buildings

Review

A Systematic Review of Artificial Intelligence Applied to Facility Management in the Building Information Modeling Context and Future Research Directions

Rodrigo Pedral Sampaio *, António Aguiar Costa and Inês Flores-Colen

Civil Engineering Research and Innovation for Sustainability (CERIS), Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais 1, 1049-001 Lisboa, Portugal
* Correspondence: rodrigosampaio@tecnico.ulisboa.pt; Tel.: +351-912-536-917

Abstract: Throughout the operation and maintenance (O&M) stage, facility management (FM) teams collect and process data from different sources, often needing to be adequately considered when making future decisions. This data could feed statistical models based on artificial intelligence (AI), thus improving decision-making in FM. Building information modeling (BIM) appears in this context, leveraging how data and information are systematized, enabling structured information and its use. This article addresses the state-of-the-art of using AI techniques applied to FM in the BIM context, analyzing articles between 2012 and 2021 related to this area. It is interesting to note that only from 2018 onwards, there is a substantial increase in these publications, from about 8 publications (2012 to 2017) to 24 publications (2018 to 2021) on average. This growth shows the progressive application of the optimization methods mentioned above, which opens new opportunities for the FM profession. This study contributes to the body of knowledge by highlighting the investigated tendency and gaps in critical areas and their relationship with the research topic. Noteworthy future directions are suggested, directing on (i) data and system integration; (ii) predictive models; (iii) automatic as-built/classification; (iv) internet of things; (v) energy management; and (vi) augmented/virtual reality.

Keywords: digital transition; facility management; buildings; artificial intelligence; building information modeling; internet of things; predictive models; literature review

Citation: Pedral Sampaio, R.; Aguiar Costa, A.; Flores-Colen, I. A Systematic Review of Artificial Intelligence Applied to Facility Management in the Building Information Modeling Context and Future Research Directions. *Buildings* **2022**, *11*, 1939. https://doi.org/10.3390/buildings12111939

Academic Editors: Salvatore Antonio Biancardo and Andrej Tibaut

Received: 29 September 2022
Accepted: 7 November 2022
Published: 10 November 2022

1. Introduction

Facility management (FM) is a professional activity that integrates people, spaces, processes, and technology within the built environment, and the main objective is to ensure its utmost functionality [1]. Traditionally, architecture, engineering, construction (AEC), and FM have been disconnected from the built asset life cycle, and the FM sector is far behind the latest technological trends in other sectors [2–6]. Notwithstanding, the management of buildings in usage conditions should be efficient during their life cycle, with a sustainable way of considering the new challenges of the European Union (EU): resilience and digital transition, so FM contributes to achieving these goals. Furthermore, 85% of the project's total life cycle cost is spent on these activities and covers more than 50 years of the whole life span [7]. Throughout the building life cycle, the most significant fraction of expenses is incurred during the operation and maintenance (O&M) stage and represents 50–70% of the total annual operating costs [8]. Hence, considering these high costs in the operational phase, there is an increasing need to develop more efficient practices to manage the built environment.

In the last decade, the architecture, engineering, construction, and facility management (AECFM) has enhanced the implementation of essential innovations for its management and design processes, experiencing a paradigm shift driven by new computational tools. Nevertheless, FM's management of operations and integration of products are still carried out manually, separately, and independently, making it even more complex [9].

A study in the United States in the early 2000s estimated potential yearly savings in the US facilities industry of over $2 billion for owners and operators, related to inefficient business process management [10]. These costs arise from ineffective management processes, unnecessary facility management systems and training costs, productivity loss, and rework costs, among others [10]. In other words, the complexity of the FM integration process and the FM activity have compelled facility managers to surround themselves with efficient and specialized tools, which are still in the initial stage. These tools help automate routine tasks, manage information, monitor the building's performance, and assist decision-making processes [5]. However, information systems organize data from various FM processes, and most share similar asset and maintenance management purposes, mainly focusing on capturing valuable information. Consequently, some fail to include the diversity of all necessities of FM and interoperability [6,11].

Information technology (IT) is gaining increasing importance in the sector, and its potential to provide the tools and systems for facilities information management is widely recognized [12–14]. Digital transition in FM is reinventing how we plan our strategy, deliver, operate, maintain and manage infrastructures, offering an excellent opportunity to improve facility information management and provide a more sustainable path in non-core activities. Indeed, the digital transition requires high levels of integration, connectivity, real-time collaboration, and intelligent technology novelties that meet the demand for customized and sustainable methods, which are crucial to the Construction 4.0 concept [15].

Construction 4.0 emerged as a new industrial revolution, providing a set of new approaches and tools to enhance the efficiency of industrial processes, especially considering the various social and current challenges. The Internet of Things (IoT), immersive technologies such as virtual reality (VR) and augmented reality (AR), big data, and artificial intelligence (AI) are examples of these digital technologies [16]. These trends can potentially improve planning and management of scope, costs, environment, and safety in the value chain of projects and assets, thus creating a more resilient and sustainable industry [17].

Building information modeling (BIM) methodology, which upgraded the digitalization of buildings from 2D to 3D, triggered a new vision of the industry paradigm. BIM supports and structures data, potentiating a more comprehensive digitalization of processes and promoting more intelligent approaches. This methodology suggests the integrated management of the building by using parametric digital models and combining other dimensions such as time, finance and environmental variables, security/safety, and facilities [15].

Since BIM models can be used throughout the whole life cycle and maintained over time, the connection between digital data systems and physical systems offers owners and operators a powerful means of rapidly saving information from a virtual facility model [18]. However, when the data repository in BIM increases, more sophisticated analytical tools are required [18]. These data science tools, including artificial intelligence (AI), minimize uncertainties and find new solutions, thus increasing the precision of the decision-making process. So, based on a unique multidimensional data source, AI tools can discover patterns, relations, and correlations between information using some algorithms [19]. The term AI itself encompasses many methodologies, applications, and technologies, such as machine learning (ML), data mining (DM), deep learning (DL), and expert systems (ES), among others. AI refers to machines' ability to solve complex problems using algorithms inspired by human intelligence [20].

The digitalization process now faces significant challenges where AI is indicated as a potential solution to integration, automation, and the inclusion of broader environmental contexts. Therefore, facility managers have the expertise and historical information to create a starting point for more intelligent approach models. For instance, it can be used in FM projects to control equipment, the presence or movement of people, to settle the fundamental components to their corresponding 3D model, or to take advantage of all this intelligence inserted into the system to accomplish the work plan [21–23].

Hence, the recent concern about an effective digital transition in FM offers an excellent opportunity to improve facility information management in existing buildings through powerful tools for data analysis, ML, and simulation, such as interoperable BIM platforms.

This paper carries out a systematic analysis of published research on the AI applied to FM in the BIM context, giving the readers an overview of the growth of this subject over the last decade. After the introduction, the paper is structured as follows: Section 2 describes the research methodology; Section 3 clusters a bibliometric analysis; Section 4 debates the contents and identifies tendencies and research gaps discovered in the literature; and Section 5 gives conclusions and further research directions.

The Review's Novelty

Between 2012 and 2021, a few literature reviews on BIM and FM were published. Volk et al. [6] described the implementation of BIM applied to FM in existing buildings and discovered a lack of optimizing and automating tools. Also, Turner et al. [24] discussed the relevance of cognitive computing and artificial intelligence as a key for industry 4.0 technologies.

For Ilter and Ergen [4], one of the future challenges for BIM in FM involves developing a more efficient system capable of building survey and as-built BIM, modeling and managing energy, maintenance information/knowledge integration, and access (identifying assets and capturing data using bar codes and radio frequency identifiers (RFID)), and information exchange.

Ahmed et al. [25] explored the condition of the big data model with its related difficulties, drivers, breaks, and insights in the AEC industry applied to FM. The AEC industry operates in a data-rich business context, and those business data are becoming more significant. Thus, emerging technologies and analytic methods hold great potential to add value to FM.

In an in-depth literature review, Santos et al. [13] consider that developing new tools based on BIM and applying them to FM has excellent growth potential. Likewise, Wong et al. [3] recommend future studies using AI technology to improve FM activities in different environments or indoor conditions. For Rasheed et al. [26], a hybrid analysis and modeling approach developed by combining ML with a physics-based model contributes to integrated computational modeling and simulation of complex problems in many FM tasks.

Standardization greatly supports the management and production of information in FM processes. For instance, ISO 19650-3 [27] and ISO 23387 [28] set out the suggested ideas and values for business procedures across the built environment sector to support the management of information during the building life cycle when using BIM. Also, machine-readable data is critical for reliable and sustainable interoperability in the life cycle of the built assets. However, the issues in the AECFM sector are still large enough. From an FM perspective, the opportunity and advancement in digitization represent an opportunity to join AEC and FM.

Given the number of publications, especially in the last four years, combined with the challenges already identified, it is pertinent to study the current state of knowledge on the use of artificial intelligence techniques applied to FM.

2. Methodology

This study analyzes and categorizes existing research on AI techniques applied to FM in the BIM context from the last decade until 2021 by carrying out a quantitative and qualitative method in bibliometric analysis. This bibliometric analysis aims to provide quantitative analysis through statistical methods to analyze publication trends and academic citations to assess the performance of existing research and understand patterns. To carry this out, the authors perform a systematic literature review to ensure that the research outcomes follow a pre-defined and reproducible methodology and that the research quality is not predisposed by either a priori assumptions or the researcher's experience (typical features of narrative literature reviews).

This systematic analysis consists in this study of four main steps (Figure 1): (i) keyword search in the Scopus and Web of Science database; (ii) selection of international journals with the citescore (“*the number of citations received by an article in a year of documents published in the previous three years, divided by the number of documents indexed in Scopus published in the same three years*”) upper or equal to 1.0; (iii) application of filters only to include articles related to the use of AI techniques applied to FM in the BIM context; and (iv) categorization of articles based on content. Only journal articles in the final publications stage were admitted to the study to guarantee that all candidate’s records were peer-reviewed and provide additional quality assurance. Finally, the publication languages were restricted to English to allow the most candidate records to be reviewed.

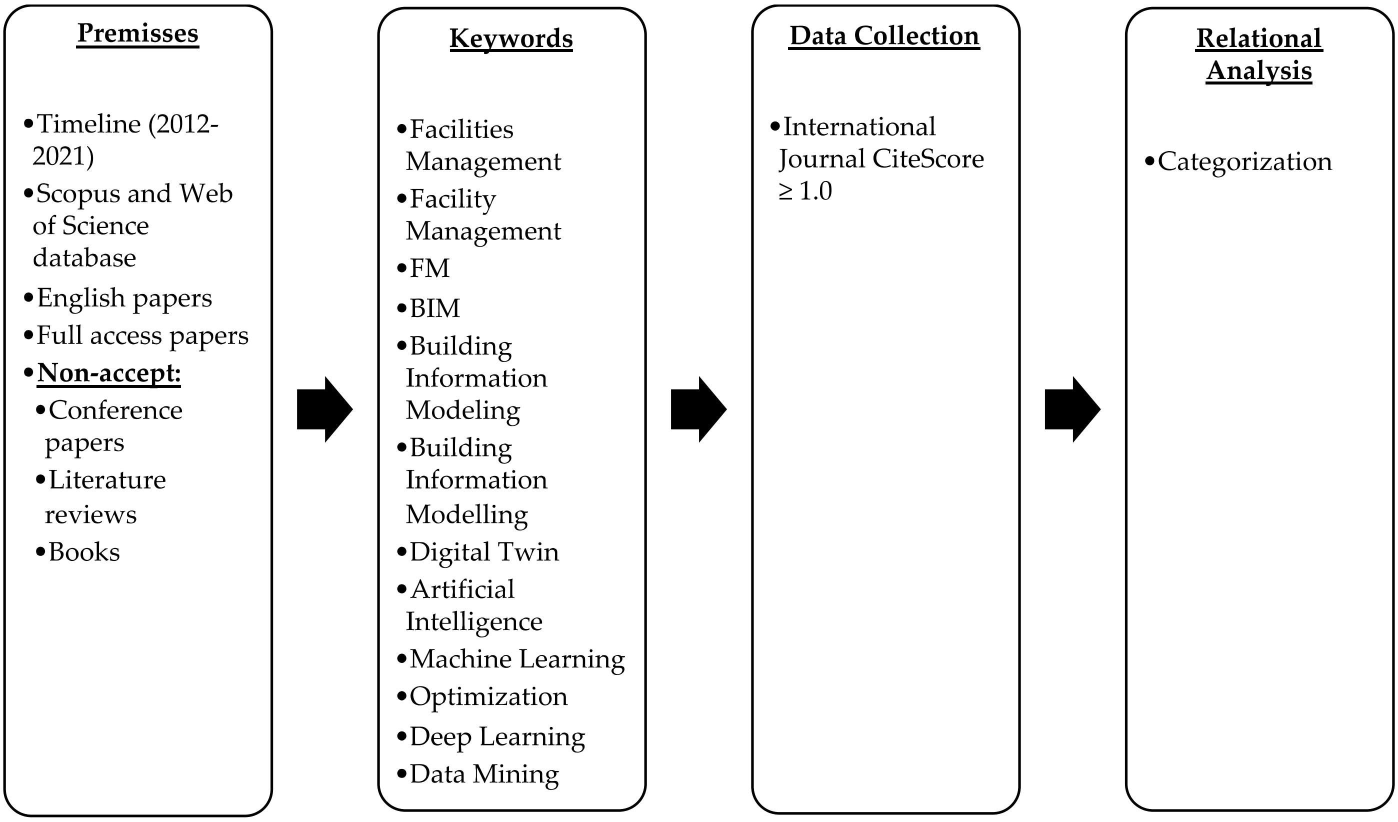

Figure 1. Research methodology.

