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ARTIFICIAL INTELLIGENCE IN CONSTRUCTION ASSET MANAGEMENT: A REVIEW OF PRESENT STATUS, CHALLENGES AND FUTURE OPPORTUNITIES

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SUMMARY: *The built environment is responsible for roughly 40% of global greenhouse emissions, making the sector a crucial factor for climate change and sustainability. Meanwhile, other sectors (like manufacturing) adopted Artificial Intelligence (AI) to solve complex, non-linear problems to reduce waste, inefficiency, and pollution. Therefore, many research efforts in the Architecture, Engineering, and Construction community have recently tried introducing AI into building asset management (AM) processes. Since AM encompasses a broad set of disciplines, an overview of several AI applications, current research gaps, and trends is needed. In this context, this study conducted the first state-of-the-art research on AI for building asset management. A total of 578 papers were analyzed with bibliometric tools to identify prominent institutions, topics, and journals. The quantitative analysis helped determine the most researched areas of AM and which AI techniques are applied. The areas were furtherly investigated by reading in-depth the 83 most relevant studies selected by screening the articles' abstracts identified in the bibliometric analysis. The results reveal many applications for Energy Management, Condition assessment, Risk management, and Project management areas. Finally, the literature review identified three main trends that can be a reference point for future studies made by practitioners or researchers: Digital Twin, Generative Adversarial Networks (with synthetic images) for data augmentation, and Deep Reinforcement Learning.*

KEYWORDS: *Asset Management, Artificial Intelligence, Machine Learning, Neural Network, Computer Vision.*

REFERENCE: *Luca Rampini, Fulvio Re Cecconi (2022). Artificial intelligence in construction asset management: a review of present status, challenges and future opportunities. Journal of Information Technology in Construction (ITcon), Vol. 27, pg. 884-913, DOI: 10.36680/j.itcon.2022.043*

1. INTRODUCTION

The Architecture, Engineering, Construction and Operations (AECO) sector is a significant player in the economy, accounting for about 6% of global GDP, and is the largest consumer of raw materials and other resources (Desruelle *et al.*, 2019). Moreover, the industry is responsible for around 40% of anthropogenic carbon dioxide (CO_2) emissions, which is central in fighting climate change (Huang *et al.*, 2020). Recently it has been accepted that to ensure minimal financial and environmental impacts of a building project, the entire life-cycle cost should be considered (Kale, Joshi and Menon, 2016). Since roughly 80% of an asset life cycle cost is spent during the operations and maintenance (O&M) phase (Lu *et al.*, 2020), the focus is widely shifting towards this stage. Despite its strategic and economic importance, low productivity and digitalization hinder operational activities, causing waste of resources, incorrect information management, and lack of optimization (Barbosa and Woetzel, 2017).

Asset management (AM), defined in the ISO 55000 standard as "the coordinated activity of an organization to realize value from assets" (ISO 55000, 2014), includes procedures and processes to realize value from assets by balancing costs, risks, opportunities, and performance benefits. The importance of AM principles in the O&M phase is crucial for the following reasons: i) assets are complex, and their systems are dynamic and change during the lifecycle and, ii) assets are voiceless, so they must be monitored and analyzed. The effectiveness of AM in the O&M stage will heavily rely on a BIM-enabled environment with continuous information on asset conditions and performances, reliable communication channels, and documented professional knowledge from experience. However, technology, information, and organization-related issues in must be addressed to fully embrace the benefits of BIM-enabled AM in O&M (Volk, Stengel and Schultmann, 2014).

Aiming to achieve a new industry concept – the so-called 'Construction 4.0'-, the entire sector is reshaping itself by opening to new technologies and digital strategies. In this context, Artificial Intelligence (AI) might act as a backbone for the innovative changes the industry faces. AI is a branch of Computer Science that provides computers with human-like capabilities, such as problem-solving and decision-making skills. According to Agrawal, J. S. Gans and Goldfarb, 2019, AI produces quality predictions based on available data, leading to better decision-making and productivity. The pandemic situation caused by the spreading of COVID-19 has even speeded up investment in automation and AI (Lund *et al.*, 2021). Therefore, there is immense interest in exploiting AI techniques in many areas, including AECO, where a flourishing ecosystem of start-up companies, commonly called "Construction Tech", has grown from $250 million in 2013 to $1,000 million in 2018 (Sacks, Girolami and Brilakis, 2020).

Previously, researchers have done different literature reviews about the deployment of AI in AECO (Loyola, 2018; Aibinu, Koch and Ng, 2019; Duan, Edwards and Dwivedi, 2019; Darko *et al.*, 2020; Hong *et al.*, 2020; Abioye *et al.*, 2021; Pan and Zhang, 2021; Debrah, Chan and Darko, 2022). However, none focuses on AM areas, which comprise a broad list of disciplines. Specifically, by investigating the scientific literature, most acknowledged standards, corporate reports, white papers, and direct work experiences, 14 core functions were identified in AM (Rampini *et al.*, 2020; Re Cecconi *et al.*, 2020).

The present literature review aims to frame AI applications within the 14 disciplines that characterize AM by answering the following research question:

- What are the most researched AM areas for AI applications?
- What are the possible future topics for researching AI in AM?

To answer these questions, this research proposes a bibliometric analysis of 578 papers and an in-depth analysis of the 83 most relevant papers. The rest of this paper is organized as follows: the fundamental terminology adopted in this study is described in Section 2; the research methodology is described in Section 3; bibliometric analysis results are shown in Section 4; the information gathered from the in-depth review is proposed in Section 5; Future research trends and topic are discussed in Section 6, while Section 7 concludes the paper.

2. TERMINOLOGIES AND FUNDAMENTALS

The concept of "Asset Management" and "Artificial Intelligence" is evolving, and different definitions are being published and produced. This section helps to clarify the scope and the meaning of the terminology used to describe the results.

2.1 Asset Management

Asset management has been highlighted as one of the most critical functions to adopt in the corporate world since the late 1990s. The primary reference for AM is represented by the ISO series 55000. These standards provide the AM discipline's general guidelines, principles, and definitions. Specifically, they define AM as the discipline that effectively controls and governs assets within an organization to realize value through managing risk, opportunity, and costs (ISO 55000, 2014). When the focus is on the physical asset, this concept can be refined further: a physical asset, such as a building, a portfolio of buildings, an urban area, or infrastructure, is managed by a set of procedures. In this scenario, Engineering Asset Management (EAM) refers to the processes, operations, and resources used to manage facilities, infrastructure, and equipment throughout their life cycle (Amadi-Echendu *et al.*, 2010). EAM has been used in various domains where a systematic and secure administration of physical assets is essential to meet business goals. For this literature review, according to (Re Cecconi *et al.*, 2020), we identified 14 main disciplines encompassed in AM (Table 1).

Table 1: 14 AM core areas identified in Re Cecconi et al.*, 2020.*

AM functions	
Strategic functions	
	Risk management
	Sustainability management
	Finance management
	Quality management
	Value management
Tactical functions	
	Resilience management
	Life Cycle Cost
	Facility management
	Energy management
	Property management
Operational functions	
	Commissioning
	Project management
	Data management
	Condition assessment and operations

2.2 Artificial Intelligence

There have been ups and downs in the history of AI, with logic-based approaches in the 1950s and early 60s, knowledge-based expert systems in the 1970s and 80s, and data-driven approaches (from 2000 onwards) with periods of disillusionment and reduced funding in-between (Russell and Norvig, 2003). Due to these constant changes, the definition of AI has always been mutable. However, the High-Level Expert Group (HLEG), appointed by the EU commission, defines AI as "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal." (Craglia *et al.*, 2018). AI branches that mimic human intelligence include machine learning (ML), computer vision (CV), and natural language processing (NLP), as shown in FIG. 1.

2.2.1 Machine Learning

In computing, ML represents a paradigm shift. Traditionally, a programmer would write computer code that established the rules for processing data inputs and producing an output. In ML, the computer is given input data as well as the expected answers, and the ML agent must then generate the rules. These rules can then be used on new data to generate unique results. Rather than being explicitly programmed, an ML system is trained. There are generally three types of ML: i) supervised learning, ii) unsupervised learning, and iii) reinforcement learning (RL).

