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Review

Recent Research Progress in Intelligent Construction: A Comparison between China and Developed Countries

Jing-Ke Yan [1], Zhe Zheng [2], Yu-Cheng Zhou [2], Jia-Rui Lin [2,*], Yi-Chuan Deng [3] and Xin-Zheng Lu [2]

1 Department of Geotechnical Engineering, Tongji University, Shanghai 200092, China
2 Department of Civil Engineering, Tsinghua University, Beijing 100084, China
3 School of Civil Engineering and Transportation, South China University of Technology, Guangzhou 510641, China
* Correspondence: lin611@tsinghua.edu.cn

Abstract: Intelligent construction (IC) has emerged as a new approach to transforming the architecture, engineering, and construction (AEC) industry through the integration of advanced information technologies such as artificial intelligence (AI) and the Internet of Things (IoT). However, due to its interdisciplinary nature, the relevant documents on IC are diverse and fragmented. To provide a comprehensive understanding of research progress and future opportunities in IC and to offer suggestions for both developing and developed countries, this study employed VOSviewer and Gephi to conduct a comparative review of relevant literature from the 21st century. A keyword search of Web of Science (WOS) identified 2788 relevant documents which were subjected to an overall co-citation and co-authorship analysis. To illustrate the differences between developing and developed countries, China, a representative developing country, was taken as the candidate to be compared with developed countries via a co-occurrence analysis. Differences between China and developed countries in the three sub-directions of IC, research foundation and domain knowledge transformation; information perception, fusion, and decision making; and embodied AI, were qualitatively discussed. Finally, four future research directions were suggested: (1) data fusion and decision-making, (2) improving the accuracy and efficiency of knowledge representation, learning, and utilization, (3) the establishment of large, pre-trained models in the field, and (4) embodied AI for taking actions according to the decisions made. This paper provides an overview of the relevant literature and the IC context for practitioners and scholars in the AEC industry in countries with different levels of development, as well as suggestions for the future development of IC. The findings of this study can serve both academia and industry in promoting IC in the AEC industry.

Keywords: intelligent construction; bibliometric review; systematic review; AEC industry; artificial intelligence (AI); knowledge learning; digital twin; data fusion; machine learning

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1. Introduction

The construction industry is a crucial component of China's national economy. In 2021, it contributed a total output value of CNY 29.3 trillion to the gross domestic product (GDP) of China. Despite strong support for economic development, China's architecture, engineering, and construction (AEC) industry is confronted with challenges such as a low levels of informatization and automation, high safety risks, and a shortage of labor. These challenges are not unique to China, as they are also prevalent in the AEC industry worldwide. Recently, the development of new-generation information technology such as artificial intelligence (AI), Big Data, the Internet of Things (IoT), 5G, and blockchain has driven industrial transformation and upgrades in many sectors, including the AEC industry. Initial efforts in the AEC industry demonstrate that this new generation of information technology can effectively enhance the efficiency of detailed design [1–3], construction [4,5], operation, and maintenance [6,7]. As a result, the AEC industry urgently needs to integrate with the new generation of information technology to overcome the challenges in the industry.

In this context, countries around the world have promulgated a series of policies to promote the development of intelligent construction (IC). However, each country's policy has its own focus. For example, the United States pays more attention to the safety, greenness, and durability of products and focuses on the economic benefits and sustainable development of construction projects. The UK places more emphasis on digital design and low-carbon and sustainable building strategies [8], while China commits to industrial intelligence and the integration of industrial chains such as design, construction, and operation and maintenance [9]. Many universities have also set up intelligent construction majors to seize IC's development opportunities. However, IC is an emerging and highly cross-disciplinary research field, and the definition and scope of IC are still evolving. Some typical definitions of IC are provided in Table 1.

Table 1. Typical definitions of IC.

