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Review

A Bibliometric Review on Artificial Intelligence for Smart Buildings

Jiaxi Luo

Dillard College of Business Administration, Midwestern State University, MSU Texas, 3410 Taft Blvd., Wichita Falls, TX 76308, USA; fleyear2018@163.com or jiaxi.luo@msutexas.edu

Abstract: This paper provides a critical review on the advancements of artificial intelligence in recent applications in building environments from the perspectives of key research hotpots, important research institutes, researchers, and their contributions. Associated technologies, such as Internet of things (IOT) technologies, and advanced operational strategies for promoting building performance are alos discussed in the paper. Bibliometric analysis on the platform CiteSpace quantitatively summarizes the key characteristics of works in the literature and their applications. IOT based sensing networks are analyzed, discussed, and summarized since they play a pivotal role in securing the accuracy and efficiencies in data acquisition so as to facilitate building energy management systems. Additionally, the algorithms associated with machine learning and data-driven technologies are reviewed in the applications such as building energy prediction, building management optimization, and their maintenance. This paper explores the emerging technologies and developing trends in the field so as to find potential routes for future studies (which will encourage the uptake of AI technologies in buildings).

Keywords: artificial intelligence; bibliometric analysis; CiteSpace; IOT; smart buildings

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1. Introduction

The concept of smart buildings has attracted tremendous interests in the field with specific attentions on the building performance, energy savings and users' interactions [1–3]. Figure 1 provides a route map of the history of smart building, including conventional buildings, intelligent buildings, and smart buildings. Before the 1980s, building design focused more on the physical structure of buildings and architectural arts. The concept of intelligent buildings emerged around 1984. Intelligent buildings, namely taking building as a carrier for the comprehensive use of Internet of things, big data, artificial intelligence technology to build a new generation of information technology and offer comprehensive service, was intended to realize the comprehensive perception, analysis, judgment and self-decision of buildings throughout their whole life of service. They can coordinate the facilities, environment, and habits of people to provide an energy-saving, safe, efficient, healthy and humanized intelligent system in building environments. Artificial Intelligence is more likely to be integrated with smart buildings in recent years [4,5].

In the context of new information technology, the concept of the building has developed from an intelligent one to a smart one. By integrating artificial intelligence technologies, buildings have the ability for self-learning, self-decision-making, and self-updating. Therefore, the operation and management of buildings is the direct embodiment of architectural intelligence. The connotation of building energy saving involves highlighting the application of various intelligent information systems and highlighting the integration and application of smart systems. The concept of artificial intelligent buildings (AIB) [6–8] has recently emerged, and has been adopted in newly constructed buildings. Moreover, optimal energy management by newly developed technologies such as artificial intelligence

(AI) algorithms, big data, Internet of Things (IOT), and other associated facilities has enhanced the development of AIB [9,10]. For instance, the researchers in [11] developed an energy management system assisted by big data (outdoor temperature, solar radiation, and the surrounding conditions of the neighborhood, and other historical climate data) to forecast the heating energy while reducing the duty time of the HVAC in the building. IOT architecture in the building environment has been exploited in the content of smart cities for a practical urban service in city of Padova, Italy [12]. The authors have designed and discussed how an advanced communication system can be developed to facility a large amount of digital devices and collect a proper number of datasets for managing energy utilization as well as for monitoring the structural health of buildings. Reference [13] provided several cases concerning how AI technologies facilitate sustainability architecture to enhance buildings. To find the energy saving potential in the content of smart city, developing an urban building database is critically important [14]. A case study to support urban information systems has been carried out, an urban building database is designed and implemented in Lisbon, Portugal, in which the process of collecting, mapping, cleaning, and data mining are introduced to reach high energy efficiency, safety and comfort while mitigating impacts on environment and climate. Data driven methods, as one of the more popular AI groups, are commonly used to predict energy usage in building environment. Reference [15] investigates and compares four different data-driven methods for energy consumption so as to optimize system control and retrofitting. Building information modeling (BIM) is getting popular in building management system. A study in reference [16] strive to include BIM and sensing networks for a building to visualize inside thermal condition virtually under the standard of the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE).

The above investigations have indicated that smart buildings use promising technologies cooperating with artificial intelligence to provide their occupants with comfort and an energy-efficient environment. Our aim in this paper was to better understand the concept of smart buildings where AI facilitates the promotion of building performance. The main contributions of this study are to provide an in-depth literature review by bibliometric analysis and to demonstrate how certain technologies are applied into smart buildings. Different from the existing review articles, the study employs a text mining tool, CiteSpace, to analyze the research field. The innovation of this article lies in the following three aspects. First, this study uses visual analytic process to reveal what topics have attracted attention and how key items of knowledge are developed where citation data from popular sources, Web of Science, and SCOPUS are collected. Secondly, the question concerning how knowledge has evolved so as to track the development of AI-smart buildings closely and extensively is explored. Thirdly, this article demonstrates what intellectual turning points exist along a critical path via the explosions of concepts in the field. Moreover, the strength of the article lies in the fact that it provides different values for stakeholders who are from diverse sectors, such as architecture, the energy industries, control engineering, and information and communications technology (ICT) via discussing key applications in various area associated with AI in smart buildings.

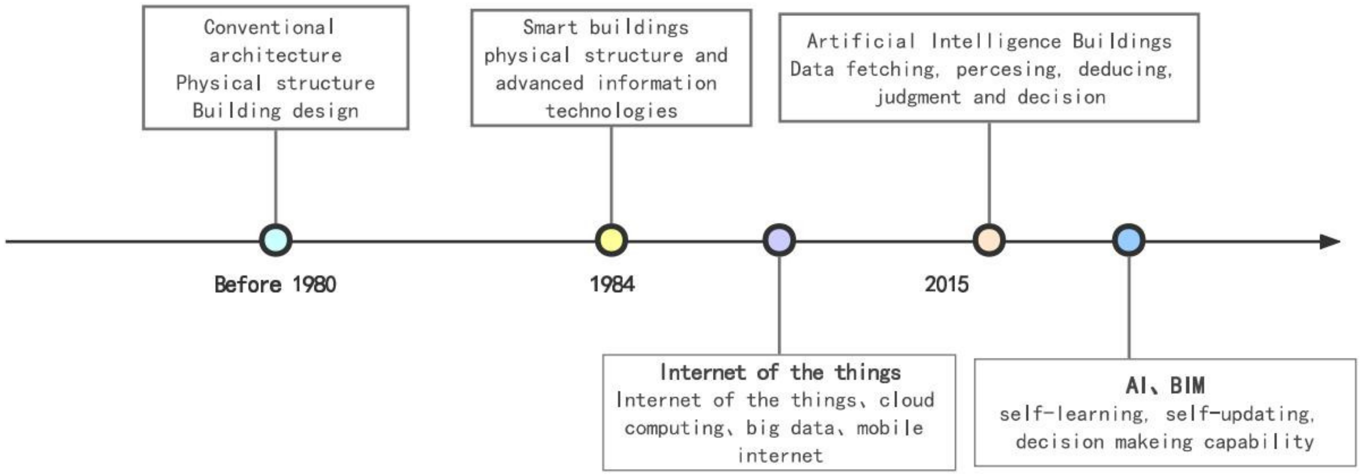

Figure 1. Three development stages of modern buildings.

2. Methods

There exist diverse definitions of the concept of smart buildings. It is commonly regarded that the formal one definition of smart buildings was first given by the Intelligent Building Institute of the US [17]. A smart building enables buildings to develop an efficient environment via reasonable structures, management, facilities, and interactions between these components. Extensive context has been added later on in references [18,19] with an emphasis on operational efficiency, involvement of its occupants, and employment of information and communication technology (ICT). In order to explore the recent progress on artificial intelligence integrated in smart buildings, CiteSpace is employed to execute scientific analysis.

