https://dx.doi.org/10.1016/j.autcon.2022.104192

Artificial intelligence in green building

Caleb Debrah

caleb.debrah@connect.polyu.hk

Albert Ping Chuen Chan

albert.chan@polyu.edu.hk

*Amos Darko

amos.darko@connect.polyu.hk

Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong

*Corresponding author

Abstract

The Architecture, Engineering and Construction (AEC) sector faces severe sustainability and efficiency challenges. The application of artificial intelligence in green building (AI-in-GB) is an effective solution to enhance the sustainability and efficiency of the sector. While studies have been conducted in the AI-in-GB domain, an *in-depth* study on the state-of-the-art of AI-in-GB research is hitherto lacking. To provide a better understanding of this underexplored area, this study was initiated via a bibliometric-systematic analysis method. The study aims to reveal the synthesis between AI and GB, as well as to highlight research trends along with knowledge gaps that may be tackled in future AI-in-GB research. A quantitative bibliometric analysis was conducted to objectively identify the major research hotspots, trends, knowledge gaps and future research needs based on 383 research publications identified from Scopus. A further qualitative systematic analysis was also conducted on 76 screened research publications on AI-in-GB. Through this mixed-methods systematic review, knowledge gaps were identified, and future research directions of AI-in-GB were proposed as follows: digital twins and AI of things; blockchain; robotics and 4D printing; and legal, ethical, and moral responsibilities of

AI-in-GB. This study adds to the GB knowledge domain by synthesizing the state-of-the-art of AI-in-GB and revealing the research needs in this field to enhance the sustainability and efficiency of the AEC sector.

Keywords: Artificial intelligence; Green building; Bibliometric analysis; Systematic analysis; Sustainability.

1. Introduction

Buildings and construction account for the largest share of both the energy use (36%) and carbon emissions (37%) in the world [1], making sustainability, including the efficient use of resources, a severe challenge facing the Architecture, Engineering and Construction (AEC) sector. To enhance the sustainability of the sector, there is a global trend of supporting and promoting *green building* (GB). The US Environmental Protection Agency [2] defines GB as "the practice of creating structures and using processes that are environmentally responsible and resource-efficient throughout a building's lifecycle". According to the World Green Building Council (WorldGBC) [3], GBs are buildings that, in their lifecycle, decrease or eliminate damages to the climate and the environment, and enhance the quality of life of people.

GB, owing to its benefits, has received increasing attention from researchers and practitioners worldwide, leading to increasing related empirical studies [4,5]. Along with this is also a number of review studies [6–8]. Despite the usefulness of these review studies, they have been based upon qualitative, manual analysis of the literature, which is prone to lack of reproducibility, subjectivity and bias, and thus reduced reliability [9]. While recent review studies attempted to address these limitations by adopting the quantitative bibliometric approach [10,11], they also lack the *in-depth* understanding that a qualitative approach could afford. To overcome these limitations while also enhancing the *depth and breadth* of understanding, this study adopts the mixed-methods systematic review approach (see section 3) to review the artificial intelligence (AI) in GB (AI-in-GB) literature for the first time.

AI is defined as the science and technology of making intelligent machines that can reason, learn, communicate, plan, move, operate objects, and solve problems [12]. AI has several benefits such as enhancing productivity and communication [13]. Although previous studies have applied AI-in-GB to enhance the sustainability and efficiency of the AEC sector [14,15], no research has thoroughly and systematically reviewed the state-of-the-art in AI-in-GB research to inform future research and improvements in practice. To fill this gap, this study reviews current literature on AI-in-GB to identify research trends and gaps that can be tackled in future research. The study seeks to answer the following research questions:

(1) What was the annual research publication trend of AI-in-GB from 2002-2021? The literature search found the first AI-in-GB publication in 2002, as shown in section 4.1, justifying the choice of 2002-2021.

(2) What are the influential AI-in-GB research journals and articles?

(3) What are the research hotspots of AI-in-GB?

(4) What are the future research needs of AI-in-GB?

2. Previous work

This section reviews existing reviews on GB and AI-in-AEC to identify the research gap, justifying the need for this mixed-methods systematic review. A summary of previous reviews is presented in Table 1 and discussed in the following sub-sections.

Table 1
Summary of reviews on GB and AI-in-AEC.

				Research theme	
SN	Source	Timespan	Research method	GB	AI-in-AEC
1.	Zuo and Zhao [6]	Not specified	Critical review	✓	
2.	Lu et al. [16]	1999-2016	Critical review	✓	
3.	Darko and Chan [7]	1990-2015	Critical analysis	✓	
4.	Darko et al. [10]	1974-2018	Scientometric review	✓	
5.	Zhao et al.[11]	2000-2016	Bibliometric review	✓	
6.	Bilal et al. [17]	Not specified	Literature review		✓
7.	Faghihi et al. [18]	1985-2014	Literature review		✓
8.	Irani and Kamal [19]	1990-2012	Systematic review		✓
9.	Pan and Zhang [20]	1997-2020	Scientometric and qualitative analysis		✓
10.	Darko et al. [21]	1974-2019	Scientometric analysis		✓

2.1. GB review

GB research has grown in recent years, with the rapid growth in practical GB implementation, leading to a number of review studies exploring various facets of GB research. One of the earlier studies that reviewed the growth and research development of GB is owed to Zuo and Zhao [6], who found that GB studies can be classified into three categories:

definitions and scope of GB; benefits and costs of GB; and ways to achieve GB. Darko and Chan [7] analyzed GB research trend in construction journals from 1990-2015 and identified that GB project delivery and developments has been a dominant topic. Other GB reviews focused on building information modeling (BIM) for GB [16]. While aforementioned reviews provide good knowledge of the GB body of knowledge, they are limited by their qualitative approach which might introduce more subjectivity and bias, which might affect their reliability. To overcome this limitation, recent reviews have employed the quantitative bibliometric approach in reviewing the GB literature [10,11]. Despite their usefulness, none of the previous reviews examined the application of AI-in-GB. The review that specifically analyzes AI-in-GB is useful to researchers and practitioners in developing cutting-edge AI-enabled solutions and technologies for application in GB projects to enhance both the sustainability and efficiency of the AEC sector. Moreover, this study adopts the mixed-methods systematic review approach to analyze AI-in-GB research for the first time.

2.2. AI-in-AEC review

The application of AI-in-AEC is leading to digital transformation in the industry while it attracts the attention of researchers. Some qualitative reviews were conducted to understand the knowledge and practice of applying AI-in-AEC. Irani and Kamal [19] reviewed and identified the historical trends and current patterns in the use of intelligent systems in the AEC industry. Bilal et al. [17] reviewed the application of big data technologies to construction. Another review focused on automation in construction scheduling [18]. These qualitative reviews, despite being prone to subjectivity and bias, had narrowed perspectives focusing on either specific AI technologies or specific AEC application areas, e.g., construction scheduling. To overcome the limitations of the qualitative reviews and offer a complete picture of the AI-in-AEC research in general, Darko et al. [21] presented a quantitative scientometric analysis of AI-in-AEC research. More recently, Pan and Zhang [20] also reviewed the roles of AI-in-AEC.

Although generic perspectives present limitations when applied to specific areas, no previous review has focused on the application of AI to the specific area of GB. AI applications to conventional construction might not be directly applicable to GB because GB projects differ, especially in their quest to address higher sustainability and efficiency standards. Therefore, it is worthwhile to specifically review and understand the application of AI-in-GB.

3. Research methodology

The aim of this study is to synthesize the domain knowledge and to identify the research needs in the AI-in-GB space. To this end, this study deployed a "mixed-methods systematic review", which encompasses a "quantitative review (i.e., bibliometric approach)" and "qualitative review (i.e., systematic approach)". This method was chosen over the "mono-method manual systematic review" because of its ability to reduce biased conclusions and subjective judgments and interpretations, as well as "to enhance the depth and breadth of understanding" [22].

The mixed-methods systematic review methodology combines both quantitative and qualitative methodologies in a single research, for synthesizing and analyzing available literature on a subject [23]. According to Pluye and Hong [24], the mixed-methods systematic review is convergent in that it synchronously integrates different data and methods of analysis. The mixed-methods systematic review has been widely used in previous studies [25]. In this study, the mixed-methods systematic review was utilized to overcome the limitations and capitalize on the strengths of both quantitative and qualitative methods when used in isolation. By integrating the bibliometric analysis with the systematic analysis, the challenge of biased and subjective judgement and interpretations could be addressed [23]. Bibliometric analysis was selected as the quantitative method, whereas systematic analysis was selected as the qualitative method. The two methods are described below.

The bibliometric approach refers to the mapping and visualization of large scientific dataset [26], which is useful in studying and comprehending the structural and dynamic features of a scientific domain [27]. Bibliometric analysis uses networks to represent how specific disciplines, scientific domains, or research fields are conceptually, intellectually, and socially structured [28]. In line, this study employed the bibliometric analysis to identify the knowledge domains, research trends, and main research outlets regarding AI-in-GB.

Systematic analysis, instead, is effective in revealing knowledge gaps and suggesting areas for future studies towards advancing knowledge [29]. Under these circumstances, the mixed-methods systematic analysis has been developed to construct the full picture of AI-in-GB knowledge while isolating key areas of AI-in-GB for in-depth analysis. Adopting this method helps to triangulate and elaborate the study results [30].

This study involved four stages: search for publications (stage 1), application of exclusion criteria (stage 2), bibliometric analysis (stage 3), and systematic analysis (stage 4). Based on the results, knowledge gaps and promising future research directions were then presented. Fig. 1 provides an overview of the research methodology, details of which are discussed next.

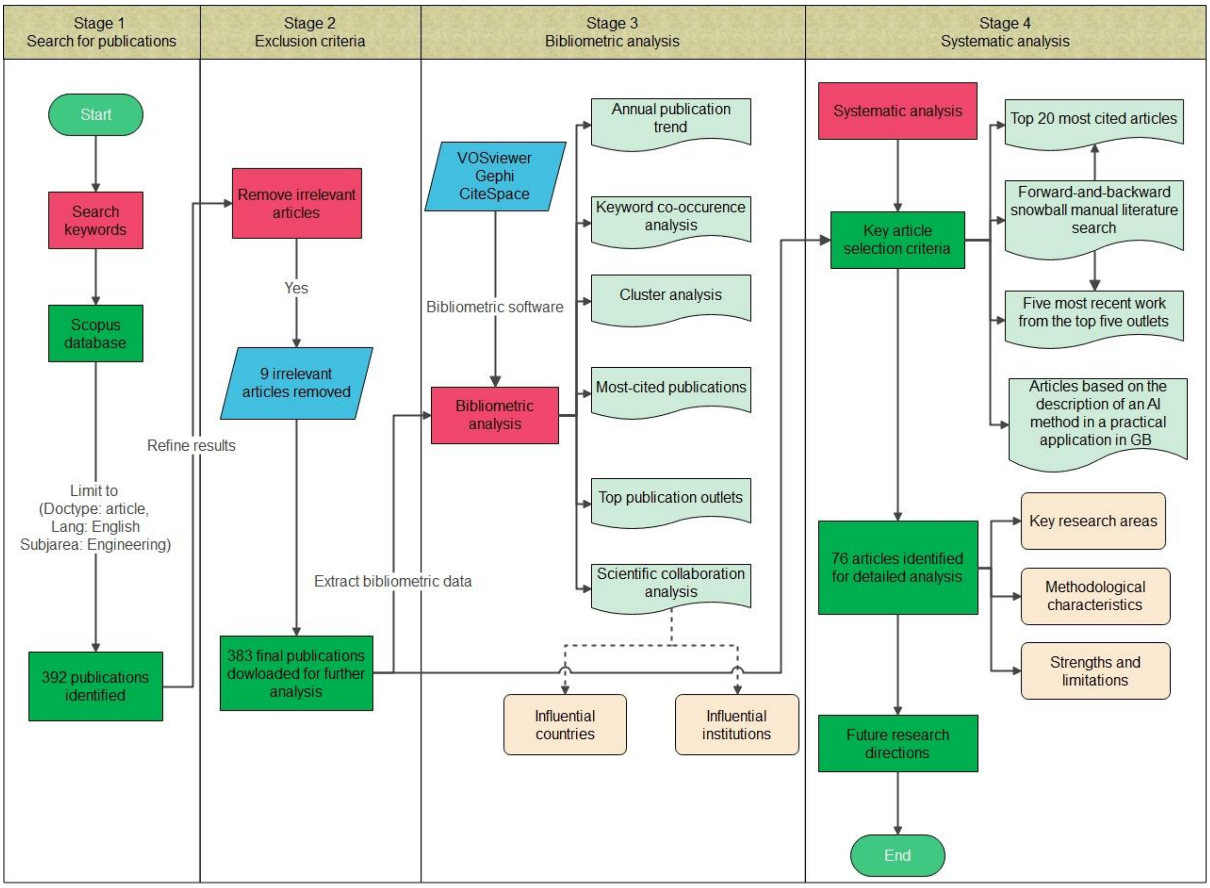


Fig. 1. Research methodology overview.

3.1. Search for publications (stage 1)

As illustrated in Fig. 1, the first stage of this study involved the search for publications. A data collection strategy was developed to retrieve the relevant data. Data collection of previous literature is critical since it defines the knowledge area from which conclusions for the study are drawn. Accordingly, the strategy and database for the literature search were selected carefully. The keywords, combined with the Boolean operators “OR” and “AND”, presented in Table 2 were used to retrieve the bibliographic data from Scopus. Scopus was used because it has a higher indexing rate with a wider and more recent publications coverage than other academic databases [31]. Besides, it has been largely acknowledged in past studies [21,25,32]. Additionally, it is critical to incorporate well-known keywords to enhance the validity and reliability of data. Nonetheless, while this study aims to incorporate well-recognized keywords, it is unfeasible to include all possible keywords in a single study [7]. Therefore, one could expand this research in future to include keywords such as zero-energy buildings, fuzzy clustering, K-Means, cognitive computing, sentiment analysis, swarm intelligence, and human-machine interface. The Scopus searches were conducted using the search keywords on the title, abstract, and keywords sections of publications with no limitations on date range, resulting in a comprehensive dataset of 392 articles.

Table 2
Keywords and literature search results.

String	Results
TITLE-ABS-KEY (("Green building" OR "Green construction" OR "Green project" OR "Green retrofit" OR "Green housing" OR "Green technology" OR "Sustainable building" OR "Sustainable construction" OR "Sustainable housing" OR "Sustainable project" OR "High performance building" OR "High performance construction" OR "High-performance building" OR "High-performance construction" OR "High performance project" OR "High-performance project") AND ("AI" OR "Artificial intelligence" OR "Machine intelligence" OR "Machine learning" OR "Expert systems" OR "Genetic algorithms" OR "Neural networks" OR "Case-based reasoning" OR "Data mining" OR "Fuzzy logic" OR "Fuzzy sets" OR "Knowledge-based systems" OR "Support vector machines" OR "Artificial general intelligence" OR "Computer vision" OR "Deep learning" OR "Reinforcement learning" OR "Transfer learning" OR "Algorithm" OR "Image recognition" OR "Natural language processing" OR "NLP" OR "Supervised learning" OR "Unsupervised learning" OR "Pattern recognition" OR "decision trees" OR "Random forest" OR "Robotics" OR cognitive* OR automation* OR augment*)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SUBJAREA , "ENGI")) AND (LIMIT-TO (LANGUAGE , "English"))	392
Manual screening based on the results of AI-in-GB [a]	76

Note: The Scopus search was conducted in October 2021.
[a] The manual screening process and criteria are described in sections 3.4 and 5.

3.2. Exclusion criteria (stage 2)

The "document type" was limited to "article" and the "subject area" was limited to "engineering". Since the main aim of this study is to review literature on AI-in-GB, it was necessary to filter out all papers outside the scope of the study. A brief review of the abstracts, and in some cases, where the abstracts failed to provide sufficient information, the contents of the initially identified studies, was therefore conducted. After filtering, 383 articles were found to be relevant and considered valid for further analyses. The reason for limiting the study to only articles was that, compared to other document types such as conference papers, articles commonly have higher quality due to their relatively rigorous peer-review process. Moreover, articles offer a more authoritative body of knowledge for bibliometric analysis [21,33].

3.3. Bibliometric analysis (stage 3)

To better understand the knowledge domains, multiple bibliometric software were utilized to analyze the data. VOSviewer 1.6.17, CiteSpace 5.8.R3, and Gephi 0.9.2 software were used for analyzing the data to develop and visualize the knowledge maps. The software were selected to take advantage of their cooperative use. As Cobo et al. [28] noted, any robust bibliometric study requires the synergetic use of alternative software for different types of analyses. Many software tools for bibliometric analysis exist, with their strengths and weaknesses identified in the literature [28]. VOSviewer, an easy-to-use software, provides distance-based visualizations of bibliometric networks – indicating relatedness [26]. CiteSpace is a Java application for analyzing and visualizing emerging trends in a body of knowledge and their interrelatedness [34]. Gephi is an open-source software that can visualize all kinds of networks [35]. The combined use of VOSviewer, CiteSpace, and Gephi allows data analysis at higher quality [29]. Thus, in stage 3, VOSviewer, CiteSpace, and Gephi were used for bibliometric analysis, forming the basis for the systematic analysis in stage 4.

3.4. Systematic analysis (stage 4)

A qualitative analysis of carefully selected papers (as illustrated in Fig. 1) was conducted, following Harden and Thomas [23]'s proposal of mixed-methods systematic analysis based on predefined criteria outlined in subsection 5.1. This stage was closely linked to the literature search and bibliometric analysis in stage 3. That is, a targeted, comprehensive, and visual examination of all the 383 papers analyzed in stage 3 was performed to identify those papers that were highly relevant to the subject matter – "AI-in-GB". Similar to previous studies [25,29], the qualitative systematic analysis comprised comparing concepts, themes, theories, developments and research focuses of the carefully selected papers. This was facilitated by a thorough discussion to provide insights into AI-in-GB and provide directions for further research. Section 5 presents detailed description of the systematic analysis process.

4. Bibliometric analysis

4.1. Annual publication trends

Fig. 2 shows the annual publication trend of AI-in-GB. It shows that the trend greatly varies annually. The first attempt of AI-in-GB was a 2002 publication in the journal "*Construction Management and Economics*", wherein the authors developed fuzzy-set theory decision-support model for sustainable housing indicators [36]. This implies that although the application of AI-in-AEC began in 1970s [21], AI-in-GB only gained grounds after almost three decades (2002). Thereafter, in the wake of recent increasing data availability and computational capabilities, AI-in-AEC interest has grown [20] leading to its application in GB at a higher level of intelligence. Since then, there has been a gradual growth in AI-in-GB research with 2021 recording the highest number of publications (72) so far. The momentous growth of AI-in-GB in the 21st century could be linked to the recent growing interest in "AI-in-AEC" and "GB" research [10,20,21]. Howbeit, the number of publications is still unsatisfactory and does not reflect the importance of AI-in-GB. Nonetheless, the growing publication trend is promising, suggesting an increase of AI-in-GB. This trend is likely to continue, as the application of AI-in-GB continues to receive support from research and practice worldwide. From Fig. 2, it is evident that AI-in-GB is an emerging area with significant scope for further research. Moreover, it is worth mentioning that the total number of publications in 2021 is up to October, where the literature searches were conducted. The figure might grow before the end of the year, as suggested by the increasing growth in annual citations (green line). To support this claim, a logistic regression model was built with high predictive power of 75%, accounting for at least 10% of the variation in publications. The Hosmer and Lomeshow test ($x^2 = 13.23$, $p > 0.05$) is considered robust with the values of Cox and Snell R^2, and Nagelkerke R^2 being 0.114 and 0.162, respectively. However, the Omnibus test result ($x^2 = 2.44$, $p > 0.05$) was insignificant, indicating that the fit was not adequate for the data [37]. More surprisingly, a negative effect was found between the time and likelihood for publications to increase (31.1%). The mixed and inconsistent logistic regression analysis results could be due to the small sample size (of 20 observations) which tend to produce inconsistent estimates [38].