Firstly, a keywords search was conducted in the selected databases using the following keywords and operators (AND/OR): (“Facility management” OR “Facilities management” OR “FM”) AND (“BIM” OR “Building Information Modeling” OR “Building Information Modelling” OR “Digital Twin”) AND (“Artificial Intelligence” OR “Machine Learning” OR “Optimization” OR “Deep Learning” OR “Data Mining”). With these standard keywords in the academic literature review, we receive a comprehensive picture of recently published research and implementation efforts about the AI techniques applied to FM in the BIM context, which is an important goal of this research. Thus, this search resulted in 226 articles in which the topic correlated with AI techniques applied to FM in the BIM context.

The next step was to filter papers that did not have: (i) an international journal citescore upper than or equal to 1.0, (ii) full paper open access, and (iii) after a complete reading of the paper, did not fit our criteria. As a result, 140 papers were identified to be further analyzed.

Finally, a categorization procedure was performed by each author independently based on a grounded approach. Thus, our proposed categories are built on this article’s contents instead of classifying the literature based on existing research topics or areas (presented in other publications). The last search was run on 25 January 2022.

3. Bibliometric Analysis

The bibliometric analysis shows increased published articles on AI techniques applied to FM in the BIM context over the last decade, from 2 in 2012 to 29 in 2021 (Figure 2 and Table 1). It is also interesting that around 77% of the 140 articles analyzed were published between 2017 and 2021, demonstrating that the last 5 years have been particularly productive on this topic. This growth results from the increasing application of these new methods of analysis and optimization, which open new opportunities to approach this problem differently, also improving the quality of the information collected from the maturation of BIM. The application of AI tools allows for optimizing the management of the built environment, which is essential for the Facility Manager's profession.

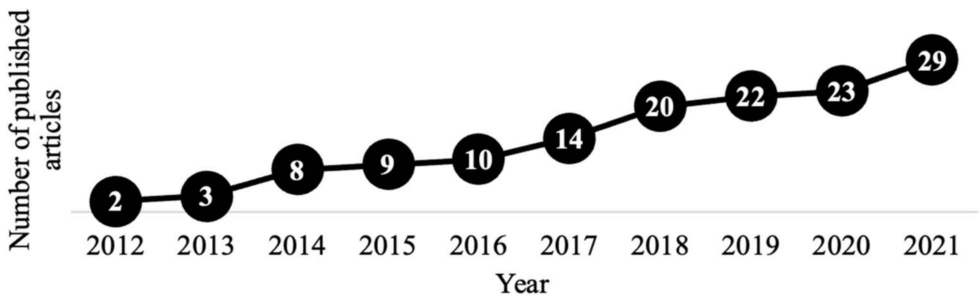

Figure 2. AI applied to FM in the BIM context reviewed papers published over the last decade (2012–2021).

During the period studied, the United States led the number of publications (30), followed by the United Kingdom (21), China (15), and Canada (11) (Figure 3). During this last decade and according to the selection conditions, automation and construction published the higher number of articles in the area (25%), followed by facilities (6%) and advanced engineering informatics, applied sciences, computing in civil engineering, and energy and buildings (4%) journals. also, the 10 top journals represent over 50% of the total reviewed papers (Table 2).

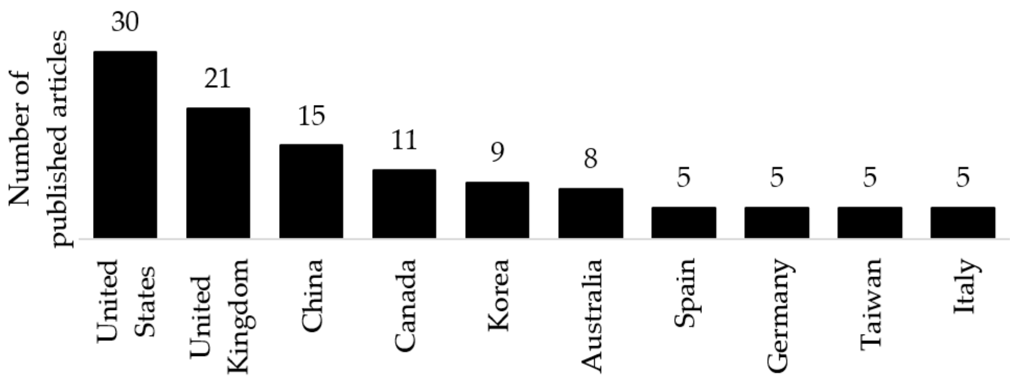

Figure 3. AI applied to FM papers published over the last decade and countries or territories (2012–2021).

Table 1. Articles published in the last decade on AI applied to FM in the BIM context (List of international journals).

International Journals	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Automation in Construction	1	1	1	3	1	4	7	6	9	2	**35**
Facilities	0	0	0	0	1	2	1	3	0	1	**8**
Advanced Engineering Informatics	0	1	0	1	1	0	1	0	0	2	**6**
Applied Sciences	0	0	0	0	0	0	1	1	1	3	**6**
Computing in Civil Engineering	0	0	0	1	3	2	0	0	0	0	**6**
Energy and Buildings	0	0	2	0	0	0	0	1	1	1	**5**
Performance of Constructed Facilities	0	0	0	0	0	1	1	1	0	1	**4**
Buildings	0	0	0	2	0	0	0	1	1	0	**4**
Engineering, Construction and Architectural Management	0	0	1	0	0	1	1	0	1	0	**4**
Sustainability	0	0	0	0	0	0	0	0	0	3	**3**
Building Engineering	0	0	0	0	0	0	0	0	3	0	**3**
Sustainable Cities and Society	0	0	0	0	0	1	0	1	1	0	**3**
Information Technology in Construction	0	0	0	0	1	0	0	1	1	0	**3**
Visualization in Engineering	0	0	0	2	1	0	0	0	0	0	**3**
Construction Innovation	0	0	1	0	0	0	0	0	1	0	**2**
Building and Environment	0	0	0	0	0	1	0	0	0	1	**2**
Applied Energy	0	0	0	0	0	0	2	0	0	0	**2**
Advances in Engineering Software	0	0	0	0	1	0	1	0	0	0	**2**
Construction Engineering and Management	1	0	0	0	0	0	0	0	0	1	**2**
Computers in Industry	0	1	1	0	0	0	0	0	0	0	**2**
Building Research and Information	0	0	0	0	0	0	0	0	2	0	**2**
Energies	0	0	0	0	0	0	1	0	0	0	**1**
Egyptian Informatics Journal	0	0	0	0	0	0	0	0	0	1	**1**
Atmosphere	0	0	0	0	0	0	0	0	0	1	**1**
ISPRS International Journal of Geo-Information	0	0	0	0	0	0	1	0	0	0	**1**
Geoscience Frontiers	0	0	0	0	0	0	0	0	0	1	**1**
Engineering with Computers	0	0	0	0	0	0	0	1	0	0	**1**
Graphical Models	0	0	0	0	0	0	0	1	0	0	**1**
Sensors	0	0	0	0	0	0	0	0	0	1	**1**
IEEE Access	0	0	0	0	0	0	0	0	0	1	**1**
Electronics	0	0	0	0	0	0	0	1	0	0	**1**
Facilities Management	0	0	0	0	0	0	0	0	1	0	**1**
Architectural Engineering	0	0	0	0	0	1	0	0	0	0	**1**
Management in Engineering	0	0	0	0	0	0	1	0	0	0	**1**
Construction Management and Economics	0	0	1	0	0	0	0	0	0	0	**1**
KSCE Journal of Civil Engineering	0	0	0	0	0	0	1	0	0	0	**1**
At-Automatisierungstechnik	0	0	0	0	0	0	0	1	0	0	**1**
Mechanical Systems and Signal Processing	0	0	0	0	0	0	0	0	1	0	**1**
Transportation Research Part B: Methodological	0	0	0	0	0	0	1	0	0	0	**1**
Applied Geophysics	0	0	0	0	0	0	0	0	0	1	**1**
Accident Analysis and Prevention	0	0	0	0	0	0	0	0	0	1	**1**
Lecture Notes in Computer Science	0	0	1	0	0	0	0	0	0	0	**1**
Information Systems	0	0	0	0	0	0	0	0	0	1	**1**
MIS Quarterly Executive	0	0	0	0	0	0	0	0	0	1	**1**
Information Systems Management	0	0	0	0	0	1	0	0	0	0	**1**
Production and Operations Management	0	0	0	0	0	0	0	0	0	1	**1**
International Journal of Building Pathology and Adaptation	0	0	0	0	0	0	0	1	0	0	**1**
Computer-Aided Civil and Infrastructure Engineering	0	0	0	0	1	0	0	0	0	0	**1**
Disaster Risk Reduction	0	0	0	0	0	0	0	1	0	0	**1**
Theoretical Foundations of Chemical Engineering	0	0	0	0	0	0	0	0	0	1	**1**
Engineering Business Management	0	0	0	0	0	0	0	0	0	1	**1**
Artificial Intelligence Tools	0	0	0	0	0	0	0	1	0	0	**1**
IEEE Transactions on Intelligent Transportation Systems	0	0	0	0	0	0	0	0	0	1	**1**
IFIP Advances in Information and Communication Technology	0	0	0	0	0	0	0	0	0	1	**1**
Total	**2**	**3**	**8**	**9**	**10**	**14**	**20**	**22**	**23**	**29**	**140**

Table 2. Percentage of 10 top published reviewed articles per journal over the last decade.

International Journals	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Automation in Construction	50%	33%	13%	33%	10%	29%	35%	27%	39%	7%	**25%**
Facilities	0%	0%	0%	0%	10%	14%	5%	14%	0%	3%	**6%**
Advanced Engineering Informatics	0%	33%	0%	11%	10%	0%	5%	0%	0%	7%	**4%**
Applied Sciences	0%	0%	0%	0%	0%	0%	5%	5%	4%	10%	**4%**
Computing in Civil Engineering	0%	0%	0%	11%	30%	14%	0%	0%	0%	0%	**4%**
Energy and Buildings	0%	0%	25%	0%	0%	0%	0%	5%	4%	3%	**4%**
Performance of Constructed Facilities	0%	0%	0%	0%	0%	7%	5%	5%	0%	3%	**3%**
Buildings	0%	0%	0%	22%	0%	0%	0%	5%	4%	0%	**3%**
Engineering, Construction and Architectural Management	0%	0%	13%	0%	0%	7%	5%	0%	4%	0%	**3%**
Total	**50%**	**67%**	**50%**	**78%**	**60%**	**71%**	**60%**	**59%**	**57%**	**34%**	**56%**

A method to visualize the direction of the research result at AI-applied FM in the BIM context is by plotting the co-occurrence keywords. The visualization of similarities (VOS) Viewer software was used for generating Figure 4, presenting evidence of how related the research efforts are. The higher the number of co-occurrences, the closer they are to the map. The circle size indicates the number of occurrences of each term in the paper's title, abstract, and keywords. Colors are used to indicate clusters. The words are grouped into three clusters of closely associated terms using a grouping technique presented by Waltman et al. [29], which is based on minimizing distances between keywords. Therefore, the most associated keywords fall into one cluster.

