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Integrated applications of Building Information Modeling and Artificial Intelligence techniques in the AEC/FM industry

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Abstract

Informatization and automatization are considered mainstream trends in the future architecture-engineering-construction/facility management (AEC/FM) industry. Building information modeling (BIM) is an effective technology to digitize building information, whereas artificial intelligence (AI) techniques facilitate automation. It could be contributive to focus on how to integrate BIM with AI techniques and apply them in actual projects. However, a comprehensive review of integrated applications is still lacking. This study reviews BIM-AI integrations in the AEC/FM industry by systematic-bibliometric analysis, and 183 eligible literature items are adopted. Bibliometric analysis reveals time series, journals, keywords co-occurrence, and co-authorship of eligible literature. Findings are summarized from perspectives of techniques and applications. Three typical integrated modes are determined based on the findings. Ultimately, current challenges and future directions of the development of BIM-AI integrations are proposed. This review contributes to systematically exploring applications of BIM-AI integrations in AEC/FM industry and deliveries valuable development directions for BIM and AI.

Keywords: Architecture-engineering-construction/facility management; Building information modeling; Artificial intelligence; Automation; Systematic review; Bibliometric analysis.

1. Introduction

In the Fourth Industry Revolution, the architecture-engineering-construction/facility management (AEC/FM) industry needs to be more informationalized and intelligentized to improve efficiency. Traditionally, the AEC/FM industry is characterized by large scale, high cost, high risk and low efficiency. With the popularization of computers and growth in computing power, widespread adoption of computer-aided and intelligent technologies becomes possible, enabling the AEC/FM industry has entered into a new era of information and intelligence [1]. The informatization of the AEC/FM industry is facilitated by building information modeling (BIM), the concept of which derived from the "Building Description System" (BDS) was proposed by Eastman in 1975 [2]. Until now, this idea of building modeling has become a critical element in the AEC/FM industry to deal with the increasing amount of information and data generated in the life cycle of building projects [1]. The United States National Institute of Building Sciences (NIBS) has proposed a universal definition of BIM in the National Building Information Modeling Standard (NBIMS, pp.21), "*A BIM is a digital representation of physical and functional characteristics of a facility. As such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its lifecycle; defined as existing from earliest conception to demolition. A basic premise of BIM is collaboration by different stakeholders at different phases of the lifecycle of a facility to insert, extract, update or modify information in the BIM to support and reflect the roles of that stakeholder*."

BIM has become a widely used tool in the AEC/FM industry for providing digital information on projects, with several studies conducted in recent years. Previous reviews summarized the development of BIM from different perspectives. Most of them focused on reviewing the evolutionary development of the BIM research area [3, 4], showing that BIM gradually adapted to the requirements of different lifecycle phases for facilitating project management [5, 6], risk management [7, 8] and facility management [9, 10]. Furthermore, BIM has been widely adopted to contribute to sustainability [11], and opportunities for cooperation with other interdisciplinary technologies have also been found. The reviews have recapitulated and predicted the future trend of integration with the internet of things (IoT) [12], blockchain, and the geographical information system (GIS) [13, 14]. These integrations have assisted BIM in replenishing new data streams and enriching building models.

Artificial intelligence (AI) is a branch of computer science that deals with developing intelligent machines and computer systems with human-like reasoning, learning and problem-solving capabilities. Given these capabilities, numerous studies have been conducted using AI techniques such as machine learning (ML) to tackle the AEC/FM problems [15]. Existing reviews focused on analyzing the state-of-the-art of research on AI in the AEC industry [15] and the use of a few selected AI techniques in certain AEC areas [16]. Integrating BIM with AI plays a crucial role in the digital transformation of the AEC/FM industry through automated applications such as big data analytics. Hence, recent studies have combined BIM and AI techniques in tackling complex AEC/FM problems. Despite the usefulness of such integrated applications, there is a lack of comprehensive review on these areas in regard to future research and practice. The existing body of knowledge only consists of reviews on the separate applications of BIM and AI.

To address this gap, our study aims to review integrated applications of BIM and AI techniques in the AEC/FM industry via a systematic-bibliometric analysis. This paper is organized as follows. Section 2 establishes systematic literature review protocols for identifying relevant articles. Section 3 presents a bibliometric analysis of 81 contributive articles. Section 4 presents the findings of this review, summarizing the BIM-AI applications from diverse aspects, including the main AI techniques integrated with BIM, applications in the AEC/FM projects lifecycle, and the main application fields. Section 5 discusses diverse integrated BIM-AI modes and proposes future trends of BIM-AI applications. Finally, Section 6 concludes the study.

2. Systematic literature review

A literature review is helpful in understanding the research and development (R&D) in one domain. This study adopts a systematic literature review (SLR) as a scientific and strict procedure, in order to avoid omissions in literature selection and subjective bias in literature screening [17]. The systematic literature review methodology proposed by the Cochrane handbook [18] was adapted to conduct a detailed review of BIM-AI applications in the AEC/FM industry. The methodology follows the following principles: (1) articles applying to both BIM and AI techniques are included; (2) current evidence regarding the contributions of BIM-AI applications are explored; (3) bibliometric analysis is conducted for more in-depth analysis of the literature; and (4) knowledge gaps and future research directions are explored. The overall methodology is shown in Fig. 1 and is described below.

2.1. Literature search

This review focuses on integrated BIM-AI applications in the AEC/FM industry, so the literature search keywords should relate to BIM, AI and the AEC/FM industry. Since the AEC/FM industry consists of numerous components, it is challenging to set exact keywords for all components of AEC/FM industry, to search all relevant articles. Also, not all research indicates their application areas in detail, and omitting valuable literature cannot be avoided by searching keywords related to AEC/FM industry. Therefore, BIM- and AI-related keywords were adopted in the literature search, and literature that is irrelevant to AEC/FM industry was excluded through screening. Nevertheless, since BIM is mainly used in the AEC/FM industry, it was reasonable to use only BIM- and AI-related keywords.

The BIM-related search words included the abbreviation of "BIM" and the full name of "building information model*[1]". As for the AI-related search words, those proposed in the review of AI in AEC industry [15] were adopted, including "automatic", "artificial intelligence", "machine learning", "genetic algorithms", etc. Compared to other databases, Web of Science (WoS) provides subscription-based access to multiple databases[2], including the most influential journals belonging to different databases [19]. Thus, the literature search was decided to conduct in WoS. The language was set to English, and the document type was set as article, rather than book, conference paper, etc., since the contributions of journal articles are usually more complete, up to date, and peer-reviewed. The TS refers to search words in titles, abstracts, or keywords of

[1] The asterisk (*) represents any group of characters, model* contains "model", "modeling", and "modelling".

[2] https://en.wikipedia.org/wiki/Web_of_Science

articles, while the TI means searching key words only in titles. Boolean operators (AND, OR, NOT, SAME and NEAR) were applied to create a query of advanced search in WoS from 1979-2020. The detailed search query (resulting in 367 records) is as follows:

(TS=("BIM" OR "building information model") AND (TS=("artificial intelligence" OR "machine intelligence" OR "machine learning" OR "deep learning" OR "expert system*" OR "genetic algorithm*" OR "neural network*" OR "case-based reasoning" OR "data mining" OR "fuzzy logic" OR "fuzzy set*" OR "robotics" OR "knowledge-based system*" OR "support vector machine*" OR "Bayes classifier" OR "natural language processing" OR "artificial general intelligence" OR "computational intelligence"))) OR (TI=("BIM" OR "building information model*") AND (TI=("automation" OR "automated" OR "automatic" OR "intelligence"))) AND Language=("English") AND Type=("Article")*

2.2. Literature screening

There were irrelevant articles in the 367 records from 1970-2020. The screening was essential first to select BIM-AI-based articles related to AEC/FM industry, and then those that actually applied BIM-AI integration, not just mentioning the search keywords in their titles, abstracts or keywords. The screening process is divided into four steps:

(1) Title screening

Here, titles of articles were checked for focus on AEC/FM industry. 42 articles were excluded because their titles did not focus on AEC/FM industry.

(2) Abstract screening

Abstracts of the remaining 325 articles were checked. At this step, articles were filtered based on two criteria: (1) the article content is irrelative to AEC/FM industry; and (2) the BIM-AI integration is not the main research objective. This led to excluding 101 articles.

(3) Full-text screening

Full texts of the remaining 224 articles were downloaded and read carefully by authors. Articles proposing feasible ideas, frameworks or approaches of BIM-AI integrated application are retained. Other articles only mention the BIM and AI techniques in content, but do not focus on integrated applications of BIM and AI techniques. These articles should be removed. Finally, 42 articles were excluded from the list.

(4) Reference screening

To avoid omission of contributive articles, references of the remaining 182 articles are screened according to protocols. One eligible reference has been added to the list of articles.