Reference	Definition of IC
Liu et al., 2021 [10]	Intelligent construction encompasses all stages of a building's life cycle, including design, construction, operation, and maintenance. It is based on civil engineering construction technology and is supported by modern information and intelligent technologies. Guided by project management theory, intelligent construction is represented by intelligent management information systems. By constructing a digital twin model and establishing a bidirectional mapping between the real and virtual worlds, intelligent construction enables the perception, analysis, and control of the construction process and buildings. The result is a refined, high-quality, and efficient civil engineering construction mode.
Fan et al., 2021 [11]	Intelligent construction integrates sensing technology, communication technology, data technology, construction technology, project management knowledge, and other aspects to perceive, analyze, control, and optimize the construction process and activities of buildings, making the construction process safe, high-quality, green, and efficient.
Wu et al., 2022 [12]	The essence of intelligent construction is to (1) generate a digital twin of a project through real-time data collection and integration; (2) simulate all life cycle activities, i.e., planning, design, construction, and operation and maintenance (O&M); (3) optimize decision making in the activities; (4) carry out the physical project by following optimized decisions, which brings various benefits, e.g., minimizing costs, compressing schedules, and increasing quality, safety, and productivity.
Qian, 2020 [13]	Intelligent construction relies on information equipment such as sensors to perceive data, which are then transmitted in real time through communication systems such as the Internet of Things and the Internet. Through data analysis, processing, and simulation, this information assists in decision making.
Chen and Ding, 2020 [14]	Intelligent construction is an innovative engineering construction model that results from the deep integration of modern information and intelligent technologies as the core, in addition to advanced construction technology led by industrialization.
Zhou et al., 2021 [15]	Intelligent construction takes machine learning and other intelligent algorithms as its core, combining them with the new generation of information and engineering construction technology to design, produce, and construct buildings and infrastructure. By replacing complex tasks that traditionally require human intelligence, intelligent construction enables a high degree of automation in the construction industry.

From the above definitions, it can be summarized that IC usually involves: (1) the acquisition, storage, and utilization of full-life-cycle data, including structured data such as monitoring data and geometric dimensions and unstructured data such as normative provisions; (2) multi-source data fusion combined with blockchain and intelligent algorithms to achieve multi-disciplinary, multi-stage collaborative management and on-site construction intelligence; and (3) the use of robots to realize human–machine collaboration and achieve intelligent and safe construction.

In recent years, several reviews have summarized the research in the field of IC [16–22]. For example, Xiao et al. conducted a bibliometric analysis of the robotics in construction

(RiC) literature from 2000 to 2022 and determined the latest research topics and trends in RiC [22]. Wu et al. reviewed the underlying technologies of natural language processing (NLP) and their mainstream applications in the industry, identifying research directions for NLP in IC [12]. Milad et al. used a bibliometric and systematic literature review (SLR) to analyze the applications of BIM, the IoT, and digital twins in the construction industry [19]. However, according to the existing definitions, IC is a combination of RiC, NLP, BIM and other techniques for construction. The studies mentioned above mainly focused on a certain part of IC, and they did not consider the connections between different areas. Therefore, a comprehensive analysis of IC is still needed. Meanwhile, it is necessary to conduct a comparative analysis of countries at different levels of development in order to put forward more targeted recommendations.

In response to the aforementioned research gaps and the vast, fragmented literature, this paper aims to conduct a comprehensive review of the literature on IC. To achieve this goal, a bibliometric analysis of the literature from the past two decades is adopted, with reference to the IC literature reviews conducted by many scholars [17,18,22,23]. Therefore, this paper first conducts an impact analysis of the journals, authors, and countries in this field. Subsequently, this paper conducts a comparative analysis of research hotspots in China and developed countries [24], using China as a representative of developing countries. By doing so, we identify the research hotspots of integrated circuits in both China and developed countries. Additionally, we analyze the differences between China and developed countries in three sub-fields: domain knowledge transformation; information perception, fusion, and decision-making; and embodied artificial intelligence. Our findings provide valuable guidance for the transformation of the AEC industry in not only China but also other developing countries. Moreover, the future research directions proposed in this paper can serve as an up-to-date reference for researchers in the AEC industry.

The remainder of this paper is structured as follows. Section 2 outlines the methodology and data collection process used in this study. In Section 3, we present the trends in IC and identify key journals and authors in this field. Section 4 describes the research hotspots in China and developed countries. In Section 5, we conduct a comparative analysis of the differences between China and developed countries in the area of IC. Finally, Section 6 concludes this research paper.