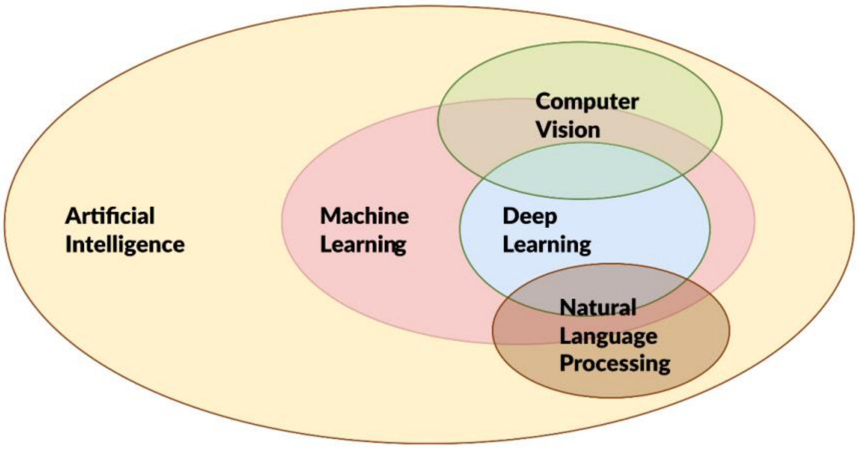

FIG. 1: AI types to simulate human intelligence include machine learning, deep learning, computer vision, and natural language processing.

- The main early algorithms used in supervised learning are Logistic Regression (Cox, 1959), Perceptron (Rosenblatt, 1958), and kNN (Nearest Neighbour) (Cover and Hart, 1967). While the Perceptron algorithm undoubtedly laid the groundwork for ML algorithms, they were fragmented and unstructured prior to the publication of the Decision Tree algorithm (Xu *et al.*, 2021). Support Vector Machine (SVM), AdaBoost, and Random Forest (RF) are the most widely used supervised learning algorithms in the construction industry (Xu *et al.*, 2021). The majority of the time, they are used to classify data.
- Unsupervised learning focuses on data reduction and clustering problems and discovers knowledge from unlabeled data. The main algorithms in unsupervised learning are Principal Component Analysis (PCA), t-SNE, and K-means. These algorithms are mainly used to infer implicit, previously unknown historical data and potentially useful information and knowledge from unstructured datasets (Ahmed *et al.*, 2018).
- RL is another set of algorithms that focus on experience-driven sequential decision-making, i.e., they make software agents take action to maximize some notion of accumulative reward (Craglia *et al.*, 2018). The review conducted by (Ahmed *et al.*, 2018) reveals that most RL studies (45 percent) concentrate on either building energy management or dispatch issues. Most papers on building energy management systems focus on HVAC, with a few publications focusing on lighting and blind control in conjunction with HVAC.

2.2.2 Deep Learning

Deep learning (DL) allows computational models with multiple processing layers to learn multiple levels of abstraction for data representations (Lecun, Bengio and Hinton, 2015). These techniques have vastly improved the state-of-the-art in speech recognition, visual object recognition, object detection, and various other fields like drug discovery and genomics. DL uses the backpropagation algorithm to show how a machine should change its internal parameters to compute each layer's representation from the previous layer's representation, revealing intricate structures in large data sets (Rumelhart, Hinton and Williams, 1986). The lack of sufficient data and computational power hindered the deployment of DL algorithms until 2012 when the success of AlexNet (Krizhevsky, Sutskever and Hinton, 2017) in ImageNet – an image classification competition – prompted deep neural networks to make a comeback. AlexNet's main contribution was to combine DL with large datasets effectively. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two common DL network structures:

- CNNs are an advanced form of ANN that use a mathematical operation known as convolution in place of general matrix multiplication in at least one of their layers. They are widely employed in Computer Vision since they were created primarily to process pixel data (Albawi, Mohammed and Al-Zawi, 2018).
- RNN is a class of artificial neural networks where connections between nodes can create a cycle, allowing output from some nodes to affect subsequent input to the same nodes (Sherstinsky, 2020). RNNs are primarily used in time series processing applications such as speech recognition and NLP, and are divided into two types: Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) (Cho *et al.*, 2014). LSTM and GRU work similarly: they allow storing values in "LSTM/GRU" cells and then use them when needed.

2.2.3 Computer Vision and Natural Language Processing

CV is a broad term that refers to various techniques for extracting and processing visual data from images and videos to make inferences. Some of these techniques that are important to construction management tasks are: 1) 3D scene reconstruction, 2) Image and object classification, 3) Object recognition, 4) Object tracking, 5) Segmentation, and 6) Action recognition (Paneru and Jeelani, 2021). The tasks and related challenges are furtherly explained in Table 2 below.

Table 2: Computer Vision tasks and challenges (derived from Paneru and Jeelani, 2021).

Task	Description	Challenges	References
3D Scene reconstruction	3D Scene Reconstruction is a process of creating 3D models of a scene from a set of 2D images.	Construction-related 3D reconstruction is still a difficult task. The built environment is characterized by uniformly covered, poorly textured surfaces, a dynamic job site, unwanted or obstructed backgrounds, recurring patterns of building surfaces, and occlusion.	(Fathi, Dai and Lourakis, 2015; Han and Golparvar-Fard, 2015)
Image and object classification	Image classification consists in taking an input image and determining the “class” that the image belongs to	Despite significant advancements, accurate classification still faces some difficulties because of the object's color variability, the angle at which it is located, and occlusions.	(Rawat and Wang, 2017)
Object recognition	Object recognition adds localization to the classification task.	Same as above, plus reaching a good precision in drawing bounding boxes around objects.	(Wu, Sahoo and Hoi, 2020)
Object tracking	Object tracking is a method for following moving objects while preserving their identity and trajectory over many video frames.	Re-identification: establishing a link between an object in one frame and the same object in the following frames; Scale change: Due to the camera zoom, objects in a video can have drastically different scales; Illumination: lighting changes can increase the consistency in tracking objects.	(Luo *et al.*, 2021)
Segmentation	Semantic segmentation refers to linking each pixel in an image to a class label.	Same as object classification, plus reaching a good precision in associating each pixel to the correct class.	(Lateef and Ruichek, 2019)
Action recognition	Action recognition involves feature extraction from videos to identify an activity.	Same as object tracking, plus reaching a good precision in classifying a specific activity.	(Wang, Huynh and Koniusz, 2020)

NLP is a set of techniques that aid machines in comprehending human languages by analyzing text structures and meanings. NLP is becoming more widely used, with four main application scenarios: 1) filtering information, i.e., extracting key information from noisy texts for specific purposes (e.g., finding accident causes from reports), 2) organizing documents, i.e., automatically grouping documents of different backgrounds (e.g., drawings from different disciplines) and enabling timely retrieval, 3) expert systems, i.e., integrating expert knowledge and providing answers for engineering problems, and 4) automated compliance checking, i.e., automatically comparing as-is situation (e.g., working plans) with requirements (e.g., contracts and standards) and identifying non-compliance (Wu *et al.*, 2022).

3. RESEARCH METHODOLOGY

The methodology adopted for this study is summarised in *Figure 2* and followed the path proposed by Snyder, 2019, who suggested conducting the review in stages by 1) reading abstracts, 2) screening for inclusion and, 3) reading full-text articles. Accordingly, in this study, the following steps are carried out: i) definition of the set of keywords for querying scientific databases (Section 3) and getting an article list for further analysis; ii) bibliometric analysis of the article list aimed at defining the most researched areas and topics for the literature review (Section 4); iii) abstract content analysis to select the most relevant articles in each of the areas found from the bibliometric analysis; and iv) full-text review of the most relevant outlets to define the state-of-the-art (Section 5) and future trends (Section 6) of AI in AM.

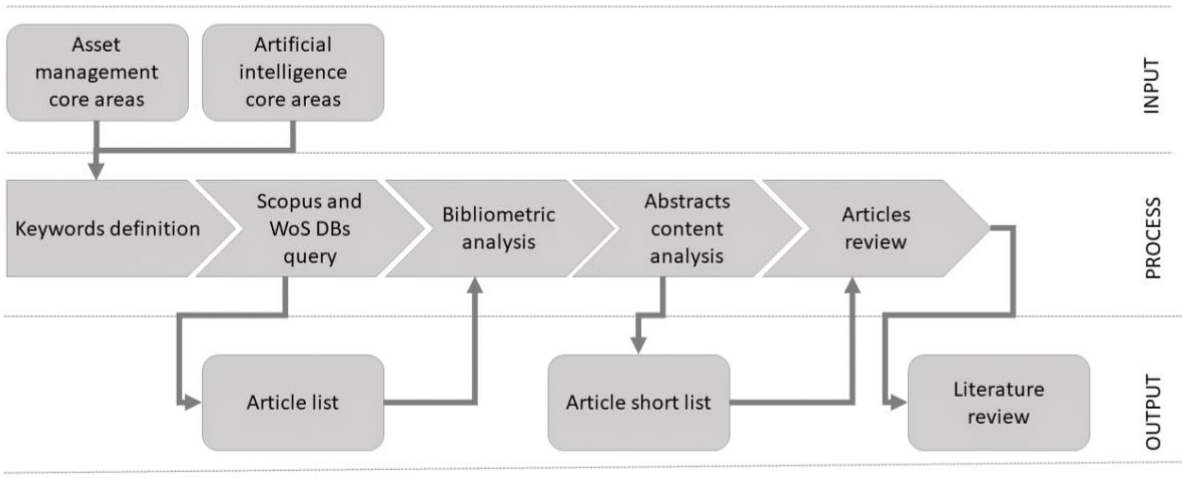

FIG. 2: Research methodology workflow.