Under an adjusted R-square of 0.957 (95% confidence interval), a Gompertz function [20] is employed to fit the predicted data, as shown by the red line in Fig. 2. When the fitted function is implemented, the number of publications is expected to rise to above 80 by the end of 2021. AI solutions that benefit GB are increasingly gaining attention in the quest to bring digital innovations to GB, hence the growth in publications.

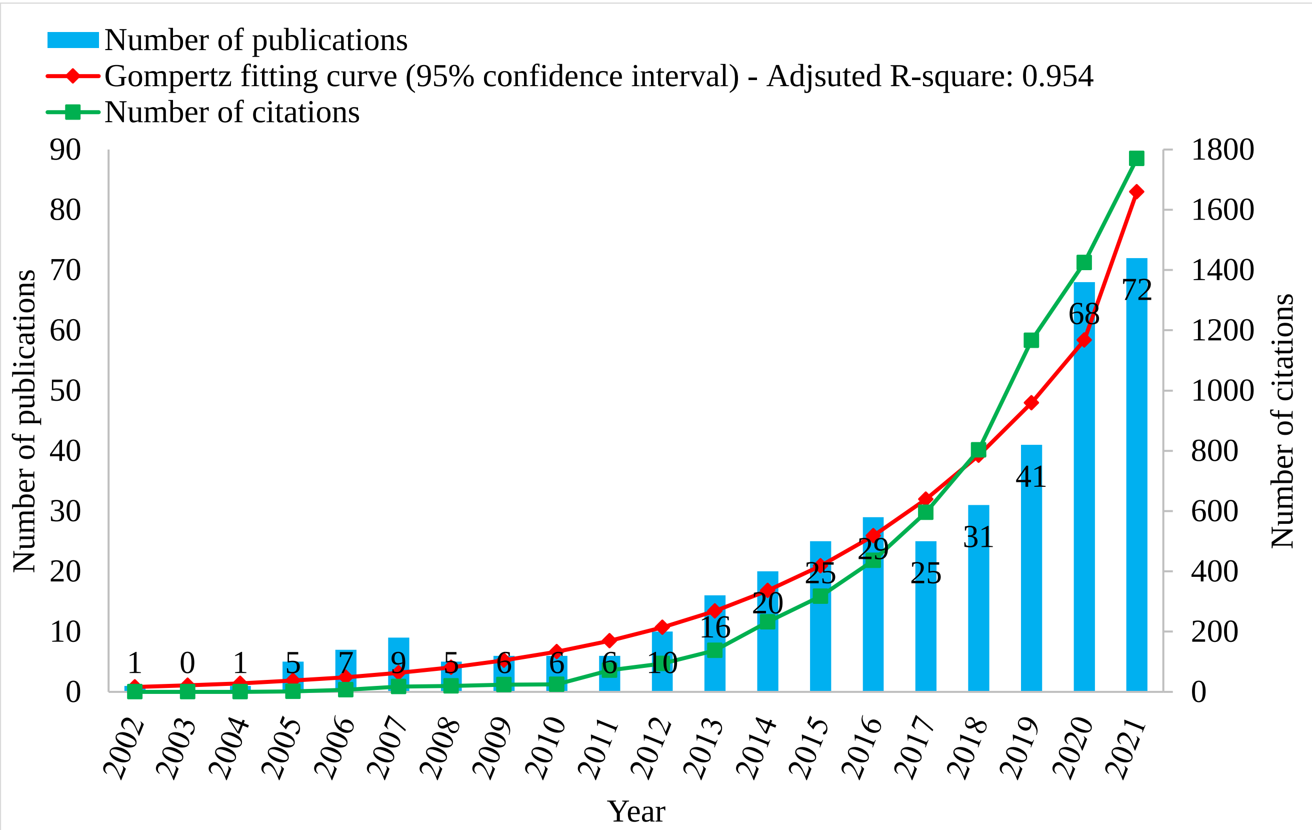


Fig. 2. Number of publications from 2002 to October 2021.

4.2 Main research areas: keywords co-occurrence analysis

VOSviewer was used to develop keywords co-occurrence networks using author keywords. Using author keywords for bibliometric analysis is widely recommended for identifying the main research areas in a domain [25,29]. Keywords co-occurrence is the synchronous occurrence of two keywords [39]. The VOSviewer generates distance-based maps, in which the distance between two items indicates the relational strength, with a smaller distance depicting a stronger relationship [26]. The item label sizes indicate the frequency of the terms in relevant publications. Different colors represents different clusters developed by VOSviewer [25]. Gephi was used to compute the degree centralities of the keywords, based on which they are ranked. High degree centrality values represent prominent research areas. However, where two or more keywords had the same degree centrality, the betweenness centrality metric (which suggests prominent nodes for the highest values within the network) was used [10]. The results of keywords co-occurrence analysis of AI-in-GB are presented next.

As noted earlier, AI-in-GB has received limited attention, as the Scopus search yielded only 383 relevant articles. From the 383 articles, a total of 1,380 keywords were found using fractional counting. The “minimum number of occurrences” was set to 2, a threshold met by 163 keywords. VOSviewer thesaurus file function was used to merge similar terms (e.g., artificial neural network and ANN were merged into “artificial neural network”). However, ‘green building’ and ‘green buildings’ keywords were not merged [10] due to their distinct use in the literature to refer to the ‘construction process’ and the ‘product’, respectively. Similar logic applies to other keywords. The resultant network comprised 130 nodes and 458 edges, as shown in Fig. 3. Table 3 shows the top 50 keywords in Fig. 3 based on degree centrality.

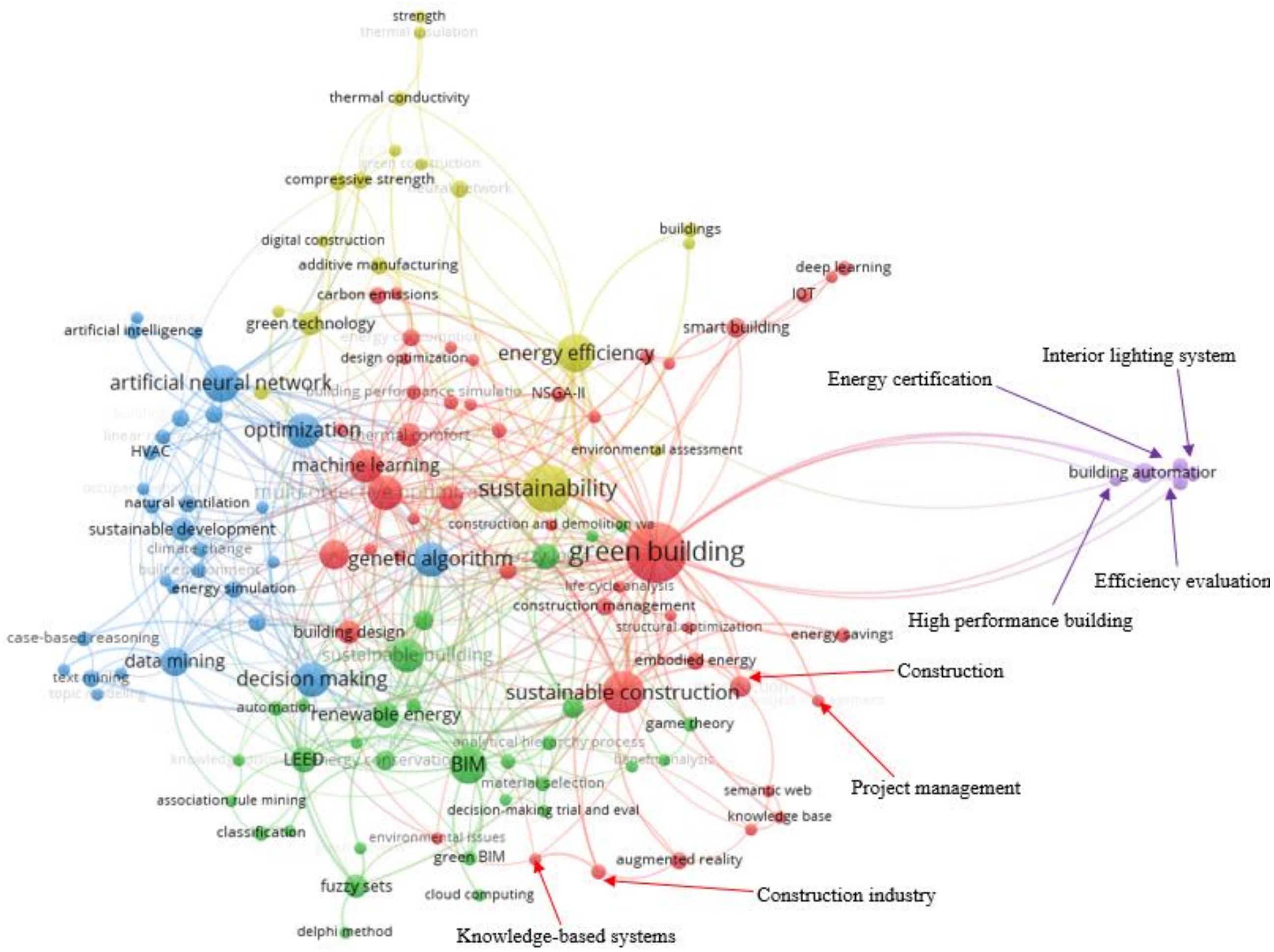


Fig. 3. Main areas of AI-in-GB research (co-occurrence network of keywords).

Table 3

Top 50 AI-in-GB research areas.

Research areas	Degree centrality	Betweenness centrality	Average year published	Relative influence
Green building	54	1328	2017	1
Sustainability	29	89	2018	2
BIM	26	136	2018	3
Multi-objective optimization	24	173	2018	4
Data mining	22	140	2018	5
Sustainable construction	22	0	2017	6
Decision making	21	242	2015	7
Artificial neural network	20	54	2018	8
Machine learning	19	290	2020	9
Genetic algorithm	18	127	2015	10
Optimization	17	159	2018	11
Energy efficiency	17	103	2018	12
Building design	17	34	2015	13
Sustainable building	17	27	2016	14
Green buildings	15	72	2016	15
Building envelope	15	50	2018	16
Life cycle cost	14	106	2013	17
LEED	14	45	2016	18
Thermal comfort	13	36	2017	19
Renewable energy	12	109	2015	20
Energy consumption	11	35	2019	21
Life cycle assessment	10	90	2016	22
Energy simulation	10	63	2017	23
Linear regression	9	35	2016	24
Material selection	9	33	2017	25

Fuzzy logic	9	28	2018	26
Sustainable development	9	0	2013	27
Sensitivity analysis	8	12	2018	28
Multi-criteria decision making	8	7	2017	29
Compressive strength	8	4	2021	30
Energy conservation	7	120	2018	31
Building energy performance	7	48	2015	32
Pattern recognition	7	16	2020	33
Indoor environmental quality	7	14	2018	34
Decision tree	7	7	2015	35
Support vector machine	7	7	2019	36
Multi-objective genetic algorithm	7	5	2010	37
Embodied energy	7	3	2019	38
NSGA-II	7	3	2019	39
Additive manufacturing	7	0	2020	40
Analytical hierarchy process	7	0	2014	41
Sustainable design	7	0	2019	42
HVAC	6	84	2018	43
Fuzzy sets	6	67	2016	44
Green technology	6	34	2016	45
Geopolymer concrete	6	9	2020	46
Knowledge discovery	6	2	2020	47
Environmental performance	6	0	2018	48
Built environment	6	0	2015	49
Building automation	6	0	2015	50

Several findings are discussed based on the rankings and how the research areas are related as presented in Fig. 3 and Table 3:

(1) First, the "average year published" of the top AI-in-GB keywords ranges from 2013-2021.

(2) Second, certain research areas have gained increased attention, while other areas have been under-studied. "Green building", "sustainability", "BIM", "multi-objective optimization", "data mining", "sustainable construction", "decision making", "artificial neural network (ANN)", "machine learning", "genetic algorithm (GA)", "optimization", and "energy efficiency" have been keen in AI-in-GB research. It may be argued that "machine learning" application in GB has gained relatively more attention, with most applications using ANN and GA. The research areas have therefore focused mainly on *AI-methods* (such as data mining, machine learning, etc) and *the application in GB* (for decision making, optimization, classification, energy efficiency, building design, material selection, etc). For instance, Wang et al. [40,41] employed GA to optimize GB designs.

(3) To better appreciate the AI-methods applied in GB, Fig. 4 visualizes the top 34 most used AI-methods. For example, it was discovered that, while decision support system (*green*

cluster) highly co-occurs with multi-criteria decision making, FAHP (fuzzy analytical hierarchy process), AHP, DEMATEL (decision-making trial and evaluation laboratory), Delphi method, fuzzy logic, and fuzzy sets; ANN highly co-occurs with linear regression, and support vector machine (SVM) (*violet cluster*).

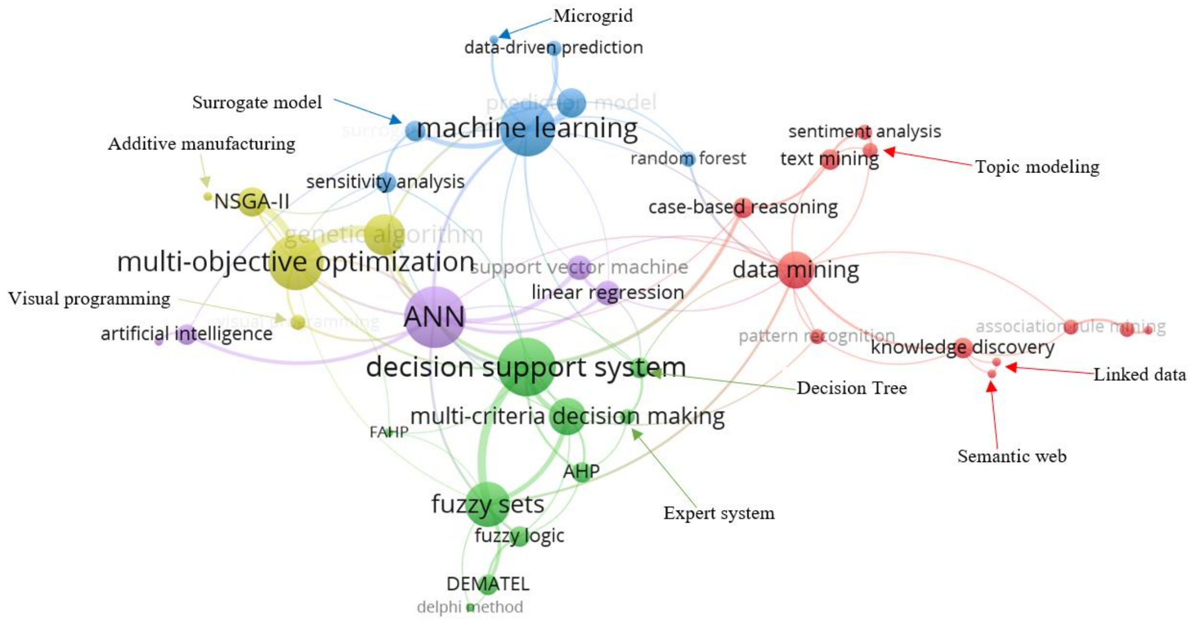


Fig. 4. AI-methods in GB.

4.3 Cluster analysis

Cluster analysis was conducted using CiteSpace to uncover the fundamental topics and research hotspots in order to appreciate the structure of the AI-in-GB knowledge domain [33]. As illustrated in Fig. 5, filtering minor clusters resulted in a network of six large clusters (identified by cluster IDs #0 to #5), as shown in Fig. 5. The cluster labels in Fig. 5 were generated using the log-likelihood ratio (LLR) [34]. The large modularity Q of the network (0.9198) suggests that clustering the network is particularly effective, with dense links between nodes within clusters, and sparse links between nodes in different clusters [21]. Similarly, the large mean silhouette value (0.9897) indicates that each cluster is highly homogeneous [21]. This implies that while few studies on AI-in-GB have been conducted, the available studies embody a network with dense connection that addresses similar issues in the research area.

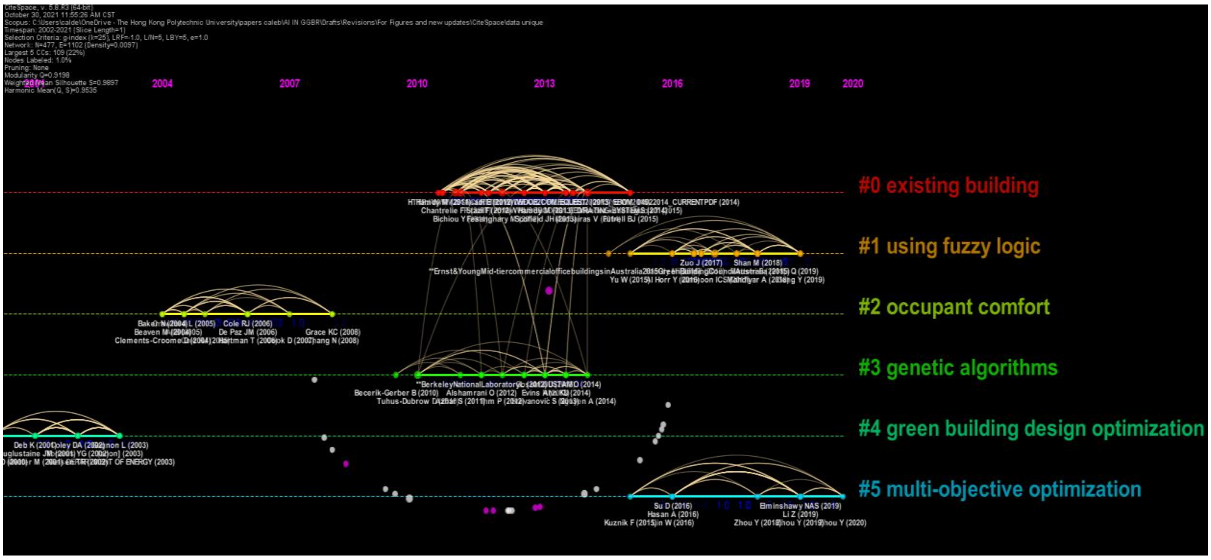


Fig. 5. AI-in-GB research clusters.

The six clusters are grouped into two types: AI-methods and GB applications (Table 4). All the silhouette values are approaching homogeneity, confirming the earlier assertion that AI-in-GB research is inward-looking, and has not benefited from adapting relevant ideas/theories from other domains. The average duration over which a particular cluster has been researched is shown by the mean (year). As shown in Table 4, the largest cluster (#1) has 22 members, a silhouette value of 1.000 and is labelled as "using fuzzy logic" by LLR. Since the introduction of fuzzy set theory by Zadeh [42] in 1965 to deal with uncertainty due to imprecision and vagueness, it has been largely applied in many fields including GB. In current research, fuzzy logic and fuzzy sets have been adopted for making multi-criteria decisions in GB projects, such as decisions regarding risk assessment, performance assessment, and selection of GB materials [43–45]. The second-largest cluster (#2) has 14 members, a silhouette value of 1.000 and is labelled as "occupant comfort". Since the advent of GB research in 1974, "occupant or thermal comfort" has been one of the major research areas [10]. Recently, AI-methods such as GA and reinforcement learning control have been applied to intelligently automate the provision of occupant comfort in GBs [46–48].