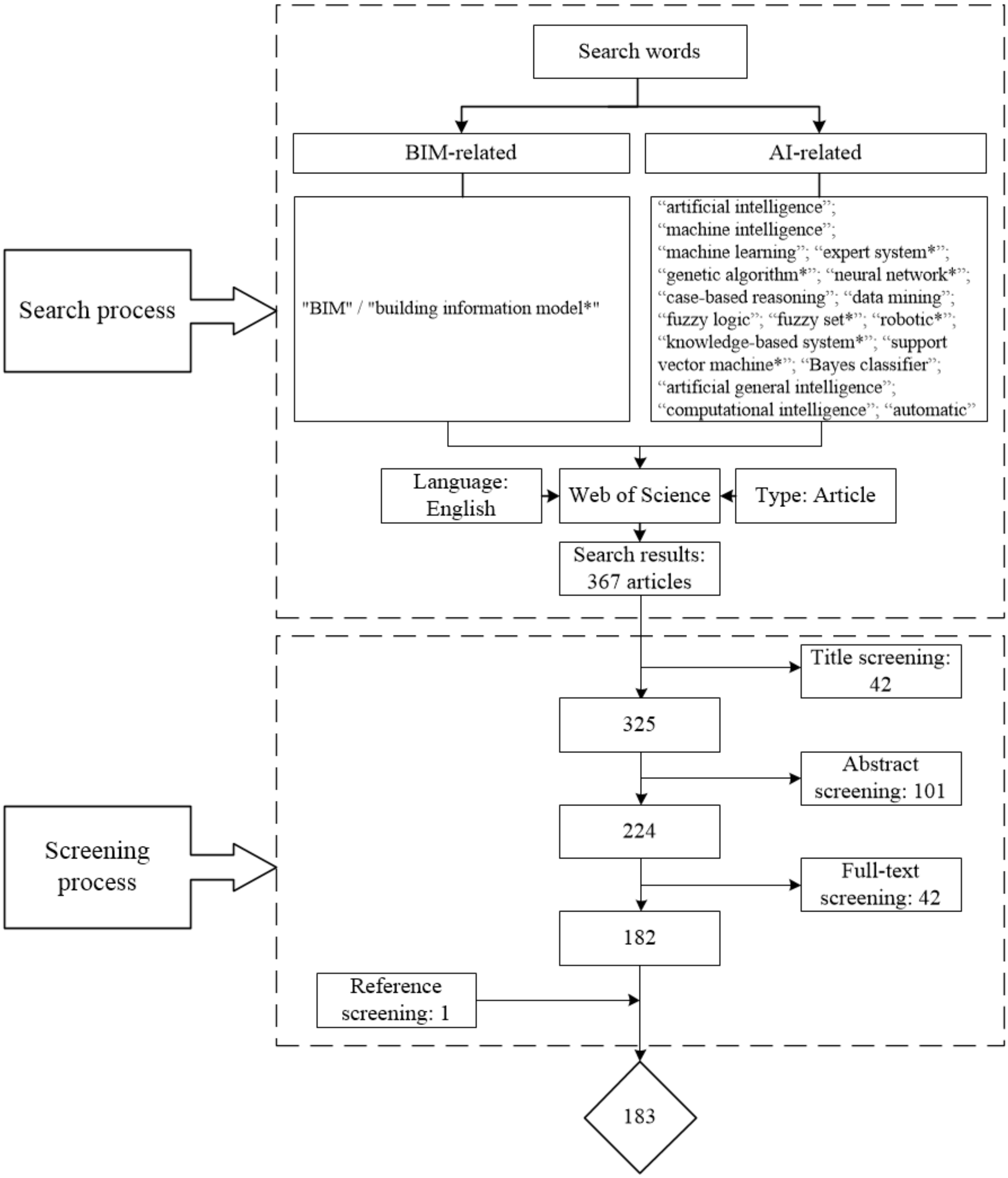

Fig. 1. Literature search and screening process.

3. Bibliometric analysis

3.1. Annual publication trend

Though the timespan for the literature search was the default setting of WoS, 1970 to 2020, all the qualified articles were published from 2010 to 2020, indicating that BIM-AI integration gained the majority of attention in the last decade. Fig. 2 illustrates the annual publication trend of the articles. At the beginning of the 2010s, BIM-related research was immature [3], and only a few studies explored the possibilities of BIM-AI integration from 2010 to 2013. After 2014, the number of articles began to increase. However, the upward trend was unstable, with several declines in 2016 and 2017. There was a significant increase in BIM-AI publications from 2017-2020, suggesting that BIM-AI applications gained momentum in the AEC/FM industry. This could be attributed to the fact that during last three years, many countries have encouraged BIM applications [20] and formulated national AI strategies [21], significantly promoting BIM-AI applications in the AEC/FM industry.

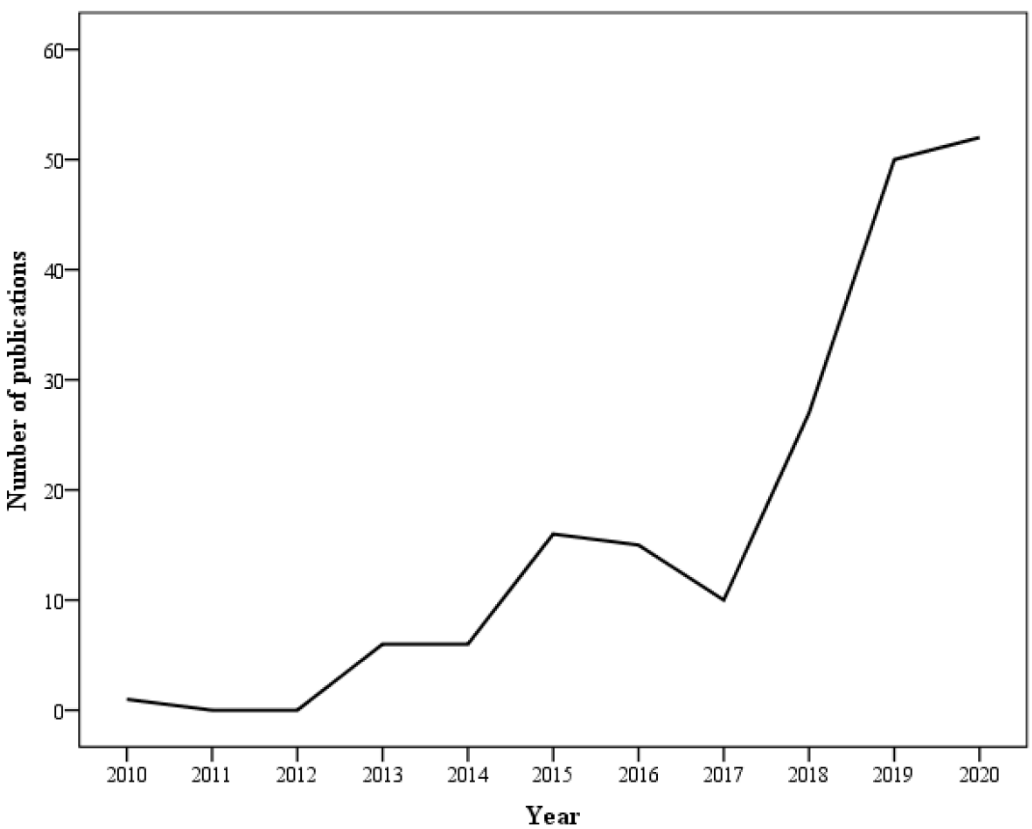

Fig. 2. Annual BIM-AI publication trend (2010-2020).

3.2. Journal analysis

183 qualified articles were published in 65 different journals. Table 1 summarizes journals where more than one article was published. As shown in Table 1, few journals published a large proportion of BIM-AI applications. For instance, 53 (29%) articles appeared in *Automation in Construction*, 16 (9%) articles in *Advanced Engineering Informatics*, 13 (7%) articles in *Journal of Computing in Civil Engineering*, while the remaining 101 were dispersed across other 62 journals from different research fields, like construction, engineering, computing and ecology. Such journal analysis can help researchers and practitioners identify useful information sources on the frontiers of integrated BIM-AI applications, and determine where they can publish their valuable relevant work.

Table 1

BIM-AI research journals

Journals	Number of qualified publications
Automation in Construction	53
Advanced Engineering Informatics	16
Journal of Computing in Civil Engineering	13
Remote Sensing	6
Applied Sciences-Basel	5
Journal of Civil Engineering and Management	4
Journal of Information Technology in Construction	4
Computer-Aided Civil and Infrastructure Engineering	3
Energy and Buildings	3
International Journal of Construction Management	3
Journal of Asian Architecture and Building Engineering	3
Sensors	3
Advances in Civil Engineering	2
Advances in Computational Design	2
Building and Environment	2
Buildings	2
Built Environment Project and Asset Management	2
Construction Innovation-England	2
Engineering Construction and Architectural Management	2
International Journal of Architectural Heritage	2
Journal of Cleaner Production	2
Journal of Construction Engineering and Management	2
Journal of Engineering Design and Technology	2
Journal of Management in Engineering	2
KSCE Journal of Civil Engineering	2
Sustainability	2

3.3. Co-occurrence analysis

Co-occurrence analysis is adopted to identify the relationships between BIM-AI research keywords [22-24], and is useful in understanding the main research topics in this area. In co-occurrence analysis, keywords refer to word-groups or phases automatically extracted from the titles, abstracts and keywords of articles, and co-occurrence is the situation where two keywords occur together. After extracting 532 keywords from the 183 articles, identical keywords (e.g. “GA” and “genetic algorithm”) were merged. The keyword “BIM”, as this study’s focus, is connected with most of other keywords, so that it is omitted for more reasonable scalability. The keyword “Artificial intelligence” was kept because there are different types of AI techniques. The keywords co-occurrence network (Fig. 3) was created using ORA-LIFE, a meta-network analysis tool developed by CASOS of Carnegie Mellon University. The network consists of 450 nodes and 863 weighted links, with nodes colored by Louvain clustering and sized by total-degree centrality. For an optimum overview, only nodes with total-degree centrality over 12 are labeled in Fig. 3.