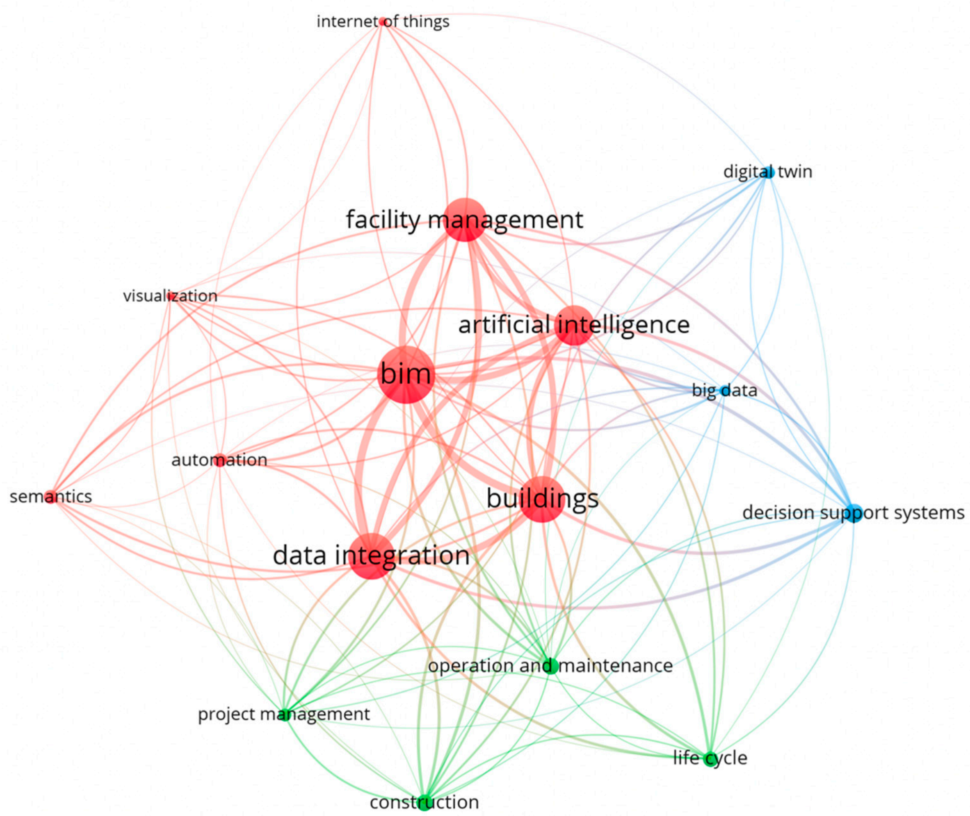

Figure 4. Keyword clustering by color (red, blue, and green).

Figure 5 is a plot of the occurring keywords according to the average publication year, which indicates the average publication year of the research in which a keyword appears. The red-colored keywords present the current topics at AI applied FM in the BIM context.

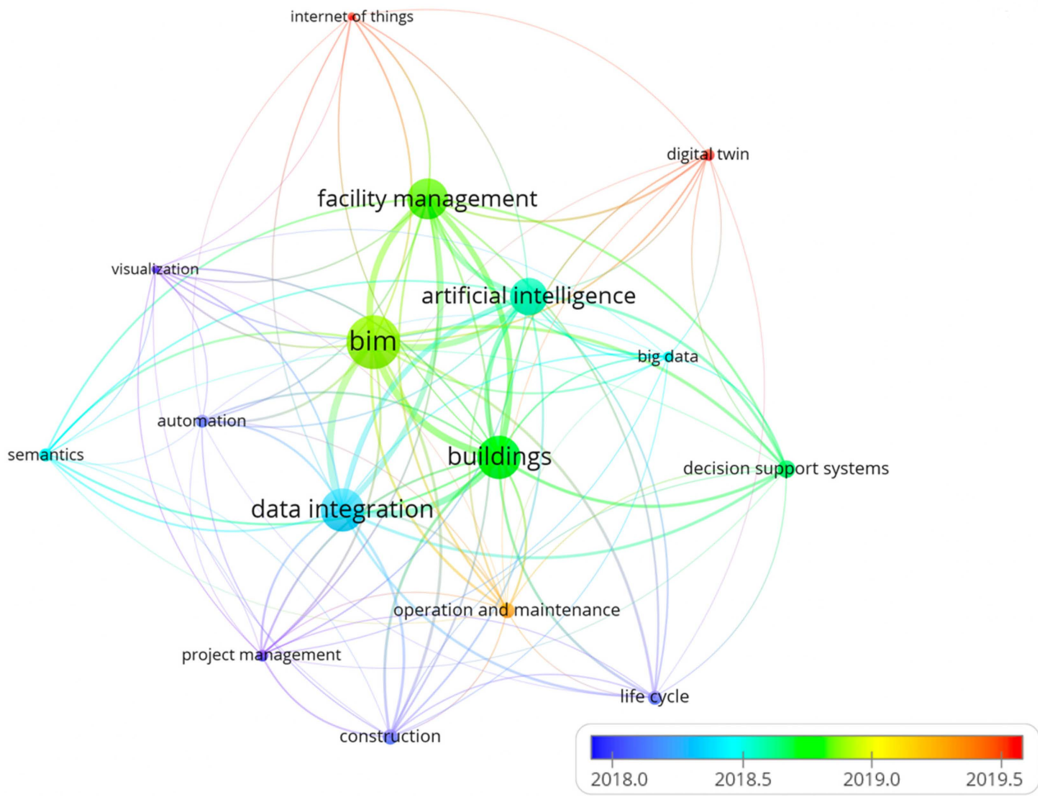

Figure 5. The current occurring keywords map per year.

The bibliometric analysis shows that FM, BIM, and AI are the most frequently used keywords. Notwithstanding, this is not surprising since our search was specific to this field. This is followed by data integration, operation, and maintenance, internet of things, and visualization, as shown in Figure 4. The keywords' clustering indicates that the most selected articles comprise the cluster data and system integration. Keyword analysis can support mapping the literature, but it is insufficient for a current and specific topic.

Based on the content analysis and the frequency of keywords, the topics involving AI applied FM in the BIM context were grouped into six categories (Figure 6 and Table 3) that support the entire intelligent building management process and which are described in Section 4: (i) data and system integration; (ii) predictive models; (iii) automatic as-built/classification; (iv) internet of things; (v) energy management; and (vi) augmented/virtual reality. The explanation of the choice of each one of these categories is listed in Section 4.

This section provides an overview of the existing research and derives trends for proposing a future agenda. This section describes and considers the main research works for each topic. Table 3 summarizes the categorization structure and the main findings.

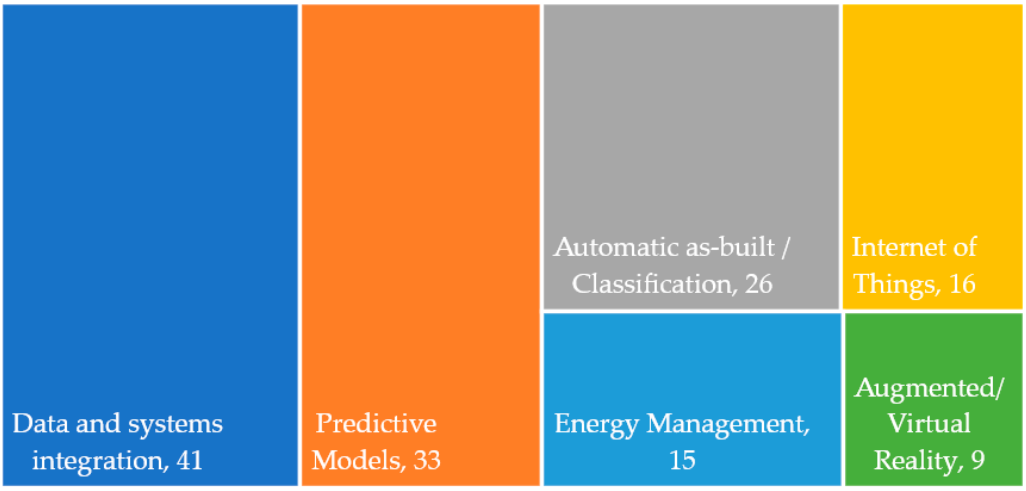

Figure 6. AI applied to FM in the BIM context categories in terms of the number of journals.

Table 3. References by topics and main findings.

Topic	Findings of Use AI Applied to FM in the BIM Context	References
Data and systems integration	Transformation of data into knowledge via ontological analyses for a decision-supporting and automatic model in facility management	[9,11,30–68]
Predictive Models	An alternative used in statistical problems. The prediction result shows very high accuracy and proves the AI model's real-time capabilities to learn, forecast, and capture risk level values.	[21,69–100]
Automatic as-built/Classification	Innovative solutions and classification algorithms are being increasingly investigated to improve the capture, complete the data and filter the unrelated information, and communication of essential information for O&M will also be an emerging topic.	[18,20,22,23,101–122]
Internet of Things	Assisting FM actions and processes	[123–138]
Energy Management	Development of suitable tools that can connect IoT and ML techniques to achieve economic, environmental, and resilience objectives	[19,139–152]
Augmented/Virtual Reality	A sophisticated and effective way of rendering spatial information, improving visualization and interaction for FM tasks.	[153–161]

3.1. Data and Systems Integration

The lack of data integration and data loss remain critical concerns in O&M [100]. FM teams spend time collecting and processing data from different sources, often not adequately considered when making future decisions [6]. In any case, the inaccessibility of historical data is one reason not to use the inefficiency and deficiencies in a continuous improvement process on a large scale. Also, this absence of automation explains productivity marks far below other industries, which is worrying in an applicable sector for the quality of spaces and the well-being of people. Consequently, the review shows that this topic was the most cited, with 29% of the 140 selected papers.

FM systems, namely, computer-aided facilities management (CAFM), computerized maintenance management system (CMMS), building management system (BMS), building energy management system (BEMS), and building automation system (BAS), carry the information of FM. On the other hand, BIM provides rich semantic details on building elements and typically supports geometric and non-geometric information.

Different participants often conduct the design, construction, and O&M stages. Overall, the formats that the FM systems support for import and export are textual such as spreadsheets and relational database files, and most of these data are heterogeneous [56]. Thus, one of the biggest tasks of adopting the BIM methodology is to ensure an efficient and rich exchange of information. Furthermore, as data increases over time, it is vital to provide information reliability, traceability, and long-term archiving, so current solutions include integrating BIM and FM systems data [5].

The entire theoretical framework of BIM data used for FM is that systems exchange data between them [65]. Information exchanges are inevitably associated with the possibility of exchanging information between different systems, a term called interoperability. However, manual integration of heterogeneous data can incur high-cost labor tasks and cause incorrect information, preventing correct decision-making.

So, interoperability and automatic integration are the main reasons for common problems during a building life cycle, such as information asymmetry and data fragmentation [2]. Nevertheless, it is difficult for computers to integrate the data when storing different data sources into diverse data formats.

Although an international standard could manage information related to the design and construction, FM systems data cannot be controlled by a communal data model since it uses different scopes and tasks in the O&M period [67]. For this purpose, open-standard data models improve this integration between BIM models and FM systems [62]. Data templates provide a uniform data structure to describe the characteristics of construction objects, enabling continuous exchanges of these industry business semantics throughout the lifecycle of any built asset.

Also, open standards and procedures minimize data loss for improved information sharing, information use and reuse, coordination, and communication, such as industry foundation classes (IFC), for interaction between computer aid design (CAD), such as Revit, Allplan, and Archicad, and data templates, for communication between stakeholders, such as construction operation building information exchange (COBie) [162].

Indeed, the foremost BIM-based data for FM consists of a COBie datasheet and an IFC-based BIM model. Nevertheless, COBie and IFC have distinctive schema and to use them for FM work, an integrated IFC-based building model should manage the required FM system data with some external data. Then, integrating the FM information from various database structures and automatically defining the data connections among FM information foreshadows a significant boost to O&M tasks.

The FM teams scuffle with information management, primarily because of the lack of interoperability between existing FM systems. So, integrating the FM information from various database structures and automatically defining the data relationships among FM information has been investigated by many researchers [56,62,66,68,146].

Conventionally, BIM is used for FM data integration in three main approaches: (i) FM system leads, and BIM supports, (ii) BIM leads and FM systems support, and (iii) as an external platform integrating BIM model and FM system, Figure 7 [163].

In the first approach, the FM systems dominate the integrated model, and the BIM model is used as a secondary model to convert the BIM data to support an FM system. The workflow starts with extracting related data from a BIM model and preparing data for transfer, typically via a data template such as COBie format, putting the data into a structure appropriate for an intended FM tool. Thus, a clear definition of which FM information they need to include in the BIM remains a necessary and critical step [164]. This data template identifies and codifies all the required information, providing a structured way to manage asset data such as installation data, warranty description, reference service life, and others throughout the building life cycle [165]. In addition, this approach is advantageous mainly because (i) FM systems are more lightweight than BIM models, (ii) they are suitable for modifications, and (iii) they do not require additional staff training [163]. On the other hand, the lack of three-dimensional visualization and interactivity are shortcomings.

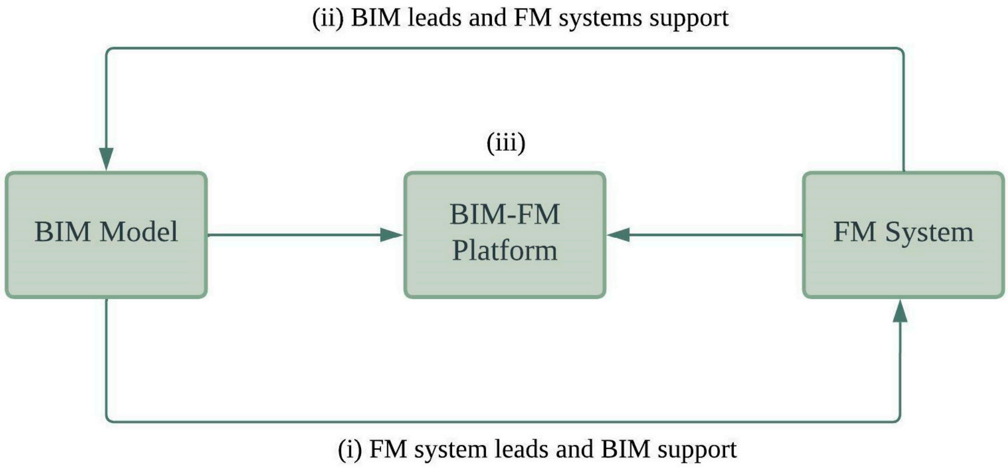

Figure 7. AI applied to FM categories conventional data integration approaches [163].