Table 4
Summary of identified clusters

Type	Cluster ID	Size	Silhouette value	Mean (year)	Cluster focus
AI-methods	#1	22	1.000	2017	Using fuzzy logic

	#3	9	0.945	2012	Genetic algorithms
	#5	11	1.000	2017	Multi-objective optimization
GB-applications	#0	13	0.973	2012	Existing building
	#2	14	1.000	2005	Occupant comfort
	#4	13	1.000	2002	Green building design optimization

4.4. Citation burst analysis

Citation burst analysis, which is undertaken using CiteSpace, tracks the keywords that have high frequency of occurrence over a certain period, such as topics with citations surges or fast-growing topics [49]. A total of 33 keywords in the dataset experienced citation bursts. Fig. 6 presents the top 25 keywords with the highest citation burst. The year range for the reviewed literature is represented by light green lines, whereas the duration of a citation burst event is represented by a red line. Optimization (burst strength, 4.99; burst period, 2016-2018), decision making (4.79; 2018-2019), design (4.6; 2011-2016), automation (4.51; 2005-2013) and energy conservation (3.82; 2013-2016) were the top five keywords with the strongest burst. However, the low burst strength ranging from 1.99 to 4.99 reinforces the need for more AI-in-GB research.

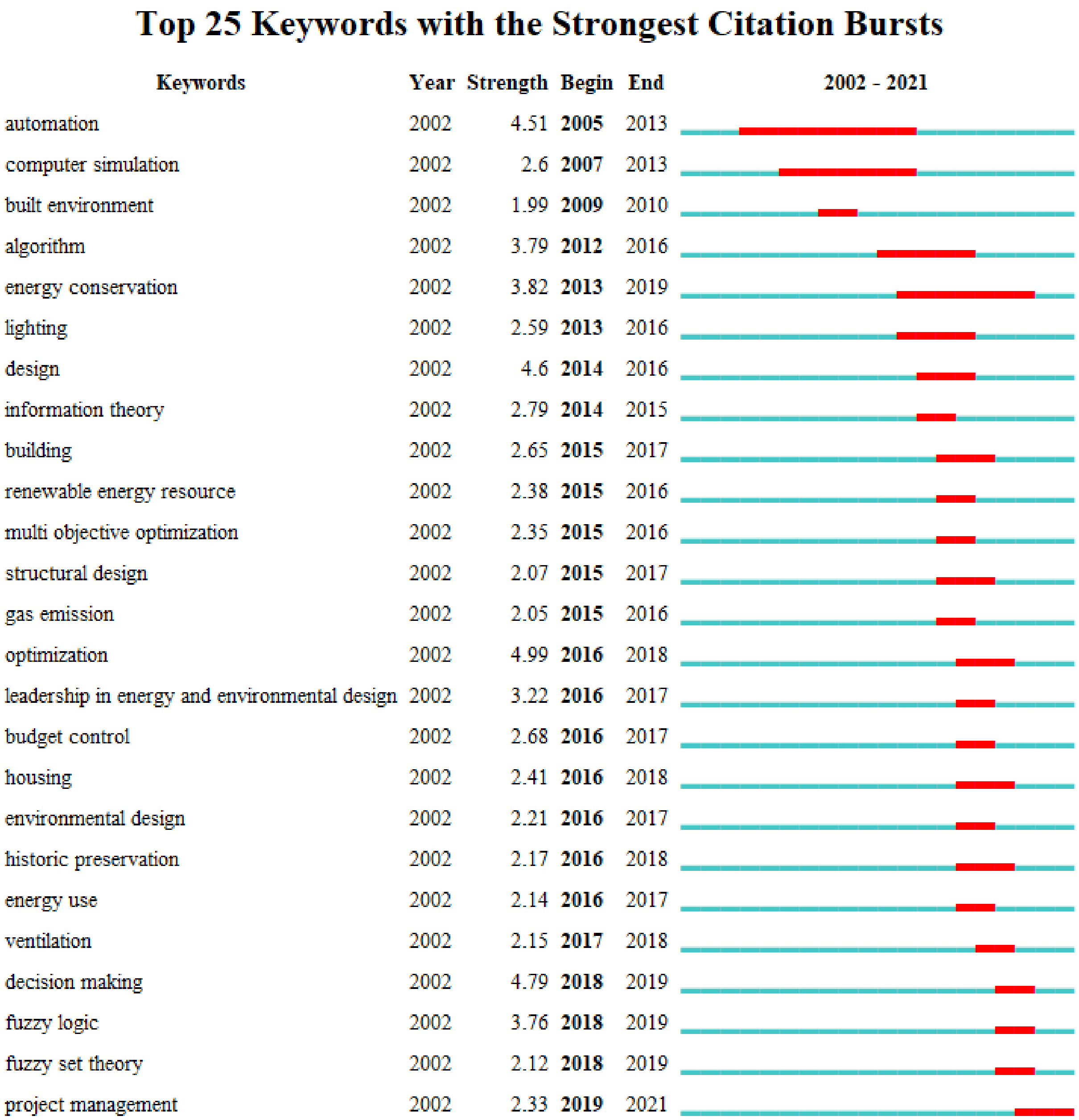


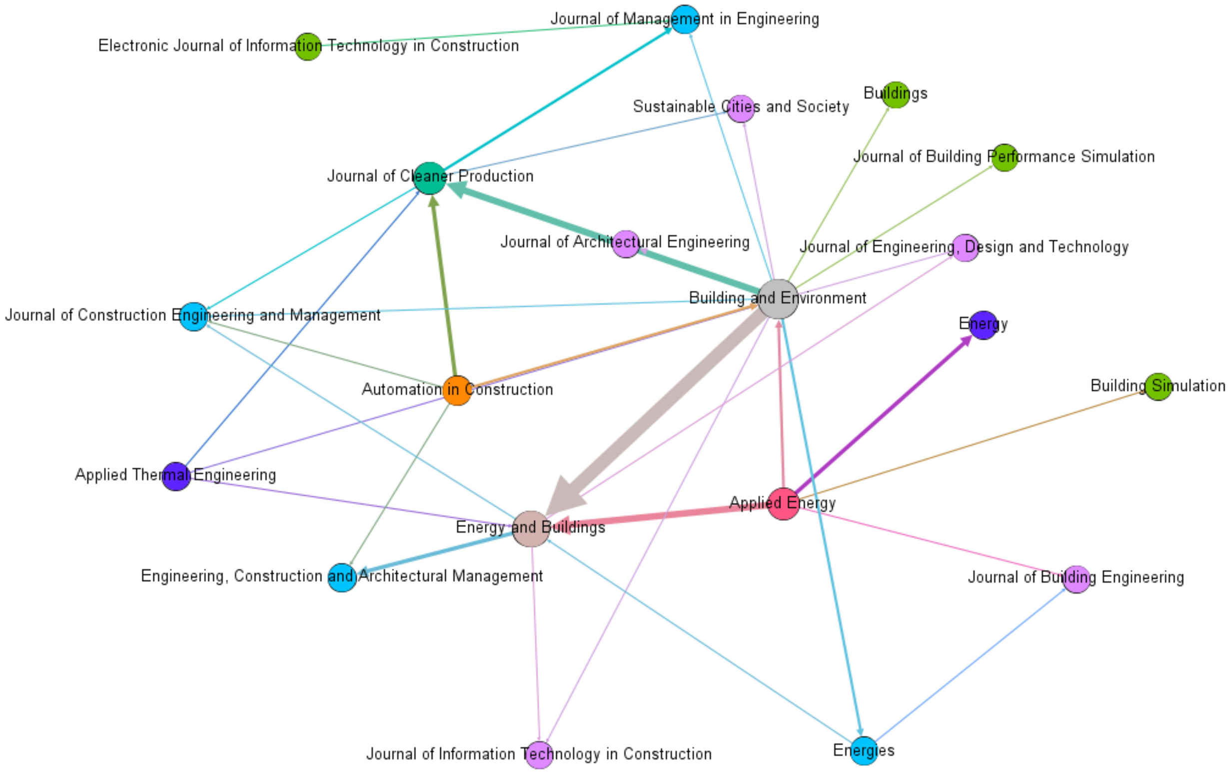
Fig. 6. Top 25 keywords with the highest citation burst in AI-in-GB literature (2002-2021).

4.5 Most cited publications

In addition to the keywords analysis, citation information of the 383 articles was also analyzed to reveal the top 20 most-cited publications on AI-in-GB (Appendix A). Knowledge of the most-cited AI-in-GB publications informs researchers and practitioners on key information sources. From top citation analysis, it is observed that AI has mostly contributed to optimizing GB design, construction, and performance. Wang et al. [40,41], for example, applied multi-objective GA to optimize GB design.

4.6. Top outlets for AI-in-GB research

Analyzing academic journals in any scientific domain is essential for readers and authors to find the best sources of information and where to best publish, and for journal editors to make relevant adjustment to their journals' goals. Institutions and libraries may also benefit in optimizing their investment in journals [21]. Table 5 presents the top research outlets for AI-in-GB, developed using VOSviewer. The type of analysis was "citation", and the unit of analysis was "sources". Additionally, the "minimum number of documents of a source" and the "minimum number of citations of a source" were each set to 2. Selection of thresholds in this study was based on past studies [21,25] and multiple experiments to generate the optimal network. Using fractional counting, of 166 sources identified, 20 met the threshold. The network comprised 20 nodes and 33 edges. Nodes and edges were resized based on their weight strengths. Using Gephi (Fig. 7), the top research outlets were ranked based on weighted degree, a widely used indicator for measuring the influence of nodes in controlling information across networks [50]. The results (Table 5) show that *Building and Environment* (31), *Energy and Buildings* (23), *Journal of Cleaner Production* (13), *Applied Energy* (12), and *Automation in Construction* (7) were the top five outlets. These outlets may serve as reference points for practitioners, researchers, and students on the state-of-the-art of AI-in-GB.



351
352 **Fig. 7.** Network of prominent outlets for research on AI-in-GB.

Table 5.
Top research outlets.

Outlets	Number of publications [a]	Citations [a]	Weighted degree value	Rank [b]
Building and Environment	18	879	31	1
Energy and Buildings	34	1671	23	2
Journal of Cleaner Production	38	1155	13	3
Applied Energy	15	796	12	4
Automation in Construction	10	331	7	5
Energies	14	117	4	6
Journal of Construction Engineering and Management	7	296	4	7
Journal of Management in Engineering	4	186	4	8
Engineering, Construction and Architectural Management	2	7	4	9
Applied Thermal Engineering	3	124	3	10
Energy	6	135	3	11
Sustainable Cities and Society	12	303	2	12
Journal of Building Engineering	9	29	2	13
Journal of Architectural Engineering	4	15	2	14
Journal of Information Technology in Construction	2	41	2	15
Journal of Engineering, Design and Technology	3	5	2	16
Electronic Journal of Information Technology in Construction	2	48	1	17
Buildings	3	22	1	18
Building Simulation	4	17	1	19
Journal of Building Performance Simulation	2	9	1	20

[a] During the studied period (2002-October 2021).
[b] Ranking based on weighted degree values.

4.7. Scientific collaboration network analysis for AI-in-GB research

Scientific collaboration, also referred to as "*co-authorship*", is necessary in any research field to expedite access to funds, expertise, and specialties; limit research isolation; and enhance productivity [33]. As such, the collaboration network analysis of influential institutions and countries in AI-in-GB research is presented in the next sub-sections.

4.7.1 Influential countries

Fig. 8 depicts the global AI-in-GB research distribution by country in terms of number of publications and citations. China and US emerged as the top contributors. However, it is interesting to find that, although China contributed most in terms of number of publications, the US received the highest number of citations. High citations numbers indicate the novelty and significance of the underlying research, and the increasing importance governments attach to it [51,52]. Countries such as Australia, Hong Kong, India, Malaysia, and UK have also made good contributions. Nonetheless, there is considerable scope for increasing the number of publications from most countries to improve global knowledge and practice on AI-in-GB.

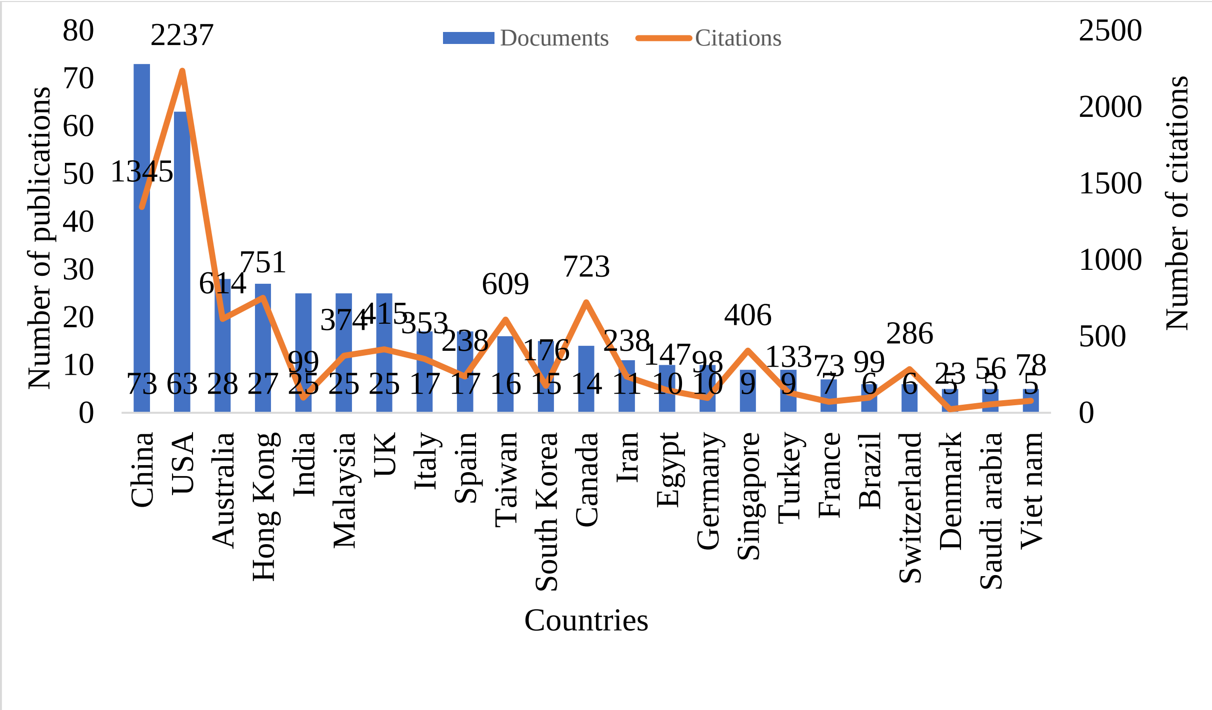


Fig. 8. Documents and country citation distribution.

A network was created with VOSviewer to provide a clearer picture of the research contributions and the scientific collaborations of the countries. This analysis can help identify countries that are highly engaged in the specific research field [49]. The type of analysis was "co-authorship", the unit of analysis was "countries", and the counting method was "fractional counting". The "minimum number of documents of an organisation" and the "minimum number of citations" were each set to 2 for optimal network. The criteria were met by 46 out of 73 countries and the Gephi was used to visualize the resultant network (Fig. 9).

Countries that were more influential in the network were identified using the weighted degree values [21]. Recoloring and resizing of nodes depended on the weighted degree values, with larger nodes and darker colors signifying greater weighted values. Table 6 shows the top 30 most influential countries in the network.

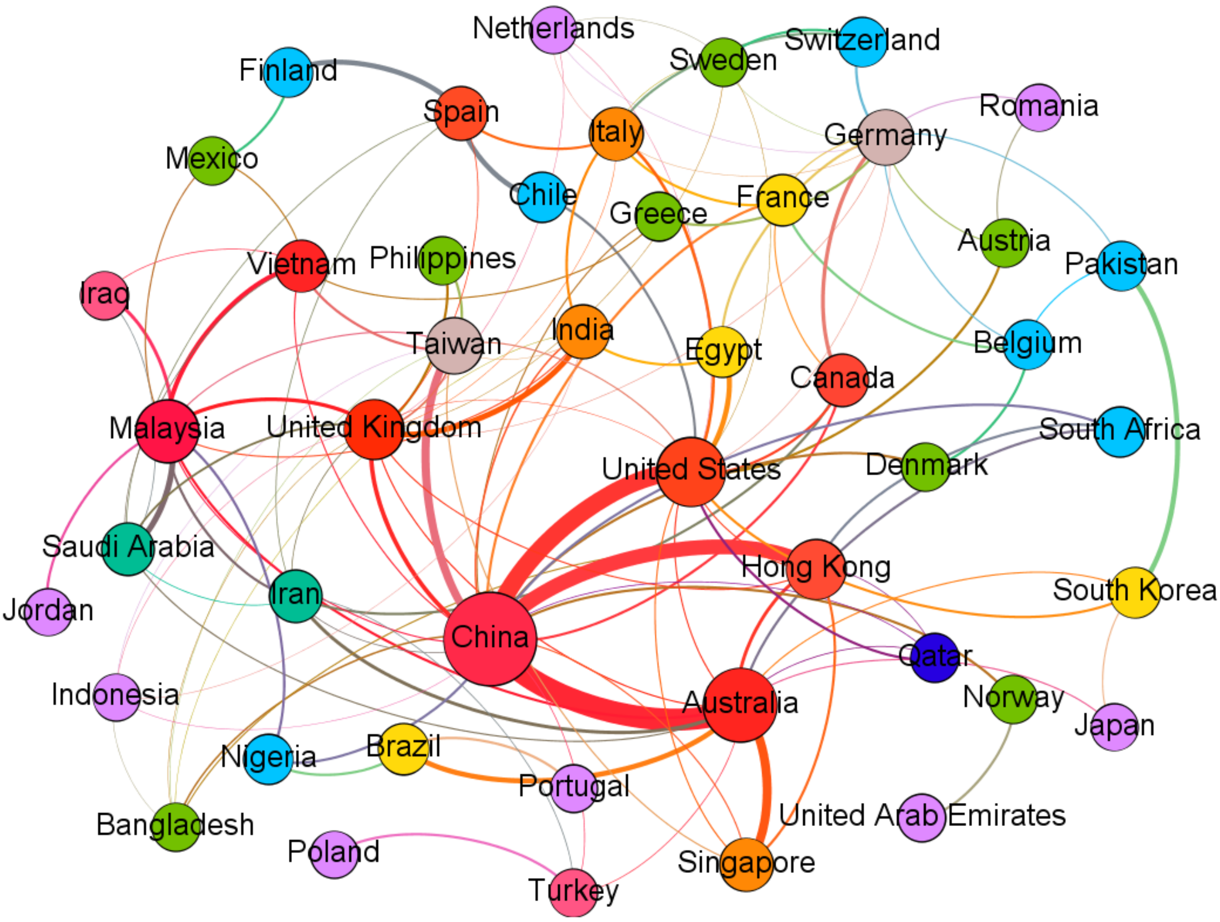


Fig. 9. Collaboration network of influential countries in AI-in-GB research.

It is noticeable within this collaboration network that China, Australia, US, Malaysia, and Hong Kong are the top five countries. China has the strongest collaboration with three of the major contributors: US, Australia, and Hong Kong. With most (19%) of the AI-in-GB publications emerging from China, such a strong relationship with other countries is expected. Besides, China has increased research on GBs in recent years due to the high greenhouse gas emissions [8]. On the contrary, US appears to have limited collaboration with other countries. This observation could be attributed to the US government's strategies to dominate the global AI markets, and the mixed signals on the willingness to work with other countries to govern AI [53]. Other strong relations identified within the network include China-UK, China-Taiwan, Australia-Singapore, UK-India, Malaysia-Vietnam, and Malaysia-Saudi Arabia. Comparatively, these nine strong collaboration relationships out of the 73 relations are very limited. This can be associated with the restricted and/or a lack of comparative and cross-country collaboration research. Generally, while developed countries exhibited strong network collaborations, weaker relations were found within many developing countries. This underlines the need for reforming policies to promote cross-country collaborations to advance AI-in-GB research in terms of global collaboration, knowledge exchange, and enhanced productivity.

