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Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities

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Abstract

The Architecture, Engineering and Construction (AEC) industry is fraught with complex and difficult problems. Artificial intelligence (AI) represents a powerful tool to assist in addressing these problems. Therefore, over the years, researchers have been conducting research on AI in the AEC industry (AI-in-the-AECI). In this paper, the first comprehensive scientometric study appraising the state-of-the-art of research on AI-in-the-AECI is presented. The science mapping method was used to systematically and quantitatively analyze 41,827 related bibliographic records retrieved from Scopus. The results indicated that genetic algorithms, neural networks, fuzzy logic, fuzzy sets, and machine learning have been the most widely used AI methods in AEC. Optimization, simulation, uncertainty, project management and bridges have been the most commonly addressed topics/issues using AI methods/concepts. The primary value and uniqueness

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of this study lies in it being the first in providing an up-to-date inclusive, big picture of the literature on AI-in-the-AECI. This study adds value to the AEC literature through visualizing and understanding trends and patterns, identifying main research interests, journals, institutions, and countries, and how these are linked within now-available studies on AI-in-the-AECI. The findings bring to light the deficiencies in the current research and provide paths for future research, where they indicated that future research opportunities lie in applying robotic automation and convolutional neural networks to AEC problems. For the world of practice, the study offers a readily-available point of reference for practitioners, policy makers, and research and development (R&D) bodies. This study therefore raises the level of awareness of AI and facilitates building the intellectual wealth of the AI area in the AEC industry.

Keywords: Architecture-Engineering-Construction; Artificial intelligence; Machine intelligence; Industry 4.0; Automation; Digital transformation; Scientometric; Review.

1. Introduction

Artificial intelligence (AI) is playing a core role in the Fourth Industrial Revolution (Industry 4.0), i.e., the digitalization era, wherein intelligent systems and technologies are used to create an active connection between the physical and virtual (digital) worlds. AI denotes the science and engineering of creating intelligent machines that exhibit reasoning, learning, knowledge, communication, perception, planning, and the ability to move and operate objects [1]. It has several benefits that have been widely documented in the literature. For instance, it can use sophisticated algorithms to "learn" from "big" data, and then use the knowledge gained to assist industry/practice [2]. Moreover, AI provides vast opportunities for significant productivity improvements via analyzing large volumes of data quickly and accurately [3]. Additionally, AI systems and technologies can tackle complicated, nonlinear practical problems and, once trained, could undertake predictions and generalizations at high speed [4].

Because of these benefits, AI has attracted substantial attention within a wide range of industries, including Architecture, Engineering and Construction (AEC) [4], capturing the attention of AEC researchers. This has resulted in an upsurge in the number of research works and publications on AI in the AEC industry (AI-in-the-AECI) [5]. This situation presents danger, as it makes it tough to grasp the status quo of the knowledge body, posing a major risk of neglecting essential areas and questions for research and practice improvement [6]. To address this scientific problem, undertaking a rigorous review and analysis of the domain is necessary.

Previous review studies in this area [7–10] have made valuable contributions. Nonetheless, they have some limitations. First, they have been qualitative and based on manual appraisals. Thus, they may be significantly impacted by subjective biases, lack of reproducibility, and reduced reliability [11]. Ref. [12] indicated that manual reviews examine the "trees", but do not provide a broad overview of the "forest". Second, existing review studies have had narrowed perspectives, focusing on limited applications or on specific AI methods. For example, Ref. [10] focused on "big" data technologies application in the AEC industry; while Ref. [9] focused on automation in construction scheduling. Ref. [13] recently published a bibliometric study of engineering applications of AI. However, their study is limited to only the publications in one single journal and gives an overview of what has already been done without providing directions for future work. In the light of these facts, these review studies do not afford a full picture of the state-of-the-art of research on AI-in-the-AECI. In fact, a study that offers a complete picture and understanding of the AI literature in the specific domain of AEC is still missing.

As an attempt to fill this gap, the present review study stands out, being the first to comprehensively survey the intellectual core and the landscape of the general body of knowledge on AI-in-the-AECI using a quantitative technique. This study contributes to the field in several ways by: identifying the scope and assessing the quality of the existing body of knowledge; detecting omissions and deficiencies; and determining where best to focus future research efforts. In practical terms, the study serves as a valuable and up-to-date reference point for enhancing the knowledge of policy makers and practitioners and assisting them in planning and funding efforts regarding adopting

AI-in-the-AECI.

2. Research methodology

The present study used the science mapping method to analyze the literature on AI-in-the-AECI. Science mapping, "a generic process of domain analysis and visualization" [14], aims at detecting the intellectual structure of a scientific domain. This method is helpful for visualizing significant patterns and trends in a large body of literature and bibliographic data [15]. It allows researchers to make literature-related discoveries that would not be possible through other methods [16]. A science mapping study typically applies a bibliometric or a scientometric analysis method [17]. While the focus of bibliometric analysis is on the literature per se, scientometric analysis offers a broader approach, which comprises bibliometric tools, methods, and data, to analyze the literature and its outputs to recognize the domain's potentially insightful patterns and trends [18]. The research methodology was structured to comprise the following phases: science mapping tools selection, data collection and analysis, modeling, visualization, and communication of findings.

2.1. Science mapping tools selection

Several science mapping tools exist, with each tool having its own strengths and capabilities. Consequently, to thoroughly examine any domain, appropriate use of different tools for different kinds of analyses is necessary [15]. In this research, the strengths and weaknesses of various science mapping tools, including VOSviewer®, Gephi®, CiteSpace®, Sci2®, and HistCite® [14], were evaluated, leading to selecting VOSviewer, Gephi, and CiteSpace. VOSviewer is a software tool that offers the basic functionality required for producing, visualizing, and exploring bibliometric networks [19]. Gephi represents a leading, open-source "all kinds of graphs and networks" exploration, visualization, and manipulation software tool that can be utilized to provide in-depth insight into the information attainable from a specific graph or network [20]. CiteSpace, a software tool "developed to meet the needs for visual analytic tasks of science mapping" [14], affords opportunity for addressing important questions about a knowledge domain: what the major research interests are, and how these are linked [21]. Information on the technical applications of the VOSviewer, Gephi, and CiteSpace can be found in Refs. [19], [22], and [21], respectively.

2.2. Data collection

This study analyzed bibliographic data collected from Scopus, rather than those from other databases, such as the Web of Science and Google Scholar. The rationale behind this is that compared to the other databases, Scopus has a wider range of scientific publication coverage [23]. Similarly, Scopus has a relatively faster indexing process, escalating the possibility of more recent publications retrieval [24]. This study could not use a combination of different literature databases particularly because of the difficulty in checking and eliminating duplications of publications from the various databases, with the large amount of dataset involved – and many previous science mapping-based studies have been based on Scopus data [25]. Keywords were selected following related previous review studies [4,8,26]. As a result, a list of keywords related to AI was created. These keywords along with the keywords "construction industry", "civil engineering", "structural engineering", "architectural engineering", "construction engineering", "construction management", and "construction engineering and management" were used for the literature search, with the query string being:

"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 "Robotics" OR "Knowledge-based systems" OR "Support vector machines" OR "Artificial general intelligence" OR "Computational intelligence" AND "Construction industry" OR "Civil engineering" OR "Structural engineering" OR "Architectural engineering" OR "Construction engineering" OR "Construction management" OR "Construction engineering and management" AND (LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (DOCTYPE, "ar")).

While the use of the keyword "construction industry" has become more popular of late, in the past, keywords "civil engineering" and "structural engineering" were more commonly used for topics related to the AEC industry [27,28], thus the inclusion of these keywords in the literature search, helping to adequately cover the related areas of this study. The literature search in Scopus using the selected search keywords was performed on the title, abstract, and keywords sections of publications; no "date range" limit was set and the "document type" was limited to "article". The rationale for limiting the document type to articles is that, for science mapping purpose, journal articles represent the most influential and reputable research work [29]. Including all publication types adds noise to the data, making analyzing and interpreting the findings "challenging and costly" [17].

As of August 26, 2019, 49,686 publications were initially identified. Scopus was used to sort these upon "relevance", and after assessing them and excluding irrelevant publications, e.g., publications in unrelated journals, 41,827 relevant publications were finally identified for further analysis. All bibliographic data for the 41,827 publications were extracted and downloaded from Scopus, forming the dataset for the present study. It should be noted that non-English language publications are outside the scope of this study.

2.3. Scientometric techniques

Science mapping was conducted in two stages. The first stage involved constructing networks through keywords co-occurrence analysis, document co-citation analysis, citation burst analysis, outlets direct citation analysis, and co-authorship analysis, as explained in the next section. The second stage involved generating maps for mining useful information from network measures, and to display “the conceptual, intellectual, or social evolution of the research field, discovering patterns, trends, seasonality, and outliers” [15].

3. Analysis and results

3.1. Trend of research on AI-in-the-AECI: the 20th and the 21st centuries

The AI research field in general was born in 1956; whereas the first study on AI-in-the-AECI appears to be Ref. [30]’s work, published in the *Computer-Aided Design* journal, where computer applications to architecture were studied. This implies that research regarding AI-in-the-AECI has been around since the 1970s. Fig. 1 shows the trend in research publications on AI-in-the-AECI from 1974 to 2019. It reveals a steady and gradual increase in interest in research about AI-in-the-AECI from 1974 onward. Compared to the 20th century (1974-2000, in Fig. 1), many more publications are available in the 21st century (2001-2019). This is in line with the argument by Ref. [31] that AI has become an increasingly important research field in the 21st century. The increasing need for the AEC industry to process huge amounts of heterogeneous data to extract useful insights for better decisions and state-of-the-art improvements on problems/tasks [10] also provides explanation for the rising interest in AI-in-the-AECI in this 21st century. Essentially, the increasing publication trend appears promising, suggesting growth in research on AI-in-the-AECI, as also concluded by Ref. [8]. This growth is likely to continue as AI – along with the Internet of Things (IoT) – is progressively permeating the field [32]. In the 20th century, AI-in-the-AECI research started gaining its momentum only in the late 1990s, where computational power and researchers' commitment to using AI for solving more specific problems in a broad spectrum of areas begun to increase [33]. This might have caused the mini-peak in the number of publications in 1996, which was not beaten until 2001, the start of the 21st century, where it has been observed that AI-in-the-AECI research is gaining even more attention.