The BIM model dominates the second approach. The FM System is used as a supplementary model to import or integrate data into the BIM model, providing non-geometric data support as necessary. Since BIM as a collaborative methodology for built environment management has many benefits, organizing and structuring the information in product data is essential to achieve this interoperability. Also, IFC files allow the sharing process for better qualification and validation of data, helping to overcome the interoperability problem among various software used in the AEC [166]. For instance, object, relation, and resource classes fulfill IFC files with information and relations, making integration possible [58].

Using BIM models to manage FM data seems to be a good patch for enhancing current FM practices. However, the shortcomings are (i) difficulty accessing or finding existing project documentation or a clear definition of FM conventions, especially on existing buildings [2,5,6], (ii) BIM authoring tools and training for facilities management staff [66], and (iii) management of big data and BIM tools limitations [163,167,168]. So, the first two approaches are opposite in terms of shortcomings, and the literature pinpoints a hybrid solution, like the third approach.

In order to reach interoperability between BIM and FM Systems, rules are generated in the third approach for mapping between IFC and COBie, which represent applications in two singular domains, to ensure correct mapping between the two information models and achieve integration of the model. However, to solve the problem of the divergency of BIM and FM systems, information is transferred to a third-party management platform called middleware.

Nowadays, middleware solutions are growing fast, and many integration solutions are going through this route [67,163,167,169]. A middleware solution allows two different software to exchange information and link applications.

The primary purpose of this third-party customization is to offer simplified solutions that reduce BIM training for facilities management staff with limited skills in advanced platforms. In that regard, Kang and Hong [56] categorized this integration approach into five groups, i.e., ontology-based, schema-based, service-based, process-based, and system-based approaches. They concluded that ontology-based data integration approaches are more flexible and generalized than other methods and integrate heterogeneous data among standard models. Also, some of these methods can miss mapping information because of inconsistencies between the types of classes and specific levels of the original and object schema.

Ontologies provide a clear representation of contexts and enable their reuse among systems. Besides ontologies, context-awareness applications can be prepared with various logic-based interpretation tools [135]. In particular, based on ontological principles, these proposals aim to reduce the redundant requirements and rules for exchanging information.

Following this, Niknam and Karshenas [68] designed a semantic web and presented a shared ontology approach to solving the information integration difficulty by creating a web of structured and connected data that machines can process. In the same way, Kim et al. [67] developed an OWL-based ontology to achieve the essential FM information from BIM-based IFC and COBie data.

Faria et al. [170] proposed a method for semi-automatically conceiving an OWL ontology for the COBie standard. The proposed method allows combining data from different bases with different fundamental schemas distributed over the internet and processing inferred knowledge by computer without human error.

In the literature, it seems that translating the IFC schemes into web ontology language (OWL) corresponds to generating an ontology from IFC schemas and substantially improves the integration process. Furthermore, ontology serves as the core mechanism for ML flows, such as the complex interactions representing machine-understandable data and ML algorithms, making it simpler for data and information extraction tools to communicate [60].

As the ontology studies in the AECFM industry increase, this hybrid approach, using middleware, will also increase due to the systems' communication. The benefits of AI and the transformation of information into knowledge via ontological studies for a decision-supporting and automated model in facility management emerge as insights into the future trend. In contrast, due to the BIM-FM interoperability problems, a future agenda involves: (i) tailored solutions for each case study to make data exchangeable, (ii) the development of a taxonomy of non-geometric information and each ontology, and (iii) the optimization of O&M processes and complex programming tasks.

3.2. Predictive Models

Buildings are complex structural systems that deteriorate over time, with differentiated degradation rates, subject to several factors, including aggressive environmental agents, insufficient maintenance programs, construction problems, and inadequate design [171]. Corrective maintenance incurs unplanned downtime costs, estimated to be $50 billion annually [172]. Therefore, predictive maintenance becomes increasingly important, influencing buildings' long-term longevity and components, reducing almost 98% of the maintenance cost and ensuring occupants' comfort level, productivity, and health [172].

Given the vast number of existing buildings, the asset manager's primary task is to guarantee that existing assets function as expected within predetermined quality requirements while minimizing costs [173]. However, facility managers plan work orders subjectively based on work background [99], resulting, for example, in lower energy efficiency and decreased occupant satisfaction [98].

The conducted review showed that 83% (26) of the total category selected articles (33) were published between 2019 and 2021. Currently, facility managers have large amounts of data that require time and resources. Additionally, the key to scheduling when a required intervention is necessary depends on the ability to predict the future condition of the asset and, in most cases, the interconnections between the various building mechanisms and systems, the diversity of building components, and several changing environmental factors that are overlooked.

When physical-based models are unavailable or difficult to deploy, medium- to long-term intervention planning is often based on periodic inspections combined with statistical models. Thus, AI can intelligently connect this data, whereas humans' capacity to process this information is often limited [20].

Briefly, Sousa et al. [174] evaluated the performance of AI-based models, namely artificial neural networks (ANNs) and support vector machines (SVMs), in predicting the structural state of sewers and improved the performance condition predicted from around 66% to 75% and 71%, respectively, when compared with traditional models. Cheng et al. [21] applied ANNs and SVM to predict the condition to maintain or repair mechanical, electrical, and plumbing (MEP) components and found around 96% and 97% of prediction accuracy. Ivanko et al. [96] used several ML to perform the uses of domestic water heaters and found a prediction accuracy of over 80% with ANNs, Prophet, and XGBoost techniques.

Towfiqul Islam et al. [97] applied three ML benchmark models, namely ANNs, SVMs, random forest (RF), and two new hybrid ML models called subspace random (SR) and dagging (Da), to prepare flood susceptibility maps for the Teesta River basin of Bangladesh. The primary flexibility and predictive capability were found in the case of the Da model, the area under the curve (AUC) equal to 0.873, followed by the SVMs (AUC = 0.860), the RS, the ANNs (AUC = 0.830), and the RF model (AUC = 0.810), respectively. However, the results suggested that the five models had high prediction accuracy with an AUC over 0.80.

Indeed, the modeling for predictive maintenance involves tasks such as selecting entered variables for extrapolation and determining the model's prediction technique and parameters. Also, these advanced analytical tools should be capable of distinguishing between different patterns behind the operational data, increasing the efficiency of the maintenance tasks, and upgrading the user's occupancy satisfaction in buildings. Hence, predictive maintenance is a cog in the wheel of intelligent building management to predict the condition before the damage occurs.

The concept of AI emerges as an alternative used in statistical problems. There is no predefined expression relating the inputs with the results. The fitting process simultaneously adjusts the relation between the enters, the results and the relative weight of each input [174]. Also, AI is triggering several developments in many fields, such as ML, problem-solving and planning, and many others. The prediction result is very accurate and proves the AI model's real-time capabilities to learn, forecast, and capture risk level values.

Finally, as a future agenda, significant database improvements and other ML techniques, such as ensemble and bagging, could improve the prediction model's stability and accuracy and may need to be tested.

3.3. Automatic As-Built and Classification

As-built models and drawings are required documents used by the facility managers in the FM of buildings to manage facility spaces, maintenance, and energy systems [121]. An as-built information model is a critical starting point for a building's efficiency management and analysis process. However, preparing for BIM as-is is often time-consuming, labor-intensive, and expensive. The review shows that this topic was the third most cited and was found in 19% of the 140 reviewed articles.

Having the as-built models in mind, Klein et al. [121] investigated the benefits and restrictions of photogrammetric image processing to record and prove actual as-built conditions. The image-based survey method, identified by them, offers benefits to the presently employed manual survey technique, including less time and labor spent on-site and boosting accessibility to building geometry and features beyond the limits of conventional measuring devices.

So, the development of many realities capture technology (RCT) tools, such as laser scanning and photogrammetry, has shown promising results, offering potential opportunities to overcome the currently employed manual survey method [121,175]. However, the post-process of these tools is usually time-consuming, labor-intensive, and costly. Thus, developing an utmost automatic and efficient post-processing has emerged as a future agenda by many researchers in the past few years.

Golparvar-Fard et al. [119] studied an automated approach to recognizing physical progress and proposed an SVMs machine learning to detect physical progress automatically. This model quantifies improvement automatically, accounts for occlusions, and identifies whether restructured building elements are lacking from occlusions or changes. Nonetheless, the model needs improvements by incorporating surface-recognition techniques to detect progress according to operational details.

Yuan et al. [118] developed an automatic classification technique for usual building materials based upon terrestrial laser scanner data using different supervised learning classifiers algorithms such as decision trees (DTs), discriminant analysis (DAs), naive Bayes (NBs), SVMs, k-nearest neighbors (KNNs), and ensembles.

Werbrouck et al. [120] proposed a framework called scan-to-graph to integrate scan-to-BIM concepts with semantic web technologies. They investigated how linked data techniques can cope with several known tasks that prevent a more common application of as-is BIM models for built environments. Anyway, using the web technologies' flexibility, a workflow is initiated that can be part of numerous existing building set-ups.

Incomplete construction information on delivery and the lack of interoperable tools devoted to FM are fundamental reasons for the delay in developing more intelligent management of the sector. Thus, in the reviewed papers, innovative solutions and classification algorithms are being increasingly investigated to improve the capture, and complete the data and filter the unrelated information. Communication of essential information for O&M will also be an emerging topic.

3.4. Internet of Things

The Internet of Things (IoT) is another relevant technology to be considered within the FM industry innovation framework. The IoT integrates various processes such as identifying, sensing, computation, and networking interconnection. Objects are embedded with electronic sensors and are often equipped with universal intelligence to collect and exchange data [176]. As we have seen, most of the papers in this category are from the last 3 years, which is a very recent area of study.

In addition to BIM applied to FM, IoT can improve the efficiency of facility maintenance management, ensuring maintainability, creating and updating digital assets, and real-time data access from devices such as wireless communication standards and RFID, to improve operational efficiencies [177]. Identifying physical building mechanisms and linking them with BIM models through RFID tags for asset tracking [132,137,138] allows the development of systems for automatic facility identity recognition and the behavior of the building asset during its lifecycle.

These devices serve as a building's identification assets to access the related information linked with the equivalent objects in the database. Seghezzi et al. [131] used IoT camera-based sensor systems to monitor the occupancy in calibration and test campaigns. They aimed to optimize the operational building stage through innovative monitoring techniques and data analytics.

As BIM offers a rigorous project representation with all required information, IoT enhances the information model by providing real-time data. Thus, integration of these technologies is emerging, having excellent potential for extending the application of these devices to capture, transfer and store extensive data/information on the O&M stage. Combining the BIM methodology with the IoT technology, it is possible to obtain a digital version of the built environment, or in other words, the digital twin (DT). Thus, the IoT is the way to connect the real world to the virtual world, which represents a vast potential for the FM sector.

The DT can be defined as the virtual replica of an object or physical environments, such as a building, infrastructure, or city. Also, the physical and virtual components are interconnected in real-time. Thus, at least three elements are necessary: (i) the physical environment, (ii) the digital model, and (iii) the link between the two [26].

In this context, Lu et al. [134] developed a pump DT-enabled anomaly detection system to provide a complete asset monitoring solution in the O&M phase. They used vibration sensors connected to a BAS and integrated into the DT. Based on the same concept, Booyse et al. [133] demonstrated the representative of the data manifold of healthy information implanted in the data captured by a sensor network of the asset for the DT model.

IoT has great potential for assisting FM actions and processes, including linking physical objects with digital objects by linking CMMS and BIM [64,178]. However, (i) storing, process, managing, and maintaining big data from these devices, (ii) low accuracy for recognizing indoor locations, and (iii) integration of IoT-BIM-FM are shortcomings and emerge as a future agenda.

3.5. Energy Management

An analysis of the energy's end-use in the EU in 2018 shows that services, households, and industry were responsible for more than 66% of the total consumption in this continent [179]. Thus, monitoring facilities' energy performance throughout the O&M stage is essential to compare the energy performance during the life cycle. Moreover, to achieve the first climate-neutral continent by 2050, energy efficiency in the built environment can significantly contribute to achieving this target.

The bibliometric analysis results reveal that this topic was found in 15 papers of the total reviewed documents, and 11 were published in the past 5 years, which denotes a recent high interest from the researchers on this topic.