The first step was the definition of keywords to query the Scopus and Web of Science (WoS) databases. The keywords related to AI technologies are derived from (Craglia *et al.*, 2018), while AM core areas are taken from (Re Cecconi *et al.*, 2020). Therefore, the two databases were investigated using the following query strings (1) (2):

“artificial intelligence” OR ai OR “machine learning” OR “deep learning” OR “neural network*” OR “reinforcement learning” OR “computer vision” OR “natural language processing” (1)

AND

“risk management” OR rm OR “sustainability management” OR sustainability OR “financial management” OR “value management” OR “quality management” OR “resilience management” OR resilience OR “Life Cycle Costing “ OR lcc OR “energy management” OR “property management” OR “Facility Management” OR fm OR “Commissioning” OR “Project Management” OR “Data Management” OR “Condition Inspection*” OR “Condition Monitoring” (2)

In both (1) and (2), “AND” and “OR” are the standard Boolean operators used as conjunctions to combine keywords, and the “*” sign means that both singular and plural forms of the keywords are considered.

As of March 2022, the query gave 894 results in the Scopus DB and 1026 in WoS DB. However, the findings required further refinement for selecting outlets relevant to the research objectives. The refinement process is summarized in the flowchart in FIG. 3 . To limit the results to articles related only to AECO disciplines, the journals and books selected were limited to the ISSN and ISBN numbers listed in Scott, Broyd and Ma, 2021. Moreover, all the duplicates were removed, leaving a total of 767 outlets. The articles were further refined through the exclusion and inclusion criteria for primary data derived from (Yigitcanlar *et al.*, 2020) (Table 3). In this way, the bibliometric analysis was performed with 578 papers. It is noteworthy that the bibliographic metadata collected in WoS has better quality than Scopus since the latter presents cited references that are not standardized (e.g., the journal *Automation in Construction* is reported in three different ways), thus requiring some hand adjustments to provide correct information.

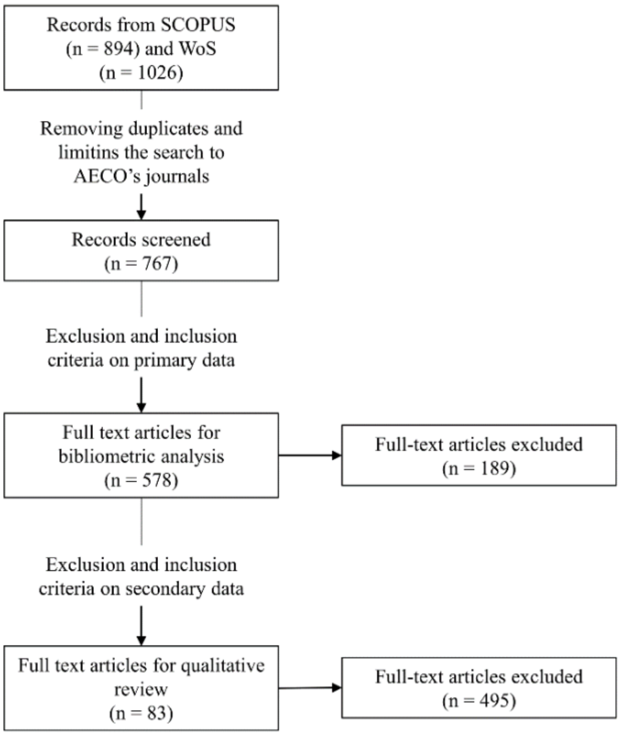

FIG. 3: PRISMA flowchartthat describes the outlets selection process.

The metadata was used to perform the bibliometric analysis, which helps identify insightful trends and streamlines the essential papers' in-depth review analysis (Ellegaard and Wallin, 2015). Finally, according to the secondary exclusion and inclusion criteria (Table 3), the number of articles to be read in-depth was eventually reduced to 83.

Table 3: Exclusion and inclusion criteria, derived from (Yigitcanlar et al., 2020)

Primary data		**Secondary data**	
Inclusionary	**Exclusionary**	**Inclusionary**	**Exclusionary**
Journal articles Conference articles Peer-reviewed English Full-text available online	Books and chapter Industry reports Non-English language	AI in AM Opportunities and challenges in construction relevant to the research objective	Not AI in AM related Irrelevant research objectives

4. BIBLIOMETRIC ANALYSIS

This section discusses the results obtained from the bibliometric analysis, which helped define the main topics, countries, and journals. FIG. 4 shows the annual publication in the last decade. Essentially, the rising publication trend shows an increase in AI in AECO research. This trend will likely continue as AI, and the Internet of Things (IoT) become more prevalent in the field (Internet Society, 2017).

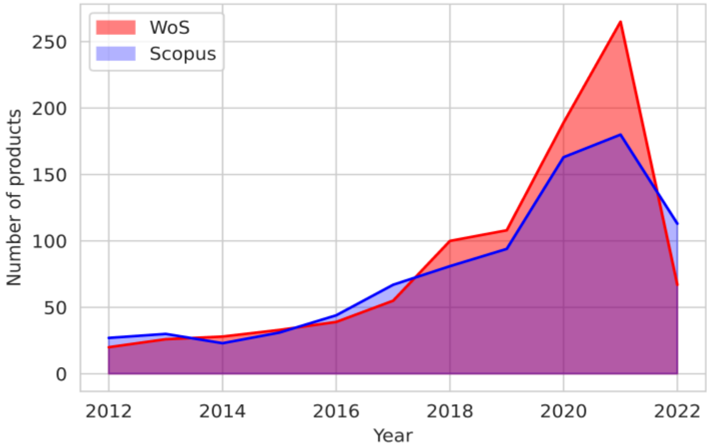

FIG. 4: Trend in research studies on AI in the AM core areas (2012-Mar 2022). The publication number might increase for the year 2022.

4.1 Keywords co-occurrence analysis

A co-occurrence keywords analysis provides hints and suggestions for discovering research trend areas. As He, 1999 stated, a network of correlated words gives a good picture of a knowledge domain. Thus, a co-occurrence keywords analysis was performed with VOSviewer software. A co-occurrence is verified when two keywords occur in the same study. FIG. 5 shows the results, where the nodes' dimension denotes the frequency of a keyword, i.e., how many times it occurs inside the analyzed dataset, and the number of links reveals which keywords are bounded more than others. For better visualization, keywords with at least ten co-occurrence were represented.

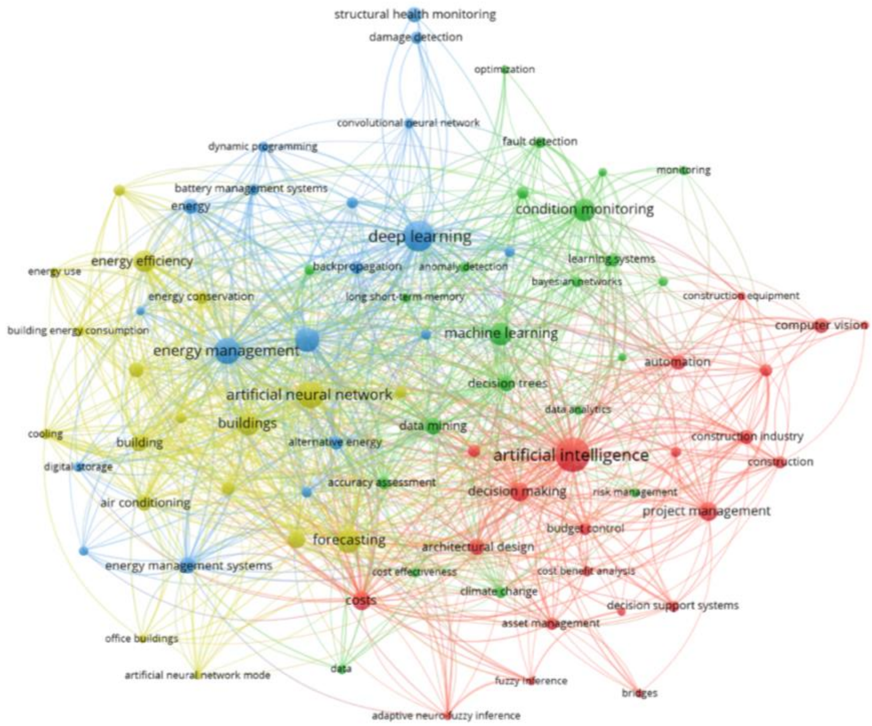

FIG. 5: Main research interests on AI in AECO (co-occurrence network of keywords).