Fig. 3. Co-occurrence network of keywords of identified articles.

Two main topics can be discovered from labeled keywords: One reveals the hottest applications of BIM-AI integrations, including facility management, safety management, fault detection and diagnosis, etc. The other type of keywords shows the main AI techniques integrated with BIM, such as genetic algorithm, machine learning (e.g. artificial neural network), knowledge-based system, and laser scanning, etc. As a neutral and open file format for describing and exchanging construction data, the IFC(industry foundation classes) standard is also highlighted, as it plays vital interoperability roles in BIM-AI application.

3.4. Co-authorship analysis

Co-authorship analysis was conducted to detect the cooperation among different researchers and experts in BIM-AI research. VOSviewer was used to construct the co-authorship network (Fig. 4). In Fig. 4, the node represents identified authors, the node size indicates the frequency of authors, the line between two nodes shows the cooperation of two authors, and the color of nodes and lines presents the time of co-authorship. Previous research on BIM-AI integrations was carried out fairly independently. Authors usually cooperate with fixed partners each time, but seldom cooperate with other research groups.

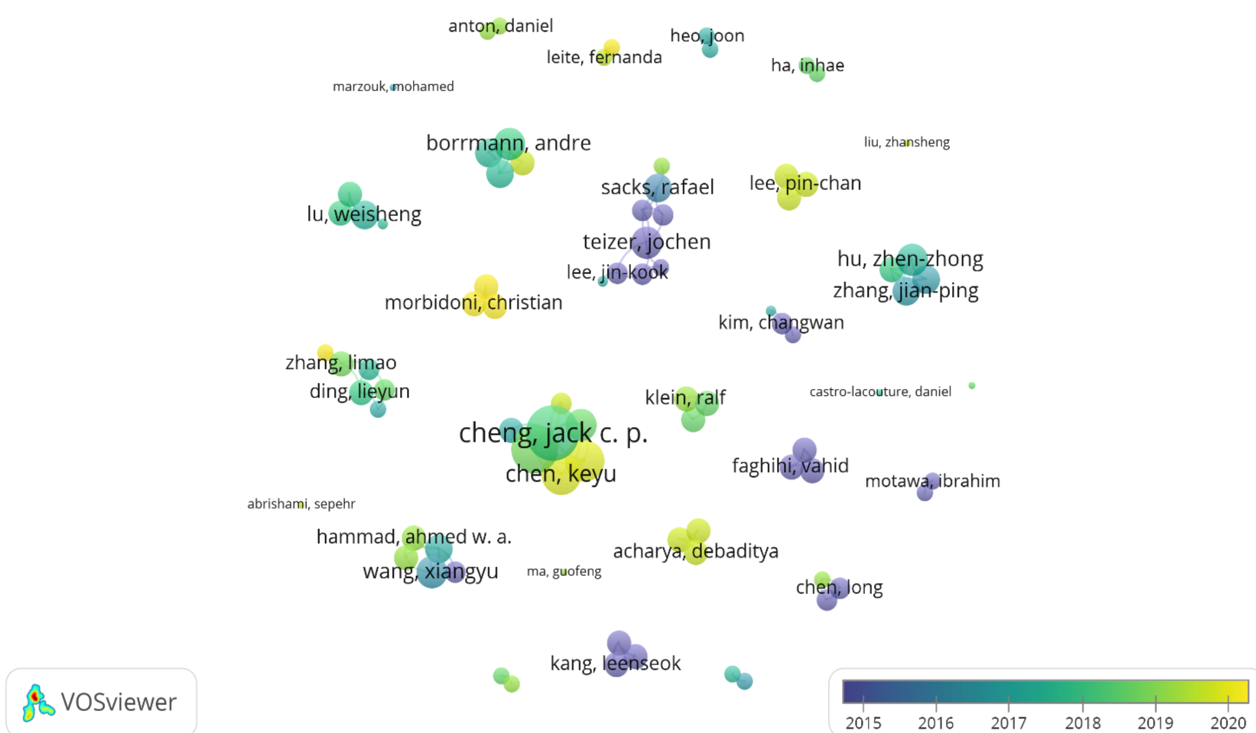

Fig. 4. Co-authorship network for BIM-AI research.

4. Findings

After analyzing the contributions of the 183 articles, the findings of this review are summarized from the perspectives of techniques and applications: main AI techniques integrated with BIM, and the main applications in AEC/FM projects.

4.1. Main AI techniques integrated with BIM

Based on the analysis of the reviewed papers, four main categories of AI techniques integrated with BIM were determined: knowledge-based reasoning, metaheuristics, machine learning and hybrid AI (Fig. 5).

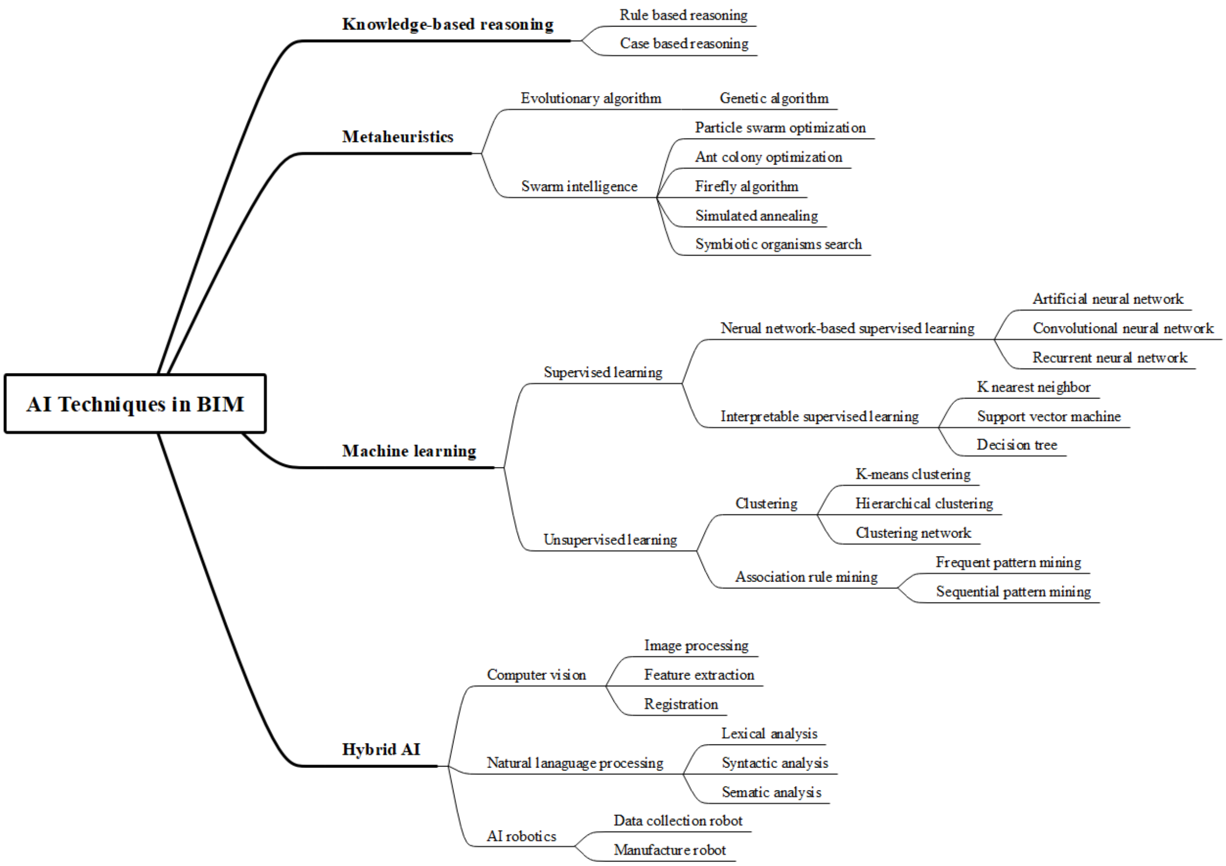

Fig. 5. The summary of main AI techniques integrated with BIM

4.1.1. Knowledge-based reasoning

Knowledge-based reasoning (KBR) is an early form of AI, which uses a symbolic representation of domain knowledge (e.g. experience of experts and previous cases) to build knowledge-based systems rather than using complex algorithms. Therefore, computers can rationally draw valid inferences efficiently from the real world [25]. Integrating KBR with BIM is the so-called extension to building knowledge modeling (BKM) [26]. According to Ref.[27], KBR can be categorized into rule-based reasoning (RBR) and case-based reasoning (CBR).

(1) Rule-based reasoning

The RBR system is principally composed of two modules: a knowledge base and an inference engine [28]. It constructs knowledge base based on not only explicit knowledge (e.g. technical manuals, standard specifications) but also tacit knowledge, which is empirical and associated with diversity and uncertainty [27]. Specifically, experts are interviewed to retrospectively share their tacit experiences in similar cases, such as how to determine the types of BIM clashes [29] or how to check the safety of BIM designs [30]. Most knowledge is in the form of unstructured human language, so that symbolic rule "IF (premise) THEN(conclusion)" is typically used for representation. Given the constructed knowledge base, the inference engine performs knowledge searching by either forward chaining or backward chaining, in order to find an applicable action or conclusion. RBR is widely integrated with BIM in the AEC/FM industry, and some application examples are shown in Table 2.