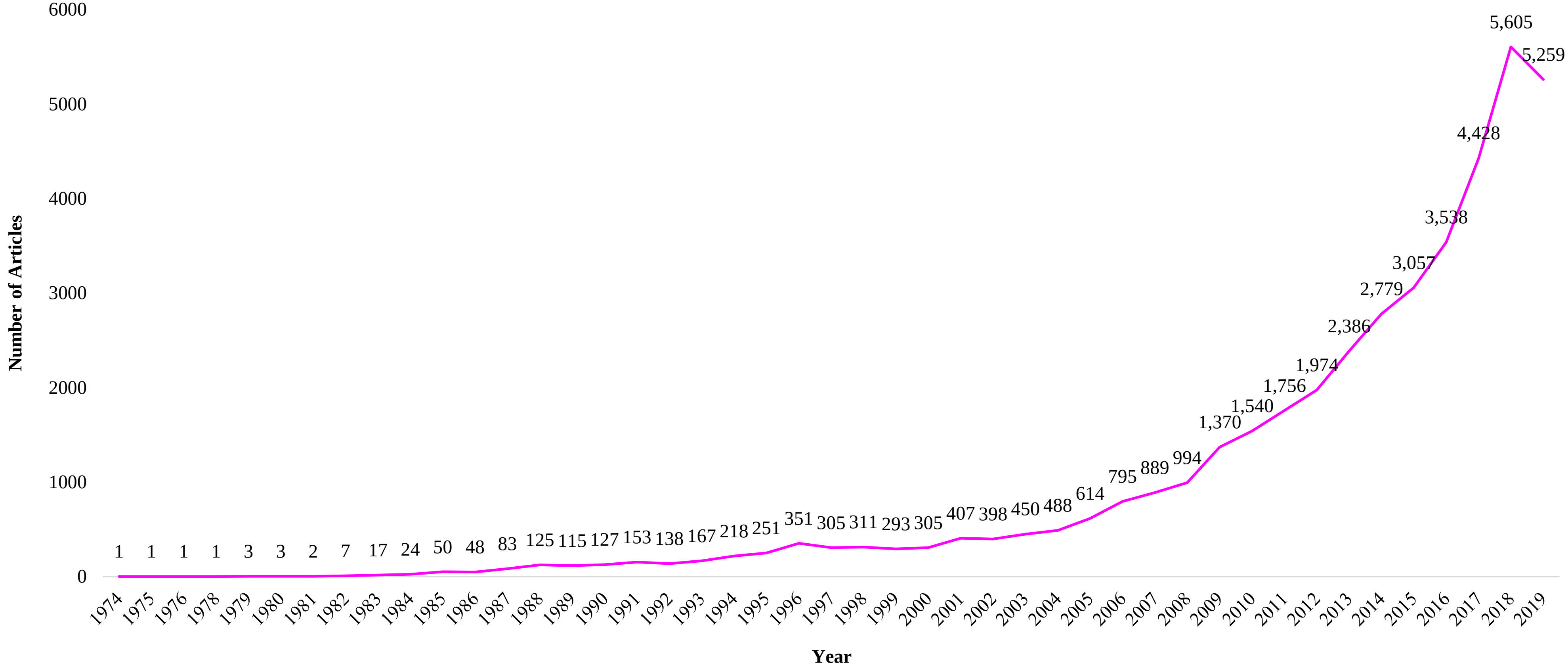

Fig. 1. Trend in research publications on AI-in-the-AECI (1974–Aug 2019). The 2019 publications number may increase at the end of the year.

3.2. Structure of the body of knowledge on AI-in-the-AECI

3.2.1. Main research interests: keywords co-occurrence analysis

As Ref. [26] noted, analyzing keywords affords an opportunity for discerning the main research interests in any field. A network of keywords offers a good picture of a knowledge domain, providing an understanding of the existing research interests, and how they are intellectually connected and organized [34]. Thus, a keywords co-occurrence network was produced using VOSviewer 1.6.11 software. Co-occurrence could simply be defined as the situation where two things (keywords in this case) occur at the same time. A typical co-occurrence network of keywords consists of nodes (representing the keywords) and edges (representing relations among sets of keywords). These descriptions apply to other networks later on, substituting keywords with journals, institutions, or countries, and the co-occurrence relations with direct citation relations, co-citation relations, or co-authorship relations. As networks of these relations are usually weighted networks, edges indicate not only relations among nodes but also the strengths or weights of the relations [34]. In a keyword co-occurrence network, for example, the strength of the relation between two keywords is computed based on the number of publications in which the keywords occur together, reflecting the affiliation of their respective research interests [19].

To attain a reproducible/readable picture of the keywords, author keywords, rather than all keywords, were used. Although this approach has been widely used in previous science mapping-based studies [6,13,17,25], its limitation is that it is largely reliant on authors' experience and knowledge in choosing appropriate research keywords. This limitation could be addressed in future work by using all keywords instead of author keywords, while attempts to address it in the present study led to unmanageable/illegible network because of the large amount of dataset and thus keywords. Based on the fractional counting, a total of 45,790 keywords were extracted from the dataset. Fractional counting represents a counting method that provides convenience for reducing the impact of publications with many authors, in co-authorship analysis [19]. Regarding the "minimum number of occurrences" for a keyword to be included in the network, a value of 50 was selected, an inclusion criterion met by 147 of the 45,790 keywords. This criterion was selected following previous studies [25] and based upon multiple experiments to generate the optimum, controllable, legible, and reproducible, network. Other criterion selections in this research were based on this same approach.

Identical terms (e.g., safety and construction safety; BIM and Building Information Modeling; regression and regression analysis) were merged (as safety, BIM, and regression, respectively) and generic keywords related to research methods (e.g., survey) were omitted. The resultant network consisted of 106 nodes and 1,654 relations, as displayed in Fig. 2. This figure therefore illustrates the main research interests on AI-in-the-AECI, reflected in terms of co-occurrence between AI keywords and keywords representing various areas of AEC research. Some keywords, for example, concrete and reinforced concrete were not merged because concrete covers a range of different types, such as reinforced concrete, plain concrete, glass concrete, etc. [35]. The presence of reinforced concrete as well as the absence of the other types of concrete in the network suggest that compared to the other types of concrete, reinforced concrete has received relatively more attention in the field. Other examples involve the keywords monte Carlo simulation, system dynamics, and finite element analysis, which are some of the different types of simulation [36]; energy efficiency and energy consumption, which are some of the different energy-related issues; shear strength and compressive strength, which are some of the different types of mechanical properties; etc. This rationale for not merging such keywords was adopted from Ref. [37].

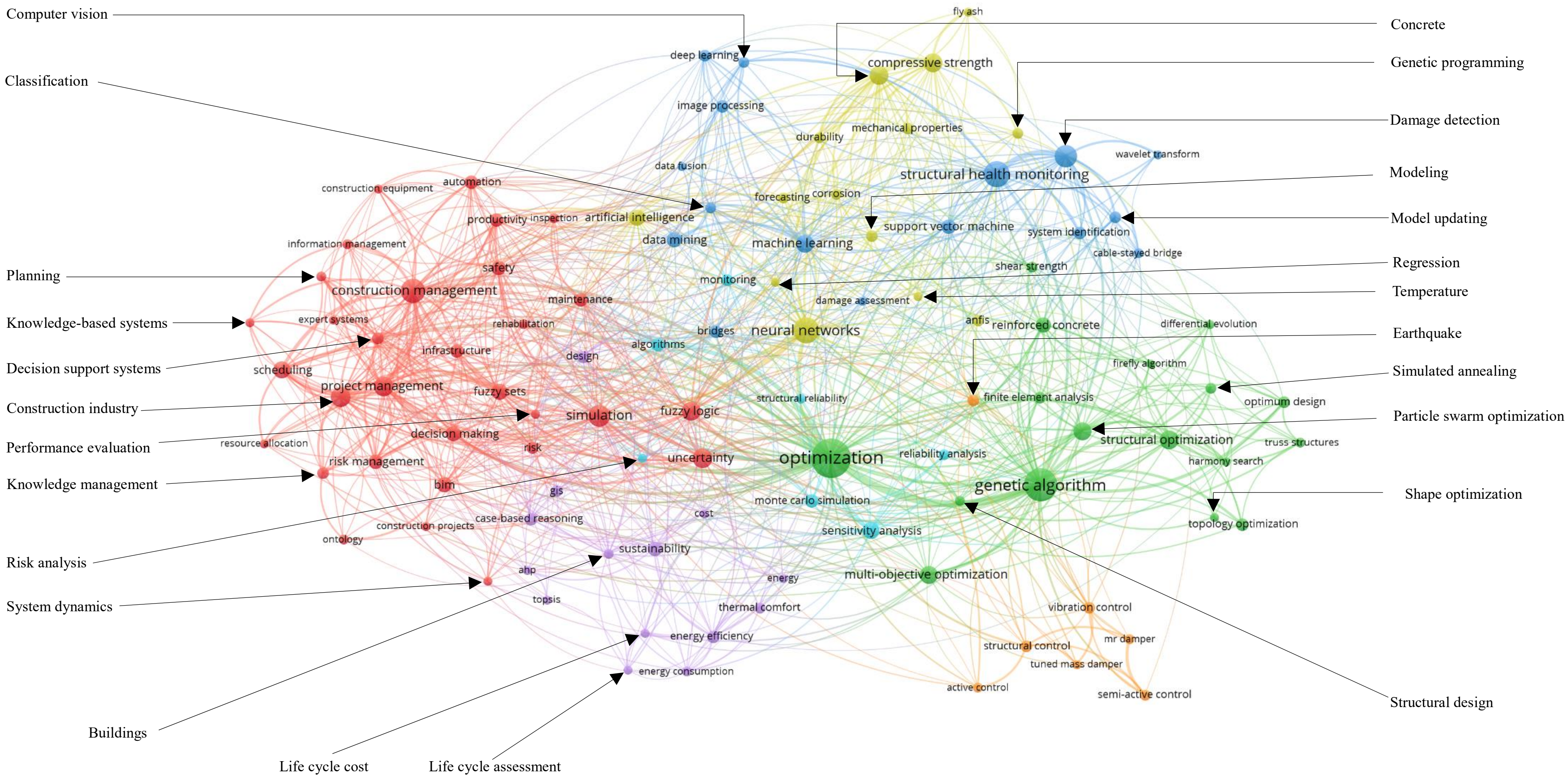

Fig. 2. Main research interests on AI-in-the-AECI (co-occurrence network of keywords).

The measurement of the centrality of nodes represents the most reliable and simplest approach to detecting what is crucial within a network [38]. Centrality can be measured via computing degree centrality, which reflects the number of relations a node has to other nodes [17]. Calculating importance based on the number of relations helps to determine the influence of a node upon other nodes. Regardless of the value of all existing relations, degree centrality is computed using Equation 1 [38].

$$D_i = \sum_{j=1}^{n} X_{ij} \qquad \text{Equation 1}$$

Where D_i = degree centrality value for node i; X_{ij} = sum of all relations between node i and node j; and n = total number of nodes in the network. The network was submitted to Gephi 0.9.2 for calculating the centrality of nodes. The analysis results are shown in Table 1. The main research interests were ranked based upon the degree centrality values. The higher the degree centrality value, the more influential the research area, and where two or more research interests have equal value, the one with the highest betweenness centrality value is deemed more influential. The betweenness centrality metric "indicates influential nodes for highest values" [22], by evaluating how often a node appears on the shortest paths between nodes in the network.

Table 1

Relative influence of existing research interests on AI-in-the-AECI.