The co-occurrence representation reveals several research interests:

- Energy-related problems have received special attention, with studies on optimizing or predicting energy consumption (Aguilar *et al.*, 2021). ANNs are strongly linked with energy management (EM), while RL (Mason and Grijalva, 2019) and Genetic algorithm (Luo *et al.*, 2020) are investigated in fewer research. Thermal comfort is another topic of EM (Halhoul Merabet *et al.*, 2021).

- Condition monitoring is another key research area: there is a cluster formed by structural health monitoring, condition assessment, and damage inspection that is correlated chiefly with infrastructures (e.g., bridges, road pavements, and so on) (Sun *et al.*, 2020), and a second cluster closely related to buildings Mechanical Electrical and Plumbing (MEP) systems' assessment and maintenance (Carvalho *et al.*, 2019)
- ANN is the most investigated AI technique that is used in different AM applications (energy optimization, scheduling, project management, etc.), while other techniques are used only for specific areas (e.g., genetic algorithm for building energy optimization (Waibel *et al.*, 2019) or Adaptive neuro-fuzzy inference system (ANFIS) for project cost estimation (Dastgheib *et al.*, 2022))

4.2 Top outlets for research on AI in AM

The importance of analyzing academic journals in any scientific field has been highlighted and explained in numerous studies (Dastgheib *et al.*, 2022). Journal analysis help in determining the best sources of information, while authors discover which journals are best suited for publication. A direct citation analysis of outlets was used in this study to show the importance of academic journals that publish AI in AM research. VOSviewer was used, with "citation" as the type of analysis and "sources" as the unit of analysis. For the best network, the "minimum number of documents of a source" and "minimum number of citations of a source" were set to 10. Only 23 of the 110 sources met the criteria and were included in the resulting network, represented in FIG. 6.

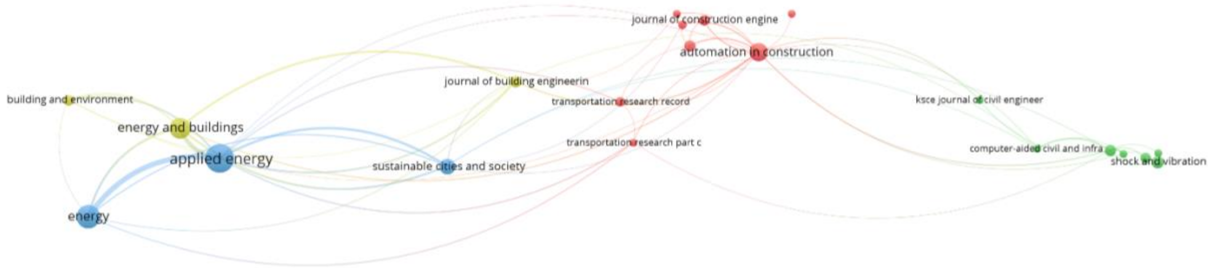

FIG. 6: Relevant outlets network.

According to the findings, *Applied Energy* has been the most influential outlet for AI in AM research. As shown in Fig. 5, there is a significant flow of information (via citations) from *Applied Energy* to the second tier of influential outlets in the field, *Energy*, *Energy and Buildings*, *and Sustainable cities and Societies*, as shown in Table 4. This group of journals is strongly correlated with energy-related research, while *Automation in Construction* represents the main source with a broader scope.

Table 4: Top 10 outlets for research on AI in AM.

Source	Documents	Citations
Applied energy	141	4883
Energy	92	2018
Energy and buildings	75	1946
Automation in construction	59	1706
Sustainable cities and societies	41	684
Journal of computing in civil engineering	21	450
Structural control & health monitoring	22	358
Journal of information technology in construction	18	326
Journal of building engineering	24	318
Journal of construction engineering and management	19	314

4.3 Scientific collaboration networks: co-authorship analysis

In any research domain, understanding current scientific collaboration networks can help to a) increase access to specialties, funds, and expertise and b) increase productivity. Specifically, with VOSviewer we created a network to identify the most influential countries and the collaborations between them: "co-authorship" was the type of analysis, "countries" was the unit of analysis, and "fractional counting" was the counting method. For the best network, the "minimum number of documents of a country" and "minimum number of citations of a country" were set to 10. 26 countries out of 77 met the criteria and were included in FIG. 7. From the results, the United States and China stand out as the top-ranked countries. Moreover, England, Australia, and Canada were the third, fourth, and fifth largest contributors.

FIG. 7: Collaboration network of countries.

5. LITERATURE REVIEW

The first study about AI in AM appeared in the journal "*Urban System*" in 1978 (Bohl, 1978). Initially, research studies were limited on this topic until the beginning of the 21st century, when the growing interest and spreading of AI in various fields also increased attention in the AECO sector. In this paragraph, we investigated the literature in the AM areas identified from the bibliometric analysis by thoroughly reading the most relevant articles selected with the abstract content analysis. Therefore, the following subparagraphs show the main core AM areas where AI applications are currently being researched (FIG. 8).

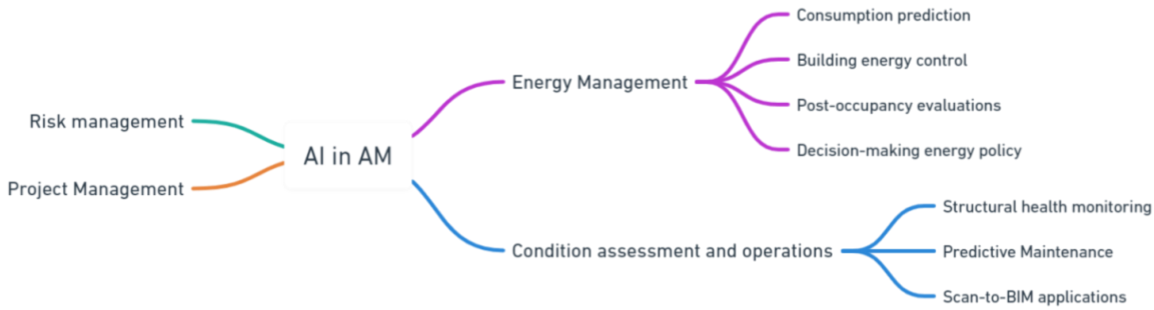

FIG. 8: Summary of the AM core areas where AI is mostly investigated.

5.1 Energy Management

The objective of EM is to keep the asset under an acceptable level of energy consumption and relative comfort through technical (maintenance) and administrative actions (contracts). Residential, educational, office, healthcare, and industrial buildings are increasingly energy consumers. Buildings consume 30–45 % of global energy (Ashouri *et al.*, 2019); thus, efforts are currently focused on meeting the requirements for energy-efficient buildings by ensuring operative needs at the lowest possible energy cost while remaining environmentally friendly. In this context, three different approaches for modeling building energy analysis have been developed:

- The white-box method, also known as the engineering method, is divided into two categories: simplified and elaborate. Both white-box approaches' sub-categories use physical principles to calculate thermal dynamics and energy behaviors for individual building components or the entire building (Ahmad *et al.*, 2014).
- The AI-based method (also called the black-box method) investigates building-energy-related output without knowing its internal relationships.
- The hybrid method (also known as the grey method) combines white-box and black-box methods to overcome the limitations of each.

The white-box and grey-box methods require detailed building information as inputs to simulate the inner relation and build the energy model, that is often limiting the accessibility of these methods. Furthermore, constructing a building energy model is time-consuming and labor-intensive, making it difficult to apply widely (Fumo, 2014). However, AI-based building energy modeling methods can forecast desired building energy outputs based on correlated variables like environmental conditions and occupancy status (Fumo, 2014). This section reviews AI applications in EM for i) energy consumption prediction, ii) building energy control, iii) post-occupancy evaluation, and iv) decision-making energy policy.

5.1.1 AI for energy consumption prediction

The rising of AI significantly impacts economics, reducing the cost and accessibility to data-driven predictions (Agrawal, J. Gans and Goldfarb, 2019). In EM, AI methods have been used to predict electricity or HVAC prices and various load types. For instance, short-term forecasts can help with electricity scheduling, allowing aggregators to provide better services and consumers to react more quickly. On the other hand, better long-term forecasts (i.e., more than 24 hours) can help service providers and operators better understand the available flexibility, which consumers to target for disaster recovery, and set demand/response signals.