Table 6
Top 30 countries collaborating in AI-in-GB research.

Countries	Number of publications [a]	Weighted Degree value	Relative influence
China	73	37	1
Australia	28	22	2
United States	63	18	3
Malaysia	25	13	4
Hong Kong	27	11	5
United Kingdom	25	11	6
Taiwan	16	8	7
Germany	10	8	8
India	25	6	9
Spain	17	6	10
Italy	17	6	10
Singapore	9	6	12
Canada	14	5	13
Iran	11	5	14
Vietnam	5	5	15
Saudi Arabia	5	5	15
South Korea	15	4	17
Egypt	10	4	18
France	7	4	19
Brazil	6	4	20
Nigeria	8	3	21
Switzerland	6	3	22
Pakistan	5	3	23
South Africa	4	3	24
Belgium	3	3	25
Chile	3	3	25
Finland	3	3	25
Austria	3	3	25
Denmark	5	2	29
Bangladesh	2	2	30

[a] During the studied period (2002-October 2021).

4.7.2 Influential institutions

Knowledge of institutional collaboration is critical to high investments and increased interest in AI-in-GB research. Such a discovery is key to developing policies and building lasting academic partnerships [54]. The type of analysis was “co-authorship”, the unit of analysis was “organisations”, and the counting method was “fractional counting”. The “minimum number of documents of an organisation” and the “minimum number of citations” were each set to 2 for obtaining the optimal network. The resultant VOSviewer network comprised 84 out of 574 organizations that met the criteria. The network (Fig. 10) visualized with Gephi comprise 84 nodes and 71 edges. Nodes and edges sizes were resized and recolored based on their weight strengths using the "hyperlink-induced topic search" in Gephi based on their hub scores [21].

Fig. 10. Collaboration network of institutions in the literature on AI-in-GB.

Fig. 10 shows that only a few institutions in China, Hong Kong, Singapore, Taiwan, UK, Australia, and South Africa have established AI-in-GB collaborative research relations. However, the thickness of the edges suggest that these collaborations are not strong. To attain the highest standard of academic research and discussion on AI-in-GB, institutions should collaborate to benefit from varied knowledge and research experience as this is currently lacking in body of knowledge. This is necessary to facilitate the sharing of knowledge and ideas [21] on AI required in GB research and practice globally.

5. Systematic analysis

To provide in-depth analysis of research integrating AI-in-GB, a systematic analysis of carefully selected articles is presented in this section. A qualitative screening and examination of the 383 publications identified in stage 3 (Fig. 1) revealed 76 relevant articles, which were included in the systematic analysis. The criteria for the selection of the articles are outlined as follows:

5.1 Key article selection criteria for systematic analysis

Based on 383 AI-in-GB bibliometric records retrieved from Scopus, we adapted Kirchherr and van Santen [55]'s and Antwi-Afari et al. [56]'s approaches to select the key articles for the systematic analysis as outlined below:

(1) First, the 20 most cited articles were collected.

(2) Second, we selected five most recent works from the top five AI-in-GB journals based on the weighted degree values: *Building and Environment; Energy and Buildings; Journal of Cleaner Production; Applied Energy; and Automation in Construction* (Table 6).

(3) Finally, we selected 55 articles at random based on their prominence in the literature using forward-and-backward snowball manual search method [57]. This strategy begins with identification of an initial set of papers (steps 1 and 2 above). Then, each study in the start set was used to conduct backward-and-forward snowballing. In the *backward snowballing*, relevant studies in the reference list of each study in the initial set were identified. In the *forward snowballing*, the articles identified from the backward snowballing formed a new start set which was subjected to another round of backward-and-forward snowballing. This cyclical process was repeated until no new papers were identified.

Titles or abstracts or full-text article, where the titles and/or abstracts were unclear, were screened and were considered for inclusion if they were empirical studies on AI-in-GB. By *empirical studies*, we refer to publications that were based on the description or assessment of AI methods in providing a practical application in GB, for instance, on/off GB sites and pre/post GB projects. After removing irrelevant articles and assessing the obtained articles on the pre-defined inclusion criteria, 76 articles were found eligible for further analysis. Given the systematic approach adopted, we believe that our sample is representative of the now-available

AI-in-GB literature. However, we do not claim to present an exhaustive overview of the AI-in-GB literature. All articles examined are listed in Appendix A.

5.2 Key research areas of AI-in-GB

Since the introduction of AI-in-AEC, there has been growing research in areas such as "knowledge representation and reasoning", "information fusion", "computer vision", "natural language processing" (NLP), "intelligent optimization", and "process mining" [20,21]. Relying on the wide AI-in-AEC approaches above, we classify AI-in-GB into four hot research areas, as summarized in Fig. 11 and detailed below. More importantly, these research hotspots are highly related to the clusters analysis (Table 4). For example, (1) "fuzzy rules and knowledge discovery" is related to "using fuzzy logic"; (2) "big data and data mining" is related to "existing building"; (3) "intelligent optimization" is related to "genetic algorithms" (GA), "GB design optimization", and "multi-objective optimization"; and (4) "building automation system" is related to "occupant comfort".

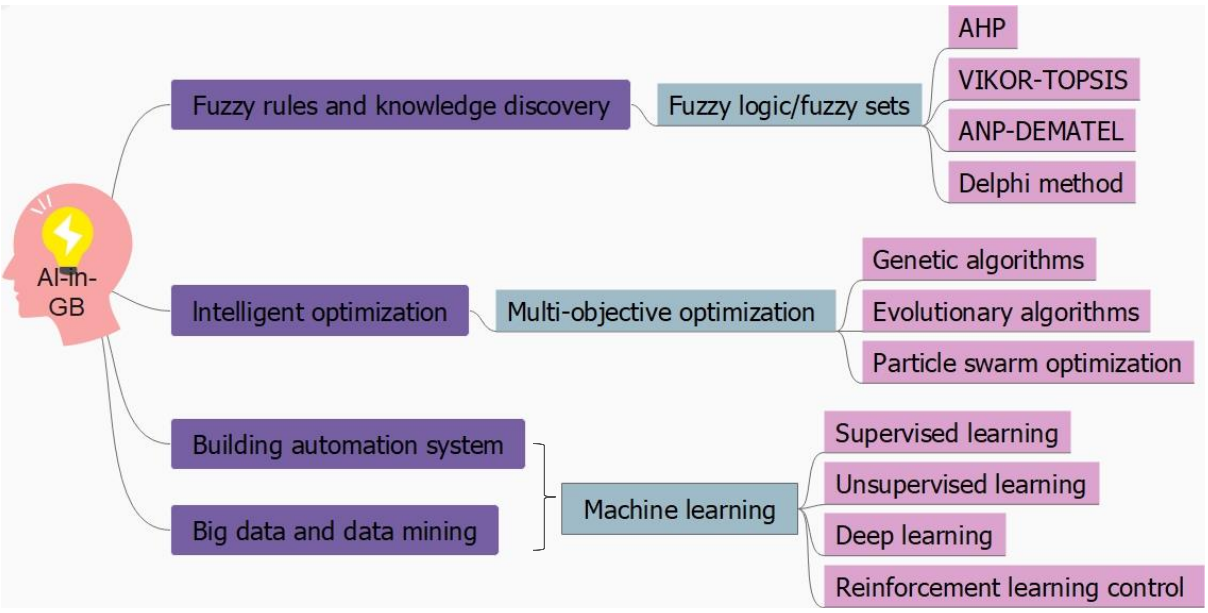


Fig. 11. Summary of main research areas.

5.2.1 Fuzzy rules and knowledge discovery

A foremost application of AI-in-GB is knowledge discovery and fuzzy rules. Fuzzy logic evolved from the desire to train computer systems with human expertise [58]. The adoption of fuzzy set theory (FST), introduced by Zadeh [42], has been applied to handle uncertainties in GB and multi-criteria objectives in a fuzzy decision environment [59]. In recent years, there has been various applications of the FST in GB such as the fuzzy synthetic evaluation (FSE), fuzzy clustering, FAHP, Fuzzy analytical network process (FANP)-DEMATEL, and the fuzzy-VIKOR-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) as presented in Table 7. For example, the "fuzzy clustering analysis" clusters objective things by establishing fuzzy similarity relations according to their characteristics, degree of affinity, and similarity [44].

Table 7.
Some studies for fuzzy rules

Method	Purpose	References
FSE	GB risk assessment and management	[45]
Fuzzy clustering	GB multi-criteria performance assessment	[44,60]
	Assessing eco-building indicators	[61]
FAHP	GB multi-criteria performance assessment	[58,62,63]
	GB material selection	[43,64]
Intuitionistic fuzzy sets	Matching management of supply and demand of GB technologies	[65]
Fuzzy-VIKOR-TOPSIS	GB risk management	[66]
	Health and safety risk assessment	[67]
FANP-DEMATEL	Ranking sustainability of GB material	[68]
	Ranking indicators for GB assessment	[69]
	Health and safety risk assessment	[67]
	Sustainable construction and demolition waste	[70]
Fuzzy-Delphi method	Sustainable construction and demolition waste	[70]
Non-dominated fuzzy decision support system	Green construction assessment	[71]

From Table 7, FSE have been applicable in many GB research areas to aid decision making. Research has shown that integrating fuzzy logic with AHP is robust to deal with decision-making problems with many alternatives [58]. AHP [72] is a structured technique for organizing and analyzing complex decisions based on the hierarchy process. It therefore has the ability to cope with the intuitive, the rational, and the irrational when making multi-objective, multi-criterion, and multi-actor decisions. For example, the fuzzy-AHP has been used to select GB materials [43,64] and to develop a green performance evaluation system for construction site layout [62]. Additionally, Khoshnava et al. [68] combined the FANP and DEMATEL to rank GB materials. The ANP, a generalization of AHP, applies a network structure instead of a hierarchical structure [73]. DEMATEL, on the other hand, converts the relationship among factors and fundamental dimensions from the complex system to a logical organizational model [74]. Other multi-criteria decision-making (MCDM) techniques such as TOPSIS [75] and VIKOR [76] have been combined with fuzzy prospect theory to solve decision-making problems in GB [66]. It is evident that MCDM methods are based on the trade-off between positive ideal solution and negative ideal solution – making it desirable in decision-making [77].

5.2.2 Big data and data mining

Big data are usually high volume and high velocity data sets beyond the ability of traditional databases to capture, manage, and process due to their high variety and sizes. Big data analytics has the capacity to analyze such structured, semi-structured, and/or unstructured data using advance AI [78]. Data mining, as a computation process, is therefore used to discover hidden knowledge from large datasets and transform such knowledge into understandable structure for future decisions [79,80]. GBs are now fitted with sensors (such as temperature sensors), power and flow meters capable of providing big rich data streams by the minute, thanks to advancement of smart metering and building automation technologies. This building data is collected on a regular basis and can be examined to assist facility managers in improving operational efficiency and reducing energy waste [81]. Recent developments in big data analytics across the board [82] including GB have led to the development and application of several data-driven machine learning algorithms such as artificial neural network (ANN), convolutional neural network (CNN), K-Nearest Neighbor (KNN), multiple linear regression (MLR), support vector machine (SVM) or regression (SVR), ensemble methods, association rule mining (ARM), clustering analysis, and logistic regression. Over time, data mining has been applicable in GB rating systems, energy consumption forecast, GB design modeling, and GB cost and price prediction. This suggests that data mining is a critical decision-making algorithm that eliminates the trial-and-error approach. Besides, due to the volume or big data mined for analysis, clustering algorithms (such as hierarchical (connectivity-based), centroid-based (k-means), distribution, and density-based clustering), are capable of dividing multidimensional and heterogenous data into several clusters that are internally coherent and externally separated [83]. Table 8 shows some of the relevant application of data mining in GB.

Table 8.
Some studies for big data and data mining.

Method	Purpose	References
ANN	GB cost and price prediction	[84–86]
	Construction schedule performance	[85]
	Building energy performance	[44,87]
	Determining influential factors of GB	[88]
	Predicting indoor environmental quality	[89]
	GB design optimization	[90,91]
	Predicting the strength of geopolymer concrete	[92,93]
	Analyzing and predicting the characteristics of wood	[94]
CNN	BIM-based GB design	[95]
KNN	BIM-LEED integration for GB design assessment	[96]
	Achieving LEED credits	[97]
MLR	GB cost and price prediction	[86]
	GB design optimization	[91,98]
	Achieving LEED credits	[97]
Multivariate adaptive regression	GB design optimization	[98]
Multi-polynomial and Stepwise regression model	GB design optimization	[91]
Logistic regression	GB cost and price prediction	[85]
Locally weighted regression	Predicting occupant energy consumption behavior	[99]
SVM/SVR	GB cost and price prediction	[85]
	Construction schedule performance	[85]
	GB design optimization	[95,98]
	Selection of target LEED for existing buildings (LEED-EB)	[100]
	Predicting occupant energy consumption behavior	[99]
Ensemble methods	GB cost and price prediction	[85]
	Construction schedule performance	[85]
	Environmental impact prediction	[101]
	Pattern recognition of GB markets	[102]
	Achieving LEED credits	[80,100]
	Predicting occupant energy consumption behavior	[99]
	Construction schedule performance	[85]
NLP	Collecting and classifying GB material information	[103]
	Assessing occupants' satisfaction with LEED-certified buildings	[104]
	Attention and sentiment analysis of GBs	[105]
Clustering analysis	Mining thermal behavior of façade systems	[83]
	Pattern recognition of GB markets	[102]
ARM	Mining thermal behavior of façade systems	[83]
	Achieving LEED credits	[106]
Naïve Bayes	Predicting occupant energy consumption behavior	[99]
CBR	Support building green retrofit decision	[107]
	Achieving LEED credits	[97]

Typically, the ANN has been used to predict the cost, price, and performance of GB [44,84–86] based on historical data. ANN is a mathematical and computational model that attempts to simulate a biological neural structure to imitate human learning process [108]. The back-propagation NN (BPNN) is the most mature and widely used configuration of ANN which conjoins a feedforward multi-layer perceptron with a BP algorithm [44,108]. The BPNN has been used to predict the compressive strength of geopolymer concrete [93], energy consumption [44], and the performance of GBs [85]. In recent years, ANNs such as the Radial basis function neural network is adopted to improve the weighted influence non-linear gauge system (RBF-WINGS) [88]. Other methods such as the SVM (a supervised learning method) [109], and logistic regression (a common statistical method) can handle both classification and regression problems [110]. Ensemble methods such as random forests, gaussian process regression, extreme gradient boosting, gradient boosted, and AdaBoost decision trees combine decisions from several weak models and vote for a final outcome [20]. For instance, Martínez-Rocamora et al. [101], combined BIM-based life cycle analysis tools with the random forest to predict the environmental impact of construction. BIM provides a collaborative platform to help construction project to be digitally modeled in a virtual environment [96] and share knowledge and information about a project to facilitate early decisions from cradle-to-grave [111]. To automate GB design assessment, Jalaei et al. [96] demonstrated that a BIM-LEED integration was feasible by using a Distance Weighted KNN (DWKNN). Apart from that, Wen et al. [95] demonstrated that BIM is effective in different phases of a GB using CNN.

Other data mining techniques such as random forests, AdaBoost decision trees, and the SVM have been useful in achieving LEED credits [80,100]. Recently, based on a NLP approach, Guo et al. [104] assessed occupants' satisfaction with LEED-certified residential buildings using social media. Moreover, using solutions of past similar problems, data mining can be employed to solve new problems [97]. A typical example is the use case-based reasoning

(CBR) approach to support green retrofit decisions [107]. The CBR process is usually comprised of five parts being, represent, retrieve, reuse, revise, and retain [107]. Others such as ontology with web crawling technologies can be used to collect and classify GB material information automatically [103].

5.2.3 Intelligent optimization

Intelligent optimization lies in the ability to locate pareto optimal solutions for GB using AI techniques over traditional approaches. A solution is said to be pareto optimal if it is not dominated by any other solution in the performance space [40]. Although an optimization problem can either be constrained to a single objective (to identify one optimal alternative) or a multi-objective (simultaneously optimize multiple objective functions) [20], the multi-objective optimization algorithm has been preferred in GB. This could be due to the complexities and time constraints associated with the optimization challenges in GB. Hence, available AI-methods which takes less time have been applied over the years in determining optimal or near-optimal solutions for multi-objective GB constraints. Multi-objective optimization algorithms, such as GA, evolutionary algorithms, and particle swarm optimization (PSO), as outlined in Table 9 have been established as AI-in-GB. GA is an optimization algorithm based on natural selection and population genetic mechanism. In a GA, every possible solution is encoded as an individual, and all individuals form the population (i.e., all possible solutions) [112]. Over time, variations of GA such as non-dominated sorting genetic algorithm-II (NSGA-II), quantum GA, etc., have been developed.

Table 9.
Some studies for intelligent optimization.

Method	Purpose	References
Multi-objective optimization	GB design optimization	[40,41,46,98,112–120]
	Life cycle costs and life cycle environmental impact assessment	[40,121]
	Energy efficiency decision making and optimization	[114,122,123]
	Optimize indoor environmental quality	[124]
	BIM-based GB design and performance optimization	[111,125]
	GB retrofits	[126,127]
	Construction and demolition (C&D) waste transportation	[128]
	Optimize prefabricated buildings	[129]

For instance, Yu et al. [46] developed a GA-BP multi-optimization model of NSGA-II to assist GB designers in obtaining a set of optimal solutions to building designs. Similarly, Chen et al. [124] incorporated a robust sensitivity analysis and the NSGA-II to optimize indoor environmental quality in high-rise residential buildings. It has been found that an ANN model can improve the performance of NSGA-II models in GB design optimization [116]. Besides, a QGA has a faster convergence speed, stronger optimization ability, and can maintain population diversity with better optimization results. Wang and Wei [112] demonstrated that the QGA can simultaneously reduce the energy load and cost of building envelope by 35.3%.

As noted earlier, the BIM platform can aid construction professionals in GB decision-making. For instance, Inyim et al. [117] integrated the NSGA-II and BIM to aid decision-making during the design stage of construction projects. Likewise, a revised PSO algorithm was applied to search for the trade-off between life cycle costs and life cycle carbon emissions in a BIM platform [111]. Apart from the application of AI for new GB, the GA has also been applicable in solving building retrofit optimization problems [126,127], optimizing C&D waste transportation [128], and to optimize prefabricated buildings [129].

5.2.4 Building automation system

Building automation system, also referred to as *smart-GB*, is a classic example of modern technologies that offers vast amounts of data on actual building operations, allowing buildings to be monitored and controlled automatically and intelligently in real-time [79]. Using smart technologies and metering system (such as temperature sensors, gas and fire sensors, power and flow meters), GBs have the ability to generate huge amounts of data for facility management [81]. For example, an automatic building energy management system is critical in monitoring and managing efficient energy use to avoid wastage and reduce cost [130]. Building automation system therefore serves two key purposes in GB: point anomaly detection and context anomaly detection. First, "point anomaly detection" builds consumption prediction models using previous energy consumption time series. For example, energy consumption is forecasted on a regular basis, and anomalies are detected by comparing actual deviation from the expected value. On the other hand, "context anomaly detection" utilizes additional information such as building and construction material, weather, etc., to define the anomalies [131]. Several AI-methods are therefore included in building automation system – especially the heating, ventilation, and air conditioning (HVAC) system – to develop automatic building diagnostic tool for health monitoring, fault detection, and diagnostics [132]. This is necessary to identify the 'black holes' of energy consumption caused by unforeseen human-related or equipment defects such as faulty sensors, inefficient energy-use, etc. For example, the fuzzy logic could be used to detect abnormal operating conditions and to generate fault signatures to classify the fault type. ANN classification technique is then applied to fault signatures for various fault types [132]. A list of some studies on building automation system is provided in Table 10.