Research areas	Degree centrality	Betweenness centrality	Relative influence
Optimization	89	440.41	1
Genetic algorithm	80	338.68	2
Neural networks	72	196.63	3

Simulation	65	141.53	4
Uncertainty	64	157.29	5
Construction management*	58	100.56	6
Fuzzy logic	54	119.16	7
Fuzzy sets	54	100.66	8
Machine learning	53	112.53	9
Artificial intelligence	51	80.59	10
Project management	51	59.70	11
Bridges	49	95.56	12
Decision making	47	41.75	13
Particle swarm optimization	45	91.05	14
Sensitivity analysis	45	90.76	15
Algorithms	45	57.61	16
Design	45	53.35	17
Maintenance	44	39.65	18
Multi-objective optimization	43	83.97	19
Structural health monitoring	43	61.19	20
Infrastructure	43	50.63	21
Support vector machine	42	54.36	22
Risk management	42	39.19	23
Damage detection	41	55.86	24
Construction industry*	41	34.27	25
Concrete	40	41.73	26
Data mining	39	45.01	27
Productivity	39	25.51	28
Structural optimization	38	53.68	29
Sustainability	38	42.65	30
Monitoring	38	36.39	31
Safety	38	28.78	32
Modeling	37	50.40	33
Risk	37	22.87	34
Reinforced concrete	36	39.96	35
BIM	36	39.54	36
Inspection	36	24.04	37
Decision support systems	35	14.27	38
Automation	34	25.58	39
Classification	34	24.01	40
Scheduling	34	23.18	41

Buildings	33	34.94	42
Earthquake	32	30.92	43
Corrosion	30	26.67	44
Case-based reasoning	30	22.19	45
Compressive strength	29	27.59	46
Damage assessment	29	18.12	47
Regression	28	17.97	48
Rehabilitation	28	13.67	49
Information management	28	12.17	50
Planning	28	8.13	51
Monte Carlo simulation	27	18.93	52
GIS	27	16.93	53
Performance evaluation	27	16.35	54
Structural control	26	19.09	55
Vibration control	26	17.63	56
Forecasting	26	15.16	57
Energy efficiency	26	15.05	58
System identification	26	11.16	59
Image processing	25	12.53	60
Expert systems	25	6.86	61
Deep learning	24	10.37	62
Cost	24	6.67	63
Construction equipment	24	6.29	64
Reliability analysis	23	15.30	65
Finite element analysis	23	15.11	66
Cable-stayed bridge	23	11.17	67
Energy consumption	23	10.78	68
Knowledge-based systems	23	10.64	69
Data fusion	23	8.45	70
Resource allocation	23	6.21	71
Structural design	22	23.86	72
Durability	22	11.83	73
TOPSIS	22	10.78	74
Knowledge management	22	9.30	75
Model updating	22	8.38	76
Computer vision	22	7.66	77
Structural reliability	22	7.62	78
Shear strength	21	9.28	79

Harmony search	20	12.93	80
Genetic programming	20	12.60	81
Firefly algorithm	20	8.28	82
Differential evolution	20	7.86	83
ANFIS	20	7.83	84
System dynamics	20	6.27	85
Risk analysis	20	5.44	86
Energy	19	9.04	87
Thermal comfort	19	8.99	88
Life cycle cost	19	8.22	89
Tuned mass damper	18	8.51	90
Temperature	18	8.46	91
Simulated annealing	18	7.78	92
Construction projects	18	5.59	93
AHP	18	2.48	94
Optimum design	16	5.38	95
Active control	16	4.91	96
MR damper	15	4.94	97
Life cycle assessment	15	4.25	98
Wavelet transform	15	2.39	99
Topology optimization	14	4.97	100
Mechanical properties	14	3.72	101
Shape optimization	13	3.16	102
Truss structures	12	2.43	103
Semi-active control	12	1.20	104
Ontology	11	1.29	105
Fly ash	9	0.77	106

Note: BIM = Building information modeling; GIS = Geographic information system; TOPSIS = Technique for Order of Preference by Similarity to Ideal Solution; ANFIS = Adaptive neuro-fuzzy inference system; AHP = Analytic hierarchy process; MR damper = Magnetorheological damper; * Construction management, in this study, refers to "a professional service which utilizes project management techniques to oversee the design, planning, and construction of a project from its start to its end" [39]; whereas construction industry refers to "those individuals, or groups whose principal activities involve one or more of demolition, design, production, alteration, renovation, maintenance and re-cycling of building works, and/or of building services works, and/or of civil engineering works and/or or process engineering works" [40].

The ranking and the relatedness of the research interests – as shown in Table 1 and Fig. 2, respectively – reveal several key findings:

- Some research interests have received special attention, while others have remained under-researched. Optimization, genetic algorithm (GA), neural networks (NNs), simulation, uncertainty, fuzzy logic (FL), fuzzy sets (FSs), machine learning (ML), project management, and bridges have received considerable attention in AI-in-the-AECI research. The results generally concur with those of Ref. [13] and indicate that these have been the top themes in the literature. The results could first be explained by the fact that one of the main aims of AI is to *optimize* processes, activities, decisions, and problems. They may further be explained by the promise of NNs, for example, to tackle prevalent analogy-based decision problems in the AEC industry [5,41]. Optimization and GA have acquired the most attention within the literature. GA is an optimization technology and the optimization goals of the AEC industry (e.g., project scheduling/cost optimization) can be attained by adopting GA [37]. The link between optimization and GA represents the strongest link in the current body of knowledge (Fig. 2). This shows that the most common AI application in the AEC industry has been the deployment of GA for optimization problems (e.g., schedule optimization) [42–44]. Ref. [45], for instance, created a multi-objective scheduling optimization model for multiple AEC projects using the fast elitist nondominated sorting GA. The model aims at obtaining optimal trade-offs amongst diverse projects' objectives. Extending the themes of optimization, GA, and NNs, further research covered issues such as: using FL and FSs to deal with uncertainty in AEC problems [46]; 3D simulation of pavements' deflection basin [47]; digitizing bridges [48]; and project management issues, e.g., using neurofuzzy genetic system to select project managers [49] and identifying their competency weights using data-driven automated methods [50]. Based on the results, it can be concluded that the most often used AI techniques in the AEC community have been GA, NNs, FL, FSs, and ML; whilst the most widely addressed topics/issues using AI techniques/concepts include optimization, simulation, uncertainty, project management, and bridges. This agrees with Ref. [51]'s finding that ML is one of the commonly adopted AI methods in structural engineering. It also shows the high applicability of the noted AI methods to AEC problems, such as those noted herein. Given the level of research on the top-ranked themes, when attempting to expand the body of knowledge on them, future studies must pay critical attention to *adding real value*; this may be highly important to journal editors and funding agencies.

- ML, an AI subfield, represents a data analytics method in which computers are taught to do what comes naturally to animals and humans: learning from experience [52]. Although ML is one of the top themes in the literature on AI-in-the-AECI, only handful of its myriad techniques (NNs, support vector machine (SVM), etc.) are present in Fig. 2, with many others [naïve Bayes (NB), gaussian mixture (GM), reinforcement learning (RL), etc.; see Refs. [51] and [52]] absent. This suggests disregard for the latter techniques, needing future research attention. Full development and exploitation of ML methods in AI-in-the-AECI research would be a promising aid in bridging the technology gap in this industry [53]. Deep learning (DL) is a specialized form of ML and ML algorithms play key roles in data mining (DM), explaining the links ML has to DL and DM in the co-occurrence network.

- Among AI-in-the-AECI research interests that have remained under-researched are: fly ash, ontology, semi-active control, truss structures, shape optimization, mechanical properties, topology optimization, wavelet transform (WT), life cycle assessment (LCA), magnetorheological (MR) damper, active control, optimum design, simulated annealing, tuned mass damper (TMD), life cycle cost, thermal comfort, energy, adaptive neuro-fuzzy inference system (ANFIS), and differential evolution (DE). All of these had degree centrality values well below those of the top-ranked research interests (Table 1), indicating that these research interests are yet to be fully integrated into the core body of AI-in-the-AECI research. The results further suggest that limited attention has been directed toward applying AI to topics such as energy, thermal comfort, life cycle cost, optimum design, and LCA in the AEC field.

This must draw AEC experts' and researchers' attention, given that AI can assist in optimizing these issues. In the existing literature, energy, for instance, is not linked to any AI technique; while energy consumption and energy efficiency are linked to only ML and GA. Thermal comfort is also linked to only ML, while life cycle cost is linked to only GA. Based on the network, similar observations have been made for other themes. Essentially, it has been identified in this study that there have been limited efforts on the utilization of AI in AEC for optimizing: energy use/efficiency [54], thermal comfort [55], LCA and life cycle costs [56], design (especially structural design) [57], mechanical properties (such as shear strength, compressive strength, etc.) (of, e.g., composites) [58], and truss structures [59]. This may be because computers have yet to be fully employed for many AEC tasks [51]. It would, therefore, be promising to develop more efficient/accurate hybrid methods involving AI methods, such as ANFIS, DE, etc., and apply such methods to the noted issues in an aim to also address the inadequacy of investigations on these intelligent methods/algorithms (Fig. 2/Table 1). DE algorithm combined with biogeography-based optimization method [60], for example, can be implemented for the design optimization of truss structures. The approach proves to be essentially useful in solving optimum design problems with discrete and continuous variables.

- Though optimization in general has been extensively tackled with AI methods and concepts in the AEC context, some types of optimization problems have been largely overlooked. A representative example is shape optimization problems [e.g., shape optimization problems in structural design [61]]. This gives a promising avenue for future AI-in-the-AECI research, development, and innovations, where AI methods, such as particle swarm optimization (PSO), GA, harmony search algorithm (HSA), etc., could be properly integrated and used to solve the problems [62]. Moreover, the field needs more studies concerning the combined use of AI methods/algorithms and concepts, and active and semi-active structural control systems, TMD, MR damper, and WT, for purposes such as damage detection/assessment, structural and vibration control, and earthquake engineering in civil infrastructure as well as building structures. The development of reliable AI models is also of interest to model and optimize the usage of fly ash in producing sustainable concretes.

- According to Ref. [37]'s review study, the topics of cost, productivity, safety, and risk management, which are key project performance indicators, have been the mainstream issues in AEC research. However, the findings of the present study show that these issues have yet to see significant development in terms of the application of AI methods and concepts in AEC. In the current research network, they are only weakly linked to few AI methods and not linked to other potentially useful ones. Risk management, for example, has no link to BIM, though BIM is proving to be an efficient alternative risk management technology to classical techniques for managing risk in the AEC industry [63]. One more observation is that cost is also (weakly) linked to only case-based reasoning (CBR) and GA, although its link to BIM is nonexistent. However, it has been expounded that BIM holds the potential for dealing with cost-associated risks to optimize cost in AEC projects [64]. The noted missing, unconfirmed, and weak links invite further research on the right integration and use of AI methods (BIM, CBR, GA, etc.) for optimizing and improving cost, productivity, safety, risk management, and sustainability in the AEC industry. Risk management entails risk analysis, which also requires more AI applications (Table 1). Quality, which is also a key project performance indicator, is missing in the network.

- Other research interests that are not of notable influence in terms of number of links in the existing literature on AI-in-the-AECI and hence need further attention include: firefly algorithm (FA), genetic programming (GP), structural reliability, computer vision, finite element model updating and analysis, knowledge management, resource allocation, data fusion, knowledge-based systems (KBS), expert systems (ESs), reliability analysis, construction equipment, system identification, forecasting, performance evaluation, geographic information system (GIS), planning, information management, rehabilitation, corrosion, etc. These have been under-researched and have no or limited weak links to the central points of interest. AI technologies afford novel approaches to the creation and capture of value and can enable exponential changes to business models and practice. Such changes can be categorized within three groups [65]: automation – when AI technologies are leveraged for automating processes/activities; extension – when AI technologies are used to back innovative ways of undertaking business which complement instead of replacing existing processes/activities; and transformation – when AI technologies are used to enable novel ways of undertaking business which replace conventional ones. This explains the presence of automation in the extant AI-in-the-AECI research network.

- A conspicuous absence of interest in the topic of robotics is observed in the network. This implies that little attention has been devoted to the topic in the existing literature. Robotics, a key subfield of AI, simply deals with the development and use of robots for tasks and, as indicated by Ref. [41], has been of interest to the AEC industry since the 1990s. Thus, the absence of robotics in the research network seems surprising but may be attributed to the fact that the AEC industry is still “behind the curve in implementing AI solutions” [53]. This industry is generally recognized to be a severely underautomated/underdigitized industry where very few robots are currently being utilized [66]. In addition, the presence of bridges [alongside cable-stayed bridge (a bridge type)] as a top-ranked research interest and the absence of other infrastructure types (e.g., roads, tunnels, and railways) shows that the existing research has placed remarkable focus on the use of AI solutions in bridge projects, while there has been limited research on AI implementation in other infrastructure projects. The research findings essentially indicate that the literature on AI-in-the-AECI is still relatively immature, needing more studies on the application of various AI methods/algorithms and concepts to various AEC problems/issues.