(2) Case-based reasoning

While RBR can provide reliable results, encapsulating all the knowledge into a set of rules is not always guaranteed. CBR is proposed as a supplementary KBR method in BIM, which focuses on reusing the knowledge from past cases [31]. Although CBR's data resources are similar to RBR's (expert interviews, technical reports, etc.), it stores knowledge by attributes representing the cases rather than the rules. These attributes extracted from BIM can be used to calculate the similarity between current and past cases by numerical calculations (e.g. Euclidean distance or cosine similarity). Non-numeric attributes require a further transformation to numeric values, like using discrete values to represent different BIM components [28]. CBR is usually used in BIM-based maintenance, as shown in Table 2. Beyond retrieving solutions from similar cases, CBR also emphasizes revising the proposed solution and retaining the new solution, making itself an incremental and self-learning KBR.

Table 2

Application examples of integrations of KBR and BIM

Algorithm	Application example	Reference
RBR	Construction safety	[27, 30, 32-35]
	Design optimization	[29, 36, 37]
	Cost estimation	[38, 39]
CBR	Building maintenance	[26, 31, 40, 41]

4.1.2. Metaheuristic algorithm

BIM provides a suitable framework to support decision-making by aggregating the necessary information, clarifying details and existing conditions [42]. At the same time, different objectives and constraints should be satisfied simultaneously for an optimal decision, namely the multi-objective optimization problem (MOOP). However, candidate solutions are generally discrete, infinite and nonlinear, which makes the optimization problem NP-hard (non-deterministic polynomial hard). The Metaheuristic approach, a generic algorithm structure for almost all optimization problems [43], is also popular in BIM-related MOOPs [44]. Among different kinds of metaheuristic algorithms, the evolutionary algorithm (EA) and swarm intelligence (SI) have received the most attention [45].

(1) Evolutionary Algorithm

The genetic algorithm (GA) is the most common EA in BIM, based on techniques from evolutionary biology, including generation, selection, crossover and mutation [44]. A population of individuals (solutions) is generated at first, and only those with higher fitness are saved to transmit their genes (components) to the next generation, while mutation is finally executed to avoid local optimum [46]. Due to the GA's ability to iteratively improve solutions without complex formulations, it is a powerful method for BIM-enabled design and construction optimization, both of which have different or even conflicting objectives. Table 3 lists some popular application examples of GA-BIM integrations. For instance, sustainable BIM design requires meeting both economic and environmental metrics, the construction schedule should fix overlapped production sequences, and parameter estimation should be optimized for facility monitoring. Related metrics can be collected from BIM or onsite, and a near-optimal plan could be finally visualized in 4D/5D BIMs. Other EAs like differential evolution and evolutionary strategies are rarely used in BIM studies.

(2) Swarm Intelligence

SI is composed of population-based iterative procedures as well, but differs from EA in its self-organization [47]. An individual in SI evolves by modifying itself according to its relationship with other individuals and the environment [48]. While this trait is claimed with selection bias [49], SI performs relatively better than GA when the number of allowed function calls is low [45]. Particle swarm optimization (PSO) is a SI variant that originated from the social behavior of fish schools and bird flocks [50], which was utilized in Refs. [51, 52] for BIM design optimization. Two other similar SIs, the ant colony optimization (ACO) and the firefly algorithm (FA), were inspired by the ants' pheromone trail of ants and the bioluminescence of fireflies respectively. ACO is proven to perform well in evacuation planning on a lightweight BIM platform [53], and FA shows good performance in BIM-based layout planning [54]. Simulated annealing (SA) is a special SI variant allowing worse resolutions during the initial phase, so that users can make significant changes during preliminary iterations. This property of SA was utilized in [55] to speed up the optimization of BIM design clashes. Unlike other SIs, symbiotic organism search (SOS) requires no specific algorithm parameters, which can help simplify dynamic layout planning for BIM users [56]. Table 3 lists the application examples of different SIs.

Table 3

Application examples of the integrations of the metaheuristic algorithm and BIM

Category	Algorithm	Application example	Reference
Evolutionary	GA	Design optimization	[46, 57-59]
Algorithm		Construction optimization	[60, 61]
		Facility monitoring	[62-64]
Swarm Intelligence	PSO	Design optimization	[51, 52]
	ACO	Construction safety	[53]
	FA	Layout optimization	[54]
	SA	Design optimization	[55]
	SOS	Layout optimization	[56]

4.1.3. Machine learning

Unlike KBR and the metaheuristic algorithm, ML adopts an end-to-end training system rather than traditional programming for problem analysis [65]. This process requires a large data set but less expert analysis and fine-tuning. Supervised learning and unsupervised learning are two typical ML branches in BIM, while deep learning is herein treated as a deeper extension of ML for data and hardware [66].

(1) Supervised Learning

Supervised learning is an ML task in mapping an input to an output, whose function is inferred from the labeled training set [67]. The artificial neural network (ANN) is the most basic supervised learning approach, including an input layer, one or more hidden layers, and an output layer [68]. The neurons in each layer are connected by neuron links, which have the outstanding ability to approach most non-linear patterns in BIM projects [69], especially in classification problems. For instance, ANN can find suitable commands for BIM design clashes after learning the relationship between commands and clash attributes from similar operation samples [55]. An ANN trained by correspondence between the IoT-connected BIM and the facility performance is useful to check the status of the mechanical electrical piping (MEP) or steel structure [68, 70], occupants' comfort levels [71] and building's energy consumption [72, 73]. The convolutional neural network (CNN) is a variant of ANN for image classification, whose hidden layers are further divided into convolutional, pooling, and fully connected layers. The convolutional layer can extract the prominent features from each position of the input data and form a feature map. Due to the high dimensionality of feature maps, it can be simplified by the pooling layer to relieve computation loads, while the final fully connected layer plays the role of classifier [74]. CNN architecture may vary with cases (e.g., AlexNet, VGGNet, ResNet), but it generally shares a similar principle. For one thing, CNNs are trained with semantically labeled images or point clouds from sites or BIM models, which will later identify the most similar BIM components from the input data. As shown in Table 4, the CNN shows positive performance in as-is BIM reconstruction, indoor localization and facility monitoring. Other variants of ANN are not common, so that they are not discussed in detail, but they are helpful in specific cases. For instance, the recurrent neural network (RNN) and the long short-term memory neural network (LSTMNN) can extract the spatial value of sequential data.

Neural network-based supervised learning learns sample patterns by tuning numerous neural parameters. This process promises a high accuracy but lacks transparency, and is claimed as "a black box". Hence, supervised learning with better interpretability has drawn the attention of some BIM researchers, mainly including K nearest neighbor (KNN), support vector machine (SVM) and decision tree (DT). KNN is quite straightforward supervised learning approach, whose groups are formulated by minimizing the total distance among training samples' attributes, and a new query will automatically be labeled the same as the closed set. Ref.[75] demonstrated that KNN works well in parameter estimation for BIM design assessment. SVM is slightly more complicated than KNN, where labeled classes are separated by hyperplanes in multi-dimensional feature space [76]. These identified hyperplanes visually interpret the classification rationale, and they are proven effective for BIM components classification, which is a crucial part of BIM semantic management [76, 77]. As non-parametric supervised learning, DT is extensively used for logic formalism with its IF-THEN form, consisting of nodes (attributes), branches (interval of attribute value) and leaves (classification). Its variant random forest, an ensemble of different DTs, is utilized in BIM-based cost evaluation due to good interpretability and low overfitting [78].

(2) Unsupervised Learning

Free from the need for labeling datasets, unsupervised learning is a process of learning patterns from untagged data, particularly knowledge hidden in BIM. Clustering is typical unsupervised learning technique to categorize unstructured data based on their similarity to each other [79], and has three general structures, namely K-means clustering (KMC), hierarchical clustering (HC) and clustering network (CN). KMC is extensively adopted for facility monitoring due to its simplicity [79-81]. Depending on the real-time BIM database, hidden facility status can be identified into pre-defined K clusters. Further, HC is symbolized in its multi-level hierarchy structure, and does not require a pre-defined number of clusters at first. It was demonstrated by Ref. [39] that HC is suitable for modular construction planning (e.g. MEP system) in BIM projects. CN can project non-linear statistical relationships into low-dimensional space, and keep the most crucial topological relation. An improved variant of CN named the efficient fuzzy Kohonen CN was proposed in Ref.[82] to figure out the design preference and productivity of BIM designers from BIM log files.

Apart from the similarity, causality and relevance between BIM data are also valuable, and are the focuses of association rule mining (ARM). ARM uses support to measure the probability of items containing combinations, and confidence to indicate the degree of certainty one contains another. Frequent pattern mining (FPM) is a basic ARM adopted in BIM-enabled construction scheduling, by which deep rules can be extracted for relevant work orders [80, 81]. To deal with sequential data, sequential pattern mining (SPM) is proposed to extract patterns in a source's recorded order. This feature can help managers capture the performance differences among BIM modelers according to the time spent on their operations [83], providing valuable hints for design improvement.