Artificial neural networks (ANN) (Bagnasco *et al.*, 2015), SVM (Dong, Cao and Lee, 2005), autoregressive integrated moving average (ARIMA) (D Zhao *et al.*, 2016), deep neural networks (DNNs) models (Fan, Xiao and Zhao, 2017a), and other regression algorithms have been successfully used to predict building energy loads. A general process of regression-based methods includes four steps, i.e., data transformation, feature selection, optimization of model parameters, and model training (Zhao *et al.*, 2020). The literature on this topic is sometimes controversial, and many studies confronted algorithms to determine the best for predicting energy consumption. For instance, Mocanu *et al.*, 2016 discovered that the DNN model outperformed ANN and Support Vector Regression (SVR) in predicting the electricity load of residential buildings. On the other hand, Amber, R Ahmad, *et al.*, 2018 DNN model's performance in predicting electricity load was compared to four other regression algorithms, including multiple linear regression (MLR), genetic programming (GP), ANN, and SVR. The results revealed that the DNN prediction performance was no better than that of ANN. However, recent research evidenced the power of ensemble methods in overperforming single ones. Ensemble learning is a more advanced regression algorithm that can take advantage of several different regression algorithms. Fan, Xiao and Wang, 2014 proposed an ensemble prediction model for predicting public building electricity loads. MLR, ARIMA, SVR, RF, ANN, boosting tree, multivariate adaptive regression splines, and k-nearest neighbors were among the eight base regression algorithms used in the ensemble model. The results showed that the ensemble model's prediction accuracy was significantly higher than that of base models. The methods reviewed in this section are listed in Table 5.

Table 5: A list of AI-based building energy load prediction methods.

Year	Application	Algorithms	Asset	Ref.
2014	Electricity load prediction	ANN	Large building	(Mena *et al.*, 2014)
2014	Electricity load prediction	Ensemble learning*, ARIMA, SVR, MLP, kNN	Large building	(Fan, Xiao and Wang, 2014)
2015	Electricity load prediction	ANN	Hospital	(Bagnasco *et al.*, 2015)
2015	Electricity load prediction	MLR, ANN, SVR*	Large building	(Massana *et al.*, 2015)
2016	Electricity load prediction	ANN*, SVR, ARIMA	Office	(Deyin Zhao *et al.*, 2016)

Year	Application	Algorithms	Asset	Ref.
2018	Electricity load prediction	MLR, GA, DNN, SVR, ANN*	Office	(Amber, R. Ahmad, *et al.*, 2018)
2022	Electricity load prediction	MLR, ANN*, SVR	Residential	(Seo *et al.*, 2022)
2017	Cooling load prediction	DNN, XGB*, SVR, MLR, RF	Educational building	(Fan, Xiao and Zhao, 2017b)
2019	Cooling load prediction	RNN, LSTM, GRU*	Educational building	(C. Fan *et al.*, 2019)
2022	Cooling load prediction	Hybrid method	Large commercial building	(Gao *et al.*, 2022)

* represents that the algorithm has the best performance compared with the others.

5.1.2 AI for building energy control

Traditional building control is a rule-based feedback control that uses pre-determined schedules to select set points (such as supply air and water temperatures and zone thermostat temperature) and then uses traditional control techniques to track those set points. Wang and Hong, 2020 found two significant flaws in the prescriptive and reactive control strategy: i) predictive information (such as weather) is ignored, resulting in sub-optimal performance; ii) the control strategies are predetermined, meaning they are not customized to the specific building and are unable to adapt to changes (such as retrofits). ML can help address both issues (Zhang *et al.*, 2021): ML could predict weather, occupancy, and building load (as explained in Section 5.1.1) and use those data to optimize the building. Second, ML could allow the controller to learn from building operation data, identifying states, updating parameters, and adapting to changes in the target structure. Currently, there are two major approaches for building control: Model Predictive Control (MPC) and RL (RL).

The MPC uses a system model to forecast the system's future states and generates a control vector that minimizes a specific cost function over the prediction horizon (Camacho and Bordons, 2007). The prediction is conducted in the presence of disturbances and constraints that can be represented by weather conditions, occupant activities, and equipment use. MPC controllers have been used in various HVAC systems in buildings: for example, to control the temperature of individual zones in a single-story office building with a cooling system but no heating or mechanical ventilation (Ma *et al.*, 2012).

Compared with other ML classes, RL is preferable when dealing with problems involving sequential dynamics and optimizing a scalar performance objective. The following are RL's most appealing features: i) direct application to a real-world scenario, ii) it is unnecessary to have any prior knowledge, iii) self-adapt to the surrounding environment, and iv) self-adjust to input variations, i.e., adaptation to stochastic processes like occupant behavior and preferences (Yang *et al.*, 2015). On the other hand, RL approaches can be more data-intensive and time-consuming than MPCs (Nweye *et al.*, 2021). The methods reviewed in this section are listed in Table 6.

Table 6: A list of AI-based building energy control methods.

Year	Application	Algorithms	Asset	Ref.
2014	HVAC control	MPC	Experimental room	(Zakula, Armstrong and Norford, 2014)
2018	HVAC control	MPC	Office	(Wang *et al.*, 2018)
2019	HVAC control	MPC	Virtual building	(Blum *et al.*, 2019)
2017	HVAC control	RL	Power grid	(Zhang *et al.*, 2017)
2019	HVAC control	RL	Residential	(Zhou *et al.*, 2019)
2019	Lighting control	RL	Office	(Park *et al.*, 2019)
2019	Window control	RL	Several buildings	(Han *et al.*, 2019)
2017	Hot water control	RL	Residential	(De Somer *et al.*, 2017)
2017	Hot water control	RL	Residential	(Al-Jabery *et al.*, 2017)

5.1.3 AI for post-occupancy evaluation

Another area of growing interest and research is the application of big data analytics to post-occupancy evaluations. Indoor air quality (IAQ), indoor environmental quality, occupant health and safety, occupant comfort, and occupant complaints are all factors that are frequently evaluated in these studies (Mcarthur et al., 2018). The ability to mine indoor environmental data from measurements and occupant satisfaction/comfort data from surveys open up new possibilities for facility managers to respond to occupant complaints more effectively. For instance, Kim *et al.*, 2018 introduced a novel approach for generating personal comfort models that anticipate an individual's thermal preference based on occupant feedback and heating and cooling behavior. The model is based on field data collected from 38 tenants in an office building, including human control behavior, environmental variables, and mechanical system settings, and incorporates six ML algorithms for classification.

Moreover, Cheung *et al.*, 2017 studied individual thermal acceptability and perceived air quality acceptability in relation to objective physical parameters (temperature, relative humidity, and CO2 concentration), individual location, air-conditioning status, occupants' sleeping ventilation habits, and personal environmental exposure history in longitudinal monitoring experiments. They used a Gaussian process (that performed better than MLR) to simulate individual acceptability levels. Potential applications of this study include smart air-conditioning systems that communicate with portable personal sensors to create a personal comfort environment in private spaces such as autos, offices, or beds. Finally, the methods reviewed in this section are listed in Table 7.

Table 7: A list of AI-based post-occupancy evaluation methods.

Year	Application	Algorithms	Asset	Ref.
2013	Indoor thermal comfort	SVR	Several buildings	(Rana *et al.*, 2013)
2016	Indoor thermal comfort	SVR	Office	(Jiang and Yao, 2016)
2018	Indoor thermal comfort	ANN	Office	(Deng and Chen, 2018)
2018	Indoor thermal comfort	RF, Gaussian, XGB, kSVM	Office	(Kim *et al.*, 2018)
2019	Indoor thermal comfort	Fuzzy logic	Large building	(Aguilera, Kazanci and Toftum, 2019)
2017	Indoor environmental comfort	Gaussian	Office	(Cheung *et al.*, 2017)

5.1.4 AI for decision-making energy policy

Currently, producing new high-performance buildings and effective retrofit solutions for existing structures is a major issue. Retrofit decision-making primarily relies on expert knowledge and involves time-consuming processes, including on-site building audits to collect building attributes and, in some situations, detailed building retrofit performance studies to determine the potential of each retrofit measure. Because this is unlikely to scale throughout the whole building stock, a new field of research focuses on automating the retrofit analysis process (Sun *et al.*, 2016). For example, Beccali *et al.*, 2018 trained two different ANNs: the first detected the energy performance of buildings in the southern area of Italy, while the second assessed key economic indicators. The model was conceived for a better-informed selection of energy retrofit initiatives.

Moreover, (Re Cecconi, Moretti and Tagliabue, 2019) developed a data-driven method for supporting regional energy retrofit strategies for school buildings, focused on using open data, ANN, and Geographic Information Systems (GIS). The key benefit is the ability to forecast post-retrofit energy savings without a costly on-site Condition Assessment. Finally, Re Cecconi, Khodabakhshian and Rampini, 2022 proposed a support decision system based on clustering techniques to define the optimum retrofit scenario.