2. Methodology

As previous research has shown the advantages of the reliability and objectivity of bibliometric reviews [16,19,22], this study also utilized bibliometric analysis to analyze the retrieved articles. The overall research framework is illustrated in Figure 1. First, the relevant literature was retrieved from selected databases and screened based on predefined criteria. Then, a bibliometric analysis was conducted on the filtered literature, and co-citation and co-authorship networks were generated to provide an overview of the related literature. Next, the research status was discussed, and differences between China and developed countries were analyzed through a comparative analysis. Finally, suggestions for future research directions in IC were provided. Figure 1 provides an overview of the method utilized.

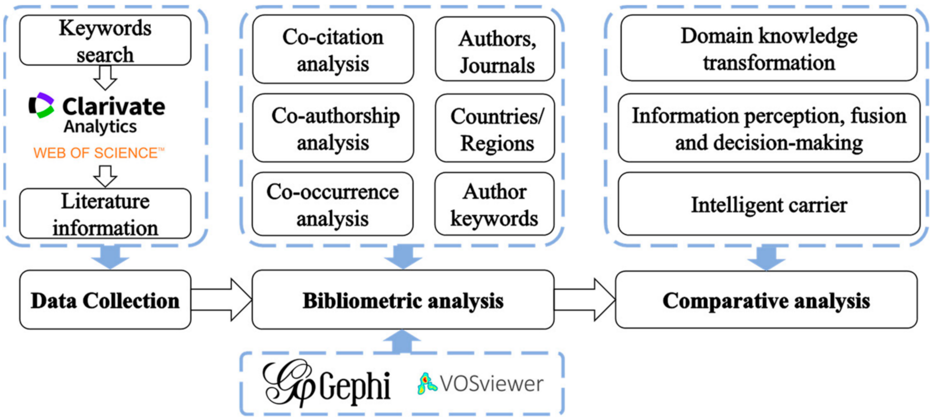

Figure 1. Schemes follow the same formatting.

2.1. Data Collection

In order to obtain more meaningful research outcomes, this study used the Web of Science (WOS) core collection database. This database contains the most important and influential literature in the world [25,26], and relevant documents from this database will be sufficient to support the research of this paper.

As per the definition of IC in Section 1, we preliminarily determined the search keywords, with ”intelligent“, ”smart“, and ”automate“ representing intelligence and “architecture engineering”, “civil engineering”, and “construction” representing the AEC industry. During the search process, we found that most of the fields covered by the keywords “architecture engineering” and “civil engineering” have nothing to do with the field of IC. For example, “architecture engineering” is also commonly used to describe the structure of a certain compound in the fields of biology and chemistry. Thus, we replaced “architecture engineering” and “civil engineering” with “building”. Furthermore, based on previous research, we also added “building” as a search keyword [20,22,23].

Therefore, the query we used was as follows:

(TS = (intelligent OR smart OR automate *)) AND (TS = (architecture engineering OR civil engineering OR construction OR building)

where “TS” stands for article subject, including the title, abstract, and indexing, and “*” represents a fuzzy search. At the same time, we limited the WOS categories to Construction Building Technology or Engineering Civil or Architecture or Management or Computer Science Artificial Intelligence.

As an emerging research direction that is combined with the new generation of information technology, IC is inseparable from new types of information technology. Therefore, referring to the time of the integration of the new generation of information technology, the AEC industry, and the existing research [17,22,23], we set the retrieval time as between 1 January 2001 and 31 December 2022.

The documents retrieved by the above strategies still contained a significant proportion of documents that were unrelated to IC. To eliminate these irrelevant documents, we conducted a preliminary screening of the journals. Our selection criteria were informed by relevant review studies in IC and included prominent journals in civil engineering, as well as those with literature that was potentially relevant to IC [16–23]. Finally, we cross-referenced the remaining documents with the definitions of IC outlined in Section 1 and excluded any papers that were deemed irrelevant to the architecture, engineering, and construction (AEC) industry. The resulting dataset comprised 2788 documents, which we used for the bibliometric analysis. Of these documents, 828 were written by Chinese authors, while the remaining 1960 were authored by individuals from other countries.