2.1. Scientometric Analysis by Citespace

CiteSpace is a scientific tool for documentary metrology. It provides a visualization method to demonstrate the results in a scientometric analysis at a specific research field. It explores a knowledge domain through an in-depth visual analytic process and provides a structural and temporal overview. Normally, it can be employed in a systematic visual analysis where key scientific literature are used to find the hot-topics and emerging trends in the subjected field. A knowledge domain is defined as a concept that cover a scientific field or research discipline. CiteSpace maps a knowledge domain by several visual and accessible graphs which are created with the purpose of accurately describing available information resources [20].

By using bibliometric analysis with CitesSpace software (CiteSpace II, Chaomei Chen: Philadelphia, PA, USA), 2974 articles concerning smart buildings with AI technologies in the core collections of the Web of Science (WoS) database were analyzed in this paper.

2.2. Data Source

Data were obtained from the Web of Science Core Collection database, Citation index selects Science Citation Index Expanded (SCI-E) and Conference Proceedings Citation Index-Science (CPCI-S). The theme was retrieved with “smart building *” OR “intelligent building *” AND “artificial intelligence” AND “big data”. Therefore, the time span was from 2008 to 2022. Afterwards, the author refined the outcomes manually. Eventually, 2974 documents were obtained.

2.3. Research Methods

CiteSpace is a Java application that visualizes input data to explore knowledge areas with specific topics, including co-authors and institutions, keyword co-occurrence, co-citation of literature, clustering, and mutation detection, which helps to present the research status and emerging terms in a research field. CiteSpace is concerned with three essential aspects: heterogeneous networks, mediation centrality, and mutation detection. These aspects can solve three practical issues, namely understanding the current status and emerging technologies, determining the relevance of those investigations, and demonstrating development trends and correlations [21–23]. In CiteSpace, the current research status and technical terms are extracted from identifiers of literature, including titles, abstracts, and keywords. The research relevance is determined by identifying nodes with high intermediary centrality, making it easier to identify key points as purple cycles in order to make them stand out in a visual network. The burst detection algorithm is used to identify the increasing research interests in a fast manner. The mediation centrality is defined in Equation (1) as follows:

$$B(i) = \sum_{i \neq j \neq k} \frac{\rho_{jk}(i)}{\rho_{jk}} \tag{1}$$

where ρ_{jk} is the node to be computed; *i* refers to the total number of shortest paths between nodes *j* and *k*; and $\rho_{jk}(i)$ refers to the number of shortest paths passing through node *i* between nodes *j* and *k*.

This paper is used to explore the knowledge map of smart buildings with regards to the applications of artificial intelligence. First, literature data related to smart buildings from the database Web of Science are collected. Secondly, the collected information is fed into the CiteSpace software and the duplicates are removed, yielding 2974 valid documents. Then, the year of publications, countries and institutions, co-cited authors, keywords and clusters, cross-cited literature and clusters, and literature mutations are analyzed. Finally, the knowledge maps in the field are formed. The following discussions will be carried out with respect to those details.

3. Results and Discussions

The methodologies of CiteSpace include exploring the key points of the research field so as to find key technologies associated with the research field, the developing road-map, and important = trends. Commonly, those key points include statistical data on the number of publications, the key nations and institutes, the most cited authors with representative publications and networking, the key words by co-occurrence and clustering, the key publications associated with technical terms, and burst words. In this study, these key points are presented. Additionally, recent applications for AI involved in smart buildings are classified and discussed in depth. Table 1 gives the main discussions in the paper.

Table 1. A summary of the main discussions in the study.

Order	Concerns	Focus
1	Annual publication amount	• From 2008 to 2022
2	Key nations/institutions and their research networks	• Most active countries • Potential corporation between nations/institutions
3	Most cited authors	• Most citations • Potential cooperation between them
4	Keywords	• Co-occurrence, clustering, frequencies • Centrality
5	Publications	• Co-citation, clustering

6	Advanced technologies in AI-smart buildings	• Burst words • Representative literature and their authors • Popular applications • IOT • Energy prediction • Performance optimization • Building energy management • Information fusion • Optimal route planning • Building maintenance and management

3.1. Analysis of the Publications

The 2974 documents are organized in an annual way, as shown in Figure 2. The statistics of the original data shows that the research on smart buildings was launched in 2008. The numbers of publications started to grow from 2019. However, the numbers shrunk in the past two years, indicating that the research interests have receded.

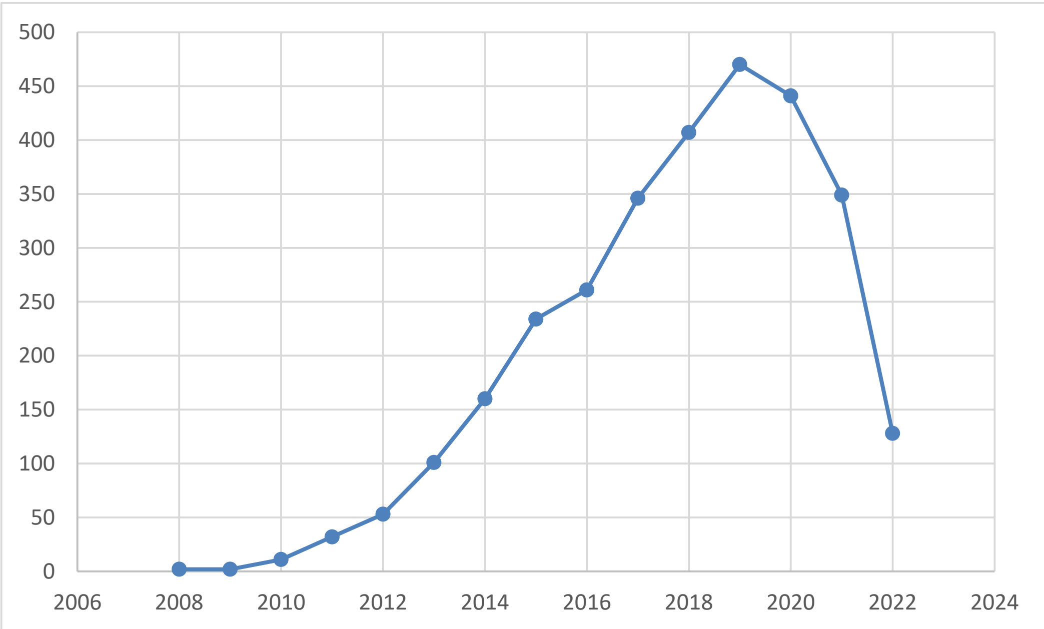

Figure 2. Statistics of annual publications database for smart buildings.

3.2. Nations and Institutions

Determining the key countries and institutions in line with their academic influence is crucial for understanding the research foundation and dynamics in the field. Therefore, the node type in CiteSpace is firstly selected with the "country" concept. A knowledge map of nation occurrence is shown in Figure 3. In the plot, there are 107 nodes, representing 107 countries. The larger the nodes, the greater the frequency, meaning the more publications are found. The nodes directly correspond to the time sheet from the center radius to the edge. The cold color of the inner circle represents the early years, and the warm color of the outer circle represents recent years. For example, the purple black at the center of the node indicates the literature published in early years while the yellow area of the node near the outer circle indicates the latest publications. The purple cycles in the plot represent the key nodes whose centrality is over 0.1. In another word, the purple cycles indicate the important authors or institutes in the field. The connection between the nodes indicates research partnerships between those countries.