5.2 Condition assessment and operations

Condition Inspection and Monitoring (CIM) is a term used to describe the process of controlling and measuring a product or service performance. CIM is formed by a set of procedures for evaluating a product or serviceability to execute as planned in real-world scenarios. Asset performance evaluation and reporting are critical in this context for creating a holistic awareness of physical items and preventing potential flaws produced by unanticipated events. CIM activities are usually conducted with manual processes that can be time-consuming and error-prone. However, the widespread deployment of sensors, images, and videos provides the essential big data to train ML and DL algorithms and develop AI-based CIM. For instance, Rampini, Khodabakhshian and Re Cecconi, 2022 used a CNN to automatically detect building façade's colors and materials, while Dias *et al.*, 2014 used an ANN to predict exterior painted facades' service life. The authors identify three main factors to establish the durability of paint coatings in Portugal: age, distance from the sea, and façade's orientation. The authors could predict the service life of painted surfaces with reasonable accuracy. In conclusion, these models can be incorporated into maintenance management procedures. In this section, we review applications of AI in CIM for i) structural health monitoring (SHM), ii) predictive maintenance, and iii) scan-to-BIM of Mechanical, Electrical, and Plumbing (MEP) elements.

5.2.1 AI for structural health monitoring

Due to the impracticality of visual inspection for vast and complex civil infrastructures and long biennial inspection intervals, condition-based evaluation methodologies have been introduced. As a result, SHM has evolved to bridge the gap between offline damage detection and near-real-time and online damage assessment. In other words, SHM is a damage detection approach that uses a succession of continuous measuring sensors to monitor a structure over time (Malekloo *et al.*, 2021).

DL techniques are commonly investigated for SHM applications, especially image processing and recognition (IPR). CNNs are one of the most widely used deep neural networks for IPR, and various architectures are increasingly being used to automate visual inspection by detecting structural faults in images. CNNs have been employed for the application of crack detection in steel decks (Xu *et al.*, 2019), asphalt pavements (R. Fan *et al.*, 2019), and concrete surfaces (Cha *et al.*, 2017), with very high accuracy being achieved in all cases. Because videos include more information than photos, they enhance data-collecting efficiency, especially in complex or risky contexts. For example, Chen and Jahanshahi, 2018 used video frames to train a CNN model to detect cracks in nuclear power plant components underwater and discovered that pooling information from many video frames could reach a 98 percent success rate on microscopic cracks. Noteworthy, Object Detection (OD) algorithms accuracy progressed in the last five years: the first step for OD optimization was made by Regional-CNN (R-CNN) (Girshick *et al.*, 2014), then fast R-CNN (Girshick, 2015), and finally, faster R-CNN (Ren *et al.*, 2017). The latest advancements in OD accuracy are reached by YOLO ("You Only Look Once") algorithm (Redmon *et al.*, 2016), now in its fourth version, which triggered real-time OD (Bochkovskiy, Wang and Liao, 2020). For instance, Pan and Yang, 2020 used YOLO v2 algorithm to assess the damage state in Reinforced Concrete (RC) columns since RC buildings are the most prevalent structures worldwide. Overall, Image classification and object localization are lower-level tasks. Instead, Semantic image segmentation, which separates target regions from the background, is a higher-level activity. Semantic segmentation can extract skeleton information from raw photos at the pixel level, allowing unstructured image data to be transformed into structured data. The full convolutional network (FCN), which replaces fully-connected layers in classic CNN with convolutional layers, is a semantic segmentation architecture. Zakeri, Nejad and Fahimifar, 2017 divided segmentation tasks into five major processes: i) pre-processing, ii) segmentation, iii) feature extraction, iv) feature selection, and v) detection and classification. In this context, Huang, Li and Zhang, 2018 used a VGG-16-based FCN model to extract defect regions of tunnel cracks and leakages and discovered that target regions might be retrieved in two-defect overlapping pictures. Although the accuracy is still restricted, Yang *et al.*, 2018 developed an FCN model based on VGG-19 to detect concrete fractures. Finally, the methods reviewed in this section are listed in Table 8.

Table 8: A list of AI-based structural health monitoring methods.

Year	Application	Algorithms	Asset	Ref.
2014	Structural Health Monitoring	RF	Dam	(Dai *et al.*, 2018)
2020	Structural Health Monitoring	XGBoost	Concrete electrical resistivity	(Dong *et al.*, 2020)
2019	Structural Health Monitoring	SVM	Bridge, building	(Zhang *et al.*, 2019)
2020	Structural Health Monitoring	ANN	Steel fatigue	(Gulgec, Takac and Pakzad, 2020)
2019	Structural Health Monitoring	RNN	Large buildings	(Perez-Ramirez *et al.*, 2019)
2021	Crack detection	CNN	Facade	(Chen *et al.*, 2021)

5.2.2 AI for predictive maintenance

Different nomenclature and categories of maintenance management strategies can be found in the literature. (Susto *et al.*, 2015) identified the following types of maintenance:

- Corrective maintenance is only performed after an item stops working. This is the simplest maintenance plan because it necessitates both a production stop and the repair of the replacement parts, resulting in a direct cost to the process.
- Preventive maintenance, often known as scheduled maintenance, is a maintenance approach conducted with a predetermined schedule in time or process iterations to predict process/equipment breakdowns. It is often a successful strategy for avoiding failures. On the other hand, unnecessary corrective actions are taken, resulting in increased operational costs.
- Predictive Maintenance (PdM) is a method of determining when maintenance is required using predictive technologies. It is based on constantly monitoring a machine's or process's integrity, allowing maintenance to be done only when required. Furthermore, predictive tools based on historical data (e.g., ML techniques), integrity variables (e.g., visual aspects, wear, coloration different from original), statistical inference methods, and engineering approaches enable early detection of failures.

Although maintenance based on periodic revisions is the most widely utilized strategy, these strategies are rapidly being categorized as flawed and unreliable (Butler and Smalley, 2002). After completing a study with identical systems evaluated under equal settings (Canizo *et al.*, 2017), it was discovered that the time it takes for a system to fail varies greatly amongst systems. Maintenance based on periodic modifications is thus unproductive because it is complicated to predict when a component of an industrial process will break over a specific period. The review by Carvalho *et al.*, 2019 revealed that RF, ANN, SVM, and k-means are the most used algorithms for PdM. For example, Pan *et al.*, 2017 deployed a CNN to predict faults in the acoustic sensor. The proposed solution allowed self-checking to reduce washing machine damage and unnecessary maintenance and increased productivity through automatic problem identification using acoustic sensor data and precise part preparation. Similarly, CNN-based PdM has been applied to photovoltaic panels (Huuhtanen and Jung, 2018) and wind turbines (Canizo *et al.*, 2017). The applications reviewed in this section are listed in Table 9.

Table 9: A list of AI-based predictive maintenance methods.

Year	Application	Algorithms	Asset	Ref.
2014	Predictive maintenance	ANN	Oil and gas pipelines	(El-Abbasy *et al.*, 2016)
2014	Predictive maintenance	SNN, SVM	Sewer	(Sousa, Matos and Matias, 2014)
2017	Predictive maintenance	CNN	Acoustic sensors	(Pan *et al.*, 2017)
2017	Predictive maintenance	CNN	Wind turbines	(Canizo *et al.*, 2017)
2018	Predictive maintenance	CNN	Photovoltaic panels	(Huuhtanen and Jung, 2018)
2013	Service-life prediction	ANN	Facade	(Dias *et al.*, 2014)

5.2.3 AI for AM Scan-to-BIM applications

Large structural components such as floors, ceilings, walls, and apertures such as doors and windows have been the focus of Scan-to-BIM research on automatic OD. BIM models with many other features, such as MEP components, are required to maintain buildings and other structures properly. MEP assets comprise a significant portion of building maintenance expenditures (Adán *et al.*, 2018). As a result, they provide crucial data for maintenance and renovation. There is an evident demand for Scan-to-BIM technology that extends current capabilities to MEP components. Detecting MEP components comes with its own set of difficulties. They are typically much smaller than structural components, making OD models challenging to detect (Li *et al.*, 2017). MEP assets also have a wider range of variation within classes than structural components, necessitating an MEP detector learning of additional feature patterns. Radiators, for example, will have somewhat varied labels, valve designs, and other characteristics depending on the brand.