2.2. Bibliometric Analysis

In this work, VOSviewer, a widely used literature analysis tool, was used to perform the bibliometric analysis, and Gephi, a social network visualization and analysis toolkit, was used to promote the analysis results. VOSviewer can perform large-scale literature analyses and visualization [27], such as co-citation/citation analyses, co-occurrence analyses, and co-authorship analyses [28]. The following is an introduction to the analysis method chosen for this paper.

(1) Co-citation analysis: A co-citation analysis refers to the identification of two papers that are cited together by other papers, creating a co-citation relationship. By analyzing the co-citation of papers published in particular journals or by certain authors, we can determine which journals or authors are frequently cited together. This analysis provides insight into influential journals and authors in a particular field. Additionally, frequently cited authors and journals tend to have similar research directions, allowing for the classification of literature in the field. Compared to the citation analysis function, a co-citation analysis more effectively groups journals and authors by their research directions [22]. VOSviewer's co-citation analysis function fulfills this need by performing a cluster analysis on retrieved documents based on the number of citations two documents receive from other documents. Authors and journals with more co-citations are more likely to be grouped into a cluster in the analysis results.

(2) Co-occurrence analysis: A co-occurrence analysis is usually adopted to analyze keywords, and it is used to count the number of occurrences of different keywords and their co-occurrences with other keywords. When a keyword appears in a document, the number of occurrences of that keyword is increased by 1. If this keyword and another keyword appear in an article at the same time, then the number of co-occurrences between the two keywords will be increased by 1. Similar to a co-citation analysis, a co-occurrence analysis can divide keywords by research direction. The more times a keyword appears, the higher the degree of attention the keyword receives in the field. Keywords with more co-occurrences are closer to the research direction and are more likely to be classified as a cluster. In VOSviewer, the co-occurrence analysis function implements the above method. At the same time, we used author keywords recommended by many studies for analysis [22,29,30].

(3) Co-authorship analysis: Co-authorship refers to a collaborative relationship between authors. If two authors, authors A and B, have completed more articles together, then their collaboration is stronger. Unlike a co-citation analysis, this method only identifies which countries/regions collaborate more closely and groups them into a cluster based on their stronger collaboration relationships. The results do not provide insight into the division of research directions but can analyze the countries/regions that have a significant influence on the domain. The co-authorship analysis function in VOSviewer can count the number of papers published in different countries/regions, the number of citations, and the number of cooperative papers with other countries/regions. The documents are classified according to the addresses of their affiliations, helping us to analyze which countries have a greater influence in the field of IC for guidance.

3. Overview

3.1. Amount of Papers

After data collection and preprocessing, trend analysis was the first step. The number of articles reflects changes in research interest in a specific field. Therefore, we initially compared the annual publication volumes of articles on IC in China and developed countries. Figure 2 shows the number of articles published in different years, and although there are some differences between the two curves, the overall trend is quite similar. Since 2009, the number of documents related to IC in China and other countries has been growing rapidly, and by 2022, the total number of such documents exceeded 400.

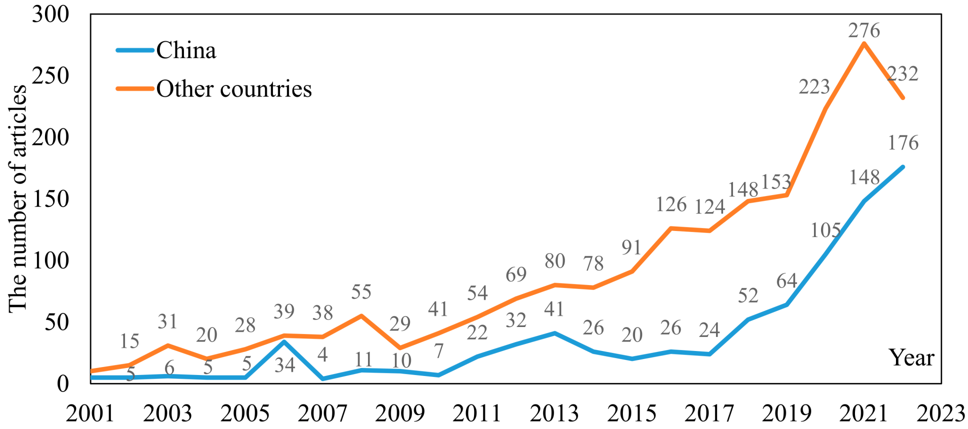

Figure 2. Number of published studies from 2001 to 2022.

