), "The protégé project: a look back and a look forward", *AI Matters*, Vol. 1 No. 4, pp. 4-12, doi: 10.1145/2757001.2757003.

Noy, N.F. and McGuinness, D.L. (2001), "Ontology development 101: a guide to creating your first ontology", Stanford Knowledge Systems Laboratory Technical Report and Stanford Medical Informatics Technical Report SMI-2001-0880, pp. 1-25.

Nuñez, D. and Borsato, M. (2018), "OntoProg: an ontology-based model for implementing Prognostics Health Management in mechanical machines", *Advanced Engineering Informatics*, Vol. 38, pp. 746-759, doi: 10.1016/j.aei.2018.10.006.

Ozturk, G. (2021), "Digital twin research in the AECO-FM industry", *Journal of Building Engineering*, Vol. 40, 102730, doi: 10.1016/j.jobe.2021.102730.

Ren, G., Ding, R. and Li, H. (2019), "Building an ontological knowledgebase for bridge maintenance", *Advances in Engineering Software*, Vol. 130, pp. 24-40, doi: 10.1016/j.advengsoft.2019.02.001.

Siricharoen, W. (2018), "Ontology editors approach for ontology engineering", *2018 4th International Conference on Control, Automation and Robotics (ICCAR)*. doi: 10.1109/ICCAR.2018.8384703.

Studer, R., Benjamins, V. and Fensel, D. (1998), "Knowledge engineering: principles and methods", *Data and Knowledge Engineering*, Vol. 25 Nos 1-2, pp. 161-197, doi: 10.1016/S0169-023X(97)00056-6.

Tahan, M., Tsoutsanis, E., Muhammad, M. and Karim, Z. (2017), "Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: a review", *Applied Energy*, Vol. 198, pp. 122-144, doi: 10.1016/j.apenergy.2017.04.048.

Tiddens, W., Braaksma, J. and Tinga, T. (2022), "Exploring predictive maintenance applications in industry", *Journal of Quality in Maintenance Engineering*, Vol. 28 No. 1, pp. 68-85, doi: 10.1108/JQME-05-2020-0029.

Tricco, A., Lillie, E., Zarin, W., O'brien, K., Colquhoun, H., Kastner, M. and Wilson, K. (2016), "A scoping review on the conduct and reporting of scoping reviews", *BMC Medical Research Methodology*, Vol. 16, pp. 1-10, doi: 10.1186/s12874-016-0116-4.

Tricco, A., Lillie, E., Zarin, W., O'Brien, K., Colquhoun, H., Levac, D. and Straus, S. (2018), "PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation", *Annals of Internal Medicine*, Vol. 169 No. 7, p. 467, doi: 10.7326/M18-0850.

Villa, V., Naticchia, B., Bruno, G., Aliev, K., Piantanida, P. and Antonelli, D. (2021), "IoT open-source architecture for the maintenance of building facilities", *Applied Sciences*, Vol. 11 No. 12, p. 5374, doi: 10.3390/app11125374.

Von Enzberg, S., Naskos, A., Metaxa, I., Köchling, D. and Kühn, A. (2020), "Implementation and transfer of predictive analytics for smart maintenance: a case study", *Frontiers in Computer Science*, Vol. 2, 578469.

Wang, T., Ali, A. and Au-Yong, C. (2022), "Exploring a body of knowledge for promoting the building information model for facility management", *Ain Shams Engineering Journal*, Vol. 13 No. 4, 101717, doi: 10.1016/j.asej.2022.101717.

Yalcinkaya, M. and Singh, V. (2014), "Building information modeling (BIM) for facilities management–literature review and future needs", in *Product Lifecycle Management for a Global Market*, Edition 11, pp. 1-10.

Yang, L., Cormican, K. and Yu, M. (2019), "Ontology-based systems engineering: a state-of-the-art review", *Computers in Industry*, Vol. 111, pp. 148-171, doi: 10.1016/j.compind.2019.05.003.

Yitmen, I., Sadri, H. and Taheri, A. (2023), "Chapter 4. AI-driven digital twins for predictive operation and maintenance in building facilities", in *Cognitive Digital Twins for Smart Lifecycle Management of Built Environment and Infrastructure. Challenges, Opportunities and Practices*, ISBN 9781003230199.

Zhao, Y., Wang, N., Liu, Z. and Mu, E. (2022), "Construction theory for a building intelligent operation and maintenance system based on digital twins and machine learning", *Buildings*, Vol. 12 No. 2, p. 87, doi: 10.3390/buildings12020087.

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