Table 10.
Some studies for building automation system.

Method	Purpose	References
Expert system	Control and monitor outdoor lighting control system; perform load estimate and fault diagnosis	[133]
Machine learning model	Fault detection and diagnosis of chillers	[134]
	Predicting the efficiency of GB natural ventilation systems	[48,135]
	Point and context anomaly detection of energy consumption	[131]
	Building energy optimization	[79,136,137]
Deep learning model	Predicting the efficiency of GB natural ventilation systems	[135]
	Estimating annual heating demand	[138]
	Predicting building energy consumption	[139]

Yan et al. [134] observed a higher prediction accuracy and lower false alarm rates for fault detection and diagnosis using machine learning techniques. In using the ANN and PSO, Gonçalves et al. [137] implemented a smart energy management system that can be applied to both new and existing buildings and with any level of HVAC technology. Likewise, to predict the efficiency of natural ventilation systems for GBs, Park and Park [135] adopted machine learning and deep learning models to measure indoor and outdoor environmental variables. Similarly, Chen et al. [48] used reinforcement learning to optimize HVAC and window systems for natural ventilation. Westermann et al. [138] used a deep temporal CNN in estimating annual heating demand based on multivariate weather data. Besides, the simplest form of AI, expert system [133] is also capable of performing load estimate and fault diagnosis in building. Additionally, it has the ability to effectively monitor and control lighting system in real-time. Expert system uses human knowledge to solve problem that normally would require human intelligence [58].

5.3 Methodological characteristics of AI-in-GB

GB is an important measure in dealing with energy and environmental problems in the construction industry [140] which is riddled with difficult and complicated challenges [21]. AI has therefore evolved as a powerful tool in solving such complex challenges [21] present in GB. As discussed earlier, AI-in-GB can be categorized into four major research areas: fuzzy rules and knowledge discovery; big data and data mining; intelligent optimization; and building automation system. AI-in-GB has been useful in augmenting or automating the decision-making process through prediction, optimization, digitalization, risk management, and construction health monitoring and evaluation. To achieve these, a number of AI-methods have been used to handle the big data in GB acquired through several techniques such as simulations and experimental tests, questionnaire and expert surveys, sensor-based technologies, wearable technologies, smart metering, and GB-related databases and websites such as the USGBC website. Table 11 provides an overview of the type of datasets required in the identified research hotspots in AI-in-GB. The datasets and sample sizes employed in the different AI methods applicable to GB are discussed as follows:

Table 11.

Summary of methodological characteristics, strengths, and limitations of AI-in-GB.

Research area	Dataset	Strengths	Limitations	References
Fuzzy rules and knowledge discovery	- Questionnaire survey - Interview - Expert panel - BIM-based environmental data	- Avoid likely risks blindly in decision-making - Deal with multi-criteria decision-making problems and uncertainties	- No criterion on the sample size - Small sample size and sampling biases - Absence of reliable databases - Inaccurate simulation results	[43,45,58,62,64–68,70,71]
Big data and data mining	- Statistical data on GBs and green finance - Historical energy consumption data - Simulated energy consumption data - Real-time energy consumption data - BIM models and data - GB certification data - GB material data - Questionnaire survey	- Increased efficiency - Cost and time savings - Reliability and improved accuracy - Simplicity - Learning from limited datasets - Large datasets	- Incomplete or missing data - Data unavailability - Poor data quality or incorrect data or noisy data - Lack of effective and convenient tools to perform the large dataset analysis - Small sample size and sampling biases - Under-reporting and under-coverage biases - Black-box problem - Internet challenges - Inaccurate simulation results - Over-fitting problem	[44,79,80,83–88,90–92,94–97,99,101–106]
Intelligent optimization	- BIM data of GB materials (quantities, cost, and sustainability data) - GB design data - Life cycle assessment data (natural resource extraction, and building material production, on-site construction, and transportation) - Prefabricated buildings - Historical building load profiles (e.g., energy, water)	- Increased efficiency - Cost and time savings - Stronger and better optimization ability - Can maintain the population diversity - Generalization ability - Reliability and improved accuracy	- Inaccurate simulation results - Data unavailability	[40,41,46,112,116,119,126–129]
Building automation system	- Historical building load profiles (e.g., energy, water) - Real-time energy consumption data - Environment data (temperature statistics, humidity statistics, weather, and holiday information)	- Best for prediction - Cost and time savings - Robust and reliable - Increased efficiency - Reliability and improved accuracy	- Limited training sample size - Training error - Inaccurate simulation results - Data unavailability - Incomplete or missing data - Poor data quality or incorrect data or noisy data - Lack of effective and convenient tools to perform the large data set analysis - Equipment failure or human operation errors	[79,131,135–139]

- Sample-size effects in research is very critical since it can easily contaminate the design and evaluation of a proposed system [141]. However, the issue of the appropriate sample size especially for AI algorithms remains unclear and are largely unreported in the literature [142,143]. In a recent review on the sample-size determination for machine learning algorithms, it was discovered that the sample sizes ranged from two to 90,000 per feature or attribute. However, there are no generally acceptable methods for calculating the required sample size for a given model [143]. Besides, since sampling cannot be done is isolation, there are no special right decision for determining sample size for a research [144]. That said, the sample-size determination methods, training and testing percentages, number of inputs and outputs, feature selection, and error estimation where necessary for an optimum performance of a model is outside the scope of this study.
- In MCDM techniques, – such as fuzzy logic, fuzzy sets, AHP, and DEMATEL – competence, qualification, and experience are more important than sample size when choosing experts [145]. This is because fuzzy rules and knowledge discovery rely on human expertise to train computer systems to solve problems hence requires human intelligence. Therefore, the accuracy is dependent on expert knowledge and experience [58]. Hallowel and Gambatese [146] defined an expert as a construction engineering and management graduate and professional with at least five years hands-on experience peculiar to the construction site. For expert opinions, five respondents are considered adequate [147]. Respondents in the questionnaire surveys, interviews, or expert panels were construction professionals (such as engineers, project managers, architects, building designers), contractors, suppliers, and government representatives. Sample sizes ranged from seven [64,67] to 120 respondents [58]. Other studies used two separate five-member expert panels in three different rounds [65]. A few studies [44]

used building historical data to simulate the actual operation to develop a prediction model based on fuzzy clustering using a total of 8,226 groups of data.

- Data mining algorithms relate to the analysis of available big data such as GB historical data [44], real-time data [87], and statistical data [88]. The datasets are obtained from certified projects (e.g., LEED) [80,84,96,97,102,104,106], green finance and GB databases [88], historical and real-time building load profiles [44,87], and questionnaire surveys [95]. Despite the characteristic large volumes of 'big data', data mining algorithms can handle both large [44] and very small datasets [87]. For instance, the ANN was used to analyze GB and green finance data retrieved from 21 major banks in China [88] and 76 LEED certified projects [96]. Besides, a survey was conducted with 16 LEED managers' to obtain their opinions based on certified projects [106]. Moreover, Wen et al. [95] used a questionnaire survey of 2000 respondents in a CNN model to assess the effectiveness of BIM in GB design. It is observed that data mining algorithms have also been used to analyze large sample sizes of building data such as 8,226 energy consumption data [44], 16,761 online GB reviews [104] and 21,000 simulation data points from buildings with conventional panels and ultra-high-performance fiber-reinforced-concrete façade panel. Nonetheless, Wang et al. [116] claim that ANN has the ability to learn from limited datasets.
- Intelligent optimization algorithms similarly can handle both small and large sample sizes. For instance, NSGA-II models can handle both small datasets (30 cases) [120] and large datasets (5,610 cases) [98]. It is observed that BIM-based data and experimental simulation data is accepted and widely used developing GB multi-objective optimization models. Other datasets are lifecycle assessment data including natural resource extraction, GB material production, on-site construction, C&D

transportation distance [110,126], building load profiles [126,127], and prefabricated buildings [129] have been useful in optimizing GB designs and green retrofits.

- Building automation system seeks to operate GB intelligently and in real-time. This is possible through real-time data collected with smart technologies such as sensor-based technologies, wearable technologies, and smart metering systems which have the ability to generate huge amounts of data for facility management [81]. Advances in expert systems, machine learning, and deep learning algorithms can handle both small and large sample datasets. To characterize building load profiles, for instance, 144 daily samples of smart metering data were obtained [131]. On the other hand, Westermann et al. [138] used deep temporal convolutional networks to process 150,000 annual hourly weather time series data. Gonçalves et al. [137] also used a large sample (35,040 cases) provided by EnergyPlus to develop an adaptable systems of intelligent supervisory predictive control for buildings. The findings suggest that the building automation system can handle both large and small sample sizes to understand the behavior of GBs for real-time intelligent operation, monitoring, and evaluation.
- Due to the high volume, high velocity, high variety, and sizes of datasets in GB, they are beyond the ability of traditional databases to capture, manage, and process [78]. The development of software applications in building design processes have grown over the years to handle complex data in GB. For example, Python has been widely used in analyzing statistical data [88], GB material data [103] and BIM data. Other software such as MATLAB [44,63,92,96,116], Statistica [84,94] and the R software [98,100] have also seen extensive use in past studies. MATLAB [148], for example, is a high-performance programming software for engineering calculation, which can perform numerical analysis, matrix calculation, scientific data visualization, modeling, and simulation of nonlinear dynamic systems. Besides, the Sina Weibo platform [105] with

web crawler technology [103,105] have been used in text mining methods. On the other hand, simulation software such as TRNSYS [44,120,129], EnergyPlus [87,98,99,113,138], jEPlus [124,129], Energy_10, Green Building Studio web tool [87,96,125], and eQuest [87] have been used in past studies. TRNSYS (Transient system simulation tool), for instance, can communicate with MATLAB through communication object module interface [44]. Besides, while EnergyPlus and eQuest are more suitable for the final design stages where a good level of detail is provided, Green Building studio, which uses DOE-2 as the simulation engine, is fit for any design stage [87]. Additionally, the Monte Carlo simulation, a powerful statistical tool, has been used to forecast lifecycle costs of GB materials [121]. Finally, MCDM methods such as ANP and AHP can be implemented in software such as Super Decision [68] and Expert Choice 2000 [58].

- Notably, case studies were used to validate the developed AI-in-GB models or results in majority of the studies.

5.4 Strengths and limitations of AI-in-GB

As presented in Table 11, there are numerous benefits that comes with the application of AI-in-GB. Research has shown that AI-in-GB has been successful in reducing carbon emissions to promote sustainability at increased profitability and reduced cost through efficient approaches such as resource and waste optimization, risk management, monitoring and evaluation, and automation. As shown in Table 11, similar strengths across the board include increased efficiency, cost and time savings, and reliability and improved accuracy. Others such as increased productivity, simplicity, reduced mistakes and omissions, faster prediction, and resource optimization have been widely discussed in the literature [149].

While acknowledging the strengths in AI-in-GB, numerous challenges persist. An overview of the limitations of AI is presented in Table 11. Data unavailability, incomplete data, poor data quality, absence of reliable databases, inaccurate simulation results, small sample size, and sampling biases were common limitations to AI-in-GB. Other limitations such as data complexity, high initial costs, data privacy and security issues, ethical and legal issues, cultural challenges, lack of expertise, and the "black-box" problem have been discussed in the literature [149–151]. Machine learning systems, for example, use a black-box approach, which implies that they do not explain the 'why' of their conclusions. It is therefore critical to employ explainable AI to create explainable models that allow humans to understand, trust, and control the systems [149,151]. Moreover, issues relating to the impact of culture, personal and religious values on the acceptance and adoption of AI [150] should be investigated further.

Additionally, as noted earlier, issues regarding sample sizes and data quality have been discussed in the literature. This is because data quantity and quality impact the accuracy of models [79,135]. Hence, data collected for analysis usually undergoes "data preparation" or "data pre-processing". Data pre-processing helps to enhance data quality by removing outliers, inconsistencies [83], and imbalances [85]. This comprises "data cleaning", "data transformation", and "data reduction" before they are used to train prediction models [79]. Besides, for robustness and validation purposes, most AI algorithms splits datasets for "training" and "testing" purposes – hence the need for large datasets. In such instances, to eliminate the issue of overfitting and minimize bias associated with random sampling of the training and testing data samples, especially when comparing the predictive accuracy of two or more research methods, researchers often use cross validation to minimize the bias [100]. To balance the class distribution in a dataset, the synthetic minority oversampling technique proposed by Chawla et al. [152] is employed. Occasionally, where setting aside a part of a small dataset for validation purposes is unaffordable, and it must all be consumed by the training dataset, the "out-of-bag' score provides a good trade-off. This provides insights on the how the model could have behaved with a larger dataset that would have allowed splitting into training and testing sets [101]. Moreover, to tackle the challenges associated with many irrelevant and redundant variables and often comparably few training samples, variable and feature selection have become the focus of many research [153]. They are essentially divided into wrappers, filters, and embedded methods [102,153]. Finally, where the data gap is extremely large, data normalization can reduce model prediction errors, improve convergence speed, and model training efficiency [139,154].

6. Discussion and future research directions

This study has explored the state-of-the-art in AI-in-GB through a bibliometric-systematic analysis. Unlike previous studies, the bibliometric-systematic analysis of AI-in-GB was employed to: (1) synthesize the full picture of the research area, and (2) reveal the gaps, and research needs thus justifying the need for the present research. To do this, bibliometric techniques with the aid of multiple software such as VOSviewer, CiteSpace, and Gephi were used to understand the key research areas, research outlets and scientific collaboration analysis of countries and institutions in AI-in-GB. A further qualitative-systematic analysis was conducted on key selected relevant articles on AI-in-GB.

So far, this study has identified the annual publication trend of AI-in-GB which reveals an increasing and promising research area. A keyword co-occurrence analysis with VOSviewer showed that GB, sustainability, BIM, multi-objective optimization, data mining, sustainable construction, ANN, and GA have received special attention in the literature. A CiteSpace cluster analysis identified six clusters which were mainly focused on AI-methods and GB application. A more in-depth systematic analysis shows that past studies have focused on four research hotspots: fuzzy rules and knowledge discovery, big data and data mining, intelligent optimization, and building automation system. Finally, we evaluated the methodological characteristics, strengths, and limitations of AI-in-GB.

It is therefore critical to identify and explore relevant directions for future research in order to strengthen this research area. As presented in Fig. 12, there are key opportunities in four major areas applicable in AI-in-GB. This suggest that more advanced technologies inspired by AI will play a major role in digitizing, augmenting, and automating GB to promote the efficiency and sustainability of the AEC sector. As discussed below, the application of AI-in-GB, though a burgeoning research area, provides good grounds for future research.

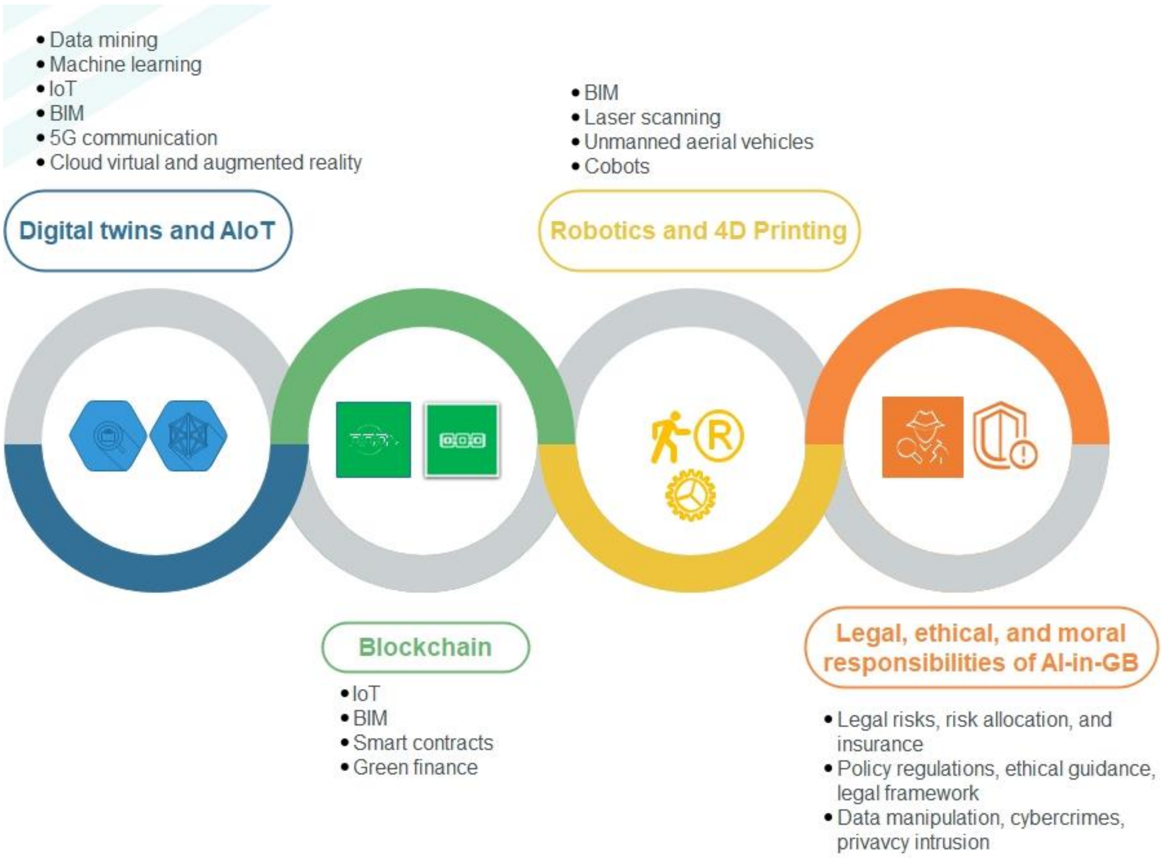


Fig. 12. Future directions of AI-in-GB.

6.1. Digital twins and AIoT

Digital twins, along with AI of things (AIoT), data mining, and machine learning opportunities [155] can offer great potential in the transformation of today's GB. The digital twin is a realization of the cyber-physical system for visualization, modeling, simulation, analyzing, predicting, and optimizing which incorporates three components: the physical entity, virtual entity, and the connection of data to form a practical loop [155]. On the other hand, AIoT is the new generation of internet of things (IoT), which incorporates AI-methods into IoT infrastructure for more efficient IoT operation and data analysis. IoT is therefore a network of interconnected physical devices such as wearable and mobile devices, sensors, wireless technologies (e.g., RFID), 3D laser scanners, sensors, actuators, and drones which is attached to a construction resource (e.g., GB) to gather real-time data about the state of operations of the project [20,149]. Since AIoT is powered by AI, it excels in the synthesis and interpretation of data acquired in high volumes and velocity via IoT infrastructure, which can then be transported to the virtual world for additional analysis via the digital twin technology. In the virtual model, simulation, prediction, and optimization are conducted by learning data from numerous sources which can provide instant solutions to direct real-world processes and make them adapt to changing environments [20,149]. With the growing need for green retrofits and investments [8], the cooperative use of digital twins and AIoT is very timely. With the aid of laser scanners, BIM models of existing buildings could be developed and delivered to a virtual world for additional analysis. The web-based integration of AIoT captures significant amounts of data to enrich the BIM for green retrofit decisions, and BIM as a digital representation can be the beginning point of the digital twin. Pan and Zhang [20] agree that the convergence of AIoT, and BIM under 5G wireless communications would become hotspots for future research. More so, a more complex approach with the inclusion of digital twins can greatly improve the efficiency of the data gathering, transporting, and processing using cloud computing methods towards smart-GB. Significant advances in cloud virtual and augment reality [20,25] could also be explored in the proposed integration of BIM, AIoT, and digital twin under 5G networks for a better comprehension of the complexities and interdependencies during the construction of both new GB and green retrofits. Besides, future research could also investigate the possibility of integrating the proposed technology with existing GB ratings systems such as LEED (US), BREAAM (UK), and BEAM Plus (Hong Kong), and Green Star (Australia), etc., to facilitate green certification processes.