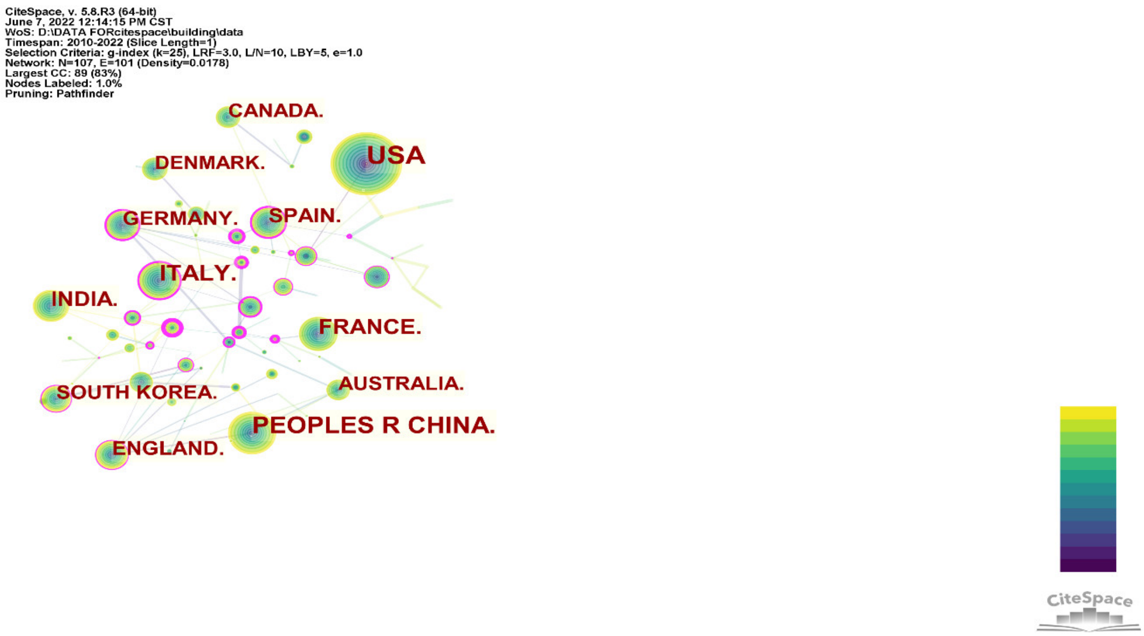

Figure 3. A knowledge map of national cooperation network.

Table 2 summarizes the country with the greatest number of publications in the field. As can be seen from Table 2, the top three countries in the ranking are the United States, China, and Italy. From the cross-connection, the cooperation between the countries differs. For instance, China and United States post the closest partnership in the field while they showing weak connections with other countries. Those connections indicate that the cooperation level between China, United States, European countries, and other countries worldwide.

Table 2. Country rank with the top publications.

No.	Country	Number of Investigations/Articles	Betweeniess Centrality
1	USA	651	0.06
2	People Republic of China	332	0.03
3	Italy	246	0.29
4	France	203	0.03
5	India	174	0
6	Spain	154	0.36
7	UK	124	0.16
8	Germany	120	0.34

In CiteSpace, mediation centrality is used to determine and evaluate the importance of works in the literature. The nodes with a mediation centrality over 0.1 are called key nodes while the literature (or authors, institutions, etc.) nodes are highlighted with the purple-red outer circle in the map. The countries ranked in the top and the corresponding intermediary centrality are shown in Table 2. The node type in CiteSpace is set as "Institution", and the network knowledge map of the publishing institutions is obtained, as shown in Figure 4. For example, in Table 3, the top five institutions are listed in the order of their publications.

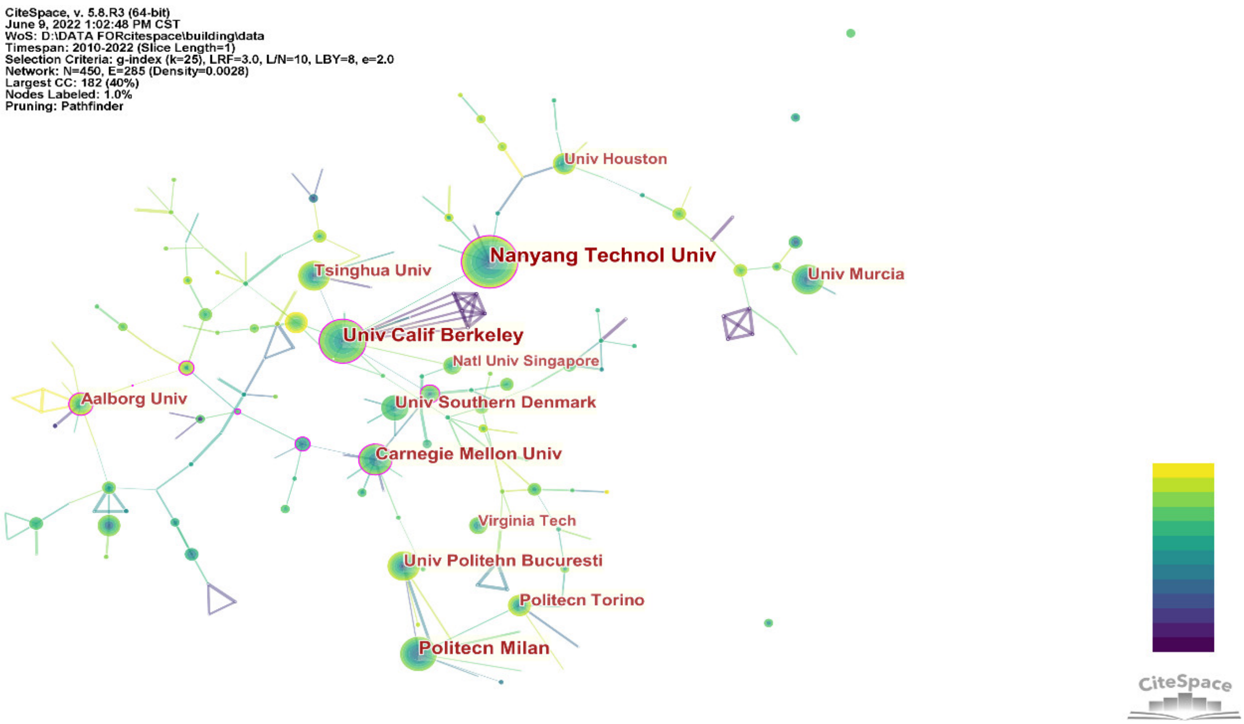

Figure 4. A knowledge map of the organizations.

Table 3. Top 5 organizations with the greatest number of publications.

No.	Country	Institution	Publication Number
1	Singapore	Nanyang Technological University	62
2	America	UC, Berkeley	54
3	Italy	Milan University of Technology	43
4	America	Carnegie Mellon University	37
5	Denmark	The University of Southern Denmark	8

It can be found from Tables 2 and 3 that countries such as China, the United States, and Australia have a large number of publications in the field. However, those publications do not come from several specific institutions, which means those work are scattered domestically. Knowledge exchanges or academic cooperation can be further strengthened in those countries. In Figure 4, the cycles in red or pink emphases some recent publications from those institutions are cited while demonstrating their research importance in the field.

3.3. Co-Citation Network

A co-citation analysis can explore the more influential scholars and their articles. CiteSpace describes the interconnection between the authors in terms of networks. On this basis, the distribution of authors with high citations in the field of smart buildings is jointly observed through citation frequency and mediation centrality so as to identify the authors with influential work in the field. The node type was set to "Cited Author", and a knowledge map was conducted as shown in Figure 5 with 800 nodes and 1250 connections. Each node represents one author while the size of the node represents the number of author's publications. The connection represents the cooperation between authors where the shorter the connection distance between the two circles, the more cooperation between the authors. A short connection reflects the close relationship between authors in the research field. As can be seen from the figure, the connections between the nodes are very dense, indicating that the cooperation between the authors is relatively close. In Figure 5, the outside of cycles in warm color (yellow, read, or pink) emphases there are recent publications from those institutions are cited. The color is warmer, the year is more recent.