Table 4

Application examples of integrations of machine learning and BIM

Category	Algorithm	Application example	Reference
Supervised learning	ANN	Design optimization	[55]
		Facility monitoring	[68, 70-73]
	CNN	As-is BIM reconstruction	[84-88]
		Indoor localization	[74, 89, 90]
		Facility monitoring	[91]
	RNN	Design optimization	[92]
		Indoor localization	[90]
	KNN	Program evaluation	[75]
	SVM	BIM semantic management	[76, 77]
	DT	Program evaluation	[78]
Unsupervised learning	KMC	Facility monitoring	[79]
	HC	Construction optimization	[39]
	CN	Design optimization	[82]
	FPM	Construction optimization	[80, 81]
	SPM	Design optimization	[83]

4.1.4. Hybrid AI

Nowadays, BIM studies are undergoing rapid digital transformation. Many advanced domain-specific technologies have been adopted in BIM by integrating various AI algorithms, named here as "Hybrid AI". We focus on three crucial hybrid AI techniques: computer vision (CV), natural language process (NLP), and AI robotics.

(1) Computer Vision

CV is a hybrid topic consisting of traditional CV and ML-based CV, and the latter was discussed as CNN in Section 4.1.3. ML-based CV has proven its superiority of great accuracy and few expert interventions, but it is certainly not the panacea for all problems. Especially when the training dataset is limited and high interpretability is required, the traditional CV is more efficient with full transparency [65], consisting of data processing, feature extraction and registration. Firstly, data processing is adopted to improve the quality of the input data by filtering and transformation. For instance, Ref.[93] proposed normal vector-based filtering, where the angles of as-is BIM point clouds are calculated as a reference to remove outliers. Transformations, like scaling and translating, can be applied in data augmentation to improve the accuracy of as-is BIM classification [84]. As another branch of traditional CV, feature extraction is a process of dimensionality reduction of the input data, where the input data can be represented by feature groups without losing important information. Both low level features (e.g. edge [84], corner [94]) and high level features (e.g. shape [95], distance [96], direction [97], gradient distribution [88]) are proven to be effective in the object detection of as-is BIM data. Finally, registration should be executed to transform different sets of data into the same coordinate system, which is a crucial step for 3D reconstruction (for example, structure from motion (SfM)) [84, 98]. In particular, 3D registration is commonly used to compare the as-is BIM and the as-designed BIM, which can be realized by calculating the transformation matrix [99] or point-to-point algorithm [97]. Based on the combination of these three steps, as-is BIM reconstruction and facility monitoring can be successfully realized.

(2) Natural Language Processing

NLP integrates linguistics, computer science, and mathematics, helping extend BIM semantics through natural language. It mainly includes three processes: lexical analysis, syntactic analysis, and semantic analysis [100]. Firstly, lexical analysis containing tokenization (work segmentation) and tagging is used to divide natural sentences into tags, like nouns, verbs, adjectives. In the syntactic analysis, parsing is executed to obtain the relationship between segments [100], and classification based on feature weighting methods is used to support extract keywords [101]. Finally, semantic analysis is used to map each keyword to the wanted entity based on similarity measurement. Efficient NLP-based query methods were proposed in Refs. [100, 102]to find wanted IFC entities or properties during facility maintenance. Moreover, NLP could serve for BIM semantic management, such as regulating the information form for compliance checking [103] and sorting the functions of disordered BIM cases [101].

(3) AI robotics

AI robotics fuse AI and robots [104], regarded as quite vogue but a practical technique in BIM domains. Unlike factory robots that blindly execute preprogrammed instructions regardless of the surrounding, an AI-robot is more intelligent. It is situated in the real world, senses the external world by perceptron, maximizes its chances of success by control systems, and executes instructions by effectors [104]. The unmanned aerial vehicle (UAV) is a common robot for intelligent data collection, and is usually used to offer valuable data (images or point clouds) for BIM-CV studies [105, 106]. Most AI robots' control systems employ AI techniques to optimize the path automatically, without manual control. In addition, automated construction is another focal point of BIM-enabled AI robotics. Typically, construction robotics can orchestrate the necessary tasks by leveraging the BIM models, while other AI techniques can be used to optimize its operation (e.g. CV techniques for calculating reference coordinates, and GA for trajectory optimization [107]).

Table 5

Application example of integrations of machine learning and BIM

Category	Application example	Reference
Computer Vision	As-is BIM reconstruction	[84, 96]
	Facility monitoring	[88, 94, 95, 97, 98]
Natural Language Processing	Facility maintenance	[100, 102]
	BIM semantic management	[101, 103]
AI robotics	Automatic data collection	[105, 106]
	Automated contruction	[107-109]

4.2. Main application fields in AEC/FM industry

By summarizing the contributions of relevant articles, it is easy to find that BIM-AI integrations have been applied in the diverse fields of the AEC/FM industry, covering the whole lifecycle of projects and other key domains of development. The main applications of BIM-AI integrations are summarized in Fig. 6.

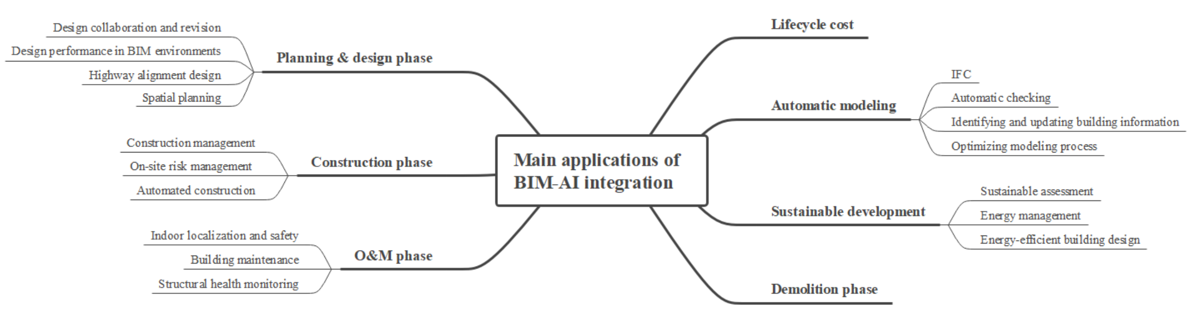

Fig. 6. The summary of main applications

4.2.1. Planning & Design phase

AEC/FM projects should start from planning and design. The initial BIM provides 3D visualization models for researchers, experts and companies [110], then the 3D model evolves into 4D by adding time series, and then 5D by adding cost dimension. The multiple dimensional models have profoundly improved the productivity of building planning and design. Now, AI techniques help to further promote the performance of BIM in planning and design.

(1) Design collaboration and revision

In the design phase, a widely used function of BIM-AI applications is AI-aided design collaboration and revision in BIM. The BIM-based design support system has been developed to facilitate building design. AI techniques are adopted to extend the functions of the design support system, making it more intelligent to use. NLP can automatically interpret natural language constructs as computable design constraints [111]. According to design rules and constraints, design algorithms aid in generating design alternatives of boarding [37], steel reinforcement [112], facade structural components [113], manufacturing of wood-framed panels for modular residential buildings [114], or other building elements. In addition, AI techniques have also been added to improve the efficiency of the design support system, such as providing recommendations to ensure that BIMs of the final design can pass ARC [29, 36], supporting the design decision-making by retrieving knowledge and experience [115], and optimizing building components for balancing multiple objectives [58].

Due to the large number of stakeholders involved in a single building project, different design targets may lead to conflict. AI techniques are used to balance conflicting design targets in the multi-objective optimization framework [116]. Since the different parts of drawings are generally completed by different designers, design clashes are usually inevitable as well [29]. Project managers have to coordinate with designers and constructors in reviewing drawings, and the process of revision wastes much time. Therefore, design clashes result in the suspension of construction. BIM is widely used to pre-check designs visually and automatically for reducing clashes [117], but its detection precision of design clashes is not sufficiently high. Because the detection algorithms in BIM are too simple [118], final results of detection usually contain many irrelative clashes, like the correct design, harmless design clashes to construction, or clashes that can be solved easily in construction sites. Supervised learning, especially the Jrip method, is adopted to develop classifiers to screen irrelative design clashes [117]. The remaining clashes still need a compromise between designers and constructors. SA algorithm helps to resolve design clashes based on constructors' expertise before the coordination [55].

(2) Design performance in BIM environments

Owing to the high requirement of designers' working capability in the BIM environment, assessment and prediction of the BIM capacity of design teams help to evaluate and select design teams before the designing commences [119]. Most BIM software is enabled to capture digital information during the design process and create the event log files [120]. By analyzing BIM log files with AI techniques, project managers can obtain characteristics of design behavior and the productivity of design teams [82, 83], as well as the predictive design commands for improving modeling efficiency [92]. Furthermore, user emotional feedback towards design alternatives is recognized and classified by electroencephalography-based ML, assisting designers in deciding alternative design schemes [121].

(3) Highway alignment design

BIM has great potential in building design, but has not reached a similar level of maturity in transportation infrastructure [122]. Considering a large amount of environmental, geographical, traffic and social information, traditional design approaches on highway design were complicated and time-consuming. GAs, SIs, or other AI techniques have been applied to design and optimize the highway alignment in BIM environment [51, 122] and GIS-BIM environment [123]. And the integration of the digital twin technique, ML and BIM was developed to timely predict the highway pavement performance [124].