6.2. Blockchain

Since 2008, blockchain has attracted significant interest in both financial and non-financial applications due to the immutability, transparency, auditability, security, trustworthiness, and fast-nature of its transactions [156,157]. A blockchain is essentially a distributed database of records, or a public ledger of all transactions or digital events that have been executed and shared among participating parties [157]. Blockchains can either be un-permissioned (allowing public access) or permissioned (private access). With such abilities, blockchains are being explored in various sectors including the construction sector. Some key opportunities for the adoption of the blockchain technology in construction include smart energy, cities, homes, organizations, transportation, BIM, and construction management and business [158]. Nonetheless, the now-available limited literature shows that the application of blockchain in the construction sector is very limited [158] with opportunities for increased growth. Due to the immutability, transparency, and traceability of data, blockchain can be used to promote GB development to ensure resource optimization, reduced carbon emissions, and energy efficiency of GB. For instance, green certification and verification could be digitized via blockchain and IoT chips embedded in GBs [8]. Further, sensors tagged into the blockchain through IoT chips could form the basis for assessing the performance of GBs to inform investors of the overall environmental impact of developers in accessing green finance for GB. Besides, these data can be used by developers to access incentives such as tax rebates, tax holidays, green insurance, and green credits [8]. Moreover, the decentralized feature of blockchain can be integrated with BIM to collect large amounts of data from the various stages of GB projects and share data among stakeholders for life-cycle cost and environmental assessment. Such an integration would allow the BIM model to be regularly updated to ensure an automated and streamlined project delivery to promote productivity, trustworthiness, reduced cost, transparency, security of data, effective collaboration and stakeholder management, and supply chain management and resilience [20,157]. Further, smart property via blockchain using smart contracts could be explored in GB projects to deal with the challenges associated with GB certification costs, construction cost, payment fraud, and GB ownership [20,157]. With smart contracts, all GB transactions will be accessible to all parties in real-time.

6.3. Robotics and 4D printing

Robots are intelligent machines that perform physical tasks in everyday life. Robotics is the science of designing, manufacturing, operating, and maintaining of robots and other computer activities to imitate human behavior – very typical in reinforcement machine learning problems [149]. The limited application in robotic construction [21] especially in GB presents opportunities for future research. There are opportunities in using smart robotics – either ground or aerial robots – to rapidly drive semi- or fully-autonomous construction applications such as repetitive and very dangerous construction tasks [20,21]. Hence, it will beneficial to develop cobots (collaborative robots) to work with humans to deliver the sustainable objectives of GB projects such as resource optimization, improved productivity, efficiency, safety and quality [21]. Besides, aerial robots – unmanned aerial vehicles (UAV) with integrated image acquisition systems (i.e., camera, laser scanner, go-pros) – can be trained with machine learning for green retrofits, site monitoring, and structural health monitoring, since they can ensure an economic, simpler, and effective process [20]. For instance, UAVs can fly into an existing building to capture real-time high-definition videos and images, and remotely carry-out laser scanning [20] necessary for green retrofits. Moreover, smart robotics can be integrated with the emerging 4D printing technology [20] for large scale additive manufacturing of green construction elements [159] and even modular integrated construction [21]. 4D printing are 3D printed objects capable of evolving their behaviour and shape within a period to respond to external stimuli including light, heat, temperature, etc. [20]. Hence, future studies that explore the integration of smart robotics and 4D printing would further our knowledge on GB automation systems and intelligent optimization. Moreover, integrating BIM with smart robotics and 4D printing could improve the level of automation, efficiency, productivity, safety, and quality of the AEC sector.

6.4. Legal, ethical, and moral responsibilities of AI-in-GB

From the review, it is observed that AI offers the GB industry a lot of advantages and opportunities for digitization, automation, augmentation, and optimization. GBs today provide a large amount of accumulated valuable data which undergoes continual assessment and analysis to assist facility managers in improving operational performance and reducing building energy waste [81]. As such, modern technology has generated a phenomenal wealth of data and the means of storing it in a quick and easily retrievable manner [151]. Given the growth in data collection and the application of AI, there is the need to investigate further the legal, ethical, social, and moral considerations for AI-in-GB to inform stakeholders such as project developers, software developers, financial institutions, project owners, GB occupants or tenants. Such awareness is necessary in making informed AI-in-GB decisions [160] without compromising legal, ethical, and moral duties. At present, the literature has focused on the technological development and application of AI-in-GB, with little to no attention on the legal, ethical, and moral risks associated with the technological advancement. Therefore, urgent attention is needed to inform regulators and stakeholders of present regulations and its challenges for the industry. AI-in-GB related legal issues such as risk allocation, insurance coverage, civil wrongs (tort, and breach of contract, warranty, and trust) present opportunities for future research. Additionally, future research could consider how the AI is designed, operates, and learns and how the algorithms work in the context of ethical and social problems. Likewise, due to AI-internet integration, and its associated challenges such as data manipulation, exploitation by hackers, cybercrimes, and privacy intrusion [149], further study on AI-in-GB data protection is needed. Moreover, since the government plays critical role in promoting GB, further research is required to shape the role of government in addressing the ethical and legal challenges, particularly around the responsibility for and explainability of decisions made by an automation AI system [150]. Further understanding on how government can develop adequate policies, regulations, ethical guidance, and legal framework to prevent misuses of AI-in-GB and their potential disastrous consequences on both individual and societal levels is required. Other critical issues worth exploring include: (1) accountability, (2) laws needed in an autonomous decision-making environment (3) will AI technology replace or assist the decision maker? (4) ultimate responsibility of the designer (will they be responsible only for providing data to feed the algorithm?) and (5) does the algorithm know what is best for us? Future studies are needed to explore these critical legal, ethical, moral, and social issues related to AI-in-GB.

7. Conclusions

This study reviewed the existing literature on AI-in-GB for the first time to identify research trends and knowledge gaps that may be addressed in future studies. Theoretically, this study presents the key research hotspots, strengths and limitations of AI-in-GB, and gaps in existing studies to inform the directions for future research efforts. Unlike previous isolated systematic or bibliometric reviews, this study leverages the benefits of a mixed-method bibliometric-systematic review to overcome the weakness of review methods when used in isolation. This was effective in limiting subjectivity in the analysis and the ability to replicate similar studies in future. It is observed that early research focused on expert knowledge discovery and fuzzy rules. With the advancement in AI technology coupled with the now-available high volume and rate of generating GB big data, data mining algorithms have become handy in discovering hidden knowledge from such large datasets for future GB decisions. Moreover, intelligent optimization has significantly transformed the ability to locate pareto optimal solutions for GB using AI techniques over traditional approaches. Knowledge from both data mining and intelligent optimization of GBs provide a vast quantity of data on existing building operations, allowing GBs to be automatically and intelligently monitored and controlled in real-time. The findings of the study set the tone for further studies by providing paths and recommendations for future studies in AI-in-GB. Practically, this research provides an up-to-date reference for AI-in-GB. This study identified emerging AI technologies, techniques and algorithms introduced in GB-research. As a result, the findings may be used as a reference for practitioners and policymakers to assess their level of development and readiness to embrace AI-in-GB techniques and practices. The strengths and limitations of AI-in-GB identified is this study would be a useful reference for practitioners to ascertain the potential opportunities and risks in AI-in-GB. For construction stakeholders, and first-time developers of GBs, the adoption of AI-in-GB would be a great addition towards efficiency and sustainability. It is suggested that future research would explore the integration of AI and emerging technologies such as digital twins and AIoT, blockchain, and robotics and 4D printing. Nonetheless, due to the digitalization and automation opportunities present in AI-in-GB, there is urgent need to investigate the legal, ethical, and moral challenges associated of AI technologies.

Despite the contributions, this study still has limitations which should be taken into consideration when interpreting the study findings. The analysis was based on a single database (Scopus) which may affect the coverage of publications in the study area. Moreover, the research was restricted to journal articles. To improve this study, future studies may combine different databases and document types. Additionally, the literature search was conducted using certain keywords, which might not reflect the complete picture of the research areas. Future studies may include more keywords.

Acknowledgements

The authors thank the Department of Building and Real Estate of The Hong Kong Polytechnic University for funding this research. We are extremely grateful to the

Editors and Reviewers whose constructive and invaluable comments and suggestions helped improve the quality of this paper significantly.

Appendix A. List of papers included in the qualitative-systematic analysis.

S/N	Authors	Title	Citations	Country [a]
Top 20 most-cited AI-in-GB publications [b]				
1	Wang et al. [41]	Applying multi-objective GA in GB design optimization	478	Canada
2	Juan et al. [126]	A hybrid decision support system for sustainable office building renovation and energy performance improvement	251	Taiwan
3	Yu et al. [46]	Application of multi-objective GA to optimize energy efficiency and thermal comfort in building design	197	China
4	Zhao et al. [99]	Occupant behaviour and schedule modeling for building energy simulation through office appliance power and consumption data mining	186	US
5	Akadiri et al. [43]	Multi-criteria evaluation model for the selection of sustainable materials for building projects	175	UK
6	Wang et al. [40]	Floor shape optimization for GB design	170	Canada
7	Panda et al. [159] [c]	Additive manufacturing of geopolymer for sustainable built environment	167	Singapore
8	Méndez et al. [113]	The early design stage of a building envelope: multi-objective search through heating, cooling, and lighting energy performance analysis	166	Italy
9	Zhao et al. [45]	A fuzzy synthetic evaluation approach for risk assessment: a case of Singapore's green projects	127	Singapore
10	Tam et al. [71]	Green construction assessment for environmental management in the construction industry of Hong Kong	118	Hong Kong
11	Marinakis et al. [161] [c]	An integrated system for buildings' energy-efficient automation: Application in the tertiary sector	112	Greece
12	Asl et al. [125]	BPot: A framework for BIM-based performance optimization	103	US
13	Chen et al. [48]	Optimal control of HVAC and window systems for natural ventilation through reinforcement learning	102	US
14	Wu and Issa [162]	BIM execution planning in GB projects: LEED as a use case	94	US
15	Yezioro et al. [87]	An applied artificial intelligence approach towards assessing building performance simulation tools	90	US
16	Khoshnava et al. [68]	Rank of GB material criteria based on the three pillars of sustainability using the hybrid MCDM method	85	Malaysia
17	Liu et al. [111]	Building information modeling-based building design optimization for sustainability	83	China
18	Yan et al. [134]	ARX model-based fault detection and diagnosis for chillers using SVMs	83	United Arab Emirates
19	Tatari and Kucukvar [84]	Cost premium prediction of certified GBs: a neural network approach	82	US
20	Yang et al. [136]	Reinforcement learning for optimal control of low exergy buildings	82	Switzerland
Recent five publication from the top five AI-in-GB outlets				
Building and Environment				
21	Figueiredo et al. [64]	Sustainable material choice for construction projects: A Life Cycle Sustainability Assessment framework based on BIM and Fuzzy-AHP	9	Brazil
22	Wang et al. [88]	The influencing factors of China's GB development: An analysis using RBF-WINGS method	5	China
23	Park and Park [135]	Comparative analysis on predictability of natural ventilation rate based on machine learning algorithms	5	South Korea
24	Wang et al. [116]	Multi-objective optimization (MOO) for high-rise residential buildings’ layout centered on daylight, visual, and outdoor thermal metrics in China	1	China
25	Guo et al. [104]	Occupants’ satisfaction with LEED- and non-LEED-certified apartments using social media data	0	US
Energy and Buildings				
26	Lin et al. [123]	Optimal design of a thermal energy storage system using phase change materials for a net-zero energy Solar Decathlon house	16	Australia
27	Gonçalves et al. [137]	One step forward toward smart city Utopia: Smart building energy management based on adaptive surrogate modeling	9	Portugal
28	Lu et al. [44]	Multidimensional performance-based evaluation method of high-performance cold source in GB	0	China
29	Wang et al. [118]	Experimental study and multi-objective optimisation of a novel integral thermoelectric wall	0	China
30	Briga-Sá et al. [79]	Trombe wall thermal performance: Data mining techniques for indoor temperatures and heat flux forecasting	0	Portugal

Journal of Cleaner Production				
31	Shahmansouri et al. [93]	ANN model to predict the compressive strength of eco-friendly geopolymer concrete incorporating silica fume and natural zeolite	35	Iran
32	Ganesh and Muthukannan [92]	Development of high performance sustainable optimized fiber reinforced geopolymer concrete and prediction of compressive strength	18	India
33	Yadegaridehkordi et al. [69]	Assessment of sustainability indicators for GB manufacturing using fuzzy MCDM approach	14	Malaysia
34	Mohandes and Zhang [67]	Developing a Holistic Occupational Health and Safety risk assessment model: An application to a case of sustainable construction project	6	Hong Kong
35	Negash et al. [70]	Sustainable construction and demolition waste management in Somaliland: Regulatory barriers lead to technical and environmental barriers	4	Taiwan
Applied Energy				
36	Fan and Xia [127]	Building retrofit optimization models using notch test data considering energy performance certificate compliance	16	China
37	Westermann et al. [138]	Using a deep temporal convolutional network as a building energy surrogate model that spans multiple climate zones	10	Canada
38	Ding et al. [139]	Evolutionary double attention-based long short-term memory model for building energy prediction: Case study of a GB	5	China
39	Naji et al. [129]	Multi-objective optimisations of envelope components for a prefabricated house in six climate zones	2	Australia
Automation in Construction				
40	Fernandez-Ceniceros et al. [90]	Decision support model for one-way floor slab design: A sustainable approach	21	Spain
41	Karatas and El-Rayes [115]	Optimizing trade-offs among housing sustainability objectives	17	US
42	Hong et al. [103]	Automated management of GB material information using web crawling and ontology	10	South Korea
43	Martínez-Rocamora et al. [101]	Environmental benchmarking of building typologies through BIM-based combinatorial case studies	0	Spain
Manual backward and forward snowball citation analysis				
44	Platt et al. [122]	Adaptive HVAC zone modeling for sustainable buildings	69	Australia
45	Inyim et al. [117]	Integration of building information modeling and economic and environmental impact analysis to support sustainable building design	66	US
46	Marzouk et al. [121]	BIM-based approach for optimizing life cycle costs of sustainable buildings	64	Saudi Arabia
47	Nilashi et al. [58]	A knowledge-based expert system for assessing the performance level of GBs	57	Malaysia
48	Cheng and Ma [97]	A non-linear CBR approach for retrieval of similar cases and selection of target credits in LEED projects	55	Hong Kong
49	Kasinalis et al. [120]	Framework for assessing the performance potential of seasonally adaptable facades using multi-objective optimization	53	Netherlands
50	Ma and Cheng [106]	Data-driven study on the achievement of LEED credits using percentage of average score and association rule analysis	50	Hong Kong
51	Chen and Yang [98]	A multi-stage optimization of passively designed high-rise residential buildings in multiple building operation scenarios	50	Hong Kong
52	Ren and Cao [89]	Implementation and visualization of artificial intelligent ventilation control system using fast prediction models and limited monitoring data	49	China
53	Seo et al. [60]	Fuzzy decision-making tool for environmental sustainable buildings	46	Japan
54	Jun and Cheng [100]	Selection of target LEED credits based on project information and climatic factors using data mining techniques	42	Hong Kong
55	Chen et al. [124]	A holistic passive design approach to optimize indoor environmental quality of a typical residential building	41	Hong Kong
56	Allen et al. [132]	Fuzzy neural network-based health monitoring for HVAC system variable-air-volume unit	39	US
57	Son and Kim [85]	Early prediction of the performance of GB projects using pre-project planning variables: data mining approaches	33	South Korea
58	Cheng and Ma [80]	A data-driven study of important climate factors on the achievement of LEED-EB credits	33	Hong Kong
59	Ma and Cheng [102]	Identification of the numerical patterns behind the leading counties in the US local GB markets using data mining	32	Hong Kong
60	Liu and Hu [105]	Attention and sentiment of Chinese public toward GBs based on Sina Weibo	32	China
61	Vakili-Ardebili and Boussabaine [61]	Application of fuzzy techniques to develop an assessment framework for building design eco-drivers	28	UK
62	Yin and Li [65]	Matching management of supply and demand of GB technologies based on a novel matching method with intuitionistic fuzzy sets	26	China

63	Jalaei et al. [96]	An integrated BIM-LEED application to automate sustainable design assessment framework at the conceptual stage of building projects	21	Canada
64	Zhao et al. [107]	CBR approach for supporting building green retrofit decisions	21	China
65	Atis and Ekren [133]	Development of an outdoor lighting control system using expert system	20	Turkey
66	Juan et al. [86]	Identifying customer behavioral factors and price premiums of GB purchasing	18	Taiwan
67	Yin and Li [66]	Academic research institutes-construction enterprises linkages for the development of urban GB: Selecting management of GB technologies innovation partner	16	China
68	Zhu et al. [131]	Data-driven building load profiling and energy management	13	China
69	Wang et al. [62]	Green performance evaluation system for energy-efficiency-based planning for construction site layout	13	Canada
70	Wang and Wei [112]	Design optimization of office building envelope based on QGA for energy conservation	13	China
71	Lin et al. [114]	Multi-objective optimization design of GB envelopes and air conditioning systems for energy conservation and CO_2 emission reduction	13	Taiwan
72	Bhatt and Macwan [63]	Fuzzy Logic and Analytic Hierarchy Process-Based Conceptual Model for Sustainable Commercial Building Assessment for India	10	India
73	Abediniangerabi et al. [83]	A data-driven framework for energy-conscious design of building facade systems	9	US
74	May Tzuc et al. [91]	Modeling of hygrothermal behavior for green facade's concrete wall exposed to Nordic climate using AI and global sensitivity analysis	5	Finland
75	Wen et al. [95]	Assessing the Effectiveness of BIM in Developing GBs from a Lifecycle Perspective	4	China
76	Lee and Lee [119]	Optimization of apartment-complex layout planning for daylight accessibility in a high-density city with a temperate climate	2	South Korea
77	Elshaboury and Marzouk [128]	Optimizing construction and demolition waste transportation for sustainable construction	1	Egypt
78	Bajno et al. [94]	Old and modern wooden buildings in the context of sustainable development	0	Poland

[a] Where authors are affiliated to different countries, the country of the first author is listed.
[b] The list includes only reviewed articles in systematic analysis.
[c] These two articles were among the top 20 most cited AI-in-GB studies but were not included in systematic analysis.

References

[1] UNEP, 2021 Global Status Report for Buildings and Construction, UNEP - United Nations Environment Programme. (2021). http://www.unep.org/resources/report/2021-global-status-report-buildings-and-construction (accessed October 25, 2021).

[2] US Environmental Protection Agency, Definition of Green Building., (2016). https://archive.epa.gov/greenbuilding/web/html/about.html (accessed April 4, 2021).

[3] WorldGBC, About Green Buildings, (2021). https://www.worldgbc.org/about-green-building (accessed February 24, 2021).

[4] A. Darko, A.P.C. Chan, D.-G. Owusu-Manu, E.E. Ameyaw, Drivers for implementing green building technologies: An international survey of experts, Journal of Cleaner Production. 145 (2017), pp. 386–394. https://doi.org/10.1016/j.jclepro.2017.01.043.

[5] A.P.C. Chan, A. Darko, A.O. Olanipekun, E.E. Ameyaw, Critical barriers to green building technologies adoption in developing countries: The case of Ghana, Journal of Cleaner Production. 172 (2018), pp. 1067–1079. https://doi.org/10.1016/j.jclepro.2017.10.235.

[6] J. Zuo, Z.-Y. Zhao, Green building research–current status and future agenda: A review, Renewable Sustainable Energy Reviews. 30 (2014), pp. 271–281. https://doi.org/10.1016/j.rser.2013.10.021.