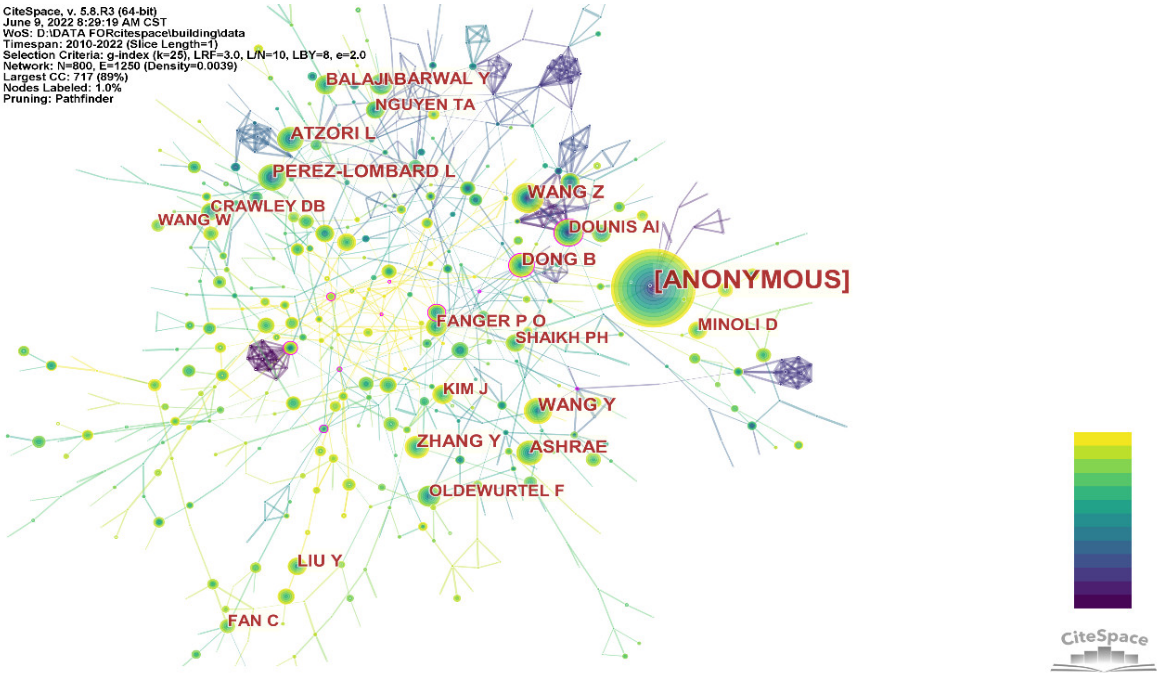

Figure 5. A network of the authors with co-citations.

Table 4 lists the total frequency of the top five highly co-cited authors, indicating that they play an important role in the field of smart building research while they make great contributions to promoting the development of the research.

Table 4. The top five most co-cited authors.

No.	Author	Frequency	Betweeniess Centrality
1	[Anonymous]	791	0.04
2	Wang, Z.	101	0.03
3	Dong, B.	87	0.19
4	Chen, X. J.	70	0.16
5	Ma, Y. D.	64	0.10

3.4. Keyword Co-Occurrence and Cluster Analysis

3.4.1. Co-Occurrence of Keywords

The keywords in the literature can reflect the key points of articles. Commonly, there are close links between several keywords in a literature. Moreover, the occurrence of the same keywords in different literature represents that there are links between these articles. Those links can form a heterogeneous network. The keywords with high frequency represent a hot topic in the research field, while the keywords with high centrality reflect the importance and the impact on the research field. The visualization of the keyword with co-occurrence are illustrate in Figure 6, while the ranks of the most popular keywords in frequency are shown in Table 5. In Figure 6, the outside of cycles in warm color (yellow, read, or pink) present recent publications are related to these keywords. The color is warmer, the year is more recent.

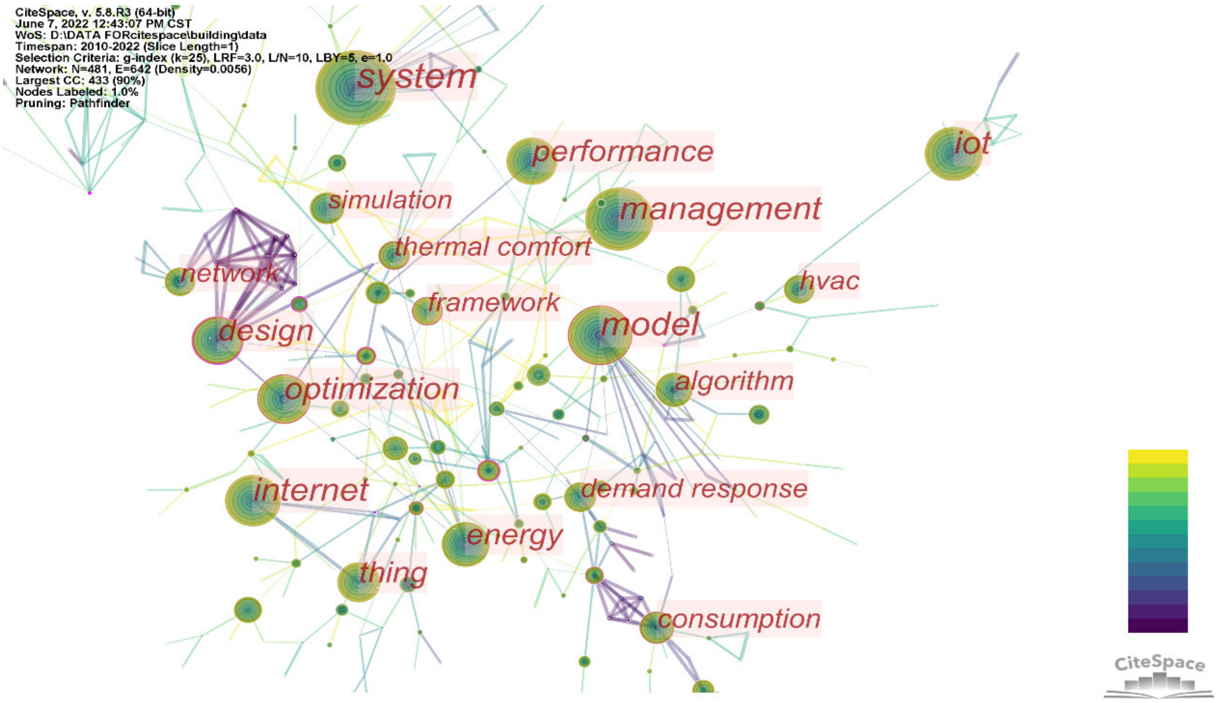

Figure 6. Co-occurrence network of the keywords.

Table 5. Keywords with frequency and centrality.

Rank	Frequency	Betweenness Centrality	Keyword
1	317	0.06	System
2	206	0.17	Model
3	181	0.1	Internet
4	176	0.06	Internet of things
5	168	0	Management
6	143	0.12	Optimization
7	117	0.33	Design
8	103	0.08	Energy
9	95	0.08	Demand response
10	72	0.14	Consumption
11	63	0.12	Framework
12	62	0.17	Thermal comfort
13	43	0.23	Efficiency
14	39	0.26	Strategy
15	33	0.27	Demand Side management

3.4.2. Clustering of the Keywords

Different from the topic clustering, keyword clustering analysis is a supplement to the key subjects in literature. A keyword clustering map is shown in Figure 7. There exist 15 clusters, with the most connected components being concerned. The clustering map has the following indicators, with 0.878 module Q, 0.8849 average contour value S. Furthermore, the contour value of each cluster exceeds 0.5, indicating that the results are reliable and meaningful.