3.2. Publication Sources

Co-citation analysis can reveal which clusters are more closely related in a research field and have more influence [31,32]. To identify the most influential publication sources related to IC, we conducted a co-citation analysis. The minimum number of citations for a journal was set to 200, and 59 journals met this criterion. The co-citation network of publication sources is depicted in Figure 3, with each journal represented by a circle node. The size of a node in Figure 3 represents the number of citations, while the width of an edge between two nodes indicates the number of times papers belonging to the two journals were co-cited. The color and distance between the nodes represent the closeness of the research areas of the journal to which it belongs, i.e., the closeness of the research direction.

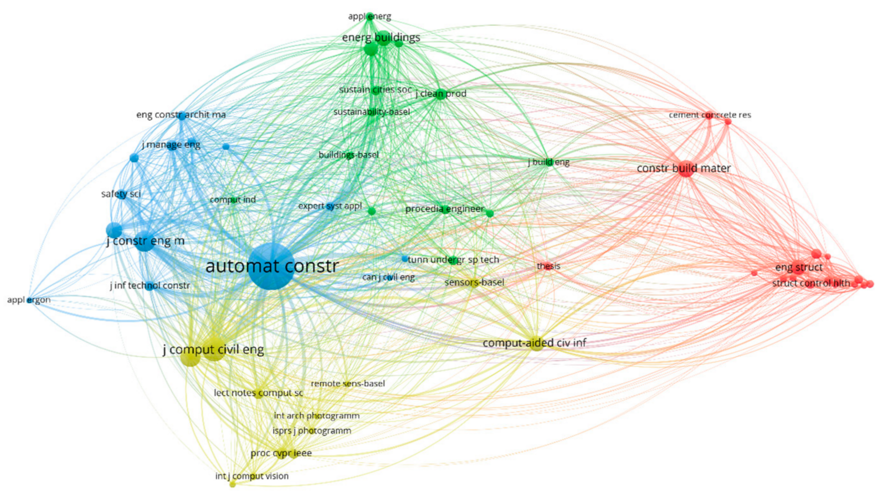

Figure 3. Co-citation network of publication sources.

Figure 3 shows that all journals are divided into four clusters represented by blue, yellow, red, and green. *Automation in Construction* is the largest item, mainly publishing articles relating to automation in the AEC industry, and other journals in its cluster (blue) also publish articles related to automation, such as the automation of infrastructure and the automation of construction project management. The yellow clusters are related to the application of computer technology in AEC, focusing on the development and application of software frameworks and algorithms in the AEC industry. The red clusters pay more attention to the structure itself and how to obtain information from it. Journals in the green cluster focus on the sustainable development of construction projects through the study of the interaction between structures and the environment.

We present a summary of some of the most influential journals in Table 2. The columns' links, citations, documents, and total link strength indicate the number of journals that have a co-citation relationship with the journal, the sum of the citations of the documents published by the journal, the number of published documents, and the total of the co-citations of the documents published by the journal, respectively. It is important to note that the co-cited papers of journal A and journal B may be duplicated with the papers of journal A and journal C, resulting in a larger total link strength.

Table 2. Journal publications versus citations related to IC.

Journal Title	Links	Total Link Strength	Citations	Documents	Citations/Documents
Automation in Construction	59	270,033	11,637	725	16.05
The Journal of Computing in Civil Engineering	59	93,815	3101	186	16.67
The Journal of Construction Engineering and Management	58	81,932	3770	132	28.56
Advanced Engineering Informatics	59	77,613	2243	117	19.17
Construction and Building Materials	59	34,871	1579	101	15.63
Engineering Structures	58	23,804	1212	77	15.74
Computer-Aided Civil and Infrastructure Engineering	59	35,765	1253	59	21.24
Building and Environment	59	28,802	1005	41	24.21
Energy and Buildings	59	38,015	1362	40	34.05
The Journal of Management in Engineering	56	24,724	658	27	25.3