(4) Spatial planning

Many AI techniques have been combined with BIM to accelerate the design process, but less applied in the planning, due to the lack of environmental and geographical information. Considering territorial planning documents, Ref.[125] processed a neural network in BIM to generate a spatial planning model of buildings as the basis of further building information modeling.

4.2.2. Construction phase

Construction is a complex and dynamic process involving many elements, like building materials, machines, workers, managers and time. BIM records, analyzes and manages the massive dynamic information generated in the construction phase. Integration with AI techniques in the construction phase can enhance construction management, risk management and automated construction.

(1) Construction management

In the construction management, BIM-AI integrations are implemented mainly for site planning and construction progress. The construction site is a complicated area containing many elements and concurrent procedures. When concurrent procedures are physically adjacent, the risk of collision will increase. To avoid accidents, BIM-AI integrations contribute to generating the construction site layouts to minimize the moving distances of workers automatically [126], simulating the interference level of the workspace on construction sites [127]. Since conditions of the construction elements are dynamic during the construction period, manual arrangement of construction site layout leads to low efficiency. AI techniques are integrated with BIM to identify the availability of site spaces [64], then the layout of construction sites is optimized automatically and visually [56], with consideration of dynamic requirements on supply, space availability, and travel paths of constructors and equipment [64, 128].

As the most crucial piece of equipment in the construction phase, the crane needs to be planned well at the beginning of the construction. The choice of crane and the location on site strongly impacts on the cost and efficiency of construction [129]. Metaheuristics algorithms help project managers to determine the best type, number and location of tower cranes, followed by BIM software to automatically generate the layout of cranes through clash detection and other 4D detections [35, 54, 129, 130]. Scaffolding is another critical temporary facility on site, which must be thoroughly designed, procured and managed [34]. With the help of BIM-AI integrations, automatic plans and safety hazard identification for scaffolding are realized in the BIM environment [34, 131].

Other main application of AI techniques in BIM environment at the construction stage is to assist in construction scheduling, monitoring, and finally delivery. The construction progress can be scheduled automatically by BIM-AI integrations, including determining the BIM construction sequence [60, 132], automating the formulation of schedule [133], seeking the optimal balance of construction duration and cost [134-136], minimizing overlaps of construction activities with high risks [137]. The construction progress monitoring is essential to ensure actual activities follow the determined schedule, owing to dynamic conditions on sites [138]. Automatic on-site process monitoring is generally realized by measuring the construction progress and comparing it with the schedule in BIM [97, 139]. However, it is quite tricky to capture and update real-time on-site data. Classification algorithms are integrated with BIM to identify objects from images [91]. Besides images, researchers have also tried to create more accurate and complete 3D point clouds to update the real-time progress in BIM [140, 141]. Photogrammetry helps to label the images of construction sites as the training database of ML [142], then trained ML can reflect the real-time progress by object detection [105, 143]. Regarding project delivery, integrated project delivery (IPD) in integration with BIM is regarded as an optimal approach for delivering construction projects [144]. AI techniques are integrated with BIM to foster the adoption of IPD [133], such as developing automated cost structure for IPD risk/reward sharing [144], automating the formulation of schedule [133].

(2) On-site risk management

Construction is dangerous with many risks on sites. Injuries may occur accidentally, like falls or crushing. Current identifications of risk mainly rely on manual inspection, lacking in efficiency [145]. For realizing automated risk management, ML algorithms are trained with numerous empirical safety reports, to predict safety outcomes of different construction sites by construction attributes in BIMs [146]. And the expert system is also a good alternative to identify risks in terms of expert knowledge [27]. Statistics reveal that risks are different under diverse scenarios. Workers are regarded as in danger under some particular scenarios, like working high above the ground. Thus, targeted integrated applications are developed to cope with high-risk work, such as automatically checking whether workers wear harness, preventing them from falling from heights [147], detecting the scaffolding safety [144].

(3) Automated construction

As mentioned above, the construction progress is dynamic, complicated and high-risk, it is necessary to advance automation for safer and more efficient construction. The robotic technique is wide-used for working in a hostile environment and in finishing repetitive tasks [107]. With the digital information provided by BIM for robots, integrations of BIM and robotic techniques enable the automated operations of tasks [108], and ensures operations without collisions between robots [107]. Even though robotic techniques cannot yet carry out a completed construction process, some tasks can be undertaken by robots [148], like brick assembly [108], routine fabricating, material dispatching [148], and welding [107].

4.2.3. O&M phase

The operation and maintenance (O&M) phase is the most prolonged period in the lifecycle of buildings. The O&M of buildings contains many tasks to guarantee building~~s~~ can perform as designed [149]. BIM has been utilized by facility managers to record, process and analyze the large-scale digital information generated during the O&M phase. O&M information recorded in BIM provides the vital basis of the following processes, but manual records often have wrong inputs. AI techniques are integrated with BIM to solve this issue.

(1) Indoor localization and safety

In the indoor environment, it is difficult to use global positioning system (GPS), which is mainly used outdoors [74]. Image retrieval is an alternative way to identify users' indoor locations. Conducting image retrieval method requires rebuilding a 3D indoor model, or establishing databases of rendered BIM images [74]. ML algorithms are trained to recognize the location by comparing images from cameras or augmented reality (AR) devices with 3D indoor models or fine-tuned rendered BIM images [89, 150]. Besides, the idea of intelligent indoor safety management system was raised by the integrated digital twin, IoT sensors and SVM with BIM, to realize automatic indoor danger warning, danger classification and level assessment [151]. For enhancing fire monitoring and awareness, ML algorithms are adopted to classify videos obtained from visual and thermal cameras, and the results of classification are linked back to BIM via semantics [152]. Regarding safety in emergency evacuation, neural networks or other algorithms are used to develop real-time evacuation systems to plan dynamic escape paths [53, 153, 154].

(2) Building maintenance

In the O&M phase, building maintenance is a major task, whose cost accounts for 65% of the total cost [155]. Much valuable maintenance information obtained from users, engineers and experts is unstructured, so this information is hard to be directly linked to BIM to deal with maintenance issues automatically. The cloud-based spoken dialogue BIM system can gather real-time structured maintenance information from users [41], and ML algorithms help classify the work orders created by users [156]. The cost information of each component replacement can be retrieved from the IFC. Based on the above information in maintenance and knowledge cases, the most suitable maintenance plan can be developed automatically [40, 41]. However, such reactive maintenances have limitations on the difficulty to prevent failure and the repairment in advance to extend the facility lifetime. Therefore, ML algorithms are used to develop predictive maintenance strategies to predict the future condition for advanced maintenance planning [68]. After damage occurs, a quick loss estimation of the building~~s~~ can be conducted to achieve timely recovery [157].

(3) Structural health monitoring

Considering damage occurs during the long-term O&M phase, so monitoring structural health, especially dynamic monitoring, is reasonably necessary to keep the building and infrastructure safe [70]. Since the performance of bridges is profoundly affected by weather, traffic conditions, earthquakes, and other factors, AI-aided dynamic monitoring methods are mainly implemented in bridge projects. According to real-time data collected by sensors or unmanned aircraft systems, BIM can visualize the time-series structural health monitoring in dynamic 3D models, and the damage patterns of bridges can be identified by ML algorithms automatically [106, 158].

4.2.4. Demolition phase

In the last period of the building lifecycle, owners have to determine whether it should be refurbished to begin a new lifecycle or demolished to build a new structure. Few AI techniques have been adopted in this phase, except construction waste management. In order to predict the waste in construction and demolition by fitting an S-curve, ANN is used to train the relations between the building characteristics and parameters of S-curve [159].

4.2.5. Lifecycle cost

The cost is critical to the whole lifecycle of buildings. According to the well-known project management triangle, time, quality and cost are three key constraints in each project. Project managers must balance the three constraints under different situations. Since BIM contains lots of financial information on buildings, it is considered as an excellent platform to manage the lifecycle cost. By taking advantage of the cost information, AI techniques are integrated with BIM for automated retrieval and optimization of lifecycle cost, such as providing cost-optimal replacement of building components [40], deciding the economic building design schemes with appropriate duration among alternatives [59, 135]. Otherwise, without detailed cost information, the lifecycle cost can be predicted according to the key features of a project [160, 161]. Besides, BIM implementation results in additional costs [78]. In order to make the exact estimation of the BIM implementation costs for initial decision-making, supervised learning algorithms are integrated with BIM to predict additional costs at different levels of development (LOD) [78, 162].

4.2.6. Automatic modeling

BIM is regarded as an efficient platform to manage and process the digital data of buildings, but the processes of building modeling, especially for as-built buildings, are quite complicated and time-consuming [163]. Several integrations of BIM and AI techniques have been proposed to facilitate automated modeling.

(1) IFC

IFC is an open international standardization organization (ISO) standard of the lifecycle data of buildings, supporting these data to be shared and exchanged among various sources. However, several issues exist in practice. IFC cannot support automatic compliance checking (ACC) conveniently. Researchers have put forward ways to extract items, which have similar concepts with the rules of compliance checking (CC), from IFC, and use ML algorithms to estimate deviations between the CC rules and similar IFC items, and then ACC can be conducted automatically based on the IFC schema [164]. Moreover, due to low semantic integrity of mapping to IFC classes, mistakes often occur during data exchange, like mismatches, omissions, and contradictions [76]. BIM-AI integrations are proposed to detect these mistakes in mapping [77], then perfect the semantic integrity [76]. Because the general semantics of BIM cannot meet increasing requirements on integration, exchange and query of data, AI techniques are also introduced to extend the semantic BIM, such as fuzzy-logic-based semantic extension for imprecise query and representation of knowledge and information [165], and ML-based semantic enhancement for classifying building objects [166].