As can be seen from Figure 7, the clustering map explores the main research methods and objects in the field of smart building. Basically, the key subjects mainly involve in:

wavelet transform (#0), ifc (#1), requirements (#2), algorithm design and analysis (#3), privacy (#4), adaptive attitude (#5), wifi (#6), thermal dynamics (#7), etc. In Figure 7, the different color groups demonstrate the various clusters accordingly.

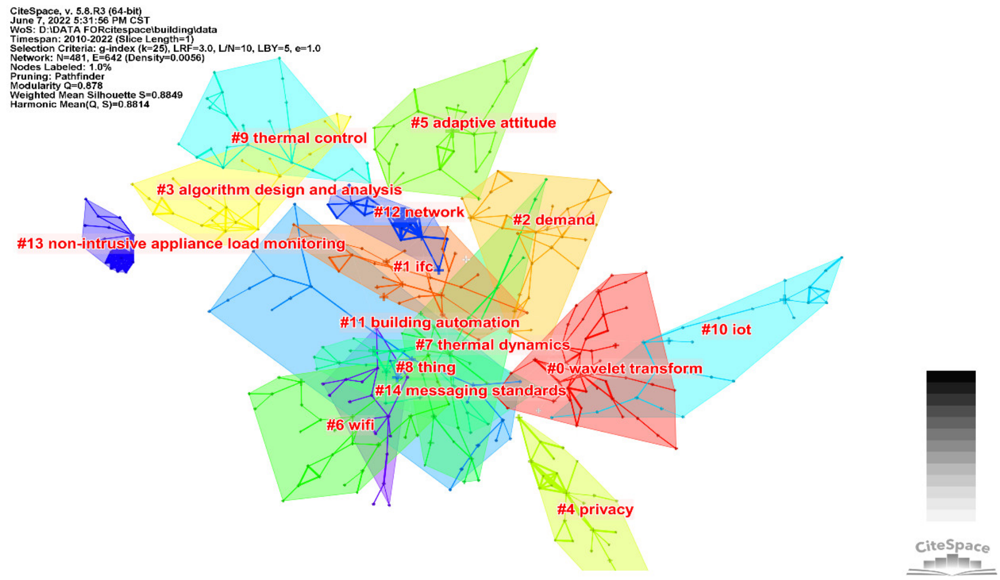

Figure 7. Cluster visualization of the keywords from the literature over the 2008–2021 period.

3.5. Literature Co-Citation, Clustering, and Burst Word Detection

3.5.1. Literature Co-Citation

The research basis in a certain field can be obtained through the key references. If one literature is cited by multiple articles. It may show, on the one hand, that these articles have the same research concerns. On the other hand, the cited literature may concern the key points in this field. The more the literature is cited, the greater its academic values. More fundamental knowledge or commonly concerns in the filed can be derived from this article. Based on the literature co-citation, a network involving the key references with high frequency is conducted by CiteSpace, as shown in Figure 8. There are several large nodes in the figure. The larger the node, the greater the co-citation involved. Special attention is also paid to centrality here. Generally, the greater centralization represents the more importance of the literature in this field. From this perspective, the nodes such as Palensky P [24], Gubbi J [25] and Oldewurtel F [26] are large, indicating that these articles have great impact in the research field of smart buildings. It is also found that the research interests of smart buildings have been growing in the past two decades along with specific developing routes.

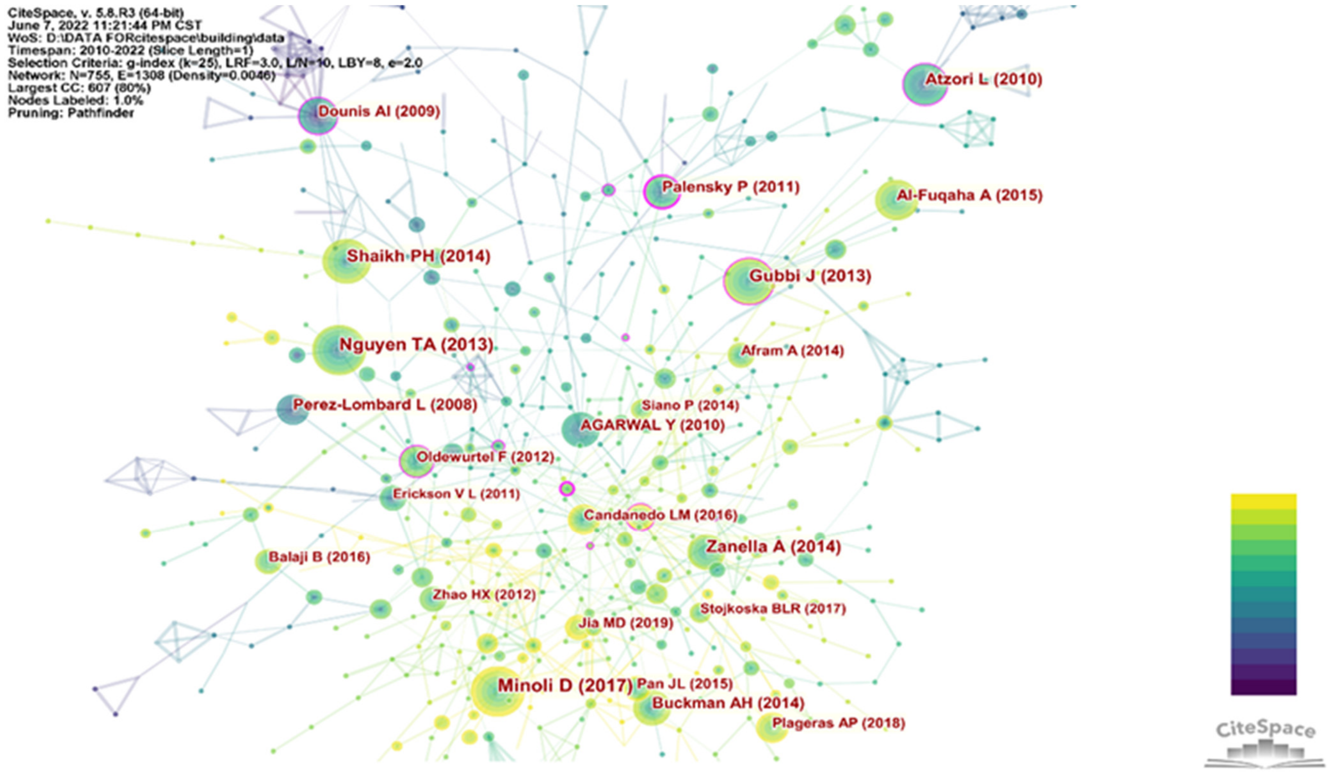

Figure 8. Network of literature co-citation. [6,10–12,24–42].

3.5.2. Subject Clustering

A subject clustering is extracted from the nominal terms based on the literature titles before clustering analysis. Accordingly, the research patterns and hot topics are found. The modularity values Q and the mean profile values S are two metrics for evaluating clustering. $Q > 0.3$ indicates a significant network; $S > 0.5$ indicates reasonable clustering results; and $S > 0.7$ means high clustering efficiency with convinced outcomes. A visualized results by subject clustering is shown in Figure 9 with 12 clusters (only with the most connected components). Module degree Q is 0.8734 while the average contour value S is 0.941. The profile value of each cluster exceeded 0.5, indicating that the results are reliable and meaningful.