The journals in Table 2 include *Automation in Construction*, *The Journal of Computing in Civil Engineering*, etc. These are the journals with the highest average citations (citations/documents). The number of documents published by journals from Table 1 ranges from 27 to 725, and the number of citations ranges from 658 to 11,637. It can be seen that the span of published papers and cited volumes is very large. However, the ranking of published papers is not completely consistent with the ranking of citations. For example, the number of documents from *The Journal of Construction Engineering and Management* is nearly 30% less than the number of documents from *The Journal of Computing in Civil Engineering*, but the number of citations is approximately 18% higher than that of *The Journal of Computing in Civil Engineering*. Another example is *Energy and Buildings*; although only 40 documents were retrieved, the journal has far more citations than the other journals in Table 2.

In general, despite there being slight differences in the data, the literature in the journals in Table 2 can provide guidance for IC research.

3.3. International Collaboration

The co-authorship function in VOSviewer was used to conduct a quantitative analysis of the retrieved literature, and the minimum number of publications in each country/region was set to 15. Of the retrieved documents from 83 countries, 31 countries met this threshold. It should be noted that the threshold was set to ensure the readability of the network while retaining the necessary information. The smaller the threshold, the more items and links there are on the graph, and the less readable the graph will be [33]. The co-authorship network is shown in Figure 4. Different from the size of the circle in Figure 3, which represents the number of papers published by authors from different countries, the thickness of the line represents the number of co-authored papers in the two countries. Countries/regions with the same color in the graph represent the same cluster, which means that they collaborate more closely than other regions. For example, researchers from China, Singapore, and New Zealand are placed in the same cluster, which indicates that these three countries cooperate closely in IC. According to this principle, the countries/regions in the graph are divided into four clusters (green, yellow, blue, and red). It is worth noting that although China and the United States cooperate more with each other, they are classified as distinct clusters because the number of publications produced by the two countries is equal to and far exceeds that of other countries.

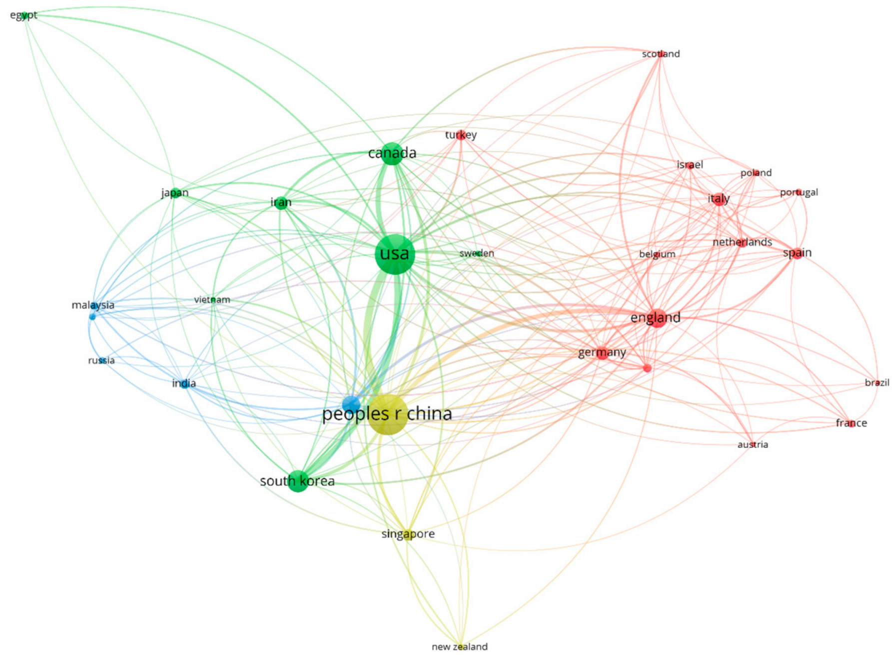

Figure 4. Co-authorship network in the IC research domain.