(2) Automatic checking

All buildings must meet the regulatory code and requirements. Since the traditional manual CC is usually costly, time-consuming and error-prone [167], automatic approaches to CC are more effective and improves checking quality. Successful ACC needs to complete and correct regulatory code information and building information. AI techniques are applied to supplement missing or incorrect information, such as semantic enrichment for automatic normalization of building information [167], extracting and coding the regulatory information from textual documents [103]. In order to guarantee the construction work, BIM-AI integrations also contribute to other checking processes, like automatic geometry checking to detect the errors in the geometry of building structures and constructions [93, 168], and automatic safety rule checking to identify and correct on-site hazards before the construction commences [30, 169].

(3) Identifying and updating building information

For as-built buildings, BIM is helpful to their maintenance, retrofits, emergency and energy management [170], while for new buildings, it is also necessary to use BIM to monitor and track changes of building information from the very beginning [171]. Images and point clouds, captured by uncalibrated cameras or laser scanners, form the basis for automatically identifying, classifying and updating building information. Since the image-based method requires lower cost and less professional operators, automatic identification from the as-constructed photos and scanned as-built drawings were proven to be feasible [172, 173]. The point cloud-based methods are more expensive and require higher operating techniques, but more flexible to adapt to different scenes. Syntactic point clouds are generated to train neural networks to promote the performance of 3D point cloud semantic segmentation [85, 86]. Until now, building materials (wood, plastic, stone, concrete, etc.) [171] and building objects (door, window, wall, floor, etc.) [84, 163, 170] are classified automatically by the features of images and point clouds. Besides, more detailed information can be added to BIM automatically, like material and textural information based on thermal infrared sensing [174] and office furniture objects based on the 3D point cloud [88].

(4) Optimizing modeling process

The automated generation framework of BIM is proposed to collaborate in multidisciplinary techniques, like scanning & sensing, feature recognition, object classification, and parameterization of BIM. Since the existing resources for modeling keep increasing with the high-speed development of BIM, repetitive 3D models can be reused to save time. Relevant existing 3D geometric models or components are automatically recommended to designers in BIM environment [175], considerably improving the efficiency of BIM modeling [176].

4.2.7. Sustainable development

The AEC/FM industry is regarded as a major industry with high energy consumption and carbon emission. AI techniques are integrated to assist BIM in sustainable development.

(1) Sustainable assessment

Authoritative sustainable assessments can guide the promotion of sustainable development further. International certifications (LEED, BREEAM, etc.) set detailed requirements on building components. Since the majority of useful building information can be extracted from BIMs, building sustainability can be assessed in BIM automatically according to international certifications. With the adoption of AI techniques, building information that cannot be extracted directly can be estimated [177], and missing data in BIM can be predicted [75]. More specifically, automatic assessment of the concrete usage index, one sustainable criteria, has proven effective in creating a sustainability report for buildings [178].

(2) Energy management

In the sustainable development of AEC/FM industry, building energy performance has attracted lots of attention with more AI techniques linked to BIM for effective energy management. AI techniques contribute to seeking the necessary data from the considerable lifecycle data in BIMs [80], enhancing the accuracy of simulation of building energy consumption by occupants' behavior [73], and providing potential energy-saving suggestions automatically [179]. In the future development at a larger scale (for example, urban scale), it is impossible to establish a detailed model and accomplish the lifecycle assessment without AI techniques [180].

(3) Energy-efficient building design

To reduce the energy consumption of a building, energy-efficient building design is indispensable. Building performance analysis and simulation are effective can assist designers in decision-making among different design schemes [181]. Specifically, researchers focus on particular building components that impact heavily on energy consumption, like thermal systems and lighting systems. In order to facilitate energy-efficient design, AI techniques have been applied to determine the optimal envelope design [182] and internal illumination [52], and to automatically provide energy-saving suggestions [71].

Moreover, considering the higher budget of energy-efficient buildings, BIM-AI integrations are developed to configure the allocation of the building envelope and the reinforced concrete structures to optimize the lifecycle cost of buildings [46, 57, 183]. Additionally, more studies have focused on operational energy, but in practice, a slight decrease in operational energy may cause a larger increase in embodied energy. AI techniques are also adopted to balance embodied energy and operational energy [184].

5. Discussion

The development of software has spurred BIM application and research, providing automated platforms to effectively manage and process 'big multi-dimensional data' during the lifecycle of buildings, and AI techniques are at the core of these platforms. This study has reviewed integrated BIM-AI applications in the AEC/FM industry. The following subsections discuss key findings.

5.1. Diverse BIM-AI integrated modes

The ways to integrate AI techniques with BIM are quite diverse and can be regarded as three integrated modes.

Mode 1: Collecting and updating BIMs by AI techniques

Since the condition of buildings keeps changing during the whole life cycle, digital information on buildings is always dynamic. It is challenging to capture real-time data generated by buildings, automatically update them, and store historical data in BIMs. The first integrated mode addresses this kind of issue, using AI techniques to collect and update digital data in BIMs. Generally, AI techniques accelerate the collection or update of BIMs by automatically identifying building information from multi-source materials, such as on-site videos, images, audios, texts and 3D point clouds, as well as knowledge from previous cases. For instance, images [163, 170] and point clouds [84, 171] are major inputs of AI techniques for updating and classifying building materials, elements, or components, and then auto-write the results in BIMs. Computer vision can provide further detailed information on buildings to BIM, and can update construction progress information using real-time images [143] and collect indoor localization using indoor images [74].

Mode 2: Managing and analyzing BIMs by AI techniques

A considerable amount of building information is stored in BIMs, and the information keeps on increasing as time goes on. It is tedious and time-wasting to process this information manually. Therefore, AI techniques are also integrated with BIM to assist the management and analysis of BIM information efficiently and automatically. In the management of life cycle data, AI techniques are efficient in eliminating design clashes in the design phase, correcting records and work orders from operational data in the O&M phase, and also managing lifecycle cost data. In further data analyses in BIM have been realized with BIM-AI integrations. AI techniques enable BIM to extend its analysis functions of optimization, forecast, assessment, decision-making, feedback and simulation. For example, based on high-quality data in BIMs, several functions of energy analysis have been developed with the assistance of AI techniques for optimizing building sustainability performance, like energy prediction, and decision-making in green design [73, 80]. In sum, AI techniques can maximize the value of the building information stored in BIMs. This is the latest trend of integrated BIM-AI applications.

Mode 3: Implementing BIM-based tasks by AI techniques

The last integrated mode deals with executing BIM-based tasks automatically with the support of AI techniques. This mode is mainly applied in automated construction based on the robotics. Manufacturing robots are usually adopted to carry out standard and repetitive tasks or high-risk tasks. In practice, BIM-based robotic models or platforms can guide and adjust the activities of robots by linking construction to design directly [108, 109].

5.2. Challenges and future directions

5.2.1. Technical aspect

(1) Challenges and future directions of problem formulation

In order to run AI techniques smoothly, problem formulation should be firstly completed for the targeted problem. However, the reality is generally too complex to be fully covered, therefore most AI methods have to simplify their scenario formulations. For instance, potential conflicts (e.g. tagline) [35] or extra installation cost [39] may be disregarded in KBR-based planning, and only limited parameters are saved in ANN-enabled studies. The chain reaction problem brought by the simplification is the decline of generalization, indicating that some AI-BIM applications are not promised success in similar scenarios [112, 126].

To deal with these challenges, three directions could be taken in the future. Firstly, more complex formulation configurations are acceptable (e.g. more parameters, more complex features) if given powerful hardware support. In addition, BIM-AI frameworks need to be tested on several case examples resembling various properties to ensure robustness. Finally, sensitive analysis and reliability analysis are highly recommended in parameter selection, allowing AI techniques to automatically identify crucial points without complicating the formulation [185].

(2) Challenges and future directions of data preparation

The data is required to be well prepared before running BIM-AI integrations. Unfortunately, data quantity cannot always be guaranteed. For instance, the expected BIM models could be unavailable for temporary facilities [34], specific BIM categories may be rare in history files [101]. In the collection stage, no matter whether labeling a training set of SL or interviewing experts is time-consuming, UGV-based collection could be quite expensive, and qualified data may not be achieved after collection. For example, KBR's rules are susceptible to human errors [27], while motion blur and perceptual aliasing are harmful to CV applications [90].

Data augmentation is favored for increasing the data quantity and meeting the various distribution [186], and recommendations have been proposed for future improvement of data preparation. Automatic tools deserve more attention, involving trained USLs for automated labeling, existing NLPs for expert interviews, and IoT sensors for relieving the UAV workload. In the final case of data errors, a standard ontology should be designed to regulate the least acceptable criterion of input data.