In the figure, the dark colour of each node represents the earlier time while the warmer colour shows the later time. The theme in the clusters mainly focused on theory-based risk-constrained scheduling risk constraints scheduling (#0), energy generation (#1), intelligent integrated building (#2), load control (#3), learning method (#4), wireless sensor network (#5), etc.

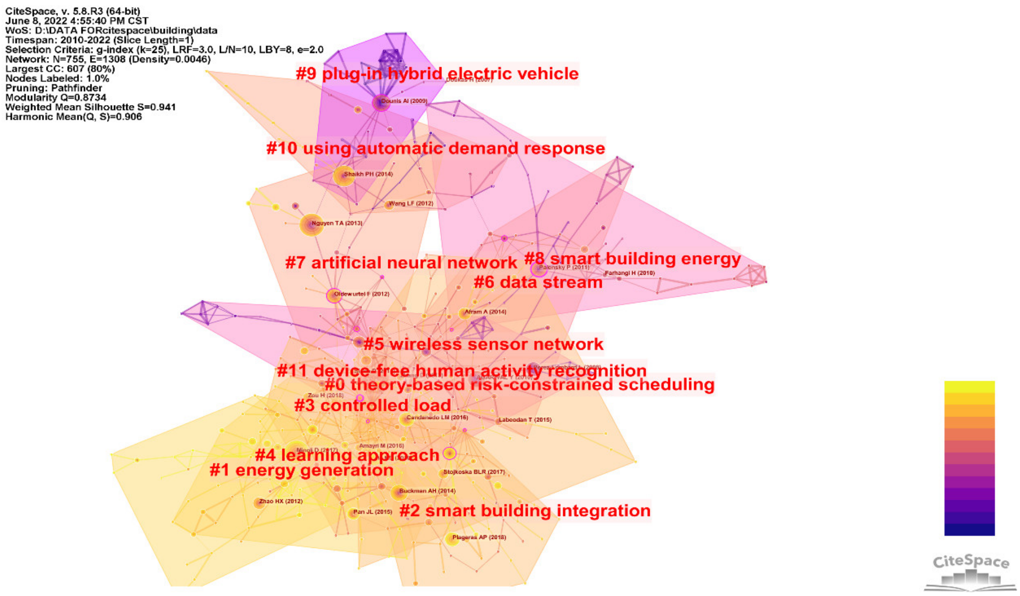

Figure 9. Clustering of literature co-citation over the 2008–2021 period.

To identify the emerging themes, classical themes, and outdated themes, the timeline is used here to classify the cited literature. After generating a cluster map, the button "Layout Timeline View" is clicked to obtain a visualization map with timeline where the cluster number is taken as the longitudinal axis and the time span is taken as the horizontal axis, as shown in Figure 10. We can observe the time span and evolution process of the smart building research from the clusters in the figure. We also receive the information on literature influences from the perspectives of the topic and the time-span of the topics. For example, cluster #7 represents big data. This hotspot ranges from 2012 to 2014 while being less popular later on. In recent years, clusters 1, 2 and 4 represent new research topics. Moreover, each cluster is supported by key literature, which is cited in different years as determined by their connection, circle size, and color discrimination. The representative literature nodes on each cluster are enumerated as shown in Table 6.

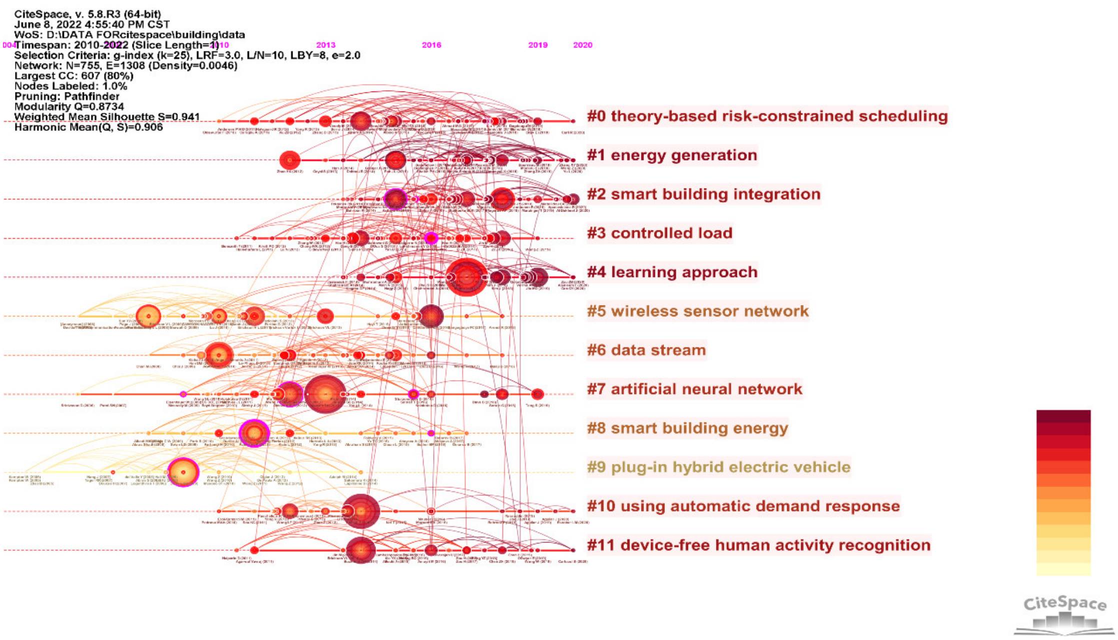

Figure 10. Visualization map by timeline.

Table 6. Representative literature on each cluster.

Cluster Number and Name	Author	Year	Frequency	DOI
#0 theory-based risk-constrained scheduling	Afram A [29]	2014	24	10.1016/j.buildenv.2013.11.016
#1 energy generation	Pan JL [40]	2015	25	10.1109/JIOT.2015.2413397
#2 smart building integration	Plageras AP [42]	2018	26	10.1016/j.future.2017.09.082
#3 controlled load	Siano P [31]	2014	21	10.1016/j.rser.2013.10.022
#4 learning approach	Minoli D [10]	2017	70	10.1109/JIOT.2017.2647881
#5 wireless sensor network	Candanedo LM [35]	2016	26	10.1016/j.enbuild.2015.11.071
#6 data stream	Labeodan T [43]	2015	29	10.1016/j.enbuild.2015.02.028
#7 artificial neural network	Nguyen TA [6]	2013	57	10.1016/j.enbuild.2012.09.005
#8 smart building energy	Palensky P [26]	2011	34	10.1109/TII.2011.2158841
#9 plug-in hybrid electric vehicle	Dounis AI [24]	2009	32	10.1016/j.rser.2008.09.015
#10 using automatic demand response	Shaikh PH [11]	2014	48	10.1016/j.rser.2014.03.027
#11 device-free human activity recognition	Buckman AH [41]	2014	36	10.1108/SASBE-01-2014-0003

3.6. Burst Detection and Analysis

Significant increase of the key technologies can be identified via citation burst from the literature so as to track the emerging trends in the field. The term of citation burst refers to a sudden surge of the research interests which have been discussed in a specific publication which been cited with increasingly number of others over a specific period of time. Citation bursts provide the evidence that the research publications cited have received relatively intensive attention in this research field. In order to understand the developing trend of the applications of AI in smart buildings, a series of representative references with strongest burst intensity as well as the start time are found (as shown in Table 7).

Table 7. Representative references ordered by burst time.