The identified studies presented distinctive approaches to AI techniques in energy management, which included: a monitoring and control interface for energy-efficient management as an eco-feedback system [148,150,151], BIM and building performance simulation (BPS) integration [149,152], and methodologies to predict energy usage [146,147,152].

It is relevant to present the work of McGlinn et al. [151]. They used an innovative energy management system as an eco-feedback system to address the issue of providing smart control suggestions to facility managers. The new energy management system is derived from an intelligent system component that combines ANNs and genetic algorithms (GA) rule generation, a fuzzy rule selection engine, and a semantic knowledge base.

Ruiz et al. [152] developed a methodology to predict energy usage as a visualization tool for eight buildings and used several ML technologies such as SVMs, ANNs, and regression trees (RT). The most refined approach to model energy consumption in this case study was the ANNs technique.

While technology developments are improving buildings' energy efficiency, the future research agenda involves suitable tools that can connect IoT and ML techniques to achieve environmental, economic, and resilience objectives. Consequently, ML offers a means of turning ubiquitous data into helpful information (e.g., recognizing some patterns that are not obvious) and transforming it into knowledge to be applied.

3.6. Augmented/Virtual Reality

Virtual reality (VR) and augmented reality (AR) is the category that has the fewest papers in this literature review but showed the highest growth rate in the study, and 98% of the category's selected articles were published after 2018.

Current technological advances in hardware and software have driven new developments in this area, thus enabling greater accessibility to game-engine technologies. Therefore, this type has started being used due to its intuitive controls, immersive 3D technology, and network capabilities, levering, for example, non-BIM users' involvement in the BIM-based design process and interacting with reality with instruments that allow visualizing and collecting information.

Nowadays, advanced interfaces such as VR and AR are becoming a sophisticated and effective way of rendering spatial information, improving visualization and interaction for FM tasks. VR is a technology that builds a virtual 3D model to visually reproduce a computer-generated simulation of a natural or made-up environment [160]. AR is a visualization technology that integrates, in a real-time view, natural habitats and virtual objects within the same setting [159].

This technology, which began in the gaming industry, allows for better visualization and simulation of various construction scenarios. The immersive environment provides a more realistic and intuitive reproduction of the location and condition of construction elements compared to traditional CAD [180]. For instance, Edwards et al. [158] developed a two-way data transferring channel into a game engine that allows multiple simultaneous users in a BIM-based design process.

El Ammari and Hammad [157] developed VR and AR tools to leverage the visualization technique and improve the facility's visual perception by overlaying 3D virtual objects and textual data on top of the view of real-world building objects. Baek et al. [161] presented an AR system for FM using an image-based indoor localization scheme that evaluates the user's indoor position and location by comparing the user's perspective to a BIM-based on a DL computation.

Finally, the bibliometric review identified a lack of (i) an automated and efficient data transfer approach between BIM and VR/AR technologies, (ii) visualization issues, and (iii) remote collaboration issues.

4. Conclusions

This article provides an overview of the current application of artificial intelligence techniques to facility management in the building information modelling context based on the available scientific literature. Between 2012 and 2021, 140 articles were adequately reviewed and classified. Artificial intelligence applied to facility management research has grown in recent years, with more than 77% of the papers published under review in the last 5 years. Furthermore, it was observed that early published articles were more generic and theoretical than the currently published papers, which are very specific and focused on applying new technologies and tools.

One of the most significant challenges for applying artificial intelligence in facility management is that facility managers waste a large percentage of their time on non-productive tasks, such as visualizing models, searching, and validating different pieces of information, primarily because of a lack of information support. Consequently, the global technological trends point to a commitment by players in the facility management sector towards integrating digital technologies, adopting new processes, and a clear focus on efficiently managing during the building life cycle. This industry is experiencing a digital boom due to integrating new technologies, concepts, and approaches. however, there is a low level of technological maturity of companies in the facility management sector.

With the emergence of intelligent buildings, which embed most spaces with smart objects, BIM provides builders new opportunities to quality upgrade these buildings at lower costs and shorter project duration, allowing information exchange between the various stakeholders involved [59]. The conventional FM practice needs to incorporate the integrated approach of intelligent management, which is embedded in information and functional integration.

After carefully analyzing the content of the 140 articles and categorizing them, the three artificial intelligence techniques applied to facility management in the building information modelling context categories that had the highest number of published papers were (i) data and system integration; (ii) predictive models; and (iii) automatic as-built/classification. However, (iv) the Internet of Things, (v) energy management, and (vi) augmented/virtual reality can also be considered hot topics in the literature, as most of the papers on these areas were published in the last 3 years of the studied period.

On the one hand, integrating facility and sensor information makes it possible to efficiently develop and operate an intelligent management system and understand the correlations among various facilities. Second, incorporating management functions, such as real-time monitoring of facility status, context awareness for event identification and response, and visualization of facility information is a core enabler of intelligent facility management. Third, the increasing use of artificial intelligence techniques shows very high accuracy and proves the artificial intelligence model's capabilities to learn, make predictions, and capture risk level values in real time. Virtual and augmented reality have created the necessary faithfulness to the truth, immersion, interaction, visualization capabilities, and adequacy to support the required facility management simulation.

5. Future Research Directions

Further research in information exchange highlights that more research is needed to solve interoperability issues between software formats and software generations used in facility management phases. Many of the existing facility management systems are totally disjointed. Some companies provide one system, but most of these systems have issues when interfacing with each other. Thus, what tends to happen is that facility managers often must look after many standalone systems and somehow become experts at all these different systems. That often causes lots of inefficiency and working processes to fail.

Other future work includes: (i) developing a set of standardized practical processes to integrate different information sources related to facility management activities; (ii) automatic transfer of real-time data from devices and monitoring to a centralized model and (iii) access and management of information, for instance by improving virtual reality and augmented reality technologies, to develop a set of operative educational, entertainment and technical tools from virtual models and its dataset. In any case, it is essential to underline that the main contribution of this paper to facility management is strongly correlated to the use of Construction 4.0 technologies such as Internet of Things (IoT), big data, artificial intelligence (AI), robotics, and digital twin.

Finally, it is hoped that this paper will contribute to further developing a more intelligent and sustainable process applied to facility management in the building information modelling context, integrating all these methodologies and technologies into a new deep digital twin, developing out-of-the-box solutions and tools, moving architecture, engineering, construction, and facility management forward to the future.

Author Contributions: Conceptualization, R.P.S.; methodology, R.P.S., A.A.C. and I.F.-C.; formal analysis, R.P.S., A.A.C. and I.F.-C.; investigation, R.P.S., A.A.C. and I.F.-C.; writing—original draft preparation, R.P.S.; writing—review and editing, R.P.S.; visualization, A.A.C. and I.F.-C.; supervision, A.A.C. and I.F.-C.; project administration, A.A.C. and I.F.-C.; funding acquisition, A.A.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by a research grant under a contract of Instituto Superior Técnico (IST), University of Lisbon, and 1018P.06013/REV@Construction number 06013, and CERIS research unit. This work is co-financed by European Structural and Investment Funds in the FEDER component, through the Operational Competitiveness and Internationalization Programme (COMPETE 2020) and Lisbon Regional Operational Programme (ROP Lisbon) [Project No. 046123; Funding Reference: POCI-01-0247-FEDER-046123 and LISBOA-01-0247-FEDER-046123].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

1. *BS EN ISO 41001:2018*; Facility Management—Management Systems—Requirements with Guidance for Use. BSI Standards Publication: London, UK, 2018; ISBN 9780539011708.
2. Bonanomi, M. Building Information Modeling (BIM) and Facility Management (FM). In *Knowledge Management and Information Tools for Building Maintenance and Facility Management*; Springer International Publishing: Cham, Switzerland, 2016; pp. 149–177.
3. Wong, J.K.W.; Ge, J.; He, S.X. Digitisation in Facilities Management: A Literature Review and Future Research Directions. *Autom. Constr.* **2018**, *92*, 312–326.
4. Ilter, D.; Ergen, E. BIM for Building Refurbishment and Maintenance: Current Status and Research Directions. *Struct. Surv.* **2015**, *33*, 228–256. [CrossRef]
5. Pärn, E.A.; Edwards, D.J.; Sing, M.C.P. The Building Information Modelling Trajectory in Facilities Management: A Review. *Autom. Constr.* **2017**, *75*, 45–55. [CrossRef]
6. Volk, R.; Stengel, J.; Schultmann, F. Building Information Modeling (BIM) for Existing Buildings—Literature Review and Future Needs. *Autom. Constr.* **2014**, *38*, 109–127. [CrossRef]
7. Teicholz, E. Bridging the AEC Technology Gap. *IFMA Facil. Manag. J.* **2004**, 1–8.
8. Rondeau, E.P.; Brown, R.K.; Lapides, P.D. *Facility Management*, 2nd ed.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2012.

9. Jallow, A.K.; Demian, P.; Baldwin, A.N.; Anumba, C. An Empirical Study of the Complexity of Requirements Management in Construction Projects. *Eng. Constr. Archit. Manag.* **2014**, *21*, 505–531. [CrossRef]
10. Gallaher, M.P.; O'Connor, A.C.; Dettbarn, J.L., Jr.; Gilday, L.T. *Cost Analysis of Inadequate Interoperability in the U.S. Capital Facilities Industry*; National Institute of Standards and Technology: Gaithersburg, MD, USA, 2004.
11. McArthur, J.J.; Bortoluzzi, B. Lean-Agile FM-BIM: A Demonstrated Approach. *Facilities* **2018**, *36*, 676–695. [CrossRef]
12. Vieira, R.; Carreira, P.; Domingues, P.; Costa, A.A. Supporting Building Automation Systems in BIM/IFC: Reviewing the Existing Information Gap. *Eng. Constr. Archit. Manag.* **2020**, *27*, 1357–1375. [CrossRef]
13. Santos, R.; Costa, A.A.; Grilo, A. Bibliometric Analysis and Review of Building Information Modelling Literature Published between 2005 and 2015. *Autom. Constr.* **2017**, *80*, 118–136.
14. Costa, A.A.; Lopes, P.M.; Antunes, A.; Cabral, I.; Grilo, A.; Rodrigues, F.M. 3I Buildings: Intelligent, Interactive and Immersive Buildings. *Procedia Eng.* **2015**, *123*, 7–14. [CrossRef]
15. Muñoz-La Rivera, F.; Mora-Serrano, J.; Valero, I.; Oñate, E. Methodological-Technological Framework for Construction 4.0. *Arch. Comput. Methods Eng.* **2021**, *28*, 689–711. [CrossRef]
16. Omar, A.; Mostafa, M.S.; Yasser, A.; Alaqeeli, M.M. Benefits and Challenges of Integrating IoT, VR & AR in the BIM-Based Facility Management Process: Literature and Case-Based Analysis. *J. Eng. Res.* **2022**, *6*, 25–40.
17. Forcael, E.; Ferrari, I.; Opazo-Vega, A.; Pulido-Arcas, J.A. Construction 4.0: A Literature Review. *Sustainability* **2020**, *12*, 9755. [CrossRef]
18. Peng, Y.; Lin, J.R.; Zhang, J.P.; Hu, Z.Z. A Hybrid Data Mining Approach on BIM-Based Building Operation and Maintenance. *Build. Environ.* **2017**, *126*, 483–495. [CrossRef]
19. Gawin, B.; Marcinkowski, B. Business Intelligence in Facility Management: Determinants and Benchmarking Scenarios for Improving Energy Efficiency. *Inf. Syst. Manag.* **2017**, *34*, 347–358. [CrossRef]
20. Marzouk, M.; Zaher, M. Artificial Intelligence Exploitation in Facility Management Using Deep Learning. *Constr. Innov.* **2020**, *20*, 609–624. [CrossRef]
21. Cheng, J.C.P.; Chen, W.; Chen, K.; Wang, Q. Data-Driven Predictive Maintenance Planning Framework for MEP Components Based on BIM and IoT Using Machine Learning Algorithms. *Autom. Constr.* **2020**, *112*, 103087. [CrossRef]
22. Motamedi, A.; Hammad, A.; Asen, Y. Knowledge-Assisted BIM-Based Visual Analytics for Failure Root Cause Detection in Facilities Management. *Autom. Constr.* **2014**, *43*, 73–83. [CrossRef]
23. Wang, C.; Cho, Y.K.; Kim, C. Automatic BIM Component Extraction from Point Clouds of Existing Buildings for Sustainability Applications. *Autom. Constr.* **2015**, *56*, 1–13. [CrossRef]
24. Turner, C.J.; Stergioulas, L.; Oyekan, J.; Griffin, D. Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities. *IEEE Trans. Ind. Inform.* **2021**, *17*, 746–756. [CrossRef]
25. Ahmed, V.; Tezel, A.; Aziz, Z.; Sibley, M. The Future of Big Data in Facilities Management: Opportunities and Challenges. *Facilities* **2017**, *35*, 725–745. [CrossRef]
26. Rasheed, A.; San, O.; Kvamsdal, T. Digital Twin: Values, Challenges and Enablers from a Modeling Perspective. *IEEE Access* **2020**, *8*, 21980–22012. [CrossRef]
27. *ISO 19650-3*; Organization and Digitization of Information about Buildings and Civil Engineering Works, Including Building Information Modelling (BIM): Information Management Using Building Information Modelling. Part 3, Operational Phase of the Assets. ISO: Geneva, Switzerland, 2020.
28. *ISO 23387*; Building Information Modelling (BIM)—Data Templates for Construction Objects Used in the Life Cycle of Built Assets—Concepts and Principles Modélisation Des Informations de La Construction (BIM)-Modèles de Données Pour Les Objets de Construction Utilisés Durant Le Cycle de Vie Des Biens Construits-Concepts et Principes Copyright Protected Document. ISO: Geneva, Switzerland, 2020.
29. Waltman, L.; van Eck, N.J.; Noyons, E.C.M. A Unified Approach to Mapping and Clustering of Bibliometric Networks. *J. Informetr.* **2010**, *4*, 629–635. [CrossRef]
30. Meske, C.; Osmundsen, K.S.; Junglas, I. Designing and Implementing Digital Twins in the Energy Grid Sector. *MIS Q. Exec.* **2021**, *20*, 183–198. [CrossRef]
31. Lietaert, P.; Meyers, B.; van Noten, J.; Sips, J.; Gadeyne, K. Knowledge Graphs in Digital Twins for AI in Production. In Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems, Proceedings of the IFIP WG 5.7 International Conference, APMS 2021, Nantes, France, 5–9 September 2021; Dolgui, A., Bernard, A., Lemoine, D., von Cieminski, G., Romero, D., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 249–257.
32. Nota, G.; Peluso, D.; Lazo, A.T. The Contribution of Industry 4.0 Technologies to Facility Management. *Int. J. Eng. Bus. Manag.* **2021**, *13*. [CrossRef]
33. Tang, S.; Shelden, D.R.; Eastman, C.M.; Pishdad-Bozorgi, P.; Gao, X. BIM Assisted Building Automation System Information Exchange Using BACnet and IFC. *Autom. Constr.* **2020**, *110*, 103049. [CrossRef]
34. Jang, R.; Collinge, W. Improving BIM Asset and Facilities Management Processes: A Mechanical and Electrical (M&E) Contractor Perspective. *J. Build. Eng.* **2020**, *32*, 101540. [CrossRef]
35. Quinn, C.; Shabestari, A.Z.; Misic, T.; Gilani, S.; Litoiu, M.; McArthur, J.J. Building Automation System—BIM Integration Using a Linked Data Structure. *Autom. Constr.* **2020**, *118*, 103257. [CrossRef]
36. Rogage, K.; Clear, A.; Alwan, Z.; Lawrence, T.; Kelly, G. Assessing Building Performance in Residential Buildings Using BIM and Sensor Data. *Int. J. Build. Pathol. Adapt.* **2020**, *38*, 176–191. [CrossRef]