3.2.2. Citations patterns: document co-citation analysis

Citations patterns among publications, in terms of the clusters formed by accrued co-citation trends, aid in appreciating the structure of a knowledge domain [17]. With its clustering function, CiteSpace affords precise means of identifying clusters [21]. Therefore, CiteSpace 5.5.R2 was utilized to create a network of document co-citation. Filtering out small clusters generated a network with 13 major clusters (with cluster IDs #0, #1, etc.), as demonstrated in Fig. 3. Each cluster represents an underlying line of research, topic, or theme [21]. Moreover, to characterize the nature of each identified cluster, CiteSpace automatically chooses a label for each cluster based on noun phrases extracted from the titles, keyword lists, and abstracts of publications in each cluster. There are three text-mining algorithms available for labelling clusters in CiteSpace – latent semantic indexing (LSI), log-likelihood ratio (LLR), and mutual information

(MI). Ref. [21] indicated that LLR usually delivers the best results. Thus, the LLR algorithm was implemented in this study for generating the cluster labels in Fig. 3. For this kind of analysis, Ref. [21] advised that “we don’t really need to see the size of a node”; i.e., the structure rather than the content of clusters must be the focus.

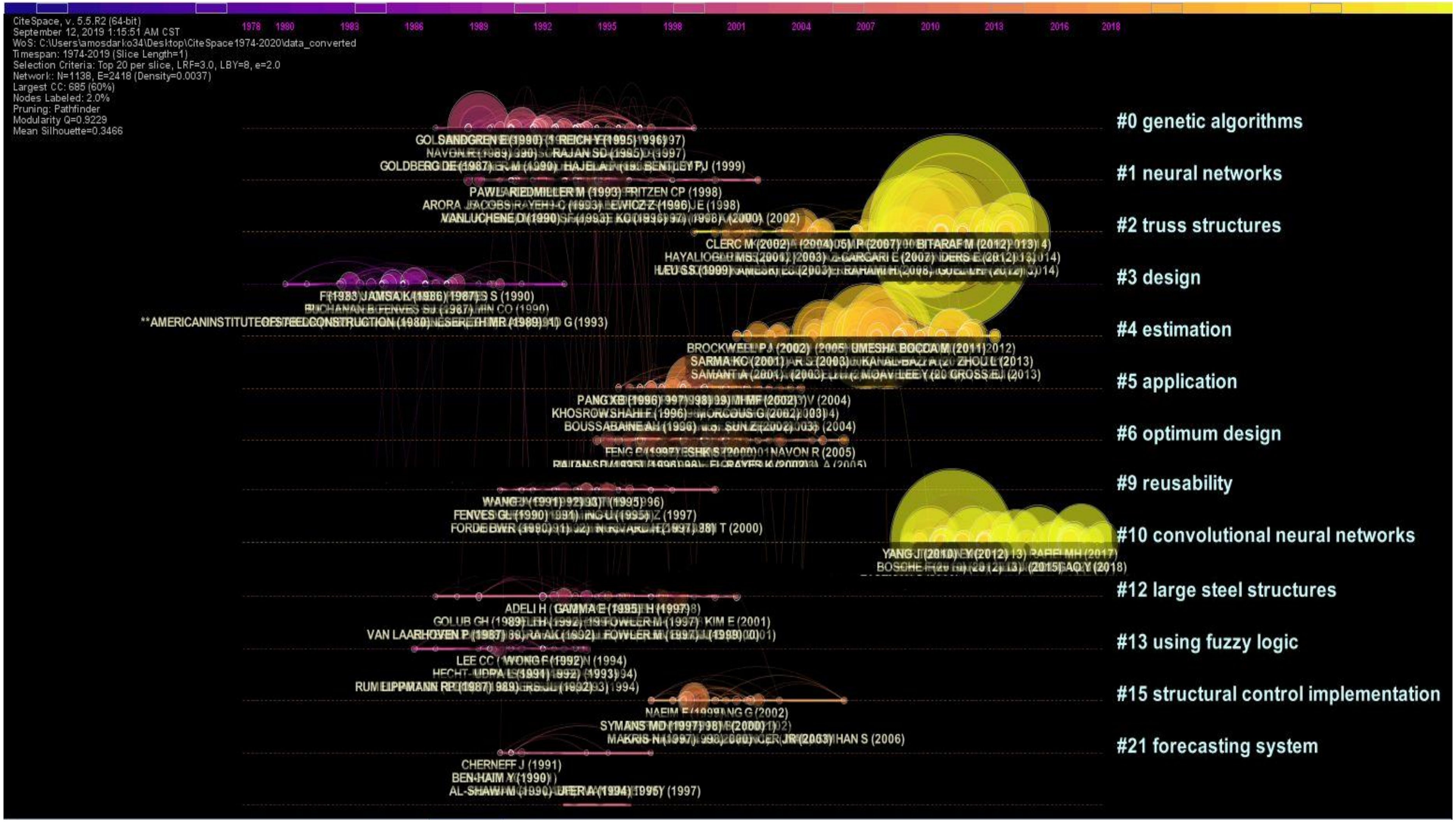

Fig. 3. Clustering structure for research on AI-in-the-AECI.

Besides picturing the clustering structure, CiteSpace assesses the network's "overall structural properties" via the computation of two fundamental metrics, the modularity Q value and the mean silhouette value [21]. The modularity Q value ranges from 0 to 1 and is used for assessing the extent to which the network can be partitioned into autonomous clusters [17]. For a network partitioned into b clusters, for instance, the modularity Q is computed from the symmetric $b \times b$ mixing matrix **D**. The elements of **D** along its main diagonal d_{ii} provide the fraction of links amongst the nodes within each cluster i. As for the other elements of **D**, $d_{ij} (i \neq j)$, they indicate the fraction of links amongst nodes within two dissimilar clusters (i, j). As such, the modularity Q value can be computed using Equation 2 [67]:

$$Q = \sum_i [\, d_{ii} - (\sum_j d_{ij})^2] \qquad \text{Equation 2}$$

A cluster's silhouette value ranges from –1 to 1 and assesses the uncertainty involved in defining the cluster's nature. A value of 1 signifies that the cluster is perfectly isolated [68]. Additionally, each cluster's silhouette value indicates which nodes fit well into the cluster as well as which nodes lie somewhere in between clusters. The whole clustering is assessed through combining all silhouette values, generating a mean silhouette value that provides a measure of clustering homogeneity [69]. Interested readers are referred to Ref. [69] for details.

The modularity Q value – 0.9229 – was higher than 0.7, indicating that the strength of dividing the network into clusters is high with dense links amid nodes within clusters, but sparse links between nodes in different clusters. The mean silhouette value, on the other hand, was 0.3466, indicating that the homogeneity of the clusters, on average, is not high [21]. That is, while the modularity Q value suggests that research on AI-in-the-AECI embodies a network with dense connections at intra-cluster level; the mean silhouette value shows that studies in the network, in general, address different issues although those in each cluster may be consistent in addressing similar issues – as suggested by the high silhouette values of individual clusters in Table 2.

Table 2
Citations patterns and identified clusters (see Fig. 3).

Cluster ID	Size	Silhouette value	Average year published	Focus of the cluster
#0	82	0.893	1993	Genetic algorithms
#1	69	0.903	1993	Neural networks
#2	58	0.918	2008	Truss structures
#3	57	0.956	1986	Design
#4	54	0.956	2008	Estimation
#5	49	0.898	1999	Application
#6	46	0.936	1999	Optimum design
#9	36	0.961	1994	Reusability
#10	36	0.999	2017	Convolutional neural networks
#12	29	0.928	1994	Large steel structures
#13	22	0.988	1991	Using fuzzy logic
#15	18	0.980	2000	Structural control implementation
#21	10	0.983	1992	Forecasting system

Regarding the results in Fig. 3 and Table 2, it is worthy to mention that:

- The current body of knowledge on AI-in-the-AECI comprises 13 major clusters. As per the cluster sizes in Table 2, genetic algorithms (GAs) and neural networks (NNs) have been the largest clusters in the existing literature. This is in line with the earlier observation in Table 1 that GAs and NNs have been among the top research interests and therefore among the most commonly used AI techniques in the AEC community. The "average year published" shows the average period within which a given cluster has been investigated by research studies. While most of the clusters acquired more attention in years over a decade ago (i.e., 1986-2008), studies focusing on the cluster convolutional neural networks (CNNs) have been published more during the recent decade, around 2017 on average. This suggests that the development and application of CNNs represents an emerging trend in research on AI-in-the-AECI. Deep learning (DL) affords a machine learning technique in which computers are taught to perform what comes naturally to humans – learning by example [70]. In DL, computer models learn to undertake classification tasks directly from sound, images, videos, or text. Most DL methods use NN architectures, explaining why DL models are normally referred to as deep NNs [70]. CNNs are a popular class of deep NNs that are typically deployed for analyzing visual imagery. They eliminate the need to manually extract and identify features applied in classifying images. The automatic feature extraction/identification renders CNN models highly accurate and efficient for many tasks in computer vision, e.g., object recognition and classification. According to Ref. [70], DL models "can achieve state-of-the-art accuracy, sometimes exceeding human-level performance.” Accordingly, as identified in this study, it is becoming a trend to apply CNNs in research to analyze and resolve AEC problems, e.g., detection of structural damage [71] and construction workers' activities/behaviors detection/monitoring [72]. This study's finding appears to concur with Ref. [51]'s claim that the utilization of CNNs in AEC for tasks such as damage detection and structural health monitoring is a very new trend.

- Ref. [68] indicated that a silhouette value around 0.7 implies that the cluster can be viewed as an isolated block of the network with clear borders and weak links across those borders. As Table 2 shows, all silhouette values were greater than 0.7, representing a homogeneous body of research formed primarily through intra-cluster citations [17]. As pointed out by Ref. [73], such homogeneous clusters are created when researchers do not cite studies outside their cluster, and thus do not draw on a broad range of knowledge sources. Consequently, the existing literature on AI-in-the-AECI appears inward-looking, not benefiting from borrowing applicable theories/ideas from other research fields. This is interesting, as AI itself is an idea borrowed from the computer science field. It was expected that this positive attitude of borrowing research ideas would be widely promoted amongst the various areas of research on AI-in-the-AECI.
- Table 2 demonstrates that cluster #21, forecasting system, and cluster #15, structural

control implementation, were the smallest clusters. These clusters respectively had only 10 and 18 studies in them, signifying insufficient research on AI applications in these areas. While this supports the earlier observation (section 3.2.1) of few studies concerning the combined use of AI methods/algorithms and concepts, and active and semi-active structural control systems, MR damper, etc. for purposes such as structural control in building and infrastructure structures; examples of forecasting system include particle swarm optimization integrated with support vector machine [74] and vector error correction model [75] for construction material prices forecasting. It was also identified in Fig. 2/Table 1 that forecasting represents a topic that needs more research attention.

3.3. Hot topics over time: citation burst analysis

Citation bursts illustrate which keywords have frequently been cited within the literature in a particular time period, namely fast-growing topics, or topics that are associated with surges in citations [21]. A citation burst analysis was conducted using CiteSpace. From the dataset, a total of 152 keywords had citation bursts. Fig. 4 presents the top 50 keywords with the strongest citation bursts. The light green lines in the figure denote the reviewed literature year range, whereas an orange line represents the length of a citation burst event.