Rank	Author(s)	Year	DOI	Strength	Duration	Scope (2010–2022)
1	Dounis AI et al. [24]	2009	10.1016/j.rser.2008.09.015	11.97	2011–2017	
2	Atzori L et al. [25]	2010	10.1016/j.comnet.2010.05.010	12.23	2013–2018	
3	Palensky P et al. [26]	2011	10.1109/TII.2011.2158841	10.46	2013–2017	
4	Perez-Lombard L et al. [30]	2008	10.1016/j.enbuild.2007.03.007	16.74	2014–2016	
5	Lu J [44]	2010	10.1145/1869983.1870005	11.69	2014–2018	
6	Minoli D et al. [10]	2017	10.1109/JIOT.2017.2647881	7.68	2020–2022	
7	Plageras AP et al. [42]	2018	10.1016/j.future.2017.09.082	5.4	2020–2022	
8	Serale G et al. [45]	2018	10.3390/en11030631	5.32	2020–2022	
9	Amasyali K et al. [46]	2018	10.1016/j.rser.2017.04.095	5.23	2020–2022	
10	Lawrence TM et al. [47]	2016	10.1016/j.build-env.2016.08.022	4.94	2020–2022	
11	Wei TS [48]	2017	10.1145/3061639.3062224	4.56	2020–2022	
12	Reynolds J et al. [49]	2018	10.1016/j.energy.2018.03.113	4.56	2020–2022	

4. Key Applications in Smart Buildings with AI

The strength in Table 7 indicates the level of the popularity of the literature. The higher the strength, the more important the literature is for this field. In Table 7, the red segment indicates the burst duration while the blue segment indicates the time period where the literature was not cited. It is important to highlight newly cited literature as they often discuss promising technologies at present. Most of the works which concerned key knowledge in AI-smart buildings are summarized as follows.

4.1. The Most Cited References and Their Topics

Traditional architecture solves the most basic living problem of human beings, which is the integration of physical systems and design art. The concept of smart building features with advanced technologies, including information, communication, and automation in buildings, not only improves the comfort and convenience of occupants but also solves the issues of the links among diverse equipment in buildings and the intelligent operation of these items.

As can be seen from Table 7, the strength of the top 5 references with the strongest burst all are over 10; these are regarded as milestones in this research field. From these representative references, we can conclude that users' preferences for thermal and lighting comfort, indoor air quality, and energy conservation have become highly involved in recent years. The research hot-topic of smart buildings mainly includes equipment control technology, Internet of Things, efficient energy management in building environments, commercial building automation and industrial plant management (as the references in Table 7 indicate). Smart networks, for example, include a variety of home appliances, smart sensors, and wireless communication technologies. The literature on these issues represents recent research hotspots.

The design of smart buildings with AI has emerged, which represent the continuous reform and innovation of intelligent architecture based on the rapid development of Internet of Things technology. Smart buildings consider the relationship and interaction of people, equipment, and the environment in a sophisticated way, which integrate comprehensively the perception of information, intelligent sensing, and reliable decision-making.

AI technologies have a very close relationship to Industry 4.0 [50]. Similar to other AI involved fields, the artificial intelligence technologies for smart buildings and associated approaches could be generally divided into two main aspects. Some of them are used for the purposes of strategies and planning. The others are more likely used to address operational or control problems. For instance, reference [51] has developed a comprehensive optimization problem involved in multi-energy sources (gas, utility electricity, thermal storage and electrical storage, renewable energy units) and diverse energy demands (heating and electricity needs). A robust model predictive control has been developed to generate control instructions with a one-hour frequency. All responses based on the previous control instructions are then fed into the optimization model so as to generate new control variants. In this approach, a close-loop control is developed to ensure the effectiveness and stability of the system. Reference [52] has developed a stochastic optimization problem for a multi-energy-source system (multi micro-grids) where the compromised program (CP) method has been used to find the solutions for each scenario. The purpose of reference [51] is to provide optimal solution for each scenario so as to form a strategical scheme for the system.

Game theory, as a typical AI group, is commonly used to find an optimal solution for energy management in a complicated energy system where various sources and demand constraints are involved. By using the game-based approach, reference [53] allocates flexible demand and maximizes renewable penetration while maintaining a grid stability which takes economic considerations into account.

Those applications are the important examples since smart buildings with an increasing number of renewable sources and flexible loads are becoming crucial constituents in smart grids and smart cities. Additionally, references [51–53] evidence the strength of AI technologies as they deal with uncertainties in applications. Also, AI technologies display their advantages for solving deterministic problems without considering uncertainties. Those AI methods typically exist in energy prediction [54], facial recognition [55], route planning in ICT facilities [56], etc. to realize the intelligence of smart buildings. The subsequent section will present such applications.

4.2. Advanced Technologies Associated with Smart Buildings

4.2.1. The Internet of Things (IOT)

IOT has a huge amount of applications for various industries, including smart cities, smart grids, smart homes, physical security, e-health, asset management, and logistics. For example, with the emergence of the smart city concept, enhanced street lighting control, infrastructure monitoring, public safety and monitoring, physical safety, shooting detection, meter reading, and traffic analysis and optimization systems are being deployed in many cities. With this new technology, other recently developed technologies, such as big data and cloud computing and monitoring, have also been vigorously developed.

First, AIB realizes people-oriented and personalized customization. The core function is to provide occupants with a safe, comfortable, efficient and convenient living space. Second, AIB uses big data to promote the services in intelligent architecture. Big data technology represents large-scale data and uses distributed storage and parallel computing. AIB is supported by preprocessed large-scale data and information so as to provide technical support and realize convenient and effective services. Third, the wisdom of AIB lies in its cable network, either wireless network or other communication technology. By means of IOT which is integrated a variety of heterogeneous system with discrepant transmission structure, media and protocol. IOT standardizes the protocol gateway and allows those communication units to be as a modular component into the information platform over network. As a technical tool, IOT is a necessary foundation to realize multiple information fusion in an AIB. Fourth, AIB is a self-learning and decision-making system based on artificial intelligence. Artificial intelligence is the process of the machine training, behaving like a human brain. An AIB system use a computer to simulate the thinking process of a human's brain. Therefore, an operational system in an AIB makes intelligent decisions through the similar way of human's thinking, perception, learning, judging and other function in a "brain". Therefore, artificial intelligence is an important technical tool of an AIB. Fifth, AIB can make the building maintenance in a whole life. It manages all equipment and their operation. AIB divides all space into different zones. Facilities in different zones can be managed separately while collecting all of the information and forming a comprehensive management system to support a convenient, cost saving, and efficient building management system (BMS). A BMS can realize the monitoring and analysis of the structure, energy consumption and other environment of buildings by using promising technologies, such as IOT, cloud computing and big data. Therefore, it fulfills daily management and maintenance of equipment so as to save manpower while facilitating maintenance. In the applications, wireless communication are involved to form diverse networks. They are popular technologies in building environment, such as blue tooth [57], RFID [58], WIFI [59], LORA [60], NB-IOT [61], M-BUS [62], GPRS [63], ZigBee [64].

4.2.2. Energy Prediction under Data-Driven Technologies

With the development of smart meters and advanced metering infrastructure, energy big data analysis has been a growing research direction in recent years. Providing these data to research groups may facilitate researchers with an unprecedented opportunity for a better understanding of building energy conservation while developing a road-map to monitor buildings by fetching representative data. They also helps to consolidate the numerous research results in building energy conservation to eliminate duplication of work and to provide common solutions to research problems so as to create a strong research influence in the field of building energy consumption prediction. Future research directions in the field of big energy data analysis include building energy saving renovation, occupant behavior analysis and intelligent energy management.

With the development of new data-driven models, machine learning algorithms, including support vector machines (support vector machines), artificial neural networks (ANN), decision trees and other statistical algorithms, and deep reinforcement learning (DRL) are important research technologies.