37. Ashworth, S.; Tucker, M.; Druhmann, C.K. Critical Success Factors for Facility Management Employer's Information Requirements (EIR) for BIM. *Facilities* **2019**, *37*, 103–118. [CrossRef]
38. Cheng, M.Y.; Chang, N.W. Dynamic Construction Material Layout Planning Optimization Model by Integrating 4D BIM. *Eng. Comput.* **2019**, *35*, 703–720. [CrossRef]
39. Zhou, X.; Zhao, J.; Wang, J.; Huang, X.; Li, X.; Guo, M.; Xie, P. Parallel Computing-Based Online Geometry Triangulation for Building Information Modeling Utilizing Big Data. *Autom. Constr.* **2019**, *107*, 102942. [CrossRef]
40. Dawood, H.; Siddle, J.; Dawood, N. Integrating IFC and NLP for Automating Change Request Validations. *J. Inf. Technol. Constr.* **2019**, *24*, 540–552. [CrossRef]
41. Ashtari Talkhestani, B.; Jung, T.; Lindemann, B.; Sahlab, N.; Jazdi, N.; Schloegl, W.; Weyrich, M. An Architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. *Automatisierungstechnik* **2019**, *67*, 762–782. [CrossRef]
42. Lee, Y.C.; Eastman, C.M.; Solihin, W. Erratum: Logic for Ensuring the Data Exchange Integrity of Building Information Models. (Automation in Construction (2018) 85 (249–262) (S0926580517307276) (10.1016/j.Autcon.2017.08.010)). *Autom. Constr.* **2018**, *93*, 388–401. [CrossRef]
43. Farghaly, K.; Abanda, F.H.; Vidalakis, C.; Wood, G. Taxonomy for BIM and Asset Management Semantic Interoperability. *J. Manag. Eng.* **2018**, *34*, 103257. [CrossRef]
44. Hartmann, T.; Amor, R.; East, E.W. Information Model Purposes in Building and Facility Design. *J. Comput. Civ. Eng.* **2017**, *31*, 04017054. [CrossRef]
45. Khan, R.R.A.; Ahmed, V. Building Information Modelling and Vertical Farming: Data Integration to Manage Facilities and Processes. *Facilities* **2017**, *35*, 710–724. [CrossRef]
46. Edirisinghe, R.; London, K.A.; Kalutara, P.; Aranda-Mena, G. Building Information Modelling for Facility Management: Are We There Yet? *Eng. Constr. Archit. Manag.* **2017**, *24*, 1119–1154. [CrossRef]
47. Rodriguez-Trejo, S.; Ahmad, A.M.; Hafeez, M.A.; Dawood, H.; Vukovic, V.; Kassem, M.; Naji, K.K.; Dawood, N. Hierarchy Based Information Requirements for Sustainable Operations of Buildings in Qatar. *Sustain. Cities Soc.* **2017**, *32*, 435–448. [CrossRef]
48. Greenwood, D.; Kassem, M. Supporting Building Owners and Facility Managers in the Validation and Visualisation of Asset Information Models (AIM) through Open Standards and Open Technologies. *J. Inf. Technol. Constr.* **2016**, *21*, 434–455.
49. Skandhakumar, N.; Salim, F.; Reid, J.; Drogemuller, R.; Dawson, E. Graph Theory Based Representation of Building Information Models for Access Control Applications. *Autom. Constr.* **2016**, *68*, 44–51. [CrossRef]
50. Hu, Z.Z.; Zhang, J.P.; Yu, F.Q.; Tian, P.L.; Xiang, X.S. Construction and Facility Management of Large MEP Projects Using a Multi-Scale Building Information Model. *Adv. Eng. Softw.* **2016**, *100*, 215–230. [CrossRef]
51. Lee, W.L.; Tsai, M.H.; Yang, C.H.; Juang, J.R.; Su, J.Y. V3DM+: BIM Interactive Collaboration System for Facility Management. *Vis. Eng.* **2016**, *4*, 5. [CrossRef]
52. Kang, T.W.; Choi, H.S. BIM Perspective Definition Metadata for Interworking Facility Management Data. *Adv. Eng. Inform.* **2015**, *29*, 958–970. [CrossRef]
53. Pittet, P.; Cruz, C.; Nicolle, C. An Ontology Change Management Approach for Facility Management. *Comput. Ind.* **2014**, *65*, 1301–1315. [CrossRef]
54. Zhou, W.; Heesom, D.; Georgakis, P.; Tah, J.H.M. User-Centred Design for Collaborative 4D Modelling. *Constr. Innov.* **2014**, *14*, 493–517. [CrossRef]
55. Chong, H.-Y.; Wang, J.; Shou, W.; Wang, X.; Guo, J. Improving Quality and Performance of Facility Management Using Building Information Modelling. In *Cooperative Design, Visualization, and Engineering*; Springer: Cham, Switzerland, 2014; Volume 8683.
56. Kang, T.W.; Hong, C.H. A Study on Software Architecture for Effective BIM/GIS-Based Facility Management Data Integration. *Autom. Constr.* **2015**, *54*, 25–38. [CrossRef]
57. Lin, C.L.; Chen, J.K.C.; Ho, H.H. Bim for Smart Hospital Management during Covid-19 Using Mcdm. *Sustainability* **2021**, *13*, 6181. [CrossRef]
58. Shalabi, F.; Turkan, Y. IFC BIM-Based Facility Management Approach to Optimize Data Collection for Corrective Maintenance. *J. Perform. Constr. Facil.* **2017**, *31*, 04016081. [CrossRef]
59. Zhang, J.; Seet, B.C.; Lie, T.T. Building Information Modelling for Smart Built Environments. *Buildings* **2015**, *5*, 100–115. [CrossRef]
60. Yitmen, I.; Alizadehsalehi, S.; Akıner, İ.; Akıner, M.E. An Adapted Model of Cognitive Digital Twins for Building Lifecycle Management. *Appl. Sci.* **2021**, *11*, 4276. [CrossRef]
61. González, E.; Piñeiro, J.D.; Toledo, J.; Arnay, R.; Acosta, L. An Approach Based on the IfcOWL Ontology to Support Indoor Navigation. *Egypt. Inform. J.* **2021**, *22*, 1–13. [CrossRef]
62. Marmo, R.; Polverino, F.; Nicolella, M.; Tibaut, A. Building Performance and Maintenance Information Model Based on IFC Schema. *Autom. Constr.* **2020**, *118*, 103275. [CrossRef]
63. Pärn, E.A.; Edwards, D.J. Conceptualising the FinDD API Plug-in: A Study of BIM-FM Integration. *Autom. Constr.* **2017**, *80*, 11–21. [CrossRef]
64. Motamedi, A.; Soltani, M.M.; Setayeshgar, S.; Hammad, A. Extending IFC to Incorporate Information of RFID Tags Attached to Building Elements. *Adv. Eng. Inform.* **2016**, *30*, 39–53. [CrossRef]
65. Kensek, K. BIM Guidelines Inform Facilities Management Databases: A Case Study over Time. *Buildings* **2015**, *5*, 899–916. [CrossRef]
66. Becerik-Gerber, B.; Jazizadeh, F.; Li, N.; Calis, G. Application Areas and Data Requirements for BIM-Enabled Facilities Management. *J. Constr. Eng. Manag.* **2012**, *138*, 431–442. [CrossRef]