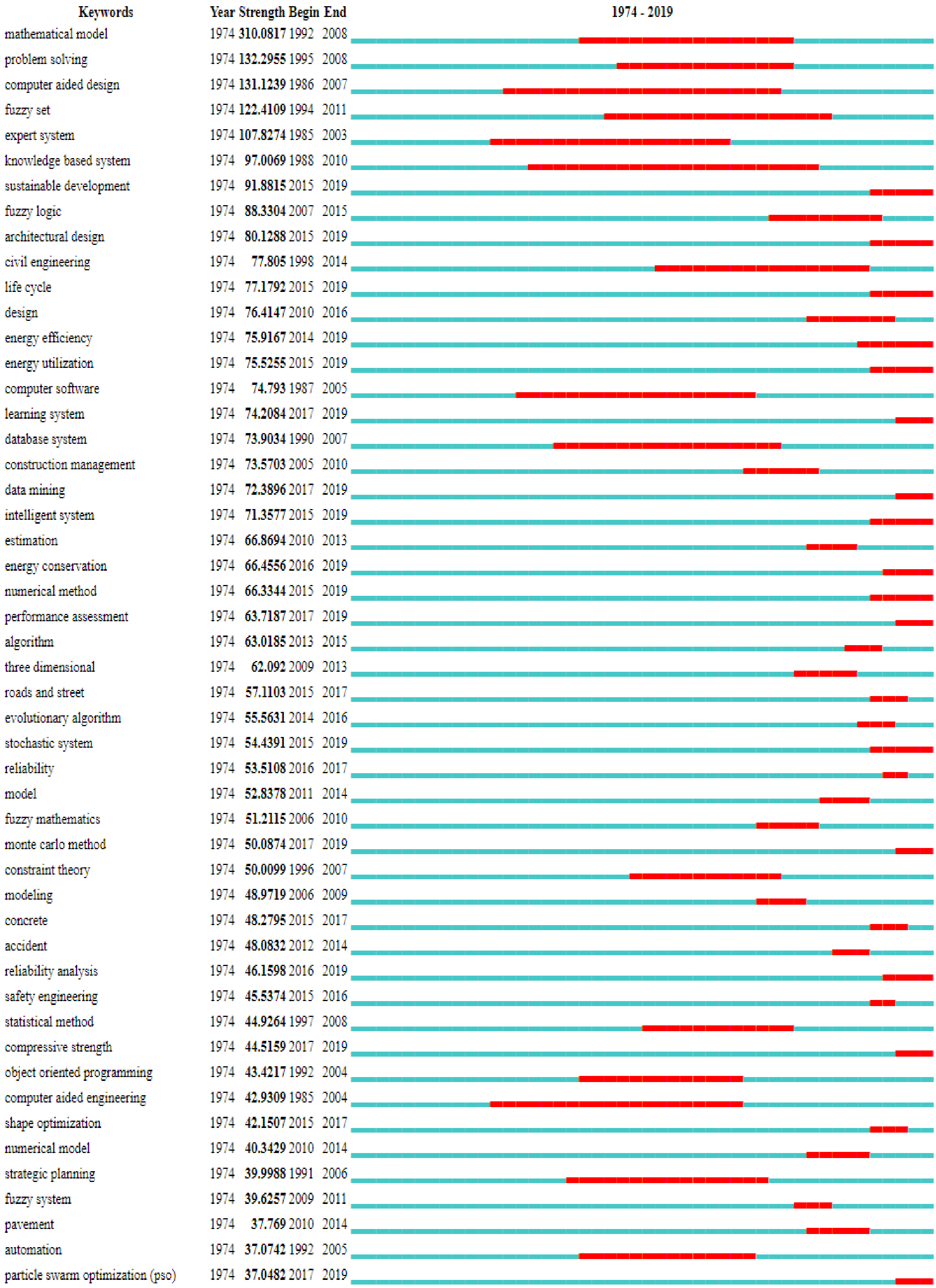

Fig. 4. Top 50 keywords with the strongest citation bursts in the literature on AI-in-the-AECI (1974-2019).

It can be observed that although some themes (e.g., expert system (ES), knowledge-based system (KBS), etc.) had strong citation bursts, as shown in Fig. 4, their influence in relation to other themes were not notable in Fig. 2/Table 1, as demonstrated by their relatively small node sizes and degree centrality values. This is because citation burst is based upon the degree of attention a topic attracted from the scientific community in a certain period of time; but node size (Fig. 2) is based on degree centrality value, which reflects the number of links a node has to other nodes within the network – as explained earlier. Taking KBS for example, the burst took place within the period 1988-2010. This reveals that its development and application obtained significant attention in this period but does not necessarily indicate that it was applied or linked to numerous-enough AEC problems/issues. It could be that it was frequently applied to few areas (e.g., knowledge management, information management, etc.), but not several others (e.g., sustainability, life cycle cost, thermal comfort, etc.), as illustrated in Fig. 2. Exploring the potential of integrating KBS with other AI techniques for tackling the latter areas in future research would be a promising approach to increase the influence of not only KBS but also these areas and the integrated AI techniques in the extant research network.

Fig. 4 shows that mathematical model (burst strength, 310.08; 1992-2008), problem solving (132.30; 1995-2008), computer-aided design (131.12; 1986-2007), fuzzy set (122.41; 1994-2011), and ES (107.83; 1985-2003) had the strongest citation bursts in the literature. This implies that these were the hot topics in the respective years. An ES "is a knowledge-based computer system which emulates the decision-making ability of a human expert" [76]. Simply put, an ES is a computer system that captures and uses the knowledge and experience of human experts in a particular field to support decision-making. This technology was commonly recognized as the "rising IT star of the eighties" [77]. It has been reported that ES development services and products sales in 1988 reached over $400 million in Europe and the US, with annual market growth of ES in excess of 30%, more than that of the IT business overall [78]. Ref. [77] also showed that the number of studies on ES in the UK also grew at a similar pace. These facts could explain the strong burst obtained by ES in the literature on AI-in-the-AECI, which started in the 1980s. However, it is identified that this burst ended in 2003, about two decades ago. The hot topics in the more recent years include: sustainable development, architectural design, life cycle, energy-related issues (e.g., energy efficiency), learning system, data mining, intelligent system, numerical method, performance assessment, stochastic system, Monte Carlo method, reliability analysis, compressive strength, and particle swarm optimization. Their burst strengths range in descending order from 91.88 to 37.05, and their bursts begun from 2015 up until now, 2019. The findings imply that these represent emerging themes in research on AI-in-the-AECI. Based on the results of this detailed literature review (Figs. 2-4), some AI techniques applicable to AEC, and certain AEC problems/issues/domains to which AI is applicable have been summarized in Appendix A and B, respectively.

3.4. Top outlets for research on AI-in-the-AECI: outlets direct citation analysis

Many studies have underlined and explicated the importance of analyzing academic journals in any scientific field [79]. Such evidence might be useful to readers on finding the best sources of information, and to authors on finding journals that may be best suited for publishing their works on AI-in-the-AECI. It can also help journal editors in making relevant adjustments to the goals of their journals, and institutions/libraries in optimizing the allocation of resources for investing in journals [6]. In this study, a direct citation analysis of outlets was conducted to provide evidence of the prominence of academic journals that publish research on AI-in-the-AECI. VOSviewer was employed; the type of analysis was "citation", and the unit of analysis was "sources". The "minimum number of documents of a source" and the "minimum number of citations of a source" were both set to 150, for achieving the optimum network. Of 103 sources found, 57 met the threshold and were included in the resultant network, which consisted of 1,167 links among the 57 outlets. The network was visualized using Gephi, as shown in Fig. 5.

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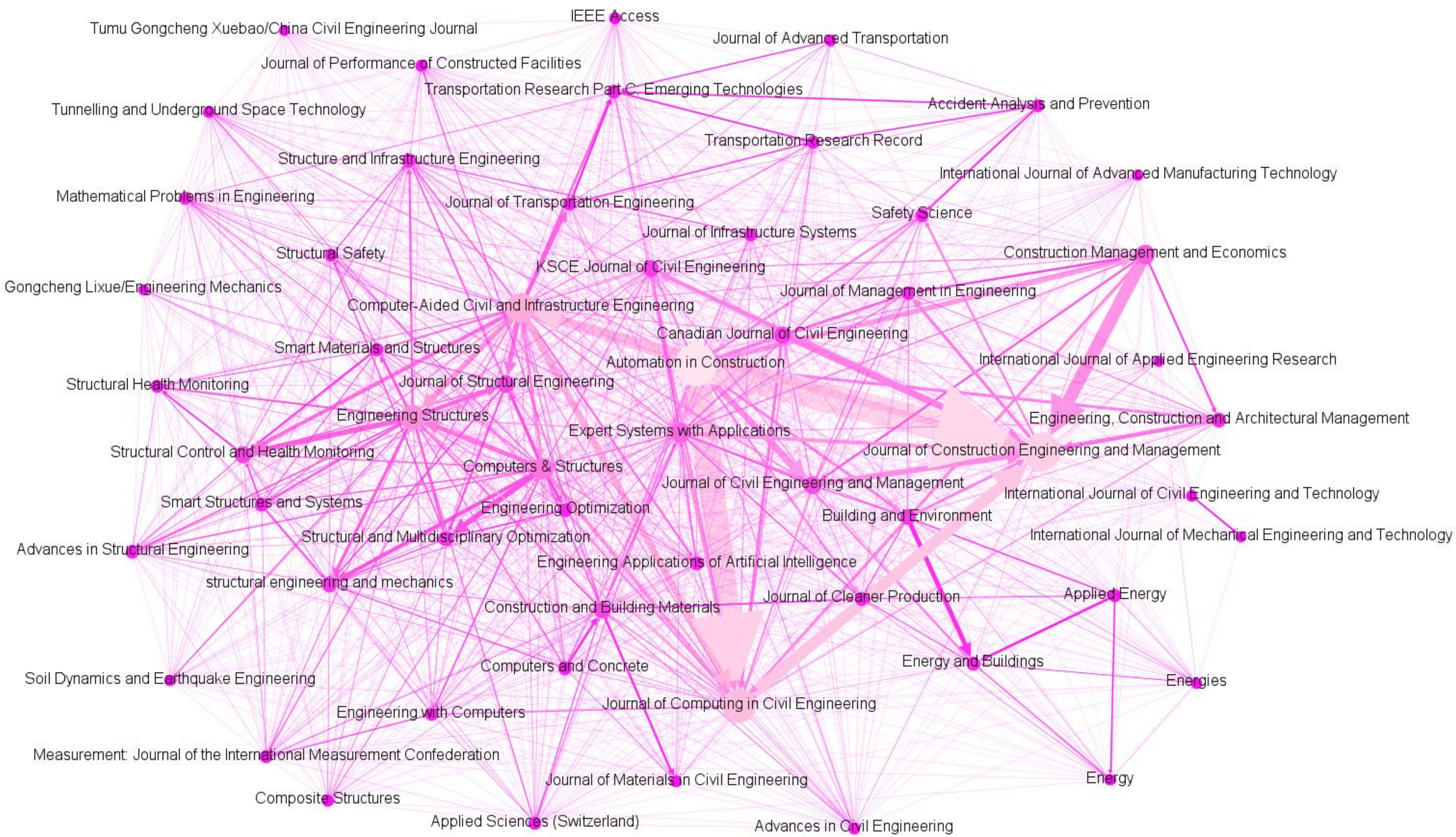


568 **Fig. 5.** Network of prominent outlets for research on AI-in-the-AECI.

Weighted degree, a modified version of degree centrality, within a network considers the average mean of the sum of the weights of the relations among all the nodes within the network. It has been the measure of influence of choice for evaluating the level of influence of nodes in the control of information flow across the whole network [38]. In this study, weighted degree values were used for resizing and recoloring the nodes in the network in Fig. 5, with lighter and larger nodes denoting higher weighted degree values. Table 3 displays the top 30 outlets for research on AI-in-the-AECI, ranked based on their weighted degree values in the network.

Table 3
Top 30 outlets for research on AI-in-the-AECI.