The wisdom of an smart buildings with AI lies in its self-learning and automatic decision-making where IOT is responsible for collecting, converting, transmitting the information needed. However, in order to realize the customized functions, such as energy management, HVAC operation, consumption or health prediction, smart maintenance or building management, smart operation, and the route planning, etc., an intelligence decision-making function is needed. Artificial intelligence has increasingly received awareness in building environment. Different AI algorithms or methods are used for different purposes. In the past investigations, AI technologies are widely discussed in relation to energy management [65] in the most literature. Few attention has been given to other aspects in line with AI technologies are applied to buildings. In reality, AI technologies can be divided into different categories, including energy prediction [66], performance optimization of energy management system [67], optimal route planning over IOT communications [46]. The following sections give the detailed discussion.

Energy consumption prediction plays an important role in building energy management system since it can be an effective tool to analyze the occupants' behavior, or estimate building energy efficiency or diagnose the fault in building systems. There are diverse AI-based algorithms are used in energy prediction, such as Back Propagation Neural Network (BPNN) [54,68,69], Multi-Layer Perceptron (MLR) [70–72], Recurrent Neural Network (RNN) [73–75], Support Vector Machine (SVM) [76,77], Long Short-Term Memory (LSTM) [78–80] and support vector regression (SVR) [81]. Different algorithms have different applications. Artificial Neural Networks (ANNs) [82–84] including BPNN, MLR and RNN are most popular methods for energy consumption prediction. SVM and SVR tends to predict a short-term energy consumption in the most cases while and BPNN algorithm performs better in a long-term prediction.

In order to evaluate prediction performance, indicators including root mean square error (RMSE), mean absolute percentage error (MAPE), and R-squared (R2) are employed in building environment [46,65].

4.2.3. Performance Optimization

Energy saving and thermal comfort are regarded as the most two concerns in building environment. AI-based techniques have been increasingly promoted for the sake of the advancement of control and optimization. Two basic algorithms, namely generic algorithm and particle swarm optimization (or their descendants) are the classic methods for optimization [66]. They are widely used for optimal operation of HVAC system so as to reduce energy uses while maintaining the occupants' comfort [85]. Genetic algorithm (GA) [86–88] and particle swarm optimization (PSO) [89–91] are discussed in certain works in literature which demonstrate their efficiency in solving different objective functions under different operational constraints. Most of the operational vectors refers to HVAC units in buildings.

In addition, multi-agent systems (MAS) [92–94] are getting popular due to advancements made for modelling comprehensive systems. For instance, MAS is used to model different entities (agents), such as lighting, heating, ventilation, etc., to find an optimal solution of minimizing energy consumption in buildings while maintaining thermal comfort [95].

4.2.4. Information Fusion and Optimal Route Planning

The concepts of information fusion, sensor fusion or data fusion have been receiving increasing attentions in the recent literature [96–100]. Especially, information fusion are commonly regarded as a technology including target detection, location information confusion, target identification, position estimation and threatening estimation [96,98]. Location determination and route planning by using artificial intelligence technologies is used in the application of a service robot in a library where the environmental information are collected by a couple of hull sensors. Information fusion by AI technologies is also highlighted in the stadium of Tokyo Olympic in 2020. Information from over 2000 gyroscope sensors are collected and and analyzed before competition strategies are determined automatically. Facial identification are also employed AI technologies in the security system in the stadium [55]. Scene recognition over narrow corridor or small space office rooms are investigated by using Octree map [99] where sensor data are collected and integrated into a 3D map for indoor navigation. A tour route prediction model is developed by integrating information of tourist behavior for a exhibition center where logistic regression method is used to identify the most influential factors on the orientation of the path selection from the tourists [56]. A heuristic algorithm is developed for optimal route planning at indoor environment. The purpose of the study is to provide a recommended strategy for evacuation in the case of emergence, such fire disaster in the buildings.

4.2.5. Building Maintenance and Management

AI plays an increasingly important role in finding an optimal solution or operational guidance [100] when a performance assessment system integrating with the information concerning building construction, conditions, facilities, key performance indicators, pipelines etc. As an important branch of artificial intelligence, machine learning [100,101] aims to make learning according to historical information or data collected a major objective. To evaluate the health condition of the steel structural connection, Reference, et al. [102] used a hybrid model by integrating a convolution neural network (CNN) and continuous wavelet transform (CWT) to evaluate the conditions of a building structural connections. Sun et al. [103] extract meaningful information from images and videos to form a structure model to assess building performance continuously. Reinforcement concrete (RC) cracks and spalling are concerned with using computer vision-based techniques coordinated with CNN to detect the loosened and corroded steel bolts [104]. Reference [105] used machine learning (ML) to identify the damage types and levels in structure. An inspection methodology was developed by Osco, et al. [106] in which a remote inspection of reinforced concrete structures using a ML algorithm allowed for the automatic identification of RC pathology. The integration of ML within BIM was also explored by Borin et al. [107]. The author has used building photogrammetry with ML algorithms to locate damaged elements automatically and presented these elements by computer vision-based algorithms over a BIM environment.

4.2.6. Building Energy Management Technology

Buildings consume a large part of the world's total electricity generation, and they must be integrated with it in order to fully develop a smart grid. Buildings can now become "producers" and "consumers" on the grid, and the continued growth of distributed renewable energy generation poses new challenges to the stability of the grid. Buildings can contribute to the stability of the grid by managing their overall power demand in response to current conditions. Building managers must balance the demand response requests of grid operators with the energy needed to maintain building operations. For example, energy is required to maintain thermal comfort within a building, so an optimized solution to balance energy use with indoor environment quality (adequate thermal comfort, lighting, etc.) is needed. The successful integration of buildings and their systems with the grid also requires interoperable data exchange. However, the adoption and integration of newer control and communication technologies into buildings may have detrimental effects on older HVAC and building control systems. The field of advanced building energy management technology needs further development (for example, to consider constraints, predict interference and multiple conflicting goals, and fully tap the potential of MPC in building energy regulation, represent an important research method in recent years).

4.2.7. Challenges and Future Trends

It is conceivable that the lack of globally accepted and unified IOT standards may hinder the widespread development of IOT. Regulators and governments need to consider how relevant standards can be developed. The diversity of standard protocols will inevitably present a challenge in finding appropriate experts in programming languages. With billions of devices operating simultaneously in smart buildings around the world, the biggest challenges lie in the storage, protection, and analysis of the data. Furthermore, developments in technology are required to handle the huge number of devices in the network and to improve the role of the central processor and the other devices involved.

5. Conclusions

Through a bibliometry review with the CiteSpace platform, we have explored the state-of-the-art advancements in the field of smart building assisted by AI technologies. By producing and analyzing knowledge map from various perspectives, the key characteristics can be identified as follows:

(1) The number of research and published articles in this field is huge. From 2008 to 2019, the number of 2019 articles has been growing. However, the number of research articles has been declining in the past two years, indicating that the research interests has been receding.
(2) China and the US have the most articles. However, neither the US nor China have connections with other countries, indicating little cooperation between these two countries and others. By contrast, European countries have pretty close cooperation amongst themselves.
(3) By clustering analysis of literature themes and keywords, it is found that the current research interests mainly focus on theory-based risk constraint scheduling, energy power generation, integrated intelligent building, load control, wireless sensor network, etc.
(4) The literature cited and co-citation analysis have found the following main research issues: preliminary research focus on HVAC control technology, Internet technology, efficient energy management in building environment, commercial building automation, industrial plant management. Moreover, great attention has been given to the technologies such as IOT, data-driven-based building energy prediction, and advanced building energy management.

The topics of the study have been discussed on the basis of CiteSpace which facilitates authors with specific knowledge in the research field, such as key technical concerns, publications, and nations etc. The cases in respect to AI in buildings, however, have not been discussed in detail due to the limitation of the words. As the main contributions, the recent progress of the key technologies in the field may inspire the authors concerning how those technologies are being developed, utilized and promoted in the future.

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