(3) Challenges and future directions of AI technique execution

Although representative BIM-AI integrations have been mentioned above, there are still uncertainties when users are faced with several qualified alternatives, and the method of random selection is likely to perform unstably. Hence, it is recommended researchers make selections based on statistical errors and precision-recall performance [187]. Furthermore, technique improvement is another challenge for users, aiming for shorter running time and better performance [188, 189]. In the future, the focus could be devoted to studying the scenario essentials rather than only the mathematics of algorithms, so that suitable variants can be realized in different datasets or environments [190, 191]. Fusing multiple AI techniques into a hybrid AI could be an upgrade direction [186, 192]. Lastly, the absence of regulation is a common but urgent challenge for advanced techniques, particularly for AI robotics [109]. Thus, relevant companies, governments and universities are encouraged to propose necessary regulations cooperatively in the future.

5.2.2. Application aspect

(1) Integrated applications in the lifecycle of projects

A main advantage of BIM is covering the lifecycle information of buildings from planning to demolishment. BIM not only helps to realize the execution of tasks in different phases, but also facilitates information sharing and interdisciplinary cooperative work. Functions of BIM in the building lifecycle have been further expanded by introducing AI techniques. In terms of elaboration of Section 4.2.1, the BIM-AI integrations have not been applied evenly in every phase of the building lifecycle. For instance, the processes of construction and O&M are complicated, and the safety of workers and occupants must be considered as well. It is therefore urgent to employ AI techniques to improve efficiency and avoid accidents. In contrast, AI techniques have not integrated with BIM very much in the demolishing phases, mainly because functions or models provided by BIM are sufficient to meet requirements of building demolition. In the future, more BIM-AI integrated applications will be developed to cope with serious issues in the demolishing phases, and it is expected that future BIM-AI integrations can gradually cover the whole lifecycle of buildings, for promoting the overall automation in AEC/FM industry.

Moreover, existing utilization of AI techniques in the lifecycle cost of buildings assists in capturing cost information from manufacturers and predicting the overall lifecycle cost. Such utilization can solve several painful points of the lifecycle cost. In the future, AI techniques may be linked to BIM to manage cost automatically in the whole lifecycle, capturing the cost information, detecting wrong cost data, predicting the lifecycle cost, balancing the cost, quality and time, and providing economic strategies to maintain building components.

(2) Integrated applications in automated modeling

Building modeling is one of the most intractable problems in the application of BIM. For large buildings or infrastructure, a considerable amount of information on building components must be inputted in BIM; while for as-built buildings, their BIMs have to be remodeled according to the actual conditions. AI techniques are imported to the modeling process to improve efficiency. Several central and urgent issues for automated modeling have been solved by appropriate AI techniques, such as semantic enhancement and IFC extensions for data exchange and retrieval, automatic identification and classification of building objects for data update, and recommendation of existing suitable models for avoiding repetitive modeling.

Even though automated modeling has already been realized to the same degree, further challenges have to be overcome in the future development of integrated applications. Despite checking and detecting errors or misclassifications of data mapping in IFC files, automatic correcting and modifications are expected to realize further semantic enhancement. It is proven that several types of AI techniques perform well in semantic enhancement. Thus, how to decide on the appropriate AI technique to solve different kinds of semantic issues should be considered more. In addition, new automated modeling approaches are designed to work separately, resulting in some functions of modeling approaches overlapping with each other. Ideally, these overlapped functions should be integrated into one completed automated modeling system, which can create and update all essential building information automatically based on collected raw data from actual buildings.

(3) Integrated applications in sustainable development

In order to protect the global environment and guarantee benign development, sustainability is regarded as the most critical index in the AEC/FM industry. AI-aided secondary developments of BIM have provided plug-ins to assess the sustainability of buildings conveniently, and to aid energy management and energy efficiency design. However, at present, AI techniques are only involved in secondary developments of BIM for particular points, rather than in the overall sustainable development. For instance, integrated applications have been proposed only for the design of building envelopes. In the future, how to enhance the overall sustainable performance of buildings by extension of the integrated applications should be taken into consideration. In addition, the assessment of sustainability usually adopts popular certification of green buildings as the basis of ranking criteria, like LEED, mainly consisting of environmental and ecological sustainability. The data on the ranking criteria are retrieved from BIMs or estimated by AI techniques, so AI techniques should assist in extracting more social and economic sustainability for sustainable assessment.

After the in-depth discussion about current challenges and future trends of the main application fields, it is evident that BIM-AI integrations are still in the early stages of development. These integrations still work separately in AEC/FM industry, omitting some critical points which should be addressed, and generating overlaps among different functions. Besides the applications mentioned above, this study also points out another three integrated applications which need further attention.

(4) Integrated applications in decision-making

Currently, AI techniques are imported in BIM to achieve a single purpose, such as automatic identification of building components, automatic assessment of building performance, and detecting potential on-site hazards. However, decision-making in the AEC/FM industry is generally complicated, and multiple objectives need to be considered, like safety, costs, performance and efficiency. During the life cycle of buildings, stakeholders need to commit considerable time in decision-making, not only determining the design, planning, materials, but also optimizing construction methods, construction equipment, and scheduling. The integrations for decision-making should be multi-purpose.

Traditional decision-making is a subjective decision-making process principally depending on experts' experience and stakeholders' opinions, and may cause uncertainty in achieving multiple purposes. Adopting AI techniques can help balance different purposes more objectively and rationally. Future research should pay more attention to multi-purpose models with the assistance of BIM and AI integrations.

(5) Integrated applications for promoting the human-computer interaction

As is known, due to the high difficulty in handling BIM software, employees need to be trained and tested to become professional BIM modelers. As functions of BIM software increase gradually, BIM modelers and users have to spend more time on learning the operational approaches. Many BIM modelers and users consider parts of the operations too complicated and inconvenient, leading to a relatively weak experience in human-computer interaction. Some simple secondary developments on BIM software have been developed for smoother operations. However, owing to the diverse habits and requirements of different users (e.g. architectural modeler, structure modelers, users of simulation function, etc.), it is hard to provide uniform BIM software to meet all requirements. The AI technique is an appropriate tool to deal with changing demands of users by recommending and optimizing procedures for different users in BIM software. In the future, AI techniques can be integrated with BIM software to ascertain the requirements and habits of users, and then offer uniform operational procedures for all users.

(6) Integrated applications with more cooperations

As shown in the bibliometric analysis and findings, it is clear that the majority of BIM-AI integrations are independent, and lack deep cooperation with other disciplines, institutions and platforms. This status quo results in several problems, such as overlapped functions, unsystematic utilizations, or non-creative improvements. Future research can enhance integrated applications in the following aspects: (1) Interdisciplinary cooperation. Architecture, construction, planning, and design are traditional disciplines in the AEC/FM industry. However, traditional disciplines cannot independently support the sustainable development of AEC/FM industry very well, since both BIM and AI techniques belong to different disciplines. For accelerating advanced and efficient functions of integrated applications, it is essential to take advantage of AI techniques to cooperate with other disciplines like management, economics, geography, transportation, computer science, automation, etc. (2) Inter-institutional cooperation. The co-authorship network (as shown in Fig. 4) reveals researchers of integrated applications are used to working independently or cooperating with few familiar institutions. However, a single institution has difficulty in handling interdisciplinary knowledge related to the AEC/FM industry. Further, contacting researchers from other institutions would be enlightening by proposing more creative integrated applications; (3) Cross-platform cooperation. Each discipline has developed its own professional and mature platforms, like GIS platform for geography, ArcBUS for facility management, DeST for energy simulation, and Anylogic for modeling and simulation. In future integrated applications, AI techniques can be used to exchange data and information between BIM and other platforms, enhancing the cross-platforms cooperation of BIM.

6. Conclusions

With the development of both BIM and AI techniques, increasing researchers have paid attention to the development of BIM-AI integrations for promoting the AEC/FM industry. In reviewing BIM-AI integrated applications, we conducted a systematic literature review and bibliometric analysis of previous articles. Based on the search and screening protocol, 183 articles were identified as eligible materials for bibliometric analysis. The bibliometric analysis revealed the characteristics of time series, journals of publication, keywords co-occurrence and co-authorship networks of eligible articles. BIM-AI integrated applications proposed by the eligible articles were summarized from two perspectives: main AI techniques integrated with BIM and main integrated applications in AEC/FM industry. According to findings, we discuss how to integrate BIM with AI techniques, and what are the current challenges and future trends of the development of integrated applications in AEC/FM industry.

Regarding theoretical terms, we reviewed BIM-AI integrated applications by combining the systematic review with bibliometric analysis, offering an appropriate way to conduct the review, pointing out three integrated modes of BIM and AI techniques. Following the research trend, which aims at making achievements in BIM-AI integrations in the AEC/FM industry, three integrated modes were determined. In addition, future research is required to deal with technical challenges. Future trends would indicate valuable directions in which to make breakthroughs. In practice terms, AI techniques will engage in BIM, and even AEC/FM industries, more deeply by developing creative integrated plug-ins and systems. This study elaborates on main application fields, recommending appropriate BIM-AI integrations to solve problems in different fields of the AEC/FM industry.

However, this review still has some limitations, such as taking WoS as the only database, and English as the only language for better authoritativeness and readability. These limitations may result in omitting some useful integrated applications. In future reviews, the protocol of the search and screening of articles should be revised, and more researchers who can understand different languages can be invited to cover contributive studies more widely.

Declaration of competing interest

None.

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Reference

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