Rank[a]	Outlets	Number of publications[b]	Weighted degree value
1	Automation in Construction	1,353	7,575
2	Journal of Construction Engineering and Management	994	6,467
3	Journal of Computing in Civil Engineering	1,037	5,453
4	Computer-Aided Civil and Infrastructure Engineering	648	4,576
5	Engineering Structures	717	3,388
6	Computers & Structures	504	2,863
7	Expert Systems with Applications	583	2,408
8	Construction Management and Economics	354	2,200
9	Journal of Civil Engineering and Management	355	1,811
10	Journal of Structural Engineering	156	1,619
11	Construction and Building Materials	737	1,579
12	Structural Control and Health Monitoring	371	1,502
13	Canadian Journal of Civil Engineering	367	1,403
14	KSCE Journal of Civil Engineering	590	1,388
15	Structural Engineering and Mechanics	456	1,324
16	Building and Environment	335	1,319
17	Structural and Multidisciplinary Optimization	282	1,264
18	Structure and Infrastructure Engineering	246	989
19	Energy and Buildings	401	953

20	Journal of Management in Engineering	237	925
21	Engineering Optimization	263	903
22	Engineering, Construction and Architectural Management	186	892
23	Journal of Cleaner Production	440	869
24	Engineering Applications of Artificial Intelligence	202	858
25	Smart Materials and Structures	265	808
26	Transportation Research Part C: Emerging Technologies	311	800
27	Smart Structures and Systems	196	797
28	Journal of Transportation Engineering	216	788
29	Computers and Concrete	206	734
30	Engineering with Computers	210	726

[a]Ranking based upon weighted degree values; [b]During the studied period (1974–Aug 2019).

The findings disclose that *Automation in Construction* – which obtained the highest value of weighted degree (7,575) – has been the most influential outlet for research on AI-in-the-AECI. As indicated in Fig. 5, there is significant flow of information (through citations) from *Automation in Construction* to *Journal of Construction Engineering and Management*, *Journal of Computing in Civil Engineering*, and *Computer-Aided Civil and Infrastructure Engineering,* which have been the second tier of influential outlets in the field, as shown in Table 3. As such, these four outlets may serve as the first points of reference for practitioners, researchers, and students on advances in AI in the domain of AEC. *Automation in Construction*, for instance, aims at advancing the field through publishing works concerning every aspect of the development and utilization of ITs in "design, engineering, construction technologies, and maintenance and management of constructed facilities" [80]. In this regard, it covers topics such as automated inspection, intelligent control systems, computer-aided design/engineering, etc. All the other noted outlets also offer useful sources/references for researchers and practitioners working in the area of AI-in-the-AECI. However, it is worth mentioning that aside from *Expert Systems with Applications*, which is the only truly general journal in the top 30, all the others are AEC industry journals, though the *Journal of Cleaner Production*, and some of the other Engineering journals (*Journal of Management in Engineering*, *Engineering Optimization*, *Engineering Applications of Artificial Intelligence*, *Transportation Research Part C: Emerging Technologies*, *Journal of Transportation Engineering*, and *Engineering with Computers*) may include a broader range of engineering – mechanical, aerospace, manufacturing, etc. – as well. This could link to the earlier observation in section 3.2.2 that the field has been inward-looking.

3.5. Scientific collaboration networks in AI-in-the-AECI research: co-authorship analysis

Knowledge of the current scientific collaboration networks in any research domain can (1) promote access to specialties, funds, and expertise, and (2) expand productivity [17]. Ref. [81] showed that "almost every aspect of scientific collaboration can be reliably tracked by analyzing co-authorship networks." As Ref. [17] noted, "co-authorship is shorthand for scientific collaboration, with the lack of collaboration in a scientific network being a symptom of lower research productivity." In this light, a picture/analysis of the co-authorship network of institutions in the AI-in-the-AECI literature is presented in the next sub-section.

3.5.1. Institutions

Discovering the collaboration network of institutions having high investment and interest in research on AI-in-the-AECI is useful in assisting research partnership and policy-making [82]. VOSviewer was used to create this network. The type of analysis was "co-authorship", the unit of analysis was "organizations", and the counting method "fractional counting". The "minimum number of documents of an organization" and the "minimum number of citations of an organization" were both set to 15, for achieving the optimum network. Of 38,401 organizations identified, 40 met the threshold and were included in the resultant network, which was visualized using Gephi, as illustrated in Fig. 6.

623

624 **Fig. 6.** Collaboration network of institutions in the literature on AI-in-the-AECI.

The hyperlink-induced topic search (HITS) in Gephi, usually referred to as hubs and authorities, represents an algorithm whose work is to discern influential nodes [83]. For every node in the network, the HITS algorithm produces two disparate scores – an authority score and a hub score. A higher hub score shows a more influential node in terms of serving as a key reference source. Authority score, however, provides insight into the quantity of useful information stored in a node [6]. For additional information on hub and authority scores, one should see Ref. [84]. The HITS algorithm was used to rank the network nodes based on their hub scores. That is, hub scores were utilized to resize and recolor the nodes in the network in Fig. 6, with larger nodes and lighter shades indicating higher hub scores.

As Fig. 6 shows, only few institutions from Vietnam, China, Iran, Hong Kong, US, Taiwan, and Turkey have built collaborative relationships in AI-in-the-AECI research – though most of these collaborations are currently not strong – as evinced by the thickness of the lines connecting the institutions. For the most part of the network, there is an obvious lack of collaboration among the institutions, underscoring the desolate nature of the extant research. Strong institutional-level collaborative relationships should be fostered across the entire network if the highest standards of scholarship and debate on AI-in-the-AECI are to be attained [6]. It is interesting to identify the inclusion of National Center for Research on Earthquake Engineering in the network. This offers an example of the contribution of purely research institutes to research regarding AI-in-the-AECI.

3.5.2. Countries

Scientific collaboration network of countries helps in identifying countries that are particularly active in the relevant research area [21]. To identify these countries, the most influential ones, and the collaborations amongst them, a network was created using VOSviewer. The type of analysis was “co-authorship”, the unit of analysis was “countries”, and the counting method “fractional counting”. The “minimum number of documents of a country” and the “minimum number of citations of a country” were both set to 20, for achieving the optimum network. Of 196 countries identified, 67 met the threshold and were included in the resultant network, which was visualized using Gephi, as illustrated in Fig. 7.

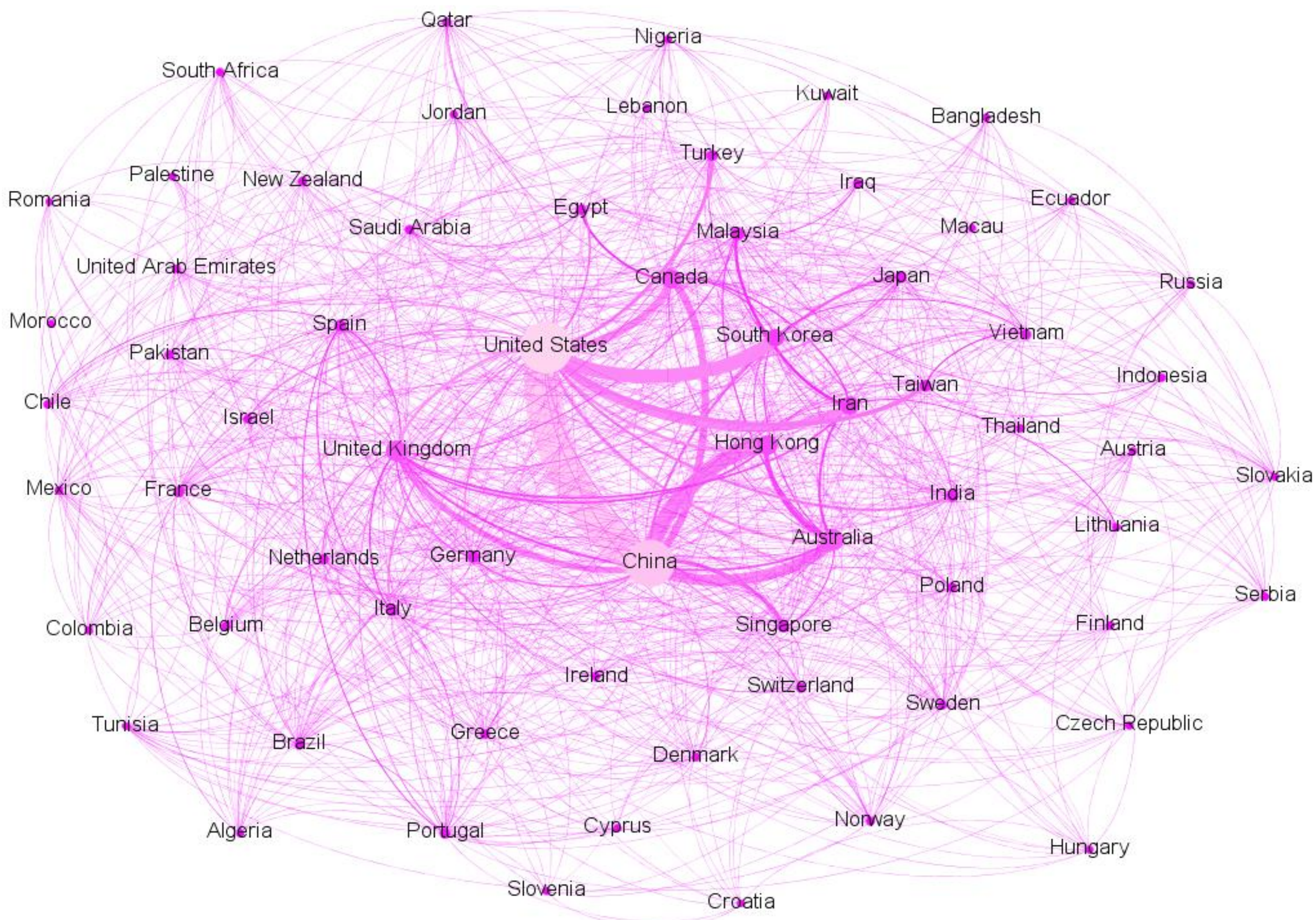


Fig. 7. Collaboration network of countries in research on AI-in-the-AECI.

Weighted degree values were used to identify the most influential countries in the network. Nodes were recolored and resized based upon their weighted degree values, with larger nodes and lighter shades representing higher weighted degree values. The network (Fig. 7) reveals these key findings:

- Based on the weighted degree values within the network, Table 4 presents the top 30 countries in the network. US and China stand out as the top-ranked countries with respect to the extent of collaboration in research on AI-in-the-AECI as well as the number of publications. This implies that US and China have been the biggest contributors to research on AI-in-the-AECI. Australia, UK, and Hong Kong were, respectively, the third, fourth, and fifth major contributors. However, the relations amongst US and these three countries are not strong. This highlights the need for institutions in such prominent countries to reform policies to nurture collaboration with each other to further improve global collaboration and knowledge exchange in this research area.
- Concerning the strength of relations, the strongest relations were amongst the paired countries US–China, US–South Korea, US–Canada, US–Iran, China–Hong Kong, China–Australia, China–Canada, and China–UK. Compared against 990 relations in the network, these kinds of strong collaborations were very limited (only eight). This may be because of limited cross-country and comparative studies in the existing

literature. Moreover, the strongest collaboration relations generally existed amongst few developed countries, with many, especially developing, countries having weak relations to the main stream of research (key nodes). This should be considered by these countries in the refinement of their research policies, as they are placed far from the main collaboration network in research on AI-in-the-AECI. Thus, strategies that facilitate exchange of ideas/knowledge on AI are needed across AEC research worldwide.

Table 4
Top 30 countries collaborating in research on AI-in-the-AECI.