Recent advances in DL have yielded impressive results in detecting a variety of small object classes (Liang *et al.*, 2018). If successful, DL will detect MEP components in photographic and point cloud data, allowing them to be integrated into Scan-to-BIM frameworks and produce more detailed BIM models. Different ML algorithms have been used to classify asset-related items: Krispel *et al.*, 2015 detect plugs and light switches using an RF classifier and a sliding window on orthophotos of walls. Huang and You, 2013 created a system for recognizing items in point cloud data, such as MEP equipment like valves and spotlights. An SVM is used to identify primitive objects like pipes and planes. Walls and other large primitives are presumed to be background elements and are eliminated. The remaining points are then grouped based on their Euclidean distance. A rigorous matching procedure compares clusters that pass the linearity filter to components in a pre-made 3D object library. When a cluster's alignment with a target component surpasses a certain threshold, the cluster is considered a discovered instance of the target.

The most promising results have recently come from DL models. For example, Babacan, Chen and Sohn, 2017 created a DL model that segregated furniture in laser images of interior rooms based on semantics. In the S3DIS point cloud data collection, Chen, Kira and Cho, 2019 employed a neural network to detect structural features like beams and columns. These achievements provide even more encouragement to look into using DL to detect MEP assets.

5.3 Risk management

Risk management (RM) is a discipline that allows for "reducing financial losses, improving health and safety, goodwill and reputation, minimizing environmental and social impact, can result in reduced liabilities such as insurance premiums, fines and penalties" (ISO 31000, 2018). In other words, RM increases the possibility and impact of positive events while decreasing the likelihood and impact of bad ones. Most of the evaluations in RM are subjective and based on experience; therefore, much research focuses on establishing a methodology for making objective, data-driven decisions and adopting AI solutions.

Case-Based Reasoning (CBR) (Adán et al., 2018) is a general term in project risk management for solving new problems based on similar past experiences. CBR helps identify and mitigate project risks at early stages, such as design and construction planning. Some efforts have been noted in gathering risk cases and building a risk case database to facilitate CBR for practical use in the construction industry. However, because risk case databases frequently contain large amounts of data and reports written in unstructured textual data, manually examining, analyzing, and comprehending these reports is time-consuming, labor-intensive, and inefficient. When it comes to collecting 'right' situations and information in a short amount of time, the necessity of learning from previous experience is sometimes overlooked. As a result, some researchers noted that a key challenge in current CBR research for project risk management is retrieving relevant data from the database quickly and accurately so that knowledge and experience can be incorporated into new risk identification and assessment on time (Tixier *et al.*, 2016). Recently, NLP has been used to handle textual document analysis and management difficulties, such as retrieval of CAD drawings (Yu and Hsu, 2013), automatic injury report analysis (Tixier *et al.*, 2016), retrieval of relevant information for assisting decision-making (Lv and El-Gohary, 2016), and automatic grouping of construction project documents based on linguistic similarity (Al Qady and Kandil, 2014). Finally, Zou, Kiviniemi and Jones, 2017 combined two NLP techniques, namely Vector Space Model (VSM) and semantic query expansion, for risk CBR. When a query is supplied, the results show that the proposed system can swiftly and effectively find and score valuable risk situations. In this way, end users rapidly locate risk examples that are useful references to new situations or difficulties, and information and experience from previous accidents might be embedded into daily work. Any new cases might be flexibly added to the risk case database for retrieval without pre-processing.

5.4 Project Management

The concept of Project Management (PM) is broad and needs to be narrowed down when used inside the scope of this literature review. In this context, the project manager ensures the proper installation and development of a new physical service-based product or service using AI tools to comply with proper quality, time, and cost.

Typically, construction projects involve enforcement and compliance with standards and codes that are manually processed. Each building compliance review cycle takes several weeks, and a construction project can go through numerous cycles of plan reviews. Failure to follow construction codes result in further fines, penalties, or even criminal court prosecutions (Zhang and El-Gohary, 2016). Many research projects attempted to automate the compliance checking process as computing technology advanced. Recently, many researchers focused on NLP-enabled automatic code compliance checking. In fact, compliance can be verified through comparisons, such as determining if the required safety information is included in project plans (Martinez-Rojas *et al.*, 2018; Moon, Lee and Chi, 2021) and detecting inconsistencies in accident categories in reports (Gerber and Tang, 2013). According to Wu *et al.*, 2022, the standard procedure involves four steps: i) extract rule patterns from texts, ii) transform rules to machine-readable logic (usually with a standardized schema like XML), iii) extract as-is information (from BIM/GIS models), and iv) fill-in rule variables and conduct checking. For example, Zhang and El-Gohary, 2017 integrated three types of algorithms into a single unified computational platform: (1) semantic NLP algorithms to extract regulatory information from regulatory documents automatically (e.g., building codes) and transform the extracted regulatory information into logic rules, (2) semantic EXPRESS data processing algorithms to automatically extract design information from building information models (BIMs) and transform the extracted design information into logic facts, and (3) semantic EXPRESS data processing algorithms to automatically extract design information from BIMs and transform the extracted design information into logic facts. The proposed system was evaluated for conformity with Chapter 19 of the 2009 International Building Code, which set the requirements for US concrete buildings. In noncompliance detection, 98.7% recall and 87.6% precision were reached when evaluatued against a manually generated gold standard (i.e., a benchmark for testing NLP performance that includes compliant and noncompliant instances). At the moment, NLP-based compliance verification is mostly used to evaluate building design, working procedure dependencies, and spatial combinations between subsurface utilities and their surroundings. In addition to the above, other minor AI applications in project management are shown in Table 10.

Table 10: A list of AI-based project management methods.

Year	Application	Algorithms	Asset	Ref.
2016	Automated compliance checking	NLP	Buildings	(Zhang and El-Gohary, 2016, 2017)
2015	Assess and predict construction labour productivity	ANN	Buildings	(Heravi and Eslamdoost, 2015)
2014	Time and cost forecasting	SVR	Buildings	(Wauters and Vanhoucke, 2014)
2015	Predict project award price	ANN	Buildings	(Chou *et al.*, 2015)
2017	Predict construction labour productivity	ANN	Buildings	(El-Gohary, Aziz and Abdel-Khalek, 2017)
2012	Litigation prediction of site condition disputes	SVM	Buildings	(Mahfouz and Kandil, 2012)
2019	Predict time and cost claims in construction projects	ANN	Buildings	(Yousefi *et al.*, 2016)
2017	Bid/no bid decision making	SVM	Buildings	(Sonmez and Sözgen, 2017)
2017	Classification of construction waste material	CNN	Buildings	(Davis *et al.*, 2021)
2021	Forecast material prices	ANN	Buildings	(Mir *et al.*, 2021)

6. FUTURE RESEARCH TRENDS

In the future, AM will continue to embrace digital transformation. More and more AI-based technologies will be adopted and spread in all the AM core areas. These future paths are increasingly researched for establishing a more inexpensive and effective way to ease the load of human labor and promote smart construction asset management. This paragraph addresses the three most relevant AI research areas promising to enhance AM.

6.1 Digital Twin

The Digital Twin (DT) is a key component of a cyber-physical system for visualization, modeling, simulation, analysis, prediction, and optimization. DT combines three fundamental components: a physical entity, a virtual entity, and a data connection. Typically, the virtual part is built on top of the physical part and replicates the physical part in a controlled environment (Min *et al.*, 2019). The connections between the two parts (physical and digital) allow data to be transferred and controlled. DTs have a comparatively short development history since it is widely acknowledged that their origin was in 2002 (Grieves and Vickers, 2016). Sometimes, the term DT is confused with cyber-physical systems (CPS) or BIM in construction. According to Davila Delgado and Oyedele, 2021, DT is an information construct that defines a digital reproduction of a physical asset and its data links, whereas CPS is a system that combines digital and physical components. Consequently, it can be assumed that in a DT solution, a physical asset will have a digital replica whose behavior can be mimicked and whose status can be monitored and anticipated. On the other hand, a CPS solution entails greater management and optimization of physical processes supported by other digital processes without the need for digital and physical components to be in sync. Finally, despite DT and BIM referring to the digital representation of physical assets, the former is an extension of BIM since it enables real-time data capture and feedback (Boje *et al.*, 2020).