Table 3 presents relevant information on the top ten countries with the highest number of publications, including China (828 documents; 14,680 citations), the United States (791 documents; 25,689 citations), Canada (257 documents; 6838 citations), and others. The number of documents from these countries/regions ranges from 67 to 827, and the number of citations ranges from 1168 to 25,689. Moreover, as shown in the table, the ranking of countries/regions based on the number of publications is not consistent with the ranking based on citations. For instance, despite ranking first in the number of publications, China's citations are over 40% lower than that of the United States, which ranks second.

Table 3. Top ten countries/regions with the most documents.

Countries/Regions	Links	Total Link Strength	Documents	Citations	Citations/Documents
China	27	333	828	14,680	17.75
The United States	29	367	791	25,689	32.48
Canada	19	135	257	6838	26.61
South Korea	16	136	233	6298	27.03
England	24	155	179	4640	25.92
Australia	21	144	174	4472	25.70
Iran	18	69	97	1168	12.04
Italy	16	40	94	1903	20.24
Germany	19	58	89	2247	25.25
Spain	17	45	67	1739	26.00

Comparing the number of papers published by these countries and the trend of papers published in Section 3.1, it can be observed that China's research in IC started later than the other countries, which explains its relatively lower research output. To provide further guidance for other developing countries and to promote the development of IC in China, it is essential to clarify China's development direction in IC. To achieve this, we will perform a keyword co-occurrence analysis on the documents from countries with citations/documents greater than 25 in Table 3 and compare the results with China's literature keyword co-occurrence analysis.

3.4. Co-Cited Authors

By conducting a co-cited author analysis of the retrieved literature, we can identify the most influential authors in IC. We set the minimum number of citations for each author to 75 and required a minimum of five articles, resulting in a total of 73 authors meeting this requirement.

Figure 5 displays five author clusters. To further explore the connections between authors within the same cluster, we reviewed the representative papers with the highest citations in each of the five clusters and summarized their research directions in Table 4. Notably, we included the works of the authors with the highest citations in Table 5 to determine the most influential authors in the field of IC. Our findings suggest that the research directions of authors within the same cluster are somewhat related.

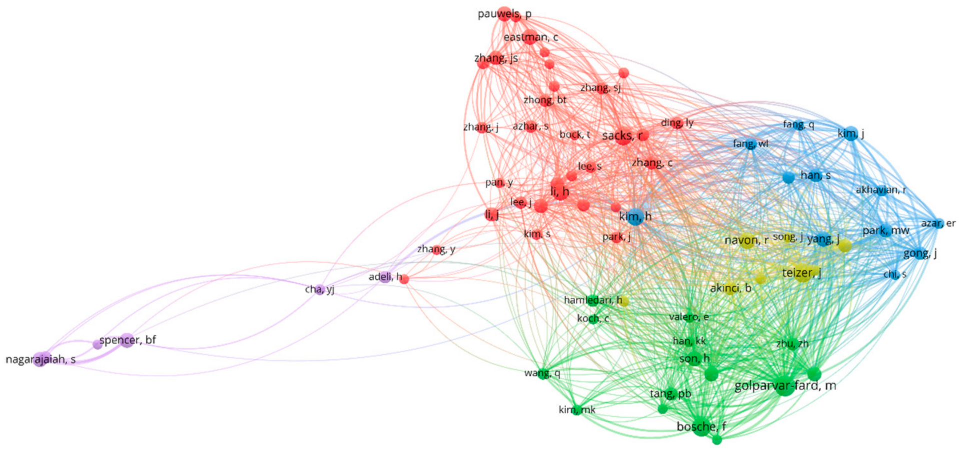

Figure 5. Co-citation network of authors.

Table 4. Representative works of other authors.

Research Direction	Reference	Cluster Color
Information perception and utilization in the AEC industry	Li et al., 2016 [34], Li et al., 2018 [35], Zhang et al., 2017 [36], Zhang et al., 2016 [37], Pauwels et al., 2017 [38], and Zhu et al., 2021 [39]	Red
Information integration and utilization based on BIM	Bosche et al., 2010 [40], Bosche et al., 2015 [41], Kim et al., 2013 [42], and Son et al., 2015 [43]	Green
CV in construction	Kim et al., 2018 [44], Kim et al., 2019 [45], Yang et al., 2016 [46], Yang et al., 2011 [47], Tian et al., 2022 [48], and Park et al., 2015 [49]	Blue
Automation in the AEC industry	Navon et al., 2005 [50], Navon and Kolton, 2006 [51], Cheng et al., 2013 [52], and Cheng et al., 2012 [53]	Yellow
Structural health monitoring, structural intelligent control, and decision making	Kurata et al., 2005 [54], Yang et al., 2002 [55], Amezquita-Sanchez et al., 2017 [56], and Gutierrez Soto and Adeli, 2018 [57]	Purple

Table 5. Representative works of the five most-cited authors.