[7] A. Darko, A.P.C. Chan, Critical analysis of green building research trend in construction journals, Habitat International. 57 (2016), pp. 53–63. https://doi.org/10.1016/j.habitatint.2016.07.001.

[8] C. Debrah, A.P.C. Chan, A. Darko, Green finance gap in green buildings: A scoping review and future research needs, Building and Environment. 207 (2022), pp. 108443. https://doi.org/10.1016/j.buildenv.2021.108443.

[9] D. Yu, H. Liao, Visualization and quantitative research on intuitionistic fuzzy studies, Journal of Intelligent & Fuzzy System. 30 (2016), pp. 3653–3663. https://doi.org/10.3233/IFS-162111.

[10] A. Darko, A.P.C. Chan, X. Huo, D.-G. Owusu-Manu, A scientometric analysis and visualization of global green building research, Building and Environment. 149 (2019), pp. 501–511. https://doi.org/10.1016/j.buildenv.2018.12.059.

[11] X. Zhao, J. Zuo, G. Wu, C. Huang, A bibliometric review of green building research 2000–2016, Architectural Science Review. 62 (2019), pp. 74–88. https://doi.org/10.1080/00038628.2018.1485548.

[12] J. McCarthy, The inversion of functions defined by Turing machines, *In Automa Studies (AM-34).* 34 (1956), pp. 177–181. Princeton University Press

[13] P. Whig, Artificial Intelligence and Machine Learning in Business, International Journal of Integrated Education. 2 (2019), pp. 334128. http://journals.researchparks.org/index.php/IJIE/article/view/516

[14] A. Jeerage, B. Erwine, S. Mallory, V. Agarwal, Predicting green building performance over time: data mining untapped information in LEED, WIT Transactions on Ecology and the Environment. 128 (2010), pp. 355–365. https://doi.org/10.2495/ARC100301

[15] H. Chen, B. Zhou, Environmental performance evaluation of green buildings based on machine learning and IOT systems, Microprocessors and Microsystems. (2020), pp. 103496. http://doi.org/10.1016/j.micpro.2020.103496

[16] Y. Lu, Z. Wu, R. Chang, Y. Li, Building Information Modeling (BIM) for green buildings: A critical review and future direction. Automation in Construction, (2017), pp. 134-138. https://doi.org/10.1016/j.autcon.2017.08.024

[17] M. Bilal, L.O. Oyedele, J. Qadir, K. Munir, S.O. Ajayi, O.O. Akinade, H.A. Owolabi, H.A. Alaka, M. Pasha, Big Data in the construction industry: A review of present status, opportunities, and future trends, Advances Engineering Informatics. 30 (2016), pp. 500–521. https://doi.org/10.1016/j.aei.2016.07.001

[18] V. Faghihi, A. Nejat, K.F. Reinschmidt, J.H. Kang, Automation in construction scheduling: a review of the literature, The International Journal of Advanced Manufacturing Technology. 81 (2015), pp. 1845–1856. https://doi.org/10.1007/s00170-015-7339-0

[19] Z. Irani, M.M. Kamal, Intelligent Systems Research in the Construction Industry, Expert Systems with Applications. 41 (2014), pp. 934–950. https://doi.org/10.1016/j.eswa.2013.06.061.

[20] Y. Pan, L. Zhang, Roles of artificial intelligence in construction engineering and management: A critical review and future trends, Automation in Construction. 122 (2021), pp. 103517. https://doi.org/10.1016/j.autcon.2020.103517.

[21] A. Darko, A.P.C. Chan, M.A. Adabre, D.J. Edwards, M.R. Hosseini, E.E. Ameyaw, Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities, Automation in Construction. 112 (2020), pp. 103081. https://doi.org/10.1016/j.autcon.2020.103081.

[22] M. Heyvaert, K. Hannes, P. Onghena, Using Mixed Methods Research Synthesis for Literature Reviews: The Mixed Methods Research Synthesis Approach, SAGE Publications, (2016). ISBN 978143358291

[23] A. Harden, J. Thomas, Mixed Methods and Systematic Reviews: Examples and Emerging Issues, in: SAGE Handbook of Mixed Methods in Social & Behavioral Research, SAGE Publications, Incorporation, 2455 Teller Road, Thousand Oaks California 91320 United States, (2010): pp. 749–774. https://doi.org/10.4135/9781506335193.n29.

[24] P. Pluye, Q.N. Hong, Combining the Power of Stories and the Power of Numbers: Mixed Methods Research and Mixed Studies Reviews, Annual Review of Public Health. 35 (2014) pp. 29–45. https://doi.org/10.1146/annurev-publhealth-032013-182440.

[25] X. Yin, H. Liu, Y. Chen, M. Al-Hussein, Building information modelling for off-site construction: Review and future directions, Automation in Construction. 101 (2019), pp. 72–91. https://doi.org/10.1016/j.autcon.2019.01.010.

[26] N.J. van Eck, L. Waltman, Visualizing Bibliometric Networks, in: Y. Ding, R. Rousseau, D. Wolfram (Eds.), Measuring Scholarly Impact: Methods and Practice, Springer International Publishing, Cham, (2014): pp. 285–320. https://doi.org/10.1007/978-3-319-10377-8_13.

[27] A. Darko, A.P.C. Chan, Applying science mapping in built environment research, Routledge, (2021). https://doi.org/10.1201/9781003000532-9.

[28] M.J. Cobo, A.G. López-Herrera, E. Herrera-Viedma, F. Herrera, Science mapping software tools: Review, analysis, and cooperative study among tools, Journal of the American Society for Information Science and Technology. 62 (2011), pp. 1382–1402. https://doi.org/10.1002/asi.21525.

[29] M. Oraee, M.R. Hosseini, E. Papadonikolaki, R. Palliyaguru, M. Arashpour, Collaboration in BIM-based construction networks: A bibliometric-qualitative literature review, International Journal of Project Management. 35 (2017), pp. 1288–1301. https://doi.org/10.1016/j.ijproman.2017.07.001.

[30] J.C. Greene, V.J. Caracelli, W.F. Graham, Toward a Conceptual Framework for Mixed-Method Evaluation Designs, Educational Evaluation and Policy Analysis. 11 (1989), pp. 255–274. https://doi.org/10.3102/01623737011003255.

[31] L.I. Meho, Y. Rogers, Citation counting, citation ranking, and h-index of human-computer interaction researchers: A comparison of Scopus and Web of Science, Journal of American Society for Information Science and Technology. 59 (2008), pp. 1711–1726. https://doi.org/10.1002/asi.20874.

[32] C. Collins, D. Dennehy, K. Conboy, P. Mikalef, Artificial intelligence in information systems research: A systematic literature review and research agenda, I International Journal of Information Management. 60 (2021), pp. 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383.

[33] M.R. Hosseini, I. Martek, E.K. Zavadskas, A.A. Aibinu, M. Arashpour, N. Chileshe, Critical evaluation of off-site construction research: A Scientometric analysis, Automation in Construction. 87 (2018), pp. 235–247. https://doi.org/10.1016/j.autcon.2017.12.002.

[34] C. Chen, CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature, International Journal of American Society for Information Science and Technology. 57 (2006), pp. 359–377. https://doi.org/10.1002/asi.20317.

[35] M. Bastian, S. Heymann, M. Jacomy, Gephi: An Open Source Software for Exploring and Manipulating Networks, Proceedings of the Third AAAI Conference on Weblogs and Social Media. 3 (2009), pp. 361-362. https://ojs.aaai.org/index.php/ICWSM/article/view/13937 (accessed March 12, 2021).

[36] H. Li, Q. Shen, Supporting the decision-making process for sustainable housing, Construction Management and Economics. 20 (2002), pp. 387–390. https://doi.org/10.1080/01446190210146812

[37] J.F. Hair, Multivariate data analysis: A Global Perspective. 7th ed. Upper Saddle River: Prentice Hall, (2009). ISBN-13: 978-0138132637

[38] A.A.T. Fernandes, D.B. Figueiredo, E.C. da Rocha, W. da S. Nascimento, Read this paper if you want to learn logistic regression, Revista de Sociologia. e Política. 28 (2021), pp. 1-19. https://doi.org/10.1590/1678-987320287406en

[39] N.J. van Eck, L. Waltman, How to normalize cooccurrence data? An analysis of some well-known similarity measures, Journal of American Society for Information Science and Technology. 60 (2009), pp. 1635–1651. https://doi.org/10.1002/asi.21075.
[40] W. Wang, H. Rivard, R. Zmeureanu, Floor shape optimization for green building design, Advances Engineering Informatics. 20 (2006), pp. 363–378. https://doi.org/10.1016/j.aei.2006.07.001.
[41] W. Wang, R. Zmeureanu, H. Rivard, Applying multi-objective genetic algorithms in green building design optimization, Building and Environment. 40 (2005), pp. 1512–1525. https://doi.org/10.1016/j.buildenv.2004.11.017.
[42] L.A. Zadeh, Information and control, Fuzzy Sets. In Fuzzy sets, fuzzy logic, and fuzzy systems. 8 (1965), pp. 338–353. https://doi.org/10.1142/9789814261302_0021
[43] P.O. Akadiri, P.O. Olomolaiye, E.A. Chinyio, Multi-criteria evaluation model for the selection of sustainable materials for building projects, Automation in Construction. 30 (2013), pp. 113–125. https://doi.org/10.1016/j.autcon.2012.10.004
[44] S. Lu, Y. Liu, Y. Li, R. Wang, Multidimensional performance-based evaluation method of high-performance cold source in green building, Energy and Buildings. 231 (2021), pp. 110618. https://doi.org/10.1016/j.enbuild.2020.110618
[45] X. Zhao, B.-G. Hwang, Y. Gao, A fuzzy synthetic evaluation approach for risk assessment: a case of Singapore's green projects, Journal of Cleaner Production. 115 (2016), pp. 203–213. https://doi.org/10.1016/j.jclepro.2015.11.042.
[46] W. Yu, B. Li, H. Jia, M. Zhang, D. Wang, Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design, Energy and Buildings. 88 (2015), pp. 135–143. https://doi.org/10.1016/j.enbuild.2014.11.063.
[47] R.J. Cole, Z. Brown, Reconciling human and automated intelligence in the provision of occupant comfort, Intelligent Buildings International. 1 (2009), pp. 39–55. https://doi.org/10.3763/inbi.2009.0007
[48] Y. Chen, L.K. Norford, H.W. Samuelson, A. Malkawi, Optimal control of HVAC and window systems for natural ventilation through reinforcement learning, Energy and Buildings. 169 (2018), pp. 195–205. https://doi.org/10.1016/j.enbuild.2018.03.051
[49] C. Chen, CiteSpace Manual, (2014). College of Computing and Informatics. http://cluster.ischool.drexel.edu/%7Ecchen/citespace/CiteSpaceManual.pdf.
[50] C. Prell, Social Network Analysis: History, Theory and Methodology, SAGE, Publications, (2012). ISBN 978-1-4129-4715-2
[51] J. Vincent, Artificial intelligence research continues to grow as China overtakes US in AI journal citations, The Verge. (2021). https://www.theverge.com/2021/3/3/22310840/ai-research-global-growth-china-us-paper-citations-index-report-2020 (accessed December 8, 2021).
[52] B. Crew, Google Scholar reveals its most influential papers for 2020, Nature Index. (2020). https://www.natureindex.com/news-blog/google-scholar-reveals-most-influential-papers-research-citations-twenty-twenty (accessed December 7, 2021).
[53] S.A. Aaronson, America's Uneven Approach to AI and Its Consequence, Great Decisions. (2020), pp. 87-96. Available at SSRN: https://ssrn.com/abstract=3589847
[54] Y. Ding, Scientific collaboration and endorsement: Network analysis of coauthorship and citation networks, Journal of Informetrics. 5 (2011), pp. 187–203. https://doi.org/10.1016/j.joi.2010.10.008.
[55] J.W. Kirchherr, R. van Santen, Research on the Circular Economy: A Critique of the Field, Resources, Conservation and Recycling. 151 (2019). https://doi.org/10.1016/j.resconrec.2019.104480.

[56] P. Antwi-Afari, S.T. Ng, Md.U. Hossain, A review of the circularity gap in the construction industry through scientometric analysis, Journal of Cleaner Production. 298 (2021), pp. 126870. https://doi.org/10.1016/j.jclepro.2021.126870.

[57] C. Wohlin, Guidelines for snowballing in systematic literature studies and a replication in software engineering, In Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering, Association for Computing Machinery, New York, NY, USA, (2014), pp. 1–10. https://doi.org/10.1145/2601248.2601268.

[58] M. Nilashi, R. Zakaria, O. Ibrahim, M. Z. Abd. Majid, R. Mohamad Zin, M.W. Chugtai, N.I. Zainal Abidin, S.R. Sahamir, D. Aminu Yakubu, A knowledge-based expert system for assessing the performance level of green buildings, Knowledge-Based Systems. 86 (2015), pp. 194–209. https://doi.org/10.1016/j.knosys.2015.06.009.

[59] S. Mu, H. Cheng, M. Chohr, W. Peng, Assessing risk management capability of contractors in subway projects in mainland China, International Journal of Project Management. 32 (2014), pp. 452–460. https://doi.org/10.1016/j.ijproman.2013.08.007.

[60] S. Seo, T. Aramaki, Y. Hwang, K. Hanaki, Fuzzy Decision-Making Tool for Environmental Sustainable Buildings, Journal of Construction and Engineering Management. 130 (2004), pp. 415–423. https://doi.org/10.1061/(ASCE)0733-9364(2004)130:3(415).

[61] A. Vakili-Ardebili, A.H. Boussabaine, Application of fuzzy techniques to develop an assessment framework for building design eco-drivers, Building and Environment. 42 (2007), pp. 3785–3800. https://doi.org/10.1016/j.buildenv.2006.11.017.

[62] C.C. Wang, S.M. Sepasgozar, M. Wang, J. Sun, X. Ning, Green performance evaluation system for energy-efficiency-based planning for construction site layout, Energies. 12 (2019), pp. 4620. https://doi.org/10.3390/en12244620

[63] R. Bhatt, J.E.M. Macwan, Fuzzy logic and analytic hierarchy process–based conceptual model for sustainable commercial building assessment for India, Journal of Architectural Engineering. 22 (2016), pp. 04015009. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000184

[64] K. Figueiredo, R. Pierott, A.W. Hammad, A. Haddad, Sustainable material choice for construction projects: A life cycle sustainability assessment framework based on BIM and Fuzzy-AHP, Building and Environment. (2021), pp. 107805. https://doi.org/10.1016/j.buildenv.2021.107805

[65] S. Yin, B. Li, Matching management of supply and demand of green building technologies based on a novel matching method with intuitionistic fuzzy sets, Journal of Cleaner Production. 201 (2018), pp. 748–763. https://doi.org/10.1016/j.jclepro.2018.08.055.

[66] S. Yin, B. Li, Academic research institutes-construction enterprises linkages for the development of urban green building: Selecting management of green building technologies innovation partner, Sustainable Cities Society. 48 (2019), pp. 101555. https://doi.org/10.1016/j.scs.2019.101555

[67] S.R. Mohandes, X. Zhang, Developing a Holistic Occupational Health and Safety risk assessment model: An application to a case of sustainable construction project, Journal of Cleaner Production. 291 (2021), pp. 125934. https://doi.org/10.1016/j.jclepro.2021.125934

[68] S.M. Khoshnava, R. Rostami, A. Valipour, M. Ismail, A.R. Rahmat, Rank of green building material criteria based on the three pillars of sustainability using the hybrid multi criteria decision making method, Journal of Cleaner Production. 173 (2018), pp. 82–99. https://doi.org/10.1016/j.jclepro.2016.10.066

[69] E. Yadegaridehkordi, M. Hourmand, M. Nilashi, E. Alsolami, S. Samad, M. Mahmoud, A.A. Alarood, A. Zainol, H.D. Majeed, L. Shuib, Assessment of sustainability indicators for green building manufacturing using fuzzy multi-criteria decision making approach, Journal of Cleaner Production. 277 (2020), pp. 122905. https://doi.org/10.1016/j.jclepro.2020.122905

[70] Y.T. Negash, A.M. Hassan, M.-L. Tseng, K.-J. Wu, M.H. Ali, Sustainable construction and demolition waste management in Somaliland: Regulatory barriers lead to technical and environmental barriers, Journal of Cleaner Production. 297 (2021) pp. 126717. https://doi.org/10.1016/j.jclepro.2021.126717

[71] C.M. Tam, V.W.Y. Tam, W.S. Tsui, Green construction assessment for environmental management in the construction industry of Hong Kong, International Journal of Project Management. 22 (2004), pp. 563–571. https://doi.org/10.1016/j.ijproman.2004.03.001.

[72] T.L. Saaty, What is the Analytic Hierarchy Process?, in: G. Mitra, H.J. Greenberg, F.A. Lootsma, M.J. Rijkaert, H.J. Zimmermann (Eds.), In Mathematical Models for Decision Support, Springer, Berlin, Heidelberg, (1988): pp. 109–121. https://doi.org/10.1007/978-3-642-83555-1_5.

[73] T.L. Saaty, Decision making with dependence and feedback: The analytic network process, RWS publications Pittsburgh, USA, 4922 (1996). ISBN 0-9620317-9-8

[74] A. Gabus, E. Fontela, World problems, an invitation to further thought within the framework of DEMATEL, Battelle Geneva Res. Cent. Geneva Switz. (1972) 1–8.

[75] C.-L. Hwang, K. Yoon, Methods for multiple attribute decision making, In Multiple Attribute Decision Making, Lecture Notes in Economics and Mathematical Systems, Springer, Berlin, Heidelberg (1981): pp. 58–191. https://doi.org/10.1007/978-3-642-48318-9_3

[76] S. Opricovic, Multicriteria optimization of civil engineering systems, Faculty of Civil Engineering. University of Belgrade. 2 (1998), pp. 5–21.

[77] B. Wang, J. Song, J. Ren, K. Li, H. Duan, X. Wang, Selecting sustainable energy conversion technologies for agricultural residues: A fuzzy AHP-VIKOR based prioritization from life cycle perspective, Resources, Conservation and Recycling. 142 (2019), pp. 78–87. https://doi.org/10.1016/j.resconrec.2018.11.011.

[78] IBM, Big Data Analytics, (2021). https://www.ibm.com/analytics/hadoop/big-data-analytics (accessed November 19, 2021).

[79] A. Briga-Sá, D. Leitão, J. Boaventura-Cunha, F.F. Martins, Trombe wall thermal performance: Data mining techniques for indoor temperatures and heat flux forecasting, Energy and Buildings. 252 (2021), pp. 111407. https://doi.org/10.1016/j.enbuild.2021.111407

[80] J.C. Cheng, L.J. Ma, A data-driven study of important climate factors on the achievement of LEED-EB credits, Building and Environment. 90 (2015), pp. 232–244. https://doi.org/10.1016/j.buildenv.2014.11.029

[81] P. Palensky, D. Dietrich, Demand side management: Demand response, intelligent energy systems, and smart loads, IEEE Transactions on Industrial Informatics. 7 (2011), pp. 381–388. https://doi.org/10.1109/TII.2011.2158841.

[82] A. Kusiak, Smart manufacturing must embrace big data, Nature. 544 (2017), pp. 23–25. https://doi.org/10.1038/544023a

[83] B. Abediniangerabi, S.M. Shahandashti, A. Makhmalbaf, A data-driven framework for energy-conscious design of building facade systems, Journal of Building Engineering. 29 (2020), pp. 101172. https://doi.org/10.1016/j.jobe.2020.101172.

[84] O. Tatari, M. Kucukvar, Cost premium prediction of certified green buildings: A neural network approach, Building and Environment. 46 (2011), 1081–1086. https://doi.org/10.1016/j.buildenv.2010.11.009.