67. Kim, K.; Kim, H.; Kim, W.; Kim, C.; Kim, J.; Yu, J. Integration of IFC Objects and Facility Management Work Information Using Semantic Web. *Autom. Constr.* **2018**, *87*, 173–187. [CrossRef]
68. Niknam, M.; Karshenas, S. A Shared Ontology Approach to Semantic Representation of BIM Data. *Autom. Constr.* **2017**, *80*, 22–36. [CrossRef]
69. Lok, K.L.; So, A.; Opoku, A.; Chen, C. A Sustainable Facility Management Outsourcing Relationships System: Artificial Neural Networks. *Sustainability* **2021**, *13*, 4740. [CrossRef]
70. Wang, J.; Zhang, J.H.; Zhang, J.L.; Lu, F.M.; Meng, R.G.; Wang, Z. Research on Fault Recognition Method Combining 3D Res-UNet and Knowledge Distillation. *Appl. Geophys.* **2021**, *18*, 199–212. [CrossRef]
71. Magalhaes, R.P.; Lettich, F.; Macedo, J.A.; Nardini, F.M.; Perego, R.; Renso, C.; Trani, R. Speed Prediction in Large and Dynamic Traffic Sensor Networks. *Inf. Syst.* **2021**, *98*, 101444. [CrossRef]
72. Ji, S.; Wang, Y.; Wang, Y. Geographically Weighted Poisson Regression under Linear Model of Coregionalization Assistance: Application to a Bicycle Crash Study. *Accid. Anal. Prev.* **2021**, *159*, 106230. [CrossRef]
73. Betz, T.S.; Grussing, M.N.; Bartels, L. Optimizing Markov Probabilities for Generation of a Weibull Model to Characterize Building Component Failure Processes. *J. Perform. Constr. Facil.* **2021**, *35*, 04021077. [CrossRef]
74. Chang, X.; Huang, Y.; Li, M.; Bo, X.; Kumar, S. Efficient Detection of Environmental Violators: A Big Data Approach. *Prod. Oper. Manag.* **2021**, *30*, 1246–1270. [CrossRef]
75. Munawar, H.S.; Ullah, F.; Qayyum, S.; Khan, S.I.; Mojtahedi, M. Uavs in Disaster Management: Application of Integrated Aerial Imagery and Convolutional Neural Network for Flood Detection. *Sustainability* **2021**, *13*, 7547. [CrossRef]
76. Luo, X.J.; Oyedele, L.O. Forecasting Building Energy Consumption: Adaptive Long-Short Term Memory Neural Networks Driven by Genetic Algorithm. *Adv. Eng. Inform.* **2021**, *50*, 101357. [CrossRef]
77. Alishahi, N.; Nik-Bakht, M.; Ouf, M.M. A Framework to Identify Key Occupancy Indicators for Optimizing Building Operation Using WiFi Connection Count Data. *Build. Environ.* **2021**, *200*, 107936. [CrossRef]
78. Chuluunsaikhan, T.; Heak, M.; Nasridinov, A.; Choi, S. Comparative Analysis of Predictive Models for Fine Particulate Matter in Daejeon, South Korea. *Atmosphere* **2021**, *12*, 1295. [CrossRef]
79. Yang, H.; Liu, C.; Zhuang, Y.; Sun, W.; Murthy, K.; Pu, Z.; Wang, Y. Truck Parking Pattern Aggregation and Availability Prediction by Deep Learning. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 12778–12789. [CrossRef]
80. Sresakoolchai, J.; Kaewunruen, S. Integration of Building Information Modeling and Machine Learning for Railway Defect Localization. *IEEE Access* **2021**, *9*, 166039–166047. [CrossRef]
81. Wu, J.; Lepech, M.D. Incorporating Multi-Physics Deterioration Analysis in Building Information Modeling for Life-Cycle Management of Durability Performance. *Autom. Constr.* **2020**, *110*, 103004. [CrossRef]
82. Yousefli, Z.; Nasiri, F.; Moselhi, O. Maintenance Workflow Management in Hospitals: An Automated Multi-Agent Facility Management System. *J. Build. Eng.* **2020**, *32*, 101431. [CrossRef]
83. Mo, Y.; Zhao, D.; Du, J.; Syal, M.; Aziz, A.; Li, H. Automated Staff Assignment for Building Maintenance Using Natural Language Processing. *Autom. Constr.* **2020**, *113*, 103150. [CrossRef]
84. Gao, X.; Pishdad-Bozorgi, P. A Framework of Developing Machine Learning Models for Facility Life-Cycle Cost Analysis. *Build. Res. Inf.* **2020**, *48*, 501–525. [CrossRef]
85. Alawad, H.; An, M.; Kaewunruen, S. Utilizing an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Overcrowding Level Risk Assessment in Railway Stations. *Appl. Sci.* **2020**, *10*, 5156. [CrossRef]
86. Moretti, N.; Re Cecconi, F. A Cross-Domain Decision Support System to Optimize Building Maintenance. *Buildings* **2019**, *9*, 161. [CrossRef]
87. Xiao, Y.Q.; Li, S.W.; Hu, Z.Z. Automatically Generating a MEP Logic Chain from Building Information Models with Identification Rules. *Appl. Sci.* **2019**, *9*, 2204. [CrossRef]
88. Chen, C.; Tang, L. BIM-Based Integrated Management Workflow Design for Schedule and Cost Planning of Building Fabric Maintenance. *Autom. Constr.* **2019**, *107*, 102944. [CrossRef]
89. Wang, T.-K.; Piao, Y. Development of BIM-AR-Based Facility Risk Assessment and Maintenance System. *J. Perform. Constr. Facil.* **2019**, *33*, 04019068. [CrossRef]
90. Rizeei, H.M.; Pradhan, B.; Saharkhiz, M.A. Allocation of Emergency Response Centres in Response to Pluvial Flooding-Prone Demand Points Using Integrated Multiple Layer Perceptron and Maximum Coverage Location Problem Models. *Int. J. Disaster Risk Reduct.* **2019**, *38*, 101205. [CrossRef]
91. Bortolini, R.; Forcada, N. Building Inspection System for Evaluating the Technical Performance of Existing Buildings. *J. Perform. Constr. Facil.* **2018**, *32*, 04018073. [CrossRef]
92. Xiao, J.; Lou, Y.; Frisby, J. How Likely Am I to Find Parking?—A Practical Model-Based Framework for Predicting Parking Availability. *Transp. Res. Part B Methodol.* **2018**, *112*, 19–39. [CrossRef]
93. Mawed, M.; Aal-Hajj, A. Using Big Data to Improve the Performance Management: A Case Study from the UAE FM Industry. *Facilities* **2017**, *35*, 746–765. [CrossRef]
94. Yang, X.; Ergan, S. BIM for FM: Information Requirements to Support HVAC-Related Corrective Maintenance. *J. Archit. Eng.* **2017**, *23*, 04017023. [CrossRef]
95. Yang, X.; Ergan, S.; Asce, M. Design and Evaluation of an Integrated Visualization Platform to Support Corrective Maintenance of HVAC Problem-Related Work Orders. *J. Comput. Civ. Eng.* **2015**, *30*, 04015041. [CrossRef]

96. Ivanko, D.; Sørensen, Å.L.; Nord, N. Selecting the Model and Influencing Variables for DHW Heat Use Prediction in Hotels in Norway. *Energy Build.* **2020**, *228*, 110441. [CrossRef]
97. Towfiqul Islam, A.R.M.; Talukdar, S.; Mahato, S.; Kundu, S.; Eibek, K.U.; Pham, Q.B.; Kuriqi, A.; Linh, N.T.T. Flood Susceptibility Modelling Using Advanced Ensemble Machine Learning Models. *Geosci. Front.* **2021**, *12*, 101075. [CrossRef]
98. Anand, P.; Deb, C.; Yan, K.; Yang, J.; Cheong, D.; Sekhar, C. Occupancy-Based Energy Consumption Modelling Using Machine Learning Algorithms for Institutional Buildings. *Energy Build.* **2021**, *252*, 111478. [CrossRef]
99. Cao, Y.; Wang, T.; Song, X. An Energy-Aware, Agent-Based Maintenance-Scheduling Framework to Improve Occupant Satisfaction. *Autom. Constr.* **2015**, *60*, 49–57. [CrossRef]
100. Lundkvist, R.; Meiling, J.H.; Sandberg, M. A Proactive Plan-Do-Check-Act Approach to Defect Management Based on a Swedish Construction Project. *Constr. Manag. Econ.* **2014**, *32*, 1051–1065. [CrossRef]
101. Ma, J.W.; Czerniawski, T.; Leite, F. An Application of Metadata-Based Image Retrieval System for Facility Management. *Adv. Eng. Inform.* **2021**, *50*, 101417. [CrossRef]
102. Kim, T.W.; Oh, J.; Min, C.; Hwang, S.Y.; Kim, M.S.; Lee, J.H. An Experimental Study on Condition Diagnosis for Thrust Bearings in Oscillating Water Column Type Wave Power Systems. *Sensors* **2021**, *21*, 457. [CrossRef]
103. Agapaki, E.; Brilakis, I. CLOI: An Automated Benchmark Framework for Generating Geometric Digital Twins of Industrial Facilities. *J. Constr. Eng. Manag.* **2021**, *147*, 0002171. [CrossRef]
104. Bortolini, R.; Forcada, N. Analysis of Building Maintenance Requests Using a Text Mining Approach: Building Services Evaluation. *Build. Res. Inf.* **2020**, *48*, 207–217. [CrossRef]
105. Bouabdallaoui, Y.; Lafhaj, Z.; Yim, P.; Ducoulombier, L.; Bennadji, B. Natural Language Processing Model for Managing Maintenance Requests in Buildings. *Buildings* **2020**, *10*, 160. [CrossRef]
106. Bortoluzzi, B.; Efremov, I.; Medina, C.; Sobieraj, D.; McArthur, J.J. Automating the Creation of Building Information Models for Existing Buildings. *Autom. Constr.* **2019**, *105*, 102838. [CrossRef]
107. Stojanovic, V.; Trapp, M.; Richter, R.; Döllner, J. Service-Oriented Semantic Enrichment of Indoor Point Clouds Using Octree-Based Multiview Classification. *Graph. Models* **2019**, *105*, 101039. [CrossRef]
108. Hu, Z.Z.; Tian, P.L.; Li, S.W.; Zhang, J.P. BIM-Based Integrated Delivery Technologies for Intelligent MEP Management in the Operation and Maintenance Phase. *Adv. Eng. Softw.* **2018**, *115*, 1–16. [CrossRef]
109. Lin, Y.C.; Lin, C.P.; Hu, H.T.; Su, Y.C. Developing Final As-Built BIM Model Management System for Owners during Project Closeout: A Case Study. *Adv. Eng. Inform.* **2018**, *36*, 178–193. [CrossRef]
110. Chen, W.; Chen, K.; Cheng, J.C.P.; Wang, Q.; Gan, V.J.L. BIM-Based Framework for Automatic Scheduling of Facility Maintenance Work Orders. *Autom. Constr.* **2018**, *91*, 15–30. [CrossRef]
111. Chen, J.; Fang, Y.; Cho, Y.K. Performance Evaluation of 3D Descriptors for Object Recognition in Construction Applications. *Autom. Constr.* **2018**, *86*, 44–52. [CrossRef]
112. Lau, L.; Quan, Y.; Wan, J.; Zhou, N.; Wen, C.; Qian, N.; Jing, F. An Autonomous Ultra-Wide Band-Based Attitude and Position Determination Technique for Indoor Mobile Laser Scanning. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 155. [CrossRef]
113. Lu, Q.; Lee, S. Image-Based Technologies for Constructing As-Is Building Information Models for Existing Buildings. *J. Comput. Civ. Eng.* **2017**, *31*, 04017005. [CrossRef]
114. Yang, X.; Ergan, S. Leveraging BIM to Provide Automated Support for Efficient Troubleshooting of HVAC-Related Problems. *J. Comput. Civ. Eng.* **2016**, *30*, 04015023. [CrossRef]
115. Tang, P.; Chen, G.; Shen, Z.; Ganapathy, R. A Spatial-Context-Based Approach for Automated Spatial Change Analysis of Piece-Wise Linear Building Elements. *Comput.-Aided Civ. Infrastruct. Eng.* **2016**, *31*, 65–80. [CrossRef]
116. Golabchi, A.; Akula, M.; Kamat, V. Automated Building Information Modeling for Fault Detection and Diagnostics in Commercial HVAC Systems. *Facilities* **2016**, *34*, 233–246. [CrossRef]
117. Valero, E.; Adán, A.; Bosché, F. Semantic 3D Reconstruction of Furnished Interiors Using Laser Scanning and RFID Technology. *J. Comput. Civ. Eng.* **2016**, *30*, 04015053. [CrossRef]
118. Yuan, L.; Guo, J.; Wang, Q. Automatic Classification of Common Building Materials from 3D Terrestrial Laser Scan Data. *Autom. Constr.* **2020**, *110*, 103017. [CrossRef]
119. Golparvar-Fard, M.; Peña-Mora, F.; Savarese, S. Automated Progress Monitoring Using Unordered Daily Construction Photographs and IFC-Based Building Information Models. *J. Comput. Civ. Eng.* **2015**, *29*, 04014025. [CrossRef]
120. Werbrouck, J.; Pauwels, P.; Bonduel, M.; Beetz, J.; Bekers, W. Scan-to-Graph: Semantic Enrichment of Existing Building Geometry. *Autom. Constr.* **2020**, *119*, 103286. [CrossRef]
121. Klein, L.; Li, N.; Becerik-Gerber, B. Imaged-Based Verification of as-Built Documentation of Operational Buildings. *Autom. Constr.* **2012**, *21*, 161–171. [CrossRef]
122. Bloch, T.; Sacks, R. Comparing Machine Learning and Rule-Based Inferencing for Semantic Enrichment of BIM Models. *Autom. Constr.* **2018**, *91*, 256–272. [CrossRef]
123. Chow, J.K.; Liu, K.F.; Tan, P.S.; Su, Z.; Wu, J.; Li, Z.; Wang, Y.H. Automated Defect Inspection of Concrete Structures. *Autom. Constr.* **2021**, *132*, 103959. [CrossRef]
124. Edirisinghe, R.; Woo, J. BIM-Based Performance Monitoring for Smart Building Management. *Facilities* **2021**, *39*, 19–35. [CrossRef]
125. Valinejadshoubi, M.; Moselhi, O.; Bagchi, A. Integrating BIM into Sensor-Based Facilities Management Operations. *J. Facil. Manag.* **2022**, *20*, 385–400. [CrossRef]