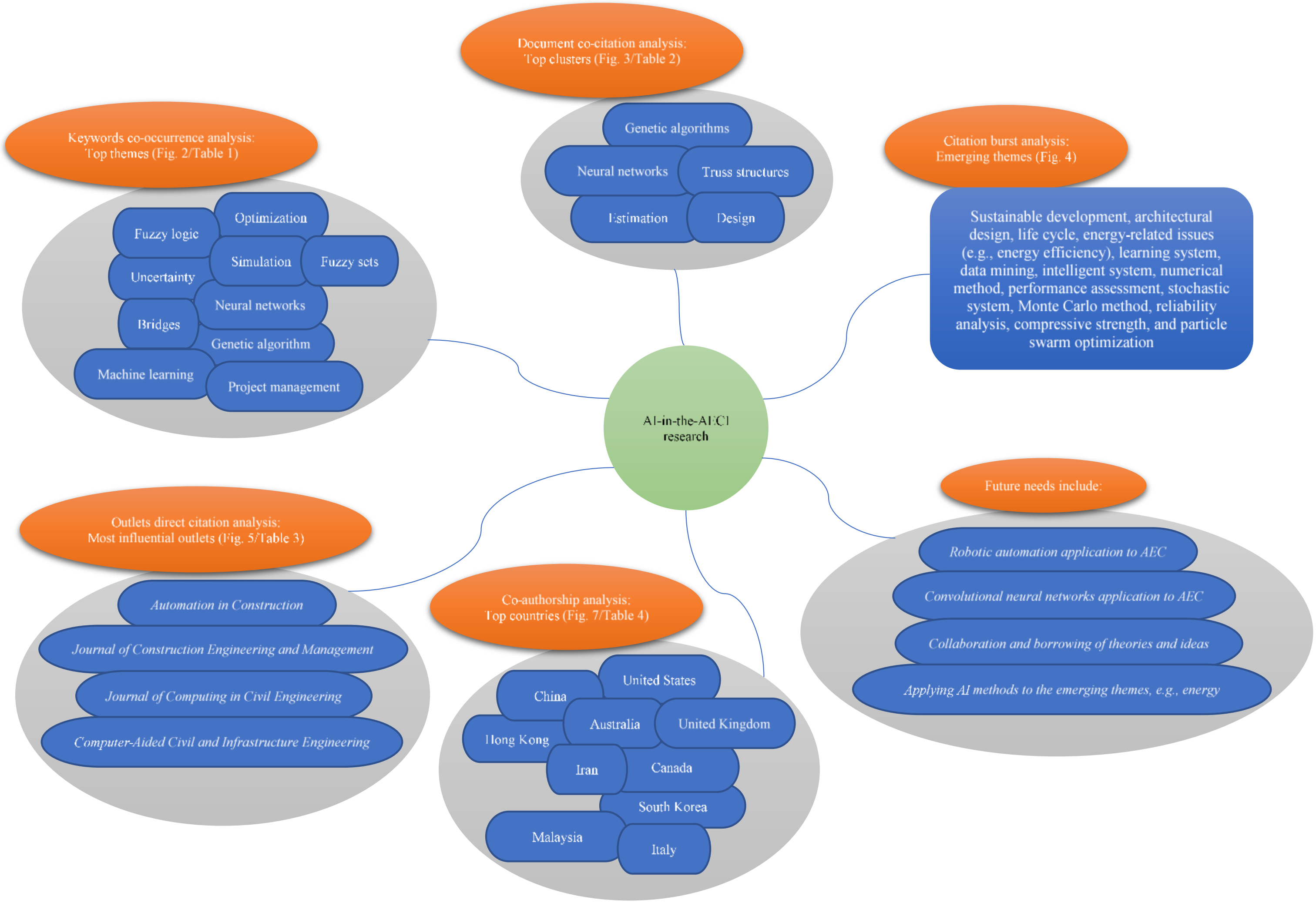
Countries	Number of publications[a]	Weighted Degree value	Relative influence
United States	5,754	2,419	1
China	5,093	2,159	2
Australia	1,235	772	3
United Kingdom	1,363	733	4
Hong Kong	1,047	670	5
Canada	1,452	627	6
Iran	1,888	577	7
South Korea	1,400	542	8
Malaysia	554	311	9
Italy	592	242	10
Singapore	418	236	11
India	1,453	227	12
Taiwan	1,048	216	13
Germany	333	214	14
Spain	550	212	15
Japan	396	191	16
Turkey	907	189	17
France	316	175	18
Egypt	255	149	19
Vietnam	186	141	20
Netherlands	251	140	21

Portugal	322	136	22
Switzerland	193	131	23
Belgium	160	98	24
Poland	325	90	25
Saudi Arabia	133	89	26
Greece	254	84	27
Brazil	237	83	28
New Zealand	105	76	29
Pakistan	100	75	30

[a]During the studied period (1974–Aug 2019).

4. Discussion and future directions

During the last few decades, there has been a growing interest in research applying AI techniques/algorithms/concepts to AEC problems. This activity has been thoroughly reviewed in this study through quantitative, text-mining approaches. The review has been conducted to identify clusters and collaboration networks of the main research interests (including various AI methods/concepts as well as various AEC topics/issues addressed using AI methods/concepts), journals, institutions, and countries in the existing body of literature. The scientometric analysis of the field is requisite to develop a full picture and understanding of the research focuses on AI-in-the-AECI and to reveal the relevant gaps and future needs. Fig. 8 presents a summary of findings of this study. The keywords co-occurrence analysis (see Fig. 2) and the document co-citation analysis (see Fig. 3) revealed that optimization, genetic algorithms, neural networks, simulation, and uncertainty are themes receiving much attention in the research on AI-in-the-AECI, while topics such as robotics, energy, thermal comfort, life cycle cost, and LCA are not receiving much attention. Therefore, potential research and development (R&D) efforts could be directed toward how to integrate robotics and other AI methods with the topics of energy, thermal comfort, life cycle cost, and LCA. It has been identified in this study that researchers working within this domain of AI-in-the-AECI often do not borrow and implement applicable theories and ideas from other research fields; they tend to only work with and cite studies within their specific areas of expertise. As well, the research institutions and countries often do not collaborate with each other. These problems need to be solved because they limit knowledge exchange and the use of potentially useful and insightful ideas, theories, and models. The borrowing of ideas, theories, and models from fields such as finance, telecommunications, and automotive, which are well ahead of AEC in AI solutions implementation [53], is proposed. The outlets direct citation analysis (Fig. 5) revealed that *Automation in Construction* is the most influential outlet for research on AI-in-the-AECI, followed by *Journal of Construction Engineering and Management*, *Journal of Computing in Civil Engineering*, and *Computer-Aided Civil and Infrastructure Engineering*. Moreover, the AI-in-the-AECI research emanates from various countries, with the US and China being the biggest contributors (see Fig. 7). This study's results are fully presented and discussed in section 3. Based on the results, several gaps and emerging trends are also highlighted, based upon which pathways for future R&D activities on AI-in-the-AECI are discussed in the following sub-sections.



720
721 **Fig. 8.** Summary of findings.

4.1. Robotic automation application to AEC

There has been limited attention to robotic systems in AEC activities, where robotics is not among the main areas of the current research on AI-in-the-AECI (Fig. 2). Thus, a significant area for future research is developing advanced, usable, human-friendly, and smart robots [85] for performing dangerous AEC tasks that can cause fatal injuries and deaths; such as tasks performed above or near the sea [86], at heights [72], and inside deep trenches [87]. Most of the existing studies have focused on using AI methods to detect, assess, monitor, and control safety hazards, rather than replacing humans with robots in dangerous situations that place workers' lives at risk. To deal with this problem, it is very important that future research focus on inventing "robots working without human intervention" [88]. In human-friendly or less dangerous situations, however, rather than completely replacing humans with robots, it would be beneficial to develop and use cobots (or collaborative robots), i.e., robots designed to work with humans, as human workers bring additional value to projects [89]. Cobots and robots can bring numerous benefits, such as improved productivity, efficiency, safety, and quality, to the AEC industry. Modularization and prefabrication as well as 3D printing are also becoming predominant approaches to achieve these benefits in the industry. Therefore, coupling robotics technology with modular construction technology and 3D printing technology is another fruitful field for further research, which could explore, for example, the invention and application of cobots for constructing buildings in factories. A crucial issue here is how working with robots/cobots would impact worker sentiment and performance – future studies could investigate this. Furthermore, future research could study: (1) the performance, effectiveness, and efficiency (and how to optimize these) of existing robots; such as 3D printing robots for printing large buildings and bridges, bricklaying robots (e.g., Construction Robotics' SAM100), and demolition robots [66,90]; and (2) how these robots could be promoted and adopted in the AEC industry in a widespread manner.

4.2. Convolutional neural networks application to AEC

An emerging trend is the development and usage of convolutional neural networks (CNNs) for AEC applications. As indicated earlier, CNNs are a popular class of deep neural networks (NNs) or deep learning (DL) architectures. Deep NNs here refer to NNs consisting of multiple hidden layers and increasing the number of layers causes deeper networks. Inspired by mammalian visual cortex [91], CNNs are capable of processing datasets that come in the form of multiple arrays [92], e.g., a color image made up of four 2D arrays with pixel intensities in the four color channels. As Ref. [92] indicated, several data modalities are in the form of multiple arrays, i.e., 1D for sequences and signals, involving language; 2D for audio spectrograms or images; and 3D for volumetric images or videos. All NNs (including CNNs) consist of fully-connected layers of software-based calculators called neurons. Each neuron within a layer is connected to every neuron in the subsequent layer. CNNs convolve learned features with input dataset and can concurrently learn and extract optimal, effective, and very complex features for recognizing visual patterns directly from the raw data. A key advantage is that, unlike conventional NNs, CNNs require little-to-no pre- and postprocessing in doing all these, meaning that they learn the filters that in conventional NNs, necessitate hand-engineering. CNNs, in addition, deliver superior performance in both computational speed and accuracy [91,93]; and are making major breakthroughs in overcoming problems that have for several decades resisted the best efforts of the AI community [70]. They often leverage four central ideas in taking advantage of natural signals' properties, namely local connectivity, the sharing of weights, pooling, and the deployment of multiple layers. Moreover, a typical CNN architecture is made up of three types of layers, convolutional layers, pooling layers, and fully connected layers. Detailed discussions/information upon CNNs could be found in, for example, Refs. [70], [92], and [94]. CNNs have a range of applications in image classification, action recognition (e.g., action recognition in still images and in video sequences), speech and natural language processing (e.g., automatic speech recognition, text classification, and statistical language modeling), visual saliency detection, pose estimation, object tracking, scene labeling, time series forecasting, object detection, text detection and recognition, etc. [94].

In the domain of AEC, CNNs have only in very recent times been classified and applied as vision and learning-based methods for solving problems such as: damage detection [95], facility operations and management [96], construction sites safety monitoring [97], concrete compressive strength estimation [98], structural health monitoring (SHM) [99], maximum gradient (MG) decision-making [100], etc. Among these, the idea of applying CNNs for damage detection has gained the most attention, besides very few CNN-based methods/models/systems developed for several of the noted problems. The studies regarding damage detection have also focused more on concrete structures damage, in particular cracks – a common type of damage. Ref. [101], for example, proposed a vision-based technique employing a deep CNN architecture to detect cracks in concrete structures of tunnels without having to compute defect features. To evaluate the performance of the proposed vision/CNN-based damage assessment technique, they conducted a comparative study, which demonstrated how the technique gives better performance than traditional damage detection methods in detecting cracks in realistic situations. Ref. [102] also presented a "highly accurate" damage detection method using a deep CNN with transfer learning and Inception-v3 for detecting concrete surface cracks of hydro-junction infrastructure; whereas Ref. [103] introduced a CNN-based method to detect concrete bridge cracks. All these works suggest that

CNNs are an effective, efficient, accurate, and powerful tool for the detection of damage, and that this class of DL models are evolving themselves as viable techniques for a novel generation of vision/learning-based structural damage detection systems. Nevertheless, there is still a critical need for further work on developing CNN-based methods for damage (such as corrosion, surface delamination, cracks, etc.) detection of steel structures (e.g., steel trusses and steel bridges). Another fertile and promising avenue for further research is the invention of more methods to detect damages (such as leakages) in underground pipeline systems [104] and tunneling shields [105]. In addition, most of the already developed CNN-based methods are limited in their ability to detect/recognize multiple damage types simultaneously; they are only able to detect one particular type of damage, e.g., concrete cracks. Thus, it would be valuable to invent more quasi real-time vision and learning/CNN-based structural damage detection techniques capable of detecting multiple types of damage (e.g., concrete cracks, and steel cracks, corrosion, and delamination) at a time [106].