[85] H. Son, C. Kim, Early prediction of the performance of green building projects using pre-project planning variables: data mining approaches, Journal of Cleaner Production. 109 (2015), pp. 144–151. https://doi.org/10.1016/j.jclepro.2014.08.071.

[86] Y.-K. Juan, Y.-H. Hsu, X. Xie, Identifying customer behavioral factors and price premiums of green building purchasing, Industrial Marketing Management. 64 (2017), pp. 36–43. https://doi.org/10.1016/j.indmarman.2017.03.004.

[87] A. Yezioro, B. Dong, F. Leite, An applied artificial intelligence approach towards assessing building performance simulation tools, Energy and Buildings. 40 (2008), pp. 612–620. https://doi.org/10.1016/j.enbuild.2007.04.014

[88] W. Wang, Z. Tian, W. Xi, Y.R. Tan, Y. Deng, The influencing factors of China's green building development: An analysis using RBF-WINGS method, Building and Environment. 188 (2021), pp. 107425. https://doi.org/10.1016/j.buildenv.2020.107425.

[89] C. Ren, S.-J. Cao, Implementation and visualization of artificial intelligent ventilation control system using fast prediction models and limited monitoring data, Sustainable Cities and Society. 52 (2020), pp. 101860. https://doi.org/10.1016/j.scs.2019.101860

[90] J. Fernandez-Ceniceros, R. Fernandez-Martinez, E. Fraile-Garcia, F.J. Martinez-de-Pison, Decision support model for one-way floor slab design: A sustainable approach, Automation in Construction. 35 (2013), pp. 460–470. https://doi.org/10.1016/j.autcon.2013.06.002

[91] O. May Tzuc, O. Rodríguez Gamboa, R. Aguilar Rosel, M. Che Poot, H. Edelman, M. Jiménez Torres, A. Bassam, Modeling of hygrothermal behavior for green facade's concrete wall exposed to nordic climate using artificial intelligence and global sensitivity analysis, Journal of Building Engineering. 33 (2021), pp. 101625. https://doi.org/10.1016/j.jobe.2020.101625.

[92] A.C. Ganesh, M. Muthukannan, Development of high performance sustainable optimized fiber reinforced geopolymer concrete and prediction of compressive strength, Journal of Cleaner Production. 282 (2021), pp. 124543. https://doi.org/10.1016/j.jclepro.2020.124543

[93] A.A. Shahmansouri, M. Yazdani, S. Ghanbari, H. Akbarzadeh Bengar, A. Jafari, H. Farrokh Ghatte, Artificial neural network model to predict the compressive strength of eco-friendly geopolymer concrete incorporating silica fume and natural zeolite, Journal of Cleaner Production. 279 (2021), pp. 123697. https://doi.org/10.1016/j.jclepro.2020.123697.

[94] D. Bajno, A. Grzybowska, \Lukasz Bednarz, Old and Modern Wooden Buildings in the Context of Sustainable Development, Energies. 14 (2021), pp. 5975. https://doi.org/10.3390/en14185975

[95] Q. Wen, Z. Li, Y. Peng, B. Guo, Assessing the Effectiveness of Building Information Modeling in Developing Green Buildings from a Lifecycle Perspective, Sustainability. 12 (2020), pp. 9988. https://doi.org/10.3390/su12239988.

[96] F. Jalaei, F. Jalaei, S. Mohammadi, An integrated BIM-LEED application to automate sustainable design assessment framework at the conceptual stage of building projects, Sustainable Cities and Society. 53 (2020), pp. 101979. https://doi.org/10.1016/j.scs.2019.101979

[97] J.C. Cheng, L.J. Ma, A non-linear case-based reasoning approach for retrieval of similar cases and selection of target credits in LEED projects, Building and Environment. 93 (2015), pp. 349–361. https://doi.org/10.1016/j.buildenv.2015.07.019

[98] X. Chen, H. Yang, A multi-stage optimization of passively designed high-rise residential buildings in multiple building operation scenarios, Applied Energy. 206 (2017), pp. 541–557. https://doi.org/10.1016/j.apenergy.2017.08.204.

[99] J. Zhao, B. Lasternas, K.P. Lam, R. Yun, V. Loftness, Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining, Energy and Buildings. 82 (2014), pp. 341–355. https://doi.org/10.1016/j.enbuild.2014.07.033

[100] M.A. Jun, J.C. Cheng, Selection of target LEED credits based on project information and climatic factors using data mining techniques, Advances Engineering Informatics. 32 (2017), pp. 224–236. https://doi.org/10.1016/j.aei.2017.03.004

[101] A. Martínez-Rocamora, C. Rivera-Gómez, C. Galán-Marín, M. Marrero, Environmental benchmarking of building typologies through BIM-based combinatorial case studies, Automation in Construction. 132 (2021), pp. 103980. https://doi.org/10.1016/j.autcon.2021.103980

[102] J. Ma, J.C. Cheng, Identification of the numerical patterns behind the leading counties in the US local green building markets using data mining, Journal of Cleaner Production. 151 (2017), pp. 406–418. https://doi.org/10.1016/j.jclepro.2017.03.083

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

[104] X. Guo, K. Lee, Z. Wang, S. Liu, Occupants' satisfaction with LEED-and non-LEED-certified apartments using social media data, Building and Environment. 206 (2021), pp. 108288. https://doi.org/10.1016/j.buildenv.2021.108288

[105] X. Liu, W. Hu, Attention and sentiment of Chinese public toward green buildings based on Sina Weibo, Sustainable Cities and Society. 44 (2019), pp. 550–558. https://doi.org/10.1016/j.scs.2018.10.047

[106] J. Ma, J.C. Cheng, Data-driven study on the achievement of LEED credits using percentage of average score and association rule analysis, Building and Environment. 98 (2016), pp. 121–132. https://doi.org/10.1016/j.buildenv.2016.01.005

[107] X. Zhao, Y. Tan, L. Shen, G. Zhang, J. Wang, Case-based reasoning approach for supporting building green retrofit decisions, Building and Environment. 160 (2019), pp. 106210. https://doi.org/10.1016/j.buildenv.2019.106210.

[108] M.W. Gardner, S.R. Dorling, Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences, Atmospheric Environment. 32 (1998), pp. 2627–2636. https://doi.org/10.1016/S1352-2310(97)00447-0

[109] C. Cortes, V. Vapnik, Support-vector networks, Machine Learning. 20 (1995), pp. 273–297. https://doi.org/10.1007/BF00994018

[110] D. Delen, G. Walker, A. Kadam, Predicting breast cancer survivability: a comparison of three data mining methods, Artificial Intelligence in Medicine. 34 (2005), pp. 113–127. https://doi.org/10.1016/j.artmed.2004.07.002.

[111] S. Liu, X. Meng, C. Tam, Building information modeling based building design optimization for sustainability, Energy and Buildings. 105 (2015), pp. 139–153. https://doi.org/10.1016/j.enbuild.2015.06.037

[112] Y. Wang, C. Wei, Design optimization of office building envelope based on quantum genetic algorithm for energy conservation, Journal of Building Engineering. 35 (2021), pp. 102048. https://doi.org/10.1016/j.jobe.2020.102048.

[113] T.M. Echenagucia, A. Capozzoli, Y. Cascone, M. Sassone, The early design stage of a building envelope: Multi-objective search through heating, cooling and lighting energy performance analysis, Applied Energy. 154 (2015), pp. 577–591. https://doi.org/10.1016/j.apenergy.2015.04.090

[114] Y.-H. Lin, M.-D. Lin, K.-T. Tsai, M.-J. Deng, H. Ishii, Multi-objective optimization design of green building envelopes and air conditioning systems for energy conservation

and CO2 emission reduction, Sustainable Cities and Society. 64 (2021), pp. 102555. https://doi.org/10.1016/j.scs.2020.102555

[115] A. Karatas, K. El-Rayes, Optimizing tradeoffs among housing sustainability objectives, Automation in Construction. 53 (2015), pp. 83–94. https://doi.org/10.1016/j.autcon.2015.02.010

[116] S. Wang, Y.K. Yi, N. Liu, Multi-objective optimization (MOO) for high-rise residential buildings' layout centered on daylight, visual, and outdoor thermal metrics in China, Building and Environment. 205 (2021), pp. 108263. https://doi.org/10.1016/j.buildenv.2021.108263

[117] P. Inyim, J. Rivera, Y. Zhu, Integration of building information modeling and economic and environmental impact analysis to support sustainable building design, Journal of Management in Engineering. 31 (2015), pp. A4014002. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000308

[118] P. Wang, Z. Liu, D. Chen, W. Li, L. Zhang, Experimental study and multi-objective optimisation of a novel integral thermoelectric wall, Energy and Buildings. 252 (2021), pp. 111403. https://doi.org/10.1016/j.enbuild.2021.111403

[119] S. Lee, K.S. Lee, Optimization of Apartment-Complex Layout Planning for Daylight Accessibility in a High-Density City with a Temperate Climate, Energies. 13 (2020), pp. 4172. https://doi.org/10.3390/en13164172

[120] C. Kasinalis, R.C. Loonen, D. Cóstola, J.L.M. Hensen, Framework for assessing the performance potential of seasonally adaptable facades using multi-objective optimization, Energy and Buildings. 79 (2014), pp. 106–113. https://doi.org/10.1016/j.enbuild.2014.04.045

[121] M. Marzouk, S. Azab, M. Metawie, BIM-based approach for optimizing life cycle costs of sustainable buildings, Journal of Cleaner Production. 188 (2018), pp. 217–226. https://doi.org/10.1016/j.jclepro.2018.03.280.

[122] G. Platt, J. Li, R. Li, G. Poulton, G. James, J. Wall, Adaptive HVAC zone modeling for sustainable buildings, Energy and Buildings. 42 (2010), pp. 412–421. https://doi.org/10.1016/j.enbuild.2009.10.009.

[123] W. Lin, Z. Ma, C. McDowell, Y. Baghi, B. Banfield, Optimal design of a thermal energy storage system using phase change materials for a net-zero energy Solar Decathlon house, Energy and Buildings. 208 (2020), pp. 109626. https://doi.org/10.1016/j.enbuild.2019.109626

[124] X. Chen, H. Yang, K. Sun, A holistic passive design approach to optimize indoor environmental quality of a typical residential building in Hong Kong, Energy. 113 (2016), pp. 267–281. https://doi.org/10.1016/j.energy.2016.07.058

[125] M.R. Asl, S. Zarrinmehr, M. Bergin, W. Yan, BPOpt: A framework for BIM-based performance optimization, Energy and Buildings. 108 (2015), pp. 401–412. https://doi.org/10.1016/j.enbuild.2015.09.011

[126] Y.-K. Juan, P. Gao, J. Wang, A hybrid decision support system for sustainable office building renovation and energy performance improvement, Energy and Buildings. 42 (2010), pp. 290–297. https://doi.org/10.1016/j.enbuild.2009.09.006

[127] Y. Fan, X. Xia, Building retrofit optimization models using notch test data considering energy performance certificate compliance, Applied Energy. 228 (2018), pp. 2140–2152. https://doi.org/10.1016/j.apenergy.2018.07.043

[128] N. Elshaboury, M. Marzouk, Optimizing construction and demolition waste transportation for sustainable construction projects, Engineering, Construction and Architectural Management. 28 (2020), pp. 2411-2425. https://doi.org/10.1108/ECAM-08-2020-0636

[129] S. Naji, L. Aye, M. Noguchi, Multi-objective optimisations of envelope components for a prefabricated house in six climate zones, Applied Energy. 282 (2021), pp. 116012. https://doi.org/10.1016/j.apenergy.2020.116012
[130] R. Chasta, R. Singh, A. Gehlot, R.G. Mishra, S. Choudhury, A smart building automation system, International Journal of Smart Home. 10 (2016), pp. 91–98. http://dx.doi.org/10.14257/ijsh.2016.10.8.10
[131] J. Zhu, Y. Shen, Z. Song, D. Zhou, Z. Zhang, A. Kusiak, Data-driven building load profiling and energy management, Sustainable Cities and Society. 49 (2019), pp. 101587. https://doi.org/10.1016/j.scs.2019.101587
[132] W.H. Allen, A. Rubaai, R. Chawla, Fuzzy neural network-based health monitoring for HVAC system variable-air-volume unit, IEEE Transactions on Industry Applications. 52 (2015), pp. 2513–2524. https://doi.org/10.1109/TIA.2015.2511160
[133] S. Atis, N. Ekren, Development of an outdoor lighting control system using expert system, Energy and Buildings. 130 (2016), pp. 773–786. https://doi.org/10.1016/j.enbuild.2016.08.066
[134] K. Yan, W. Shen, T. Mulumba, A. Afshari, ARX model based fault detection and diagnosis for chillers using support vector machines, Energy and Buildings. 81 (2014), pp. 287–295. https://doi.org/10.1016/j.enbuild.2014.05.049
[135] H. Park, D.Y. Park, Comparative analysis on predictability of natural ventilation rate based on machine learning algorithms, Building and Environment. 195 (2021), pp. 107744. https://doi.org/10.1016/j.buildenv.2021.107744
[136] L. Yang, Z. Nagy, P. Goffin, A. Schlueter, Reinforcement learning for optimal control of low exergy buildings, Applied Energy. 156 (2015), pp. 577–586. https://doi.org/10.1016/j.apenergy.2015.07.050
[137] D. Gonçalves, Y. Sheikhnejad, M. Oliveira, N. Martins, One step forward toward smart city Utopia: Smart building energy management based on adaptive surrogate modelling, Energy and Buildings. 223 (2020), pp. 110146. https://doi.org/10.1016/j.enbuild.2020.110146
[138] P. Westermann, M. Welzel, R. Evins, Using a deep temporal convolutional network as a building energy surrogate model that spans multiple climate zones, Applied Energy. 278 (2020), pp. 115563. https://doi.org/10.1016/j.apenergy.2020.115563
[139] Z. Ding, W. Chen, T. Hu, X. Xu, Evolutionary double attention-based long short-term memory model for building energy prediction: Case study of a green building, Applied Energy. 288 (2021), pp. 116660. https://doi.org/10.1016/j.apenergy.2021.116660
[140] Q. Li, R. Long, H. Chen, F. Chen, J. Wang, Visualized analysis of global green buildings: Development, barriers and future directions, Journal of Cleaner Production. 245 (2020), pp. 118775. https://doi.org/10.1016/j.jclepro.2019.118775.
[141] S.J. Raudys, A.K. Jain, Small sample size effects in statistical pattern recognition: Recommendations for practitioners, IEEE Transactions on Pattern Analysis and Machine Intelligence. 13 (1991), pp. 252–264. https://doi.org/10.1109/ICPR.1990.118138
[142] University of Alabama, Sample Size in Machine Learning and Artificial Intelligence – Perioperative Data Science, (2021). https://sites.uab.edu/periop-datascience/2021/06/28/sample-size-in-machine-learning-and-artificial-intelligence/ (accessed November 23, 2021).
[143] I. Balki, A. Amirabadi, J. Levman, A.L. Martel, Z. Emersic, B. Meden, A. Garcia-Pedrero, S.C. Ramirez, D. Kong, A.R. Moody, P.N. Tyrrell, Sample-Size Determination Methodologies for Machine Learning in Medical Imaging Research: A Systematic Review, Canadian Association of Radiologists Journal. 70 (2019), pp. 344–353. https://doi.org/10.1016/j.carj.2019.06.002.

[144] C.N. Egwim, H. Alaka, L.O. Toriola-Coker, H. Balogun, F. Sunmola, Applied artificial intelligence for predicting construction projects delay, Machine Learning with Applications. 6 (2021), pp. 100166. https://doi.org/10.1016/j.mlwa.2021.100166.

[145] E. Zarghami, H. Azemati, D. Fatourehchi, M. Karamloo, Customizing well-known sustainability assessment tools for Iranian residential buildings using Fuzzy Analytic Hierarchy Process, Building and Environment. 128 (2018), pp. 107–128. https://doi.org/10.1016/j.buildenv.2017.11.032.

[146] M.R. Hallowell, J.A. Gambatese, Qualitative Research: Application of the Delphi Method to CEM Research, Journal of Construction Engineering and Management. 136 (2010), pp. 99–107. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000137.

[147] T. Krueger, T. Page, K. Hubacek, L. Smith, K. Hiscock, The role of expert opinion in environmental modelling, Environmental Modelling & Software. 36 (2012), pp. 4–18. https://doi.org/10.1016/j.envsoft.2012.01.011

[148] S.N. Sivanandam, S. Sumathi, S.N. Deepa, Introduction to fuzzy logic using MATLAB, Springer Berlin Heidelberg New York, (2007). ISBN-10 3-540-35780-7

[149] S.O. Abioye, L.O. Oyedele, L. Akanbi, A. Ajayi, J.M. Davila Delgado, M. Bilal, O.O. Akinade, A. Ahmed, Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges, Journal of Building Engineering. 44 (2021), pp. 103299. https://doi.org/10.1016/j.jobe.2021.103299.

[150] Y. Duan, J.S. Edwards, Y.K. Dwivedi, Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda, International Journal of Information Management. 48 (2019), pp. 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021.

[151] P. McAleenan, Moral responsibility and action in the use of artificial intelligence in construction, Proceedings of Institution of Civil Engineers - Management, Procurement and Law. 173 (2020), pp. 166–174. https://doi.org/10.1680/jmapl.19.00056.

[152] N.V. Chawla, K.W. Bowyer, L.O. Hall, W.P. Kegelmeyer, SMOTE: synthetic minority over-sampling technique, Journal of Artificial Intelligence Research. 16 (2002), 321–pp. 357. https://doi.org/10.1613/jair.953

[153] I. Guyon, A. Elisseeff, An introduction to variable and feature selection, Journal of Machine Learning Research. 3 (2003), pp. 1157–1182. https://psycnet.apa.org/doi/10.1162/153244303322753616

[154] S.G.K. Patro, K.K. Sahu, Normalization: A Preprocessing Stage, ArXiv150306462 Cs. (2015). http://arxiv.org/abs/1503.06462 (accessed November 24, 2021).

[155] Q. Min, Y. Lu, Z. Liu, C. Su, B. Wang, Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry, International Journal of Information Management. 49 (2019), pp. 502–519. https://doi.org/10.1016/j.ijinfomgt.2019.05.020.

[156] S. Underwood, Blockchain beyond bitcoin, Communication of the ACM. 59 (2016), pp. 15–17. https://doi.org/10.1145/2994581.

[157] M. Crosby, P. Pattanayak, S. Verma, V. Kalyanaraman, Blockchain technology: Beyond bitcoin, Applied Innovation Review. 2 (2016), pp. 71-90.

[158] A. Shojaei, J. Wang, A. Fenner, Exploring the feasibility of blockchain technology as an infrastructure for improving built asset sustainability, Built Environment Project and Asset Management. 10 (2019), pp. 184–199. https://doi.org/10.1108/BEPAM-11-2018-0142.

[159] B. Panda, S.C. Paul, L.J. Hui, Y.W.D. Tay, M.J. Tan, Additive manufacturing of geopolymer for sustainable built environment, Journal of Cleaner Production. 167 (2017), pp. 281–288. https://doi.org/10.1016/j.jclepro.2017.08.165

[160] R. Parveen, Artificial intelligence in construction industry: Legal issues and regulatory challenges, International Journal of Civil Engineering and Technology. 9 (2018), pp. 957–62. https://doi.org/10.IJCIET_09_13_096
[161] V. Marinakis, H. Doukas, C. Karakosta, J. Psarras, An integrated system for buildings' energy-efficient automation: Application in the tertiary sector, Applied Energy. 101 (2013), pp. 6–14. https://doi.org/10.1016/j.apenergy.2012.05.032
[162] W. Wu, R.R. Issa, BIM execution planning in green building projects: LEED as a use case, Journal of Management in Engineering. 31 (2015), pp. A4014007. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000314