126. Parn, E.A.; Edwards, D.; Riaz, Z.; Mehmood, F.; Lai, J. Engineering-out Hazards: Digitising the Management Working Safety in Confined Spaces. *Facilities* **2019**, *37*, 196–215. [CrossRef]
127. Wei, Y.; Akinci, B. A Vision and Learning-Based Indoor Localization and Semantic Mapping Framework for Facility Operations and Management. *Autom. Constr.* **2019**, *107*, 102915. [CrossRef]
128. Pešić, S.; Tošić, M.; Iković, O.; Radovanović, M.; Ivanović, M.; Bošković, D. BLEMAT: Data Analytics and Machine Learning for Smart Building Occupancy Detection and Prediction. *Int. J. Artif. Intell. Tools* **2019**, *28*, 1960005. [CrossRef]
129. Chang, K.M.; Dzeng, R.J.; Wu, Y.J. An Automated IoT Visualization BIM Platform for Decision Support in Facilities Management. *Appl. Sci.* **2018**, *8*, 1086. [CrossRef]
130. Dibley, M.; Li, H.; Rezgui, Y.; Miles, J. Software Agent Reasoning Supporting Non-Intrusive Building Space Usage Monitoring. *Comput. Ind.* **2013**, *64*, 678–693. [CrossRef]
131. Seghezzi, E.; Locatelli, M.; Pellegrini, L.; Pattini, G.; di Giuda, G.M.; Tagliabue, L.C.; Boella, G. Towards an Occupancy-Oriented Digital Twin for Facility Management: Test Campaign and Sensors Assessment. *Appl. Sci.* **2021**, *11*, 3108. [CrossRef]
132. Motamedi, A.; Soltani, M.M.; Hammad, A. Localization of RFID-Equipped Assets during the Operation Phase of Facilities. *Adv. Eng. Inform.* **2013**, *27*, 566–579. [CrossRef]
133. Booyse, W.; Wilke, D.N.; Heyns, S. Deep Digital Twins for Detection, Diagnostics and Prognostics. *Mech. Syst. Signal Process.* **2020**, *140*, 106612. [CrossRef]
134. Lu, Q.; Xie, X.; Parlikad, A.K.; Schooling, J.M. Digital Twin-Enabled Anomaly Detection for Built Asset Monitoring in Operation and Maintenance. *Autom. Constr.* **2020**, *118*, 103277. [CrossRef]
135. Lee, J.; Jeong, Y.; Oh, Y.S.; Lee, J.C.; Ahn, N.; Lee, J.; Yoon, S.H. An Integrated Approach to Intelligent Urban Facilities Management for Real-Time Emergency Response. *Autom. Constr.* **2013**, *30*, 256–264. [CrossRef]
136. Marzouk, M.; Abdelaty, A. Monitoring Thermal Comfort in Subways Using Building Information Modeling. *Energy Build.* **2014**, *84*, 252–257. [CrossRef]
137. Zhan, J.; Ge, X.J.; Huang, S.; Zhao, L.; Wong, J.K.W.; He, S.X.J. Improvement of the Inspection-Repair Process with Building Information Modelling and Image Classification. *Facilities* **2019**, *37*, 395–414. [CrossRef]
138. Costin, A.M.; Teizer, J. Fusing Passive RFID and BIM for Increased Accuracy in Indoor Localization. *Vis. Eng.* **2015**, *3*, 17. [CrossRef]
139. Ruiz, L.G.B.; Pegalajar, M.C.; Molina-Solana, M.; Guo, Y.K. A Case Study on Understanding Energy Consumption through Prediction and Visualization (VIMOEN). *J. Build. Eng.* **2020**, *30*, 101315. [CrossRef]
140. Meshalkin, V.P. Current Theoretical and Applied Research on Energy- and Resource-Saving Highly Reliable Chemical Process Systems Engineering. *Theor. Found. Chem. Eng.* **2021**, *55*, 563–587. [CrossRef]
141. Xu, Y.; Ahokangas, P.; Turunen, M.; Mäntymäki, M.; Heikkilä, J. Platform-Based Business Models: Insights from an Emerging Ai-Enabled Smart Building Ecosystem. *Electronics* **2019**, *8*, 1150. [CrossRef]
142. Zhu, J.; Shen, Y.; Song, Z.; Zhou, D.; Zhang, Z.; Kusiak, A. Data-Driven Building Load Profiling and Energy Management. *Sustain. Cities Soc.* **2019**, *49*, 101587. [CrossRef]
143. Ghahramani, A.; Pantelic, J.; Lindberg, C.; Mehl, M.; Srinivasan, K.; Gilligan, B.; Arens, E. Learning Occupants' Workplace Interactions from Wearable and Stationary Ambient Sensing Systems. *Appl. Energy* **2018**, *230*, 42–51. [CrossRef]
144. Kontes, G.D.; Giannakis, G.I.; Sánchez, V.; de Agustin-Camacho, P.; Romero-Amorrortu, A.; Panagiotidou, N.; Rovas, D.V.; Steiger, S.; Mutschler, C.; Gruen, G. Simulation-Based Evaluation and Optimization of Control Strategies in Buildings. *Energies* **2018**, *11*, 3376. [CrossRef]
145. Mokhtar, M.; Liu, X.; Howe, J. Multi-Agent Gaussian Adaptive Resonance Theory Map for Building Energy Control and Thermal Comfort Management of UCLan's WestLakes Samuel Lindow Building. *Energy Build.* **2014**, *80*, 504–516. [CrossRef]
146. Kang, T.W.; Choi, H.S. BIM-Based Data Mining Method Considering Data Integration and Function Extension. *KSCE J. Civ. Eng.* **2018**, *22*, 1523–1534. [CrossRef]
147. Andriamamonjy, A.; Klein, R.; Saelens, D. Automated Grey Box Model Implementation Using BIM and Modelica. *Energy Build.* **2019**, *188–189*, 209–225. [CrossRef]
148. O'Dwyer, E.; Pan, I.; Charlesworth, R.; Butler, S.; Shah, N. Integration of an Energy Management Tool and Digital Twin for Coordination and Control of Multi-Vector Smart Energy Systems. *Sustain. Cities Soc.* **2020**, *62*, 102412. [CrossRef]
149. Abdelalim, A.; O'Brien, W.; Shi, Z. Data Visualization and Analysis of Energy Flow on a Multi-Zone Building Scale. *Autom. Constr.* **2017**, *84*, 258–273. [CrossRef]
150. Francisco, A.; Truong, H.; Khosrowpour, A.; Taylor, J.E.; Mohammadi, N. Occupant Perceptions of Building Information Model-Based Energy Visualizations in Eco-Feedback Systems. *Appl. Energy* **2018**, *221*, 220–228. [CrossRef]
151. McGlinn, K.; Yuce, B.; Wicaksono, H.; Howell, S.; Rezgui, Y. Usability Evaluation of a Web-Based Tool for Supporting Holistic Building Energy Management. *Autom. Constr.* **2017**, *84*, 154–165. [CrossRef]
152. Zhuang, D.; Zhang, X.; Lu, Y.; Wang, C.; Jin, X.; Zhou, X.; Shi, X. A Performance Data Integrated BIM Framework for Building Life-Cycle Energy Efficiency and Environmental Optimization Design. *Autom. Constr.* **2021**, *127*, 103712. [CrossRef]
153. Charissis, V.; Falah, J.; Lagoo, R.; Alfalah, S.F.M.; Khan, S.; Wang, S.; Altarteer, S.; Larbi, K.B.; Drikakis, D. Employing Emerging Technologies to Develop and Evaluate In-Vehicle Intelligent Systems for Driver Support: Infotainment AR Hud Case Study. *Appl. Sci.* **2021**, *11*, 1397. [CrossRef]
154. Ventura, S.M.; Castronovo, F.; Ciribini, A.L.C. A Design Review Session Protocol for the Implementation of Immersive Virtual Reality in Usability-Focused Analysis. *J. Inf. Technol. Constr.* **2020**, *25*, 233–253. [CrossRef]

155. Xie, X.; Lu, Q.; Rodenas-Herraiz, D.; Parlikad, A.K.; Schooling, J.M. Visualised Inspection System for Monitoring Environmental Anomalies during Daily Operation and Maintenance. *Eng. Constr. Archit. Manag.* **2020**, *27*, 1835–1852. [CrossRef]
156. Du, J.; Zou, Z.; Shi, Y.; Zhao, D. Zero Latency: Real-Time Synchronization of BIM Data in Virtual Reality for Collaborative Decision-Making. *Autom. Constr.* **2018**, *85*, 51–64. [CrossRef]
157. el Ammari, K.; Hammad, A. Remote Interactive Collaboration in Facilities Management Using BIM-Based Mixed Reality. *Autom. Constr.* **2019**, *107*, 102940. [CrossRef]
158. Edwards, G.; Li, H.; Wang, B. BIM Based Collaborative and Interactive Design Process Using Computer Game Engine for General End-Users. *Vis. Eng.* **2015**, *3*, 4. [CrossRef]
159. Liu, F.; Seipel, S. Precision Study on Augmented Reality-Based Visual Guidance for Facility Management Tasks. *Autom. Constr.* **2018**, *90*, 79–90. [CrossRef]
160. Carreira, P.; Castelo, T.; Gomes, C.C.; Ferreira, A.; Ribeiro, C.; Costa, A.A. Virtual Reality as Integration Environments for Facilities Management: Application and Users Perception. *Eng. Constr. Archit. Manag.* **2018**, *25*, 90–112. [CrossRef]
161. Baek, F.; Ha, I.; Kim, H. Augmented Reality System for Facility Management Using Image-Based Indoor Localization. *Autom. Constr.* **2019**, *99*, 18–26. [CrossRef]
162. Ozturk, G.B. Interoperability in Building Information Modeling for AECO/FM Industry. *Autom. Constr.* **2020**, *113*, 103122. [CrossRef]
163. Kula, B.; Ergen, E. Implementation of a BIM-FM Platform at an International Airport Project: Case Study. *J. Constr. Eng. Manag.* **2021**, *147*, 05021002. [CrossRef]
164. Pishdad-Bozorgi, P.; Gao, X.; Eastman, C.; Self, A.P. Planning and Developing Facility Management-Enabled Building Information Model (FM-Enabled BIM). *Autom. Constr.* **2018**, *87*, 22–38. [CrossRef]
165. Alnaggar, A.; Pitt, M. Towards a Conceptual Framework to Manage BIM/COBie Asset Data Using a Standard Project Management Methodology. *J. Facil. Manag.* **2019**, *17*, 175–187. [CrossRef]
166. Vanlande, R.; Nicolle, C.; Cruz, C. IFC and Building Lifecycle Management. *Autom. Constr.* **2008**, *18*, 70–78. [CrossRef]
167. Abdirad, H.; Dossick, C.S. Rebaselining Asset Data for Existing Facilities and Infrastructure. *J. Comput. Civ. Eng.* **2020**, *34*, 05019004. [CrossRef]
168. Thabet, W.; Lucas, J. Asset Data Handover for a Large Educational Institution: Case-Study Approach. *J. Constr. Eng. Manag.* **2017**, *143*, 05017017. [CrossRef]
169. Pavón, R.M.; Alberti, M.G.; Álvarez, A.A.A.; del Rosario Chiyón Carrasco, I. Use of Bim-Fm to Transform Large Conventional Public Buildings into Efficient and Smart Sustainable Buildings. *Energies* **2021**, *14*, 3127. [CrossRef]
170. Faria, M.; Roxin, A.; Nicolle, C. *COBieOWL, an OWL Ontology Based on COBie*; Debruyne, C., Panetto, H., Meersman, R., Dillon, T., Weichhart, G., An, Y., Ardagna, C.A., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2015; Volume 9415, ISBN 978-3-319-26147-8.
171. Barrelas, J.; Dias, I.S.; Silva, A.; de Brito, J.; Flores-Colen, I.; Tadeu, A. Impact of Environmental Exposure on the Service Life of Façade Claddings—A Statistical Analysis. *Buildings* **2021**, *11*, 615. [CrossRef]
172. Thomas, D.S. *The Costs and Benefits of Advanced Maintenance in Manufacturing*; National Institute of Standards and Technology: Gaithersburg, MD, USA, 2018.
173. Madureira, S.; Flores-Colen, I.; de Brito, J.; Pereira, C. Maintenance Planning of Facades in Current Buildings. *Constr. Build. Mater.* **2017**, *147*, 790–802. [CrossRef]
174. Sousa, V.; Matos, J.P.; Matias, N. Evaluation of Artificial Intelligence Tool Performance and Uncertainty for Predicting Sewer Structural Condition. *Autom. Constr.* **2014**, *44*, 84–91. [CrossRef]
175. Sanhudo, L.; Ramos, N.M.M.; Martins, J.P.; Almeida, R.M.S.F.; Barreira, E.; Simões, M.L.; Cardoso, V. A Framework for In-Situ Geometric Data Acquisition Using Laser Scanning for BIM Modelling. *J. Build. Eng.* **2020**, *28*. [CrossRef]
176. Xia, F.; Yang, L.T.; Wang, L.; Vinel, A. Internet of Things. *Int. J. Commun. Syst.* **2012**, *25*, 1101–1102. [CrossRef]
177. Tang, S.; Shelden, D.R.; Eastman, C.M.; Pishdad-Bozorgi, P.; Gao, X. A Review of Building Information Modeling (BIM) and the Internet of Things (IoT) Devices Integration: Present Status and Future Trends. *Autom. Constr.* **2019**, *101*, 127–139. [CrossRef]
178. Motamedi, A.; Saini, R.; Hammad, A.; Zhu, B. Role-Based Access to Facilities Lifecycle Information on RFID Tags. *Adv. Eng. Inform.* **2011**, *25*, 559–568. [CrossRef]
179. EUROSTAT. *Energy, Transport and Environment Statistics: 2020 Edition*; European Union: Brussels, Belgium, 2020.
180. Puschmann, P.; Horlitz, T.; Wittstock, V.; Schütz, A. Risk Analysis (Assessment) Using Virtual Reality Technology-Effects of Subjective Experience: An Experimental Study. *Procedia CIRP* **2016**, *50*, 490–495. [CrossRef]