The DT has been researched mainly in the operation and maintenance stage. The applications can be divided into three topics: i) monitoring, ii) analysis, and iii) action (Jiang *et al.*, 2021):

- "Monitoring" focuses on obtaining data from physical components to update virtual parts, such as defect detection and asset monitoring. By processing data such as point clouds, digital photos, thermal images, and sensor data from laser scanners, cameras, thermal imaging devices, sensors, and other devices, the DT provides a visual and efficient means for inspection and fault detection. Moreover, The DT uses sensors to upgrade data in real-time for accounting virtual parts from actual parts to achieve AM, focusing on geometric and non-geometric information. For instance, Bonci *et al.*, 2019 built a BIM-based DT for real-time automated monitoring of buildings during normal operations, which was evaluated using a tailored simulator. To aid facility managers in making decisions, the DT model can mirror the physical system and store the real status recorded by the building.
- "Analysis", focuses on analysis using virtual parts, including diagnosis and decision-making. In this context, a DT can create high-fidelity 3D models for simulation and mechanical calculation by focusing on geometric information. For example, Dong, O'Neill and Li, 2014 designed an information infrastructure for energy problem detection and diagnostics that expedited the information interchange process in a building.
- Finally, "action" refers to collecting data from physical components and doing something with the physical parts utilizing virtual parts, such as autonomous control, retrofitting, and demolition. For instance, Volk *et al.*, 2018 built a unified system with hardware sensors. Building information acquisition, 3D reconstruction, OD, building inventory generation, and project plan optimization are all software modules included in the system. Planners, experts, or decision-makers can assess a building while digitally recording, analyzing, reconstructing, and storing it.

The government and public clients increasingly recognize the importance of DT: the UK defined a set of nine guiding principles, called Gemini principles, to guide the development of a National DT (Bolton A, Enzer M, 2018). At the same time, a new standard for DT is in development (BSI, 2022).

6.2 GANs and synthetic images for AM data augmentation

DL techniques require the availability of a huge dataset, which sometimes represents a problematic limitation. This is true, especially in Construction, where extensive open databases are seldom available since companies and institutions do not share their sources willingly (World Economic Forum, 2016). Therefore, considering the limited data samples and expensive annotation costs, many researchers have attempted to increase the size and diversity of the dataset available with synthetic images (Hong *et al.*, 2021). This process is usually called data augmentation, and recently, the most popular technique to improve the quantity and distribution of data is the Generative Adversarial Network (GANs) (Bowles *et al.*, 2018). Introduced by (Goodfellow *et al.*, 2020), GANs are neural networks that learn to create synthetic samples with the same properties as a training distribution. In the case of pictures, this entails learning to generate images (via a generator) that are visually identical to a set of real photos to the point where an opponent (the discriminator) cannot detect them. However, the synthetic images created by GANs are frequently of poor quality. The discriminator can easily distinguish poor-quality samples with higher image resolution (Karras *et al.*, 2018). As a result, rendering engines are being used to create synthetic datasets in controllable virtual environments.

In the AECO sector, the introduction of synthetic images can be facilitated by the presence of several existing BIM models, which can be used to render images either at the level of structural elements (Hong *et al.*, 2021) or facility management related objects (Wei and Akinci, 2022). For example, Soltani, Zhu and Hammad, 2016 developed an automated system for producing and classifying synthetic photographs of excavators based on 3D equipment models. Di Benedetto *et al.*, 2019 created virtual employees wearing hard hats to train detectors for personal safety using the Rockstar Advanced Game Engine (RAGE) from the GTA-V computer game. Finally, Wei and Akinci, 2022 provided an approach to produce synthetic data for training semantic understanding models reflecting changes in site conditions using 4D-BIM and Unreal Engine, based on as-designed information available in building information models. The results were twofold: i) the proposed workflow addressed issues with changing scenes by generating synthetic images with ground truth semantic segmentations based on given schedule information at any stage of construction, and ii) the proposed method reduced labeling effort by utilizing the semantically rich as-designed information available in a BIM.

6.3 Deep Reinforcement Learning

As discussed in section 5.1, AI has been increasingly applied to enable smart EM of buildings. Recently, Deep Reinforcement Learning (DLR), where NNs are used to approximate optimal value functions or policies in RL, is gaining momentum (Li, 2017). According to Yu *et al.*, 2021 DRL has an excellent representation capacity and a good decision-making ability in the face of uncertainty. Specifically, the authors identified five main advantages of using DRL for smart building EM:

1) DRL agents can learn the best control rules by trial and error using information from real-world building environments. As a result, DRL can support system operation even if detailed building thermal dynamics models are not known.
2) After the training process is completed, the trained DRL agent will be used for performance testing. The DRL agent will generate an action based on the present state of an actual environment using a mapping function. DRL can deal with system uncertainties because it does not need forecasting or statistics information from building environments in the procedure above.
3) Building energy subsystems can coordinate with one another under the framework of multiagent DRL by creating appropriate incentive functions. As a result, operational restrictions that are spatially connected are guaranteed.
4) Because only forward propagation in deep neural networks (DNNs) is involved during the testing phase, the computational complexity of the DRL algorithm is very low. The best control actions can be determined almost rapidly even when given a high-dimensional raw state.
5) Because DRL approaches employ simulated or actual data to train agents, they do not require formal mathematical models or premise conditions. Furthermore, when confronted with various building conditions, the trained DRL agent can continue to work or even improve through online learning. As a result, DRL approaches can solve many smart building EM problems.

7. CONCLUSIONS

The growing adoption of AI and data-driven analytics method has attracted researchers' attention to investigating AI applications in the AECO industry. While several literature reviews focus on AI applications for the design and construction phases, this study attempts to cover the methodologies applied for Asset Management processes, which mainly focus on the operational stage. In reviewing AI in AM applications, we conducted a bibliometric analysis and an in-depth review of previous articles. The contributions of this review are:

1) To provide a basic understanding of AI techniques and AM terminologies and reveal the potential value of AI in supporting and improving AM;
2) To depict and discuss state-of-the-art papers related to AI applications in AM;
3) To identify the evolution of future research trends that can help researchers target studies about AI in AM.

Based on the screening protocol, 578 papers were identified as eligible for bibliometric analysis, while 83 articles were thoroughly reviewed for in-depth analysis. The bibliometric analysis of the relevant articles revealed the time series, journals of publication, co-occurrence of keywords, and co-authorship networks. The AI in AM applications proposed by the in-depth review were summarized and grouped according to the core discipline of AM. In particular, the findings revealed:

1) Energy Management, Condition assessment and operations, Risk management, and Project management are the four most researched areas among the 14 AM core disciplines;
2) Specifically for Energy management, most applications focused on: i) DL techniques for energy consumption prediction and decision-making energy policy; ii) RL for building energy control; and iii) ML for post-occupancy evaluation.

3) Specifically for Condition assessment and operations, the main tasks are: i) Structural health monitoring, ii) predictive maintenance, and iii) Scan-to-BIM. For these applications, DL and CV techniques are the most used.

The literature identified the status and the research gaps in the abovementioned areas. On the other hand, the industry will benefit from further research in those areas that are not yet appropriately investigated, i.e., the remaining 10 AM disciplines. Moreover, the in-depth review revealed future trends that point out valuable directions in which to make breakthroughs. In particular, we identified the following future trends:

1) Driven by the increasing need to monitor and control assets throughout their whole lifecycle, Digital Twins (DTs) – an exact digital replica of a construction asset – are more and more investigated. DTs are created by collecting and combining real-world information about the asset. Moreover, with the support of AI and IoT, a DT can learn from various sources and automatically update to reflect changes made to its real-world counterpart.
2) In order to take advantage of the vast number of virtual 3D models that are created in our industry (e.g., every object created inside a BIM model), synthetic images and GANs can be used to improve the accuracy and the precision of CV applications for enriching AM model with up-to-date information automatically
3) Combining the characteristics of DL and RL, it is possible to increase the efficiency and customization of energy management in our built environment.

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APPENDIX 1: ACRONYMS AND ABBREVIATIONS

Table 11: Acronyms and abbreviations.

AECO	Architecture, Engineering, Construction and Operations
AI	Artificial intelligence
ANN	Artificial neural Network
AM	Asset Management
ARIMA	Auto Regressive Integrated Moving Average
BIM	Building Information Modeling
CBR	Case-based Reasoning
CV	Computer Vision
CIM	Condition Inspection Monitoring
CNN	Convolutional Neural Network
DL	Deep Learning
DRL	Deep Reinforcement Learning
DT	Digital Twin
EM	Energy Management
EAM	Engineering Asset Management
FCN	Full Convolutional Network
GRU	Gated Recurrent Units
GAN	Generative Adversarial Network
GDP	Gross Domestic Product
IAQ	Indoor Air Quality
IoT	Internet of Things
kNN	k-Nearest Neighbour
LSTM	Long Short Term Memory
ML	Machine Learning

MEP	Mechanical, Electrical and Plumbing
MPC	Model Predictive Control
MLR	Multiple linear Regressor
NLP	Natural Language Processing
OD	Object Detection
O&M	Operations and Maintenance
PCA	Principal Component Analysis
PM	Project Management
RF	Random Forest
RNN	Recurrent Neural Network
RL	Reinforcement Learning
SHM	Structural Health Monitoring
SVM	Support Vector Machine
WoS	Web of Science
YOLO	You Only Look Once