It is further observed that nearly all of the AEC-based CNN-based methods have been restricted in their scope, being image-based. That is, the CNNs' application of image recognition where the architectures take images as the input dataset have been the most common use in the AEC field, wherein very limited work has been carried out in the video dataset domain. This is largely because CNNs are primarily designed for

2D spatial signals, making it hard to apply them to video recognition and classification; as videos hold an extra (temporal) dimension, which fundamentally differs from the spatial variations images hold. Besides, the sizes of signals of videos, compared to those of images, are in higher orders [94]. However, some approaches to overcome the noted drawback to enable the invention of video-based CNN-based methods for AEC problems have been proposed. One of which is to fuse the features of two CNNs, one for the spatial dimension and another for the temporal dimension [93]. Another way is to conduct three- or higher-dimensional convolution inside the CNNs' convolutional layers aiming to capture discriminative features along both the temporal dimension and the spatial dimension [107]. Using these approaches, three- or higher-dimensional (thus more robust, reliable, efficient, and accurate) CNN-based methods could be developed for tackling highly complex AEC problems. Moreover, the performance of CNNs for AEC applications largely depends upon the amount of data used for training. Large amounts of dataset are usually required for training so as to avoid the problem of overfitting. Most of the CNN-based methods developed for the AEC industry suffer from this issue, due to using relatively little training data usually collected through normal cameras. To address this problem, in the area of project or construction site safety, for instance, the application of CNNs could be integrated and enriched with Internet of Things (IoT) devices, drones, laser capabilities, BIM, and data mining methods [108]. As a result of exploiting such an intelligent approach, *millions* of project site-based drone-collected datasets of images and videos, for example, could be attained. It should be noted that videos could be more effective than images in continuous progress monitoring and critical events detection. Such datasets can be used for training and developing more efficient/reliable 1D, 2D, 3D or higher CNN-based methods for detecting events/behaviors on sites that are unsafe or not in compliance with safety measures and standards. These methods should be able to detect these events/behaviors in real-time and then report them immediately to the right persons. They should also be trained and developed to be able to learn the repetitive tasks of workers and detect and alert them of threats coming their way. In this R&D direction, researchers can collaborate with companies that could afford such large amounts and nature of datasets. The success of rightly developing and implementing the proposed CNN-based methods powered by IoT, drones, etc. would have a significant impact on improving safety, adhering to safety policies, in the AEC industry. Future research could also investigate the applicability of this approach to areas such as: sustainable development (e.g., in green/sustainable and modular/off-site construction implementations), architectural design, life cycle assessment and cost, energy, performance assessment, and reliability analysis, which are also identified in section 3.3 as emerging themes in research on AI-in-the-AECI. Furthermore, there are opportunities for future AEC studies to go beyond image recognition and classification and implement CNNs for speech and natural language processing, visual saliency detection, pose estimation, scene labeling, time series forecasting, text detection and recognition, etc.

As researchers try to augment the robustness and depth of CNN-based methods in AEC, an indispensable issue that should be considered is computational efficiency. CNN models' performance are mostly examined and judged with regard to accuracy and computational efficiency (defined as the ability to process data in real-time and rapidly – in a feasible amount of time). Although some of the existing studies showed good performance of the CNN models created, it must be highlighted that increasing the robustness of data as suggested in this review may demand some fast processing techniques of CNNs in order to achieve accurate as well as computationally efficient implementations. It is therefore essential that future studies leverage GPU- and FFT-accelerated software and hardware solutions, for example, in applying CNNs in AEC [109]. Lastly, future studies could explore the potential of combining CNNs with other DL architectures – e.g., recurrent neural networks (RNNs) that implement reinforcement learning (RL) [92], deep Q-networks (DQNs) [110], convolutional deep belief networks (CDBNs) [111], autoencoders [51], etc. – to develop CNN-based models tailored for the needs of the AEC industry. Systems combining CNNs with other DL models are currently uncommon.

4.3. Collaboration and borrowing of theories and ideas

There is an obvious lack of collaboration between institutions and countries involved in research on AI-in-the-AECI. As discussed by Ref. [112], despite having some drawbacks, research collaboration has several important benefits, such as “increased chance of success”, “grants and funding”, “avoidance of errors”, “complex projects”, and “respect”. Hence, this problem in the extant AI-in-the-AECI research should be addressed by funding agencies and research institutions through developing policies for encouraging global or cross-country and interinstitutional research collaboration as a requirement to apply for related funding. According to Ref. [113], cross-country collaboration, for instance, can help countries address major problems such as skills shortages and inadequate training, education, and research capacities, and facilitate technology and knowledge transfer among countries. However, in order to maximize the benefits from collaborating across the globe for conducting research on AI-in-the-AECI, issues such as the possibility of dealing with different time zones as well as understanding cultural differences [114] should be properly addressed.

Furthermore, in the light of the research findings, horizontal and vertical borrowing of applicable theories/ideas is recommended in research on AI-in-the-AECI. These theory borrowing types have been explained by Ref. [115]. Despite their usefulness, researchers should apply them with caution; the “validity threat” should be considered, as a borrowed theory might operate differently within a different context or at a different analysis level.

5. Conclusions and recommendations

5.1. Theoretical and practical contributions

AI deals with the science of inventing intelligent machines and computer systems that can learn and help to solve problems. It is playing a significant role in Industry 4.0, the era of digitalization, driving the digital transformation of many industries, including AEC. In the AEC industry, AI provides advantages to deal with a diversity of difficult, complex engineering and management problems that defy conventional computational methods-based solutions. Consequently, over the past few decades, researchers have been conducting research applying AI techniques/algorithms and concepts to AEC problems. This paper presented the first comprehensive scientometric study appraising the state-of-the-art of research on AI-in-the-AECI. For theory, the present study is unique in several ways: unlike prior review studies in the area, the findings are reproducible and rely on quantitative analysis of the literature, with minimal subjective judgment; the study targets research activities of AI in the AEC context, rather than focusing on use cases and applications; the findings provide the first comprehensive agenda for leveraging and advancing AI in AEC research with showcasing the existing research, spotting fundamental problems to be addressed, and offering recommendations that give directions on how to address the shortcomings in defining further research. In practical terms, this study can aid practitioners with a synthesized and readily-available point of reference that captures the state-of-the-art of research on AI in the AEC sector, through which cutting-edge technologies and methods are introduced. This gives practitioners a benchmarking tool to assess their maturity in terms of using AI techniques/concepts and also enhance their readiness for adopting AI in AEC practices.

5.2. Recommendations for theory and practice

This study encourages the widespread adoption of AI methods in the AEC industry, in which a few issues should be highlighted. First, AI methods could hone the efficiency and effectiveness of AEC tasks, but one should neither overlook the complexity of AI methods development nor this operation's cost, which could be a significant amount of time, effort, and money. Therefore, future studies could investigate how to optimize this cost and achieve *value* in the implementation of AI. The cost can be a major barrier, but applications might still come about if the benefits from them are apparent and properly understood. This necessitates future studies, grounded in *good science*, concerning the real quantitative and qualitative benefits of various individual and combined AI systems. Moreover, adopting AI in AEC requires embracement of change and re-engineering of processes so as to maximize efficiencies, capturing the full benefits of AI. Such changes include, e.g. organizational, technological, mindset, nature of business competition, and cultural changes. As such, AEC organizations ought to adopt an educative approach to tackling AI. If they wish to achieve success in their AI journey, then it is very necessary that they establish AI roadmaps and methodologies that place employee education and training first. Bill Gates's "BrainyQuote", "*Technology is just a tool. In terms of getting the kids working together and motivating them, the teacher is the most important*" [116] underlines this point. That is, AEC organizations must find innovative ways to develop the knowledge, skills, and capabilities needed for the successful AI transformation and implementation. They should develop AI-skilled workforce who could smartly embrace interdisciplinary teamworking, agile development, new thinking ways, and 'big dataset' exploration. One best way to achieve this is to use in-house capacity-building programs rather than external programs to train employees, as the latter may not afford the holistic company-specific education/training necessary to drive rapid scaling, agile and cross-functional collaboration, and deep/lasting cultural changes [117]. Finally, future AEC researchers should be more inclined towards conducting AI-related studies and developing AI-based methods/models/systems that not just add to the body of knowledge but can also be applied in real-time in real-world practice.

5.3. Limitations of this study and how they may be addressed in future studies

Despite its contributions, this study has limitations. The analysis was based upon dataset extracted from Scopus, therefore may be affected by any intrinsic limitations of Scopus's coverage of publications. Besides, the literature was searched using certain keywords. Moreover, this study was limited to only journal articles. For these reasons, the research findings might not fully reflect the whole available literature on AI-in-the-AECI. Similarly, this research was mainly guided by social network analysis principles regarding citation networks. Using citations as the main indicator of quality, impact, and connections of scholarly works might be open to criticisms. Any measurement in science has a dose of subjective judgment; researchers' cognitive limitations and values are reflected in the choice of methodology, topic, and interpretation of findings. This study is no exception. Using data collected in longitudinal studies of the literature on the topic, and using different metrics and methods provide a way forward for validating the findings here and gradual removal of subjective elements.

The above-mentioned limitations generate fertile grounds for further research, while one should consider them when interpreting the research findings. Future research may, however, attempt to address the limitations via using data from various sources and a variety of indicators for assessing impact, quality, and connections in the literature; it may also include all literature types.

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Appendix A. Some AI techniques applicable to AEC

- Genetic algorithm
- Neural network
- Fuzzy logic/Fuzzy set
- Machine learning
- Particle swarm optimization
- Support vector machine
- Data mining
- Building information modeling
- Case-based reasoning
- Deep learning
- Harmony search
- Differential evolution
- Adaptive neuro-fuzzy inference system
- Convolutional neural network
- Expert system
- Genetic programming
- Object oriented programming
- Firefly algorithm
- Evolutionary algorithm
- Knowledge-based system

Note: The techniques are listed in no order of importance or applicability to AEC.

Appendix B. Some AEC problems/issues/domains to which AI is applicable

- Optimization
- Simulation
- Uncertainty
- Construction management
- Bridges
- Project management
- Decision making
- Concrete
- Design
- Reliability analysis
- Maintenance
- Structural health monitoring
- Risk management
- Damage detection/assessment
- Forecasting
- Safety management/engineering
- Productivity
- Corrosion
- Mechanical properties
- Rehabilitation
- Cost
- Information management
- Planning
- Structural control implementation
- Image processing
- System identification
- Durability
- Energy
- Construction equipment
- Knowledge management
- Resource allocation
- Thermal comfort
- Temperature
- Life cycle assessment

- Inspection
- Modeling
- Sustainability/sustainable development
- Performance evaluation/assessment
- Buildings
- Scheduling
- Automation
- Vibration control
- Classification
- Earthquake engineering
- Truss structures
- Fly ash
- Estimation
- Reusability
- Large steel structures
- Problem solving
- Civil engineering
- Roads and streets
- Accident
- Pavement

Note: The problems/issues/domains are listed in no order of importance.

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