Cluster Color	Most Influential Author	Citations (All Scopes)	Masterpiece	Source
Green	Golparvar-Fard et al., 2011 [58]	231	"Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques"	Automation in Construction
Green	Golparvar-Fard et al., 2015 [59]	162	"Automated Progress Monitoring Using Unordered Daily Construction Photographs and IFC-Based Building Information Models"	Journal of Computing in Civil Engineering
Yellow	Teizer et al., 2013 [60]	453	"Building Information Modeling (BIM) and Safety: Automatic Safety Checking of Construction Models and Schedules"	Automation in Construction
Yellow	Teizer et al., 2013 [61]	216	"Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications"	Automation in Construction
Red	Sacks et al., 2007 [62]	149	"Tracking and locating components in a precast storage yard utilizing radio frequency identification technology and GPS"	Automation in Construction
Red	Sacks et al., 2007 [63]	140	"Assessing research issues in automated project performance control (APPC)"	Automation in Construction
Blue	Kim et al., 2015 [64]	251	"Computer vision techniques for construction safety and health monitoring"	Automation in Construction
Blue	Kim et al., 2019 [65]	68	"Patch-Based Crack Detection in Black Box Images Using Convolutional Neural Networks"	Journal of Computing in Civil Engineering
Purple	Nagarajaiah et al., 2014 [66]	85	"Study on semi-active tuned mass damper with variable damping and stiffness under seismic excitations"	Structural Control Health Monitoring
Purple	Nagarajaiah et al., 2017 [67]	58	"Negative stiffness device for seismic protection of smart base isolated benchmark building"	Structural Control Health Monitoring

Table 5 summarizes the representative works of the most-cited authors in the different clusters. Authors in the same cluster tend to be co-cited more often, which also means that their research is more connected. The most cited authors from each cluster are as follows:

- Mani Golparvar-Fard (with 320 co-citations), whose research direction includes CV, machine learning, BIM, construction monitoring, and project controls.
- Jochen Teizer (with 276 co-citations), who mainly studies project management, safety and health, BIM, automation, and robotics.
- Rafael Sacks (with 234 co-citations), whose research directions are construction management, BIM, lean construction, and digital twin construction.
- Hyoungkwan Kim (with 225 co-citations), whose research focuses on project management and construction automation.
- Satish Nagarajaiah (with 164 co-citations), whose research directions include structural dynamics, seismic isolation, adaptive stiffness structure system, system identification, and physics-guided machine learning.

4. Research Cluster Analysis

4.1. Bibliometric Analysis of Documents from China

To conduct a co-occurrence analysis of keywords in the Chinese literature related to IC research, we used VOSviewer (Figure 6). We retrieved 828 pieces of Chinese literature and identified 47 frequently occurring keywords, taking into consideration synonymous keywords that represent the same concept. Experts manually combined these synonymous keywords. The size of each circle in Figure 6 represents the number of occurrences of keywords in the retrieved documents, while the widths of the lines between different keywords represent the number of times that two keywords co-occur. However, the analysis results produced somewhat irrational color clusters. For instance, although deep learning and artificial intelligence are inseparable, they appear in the blue and red clusters, respectively. Therefore, to provide a clearer understanding of the trends in IC research in China, we reclassified the clusters based on the analysis results in Section 3.3 and the existing research (Figure 6) [12,17,18,21–23]. Cluster 1 is about information integration and digital twins and includes related keywords such as BIM, IoT, and project management. Cluster 2 represents intelligent algorithms in the whole life cycle of construction projects, and the related keywords include computer vision, natural language processing (NLP), and deep learning.

In addition, we analyzed the typical studies of the two clusters as follows:

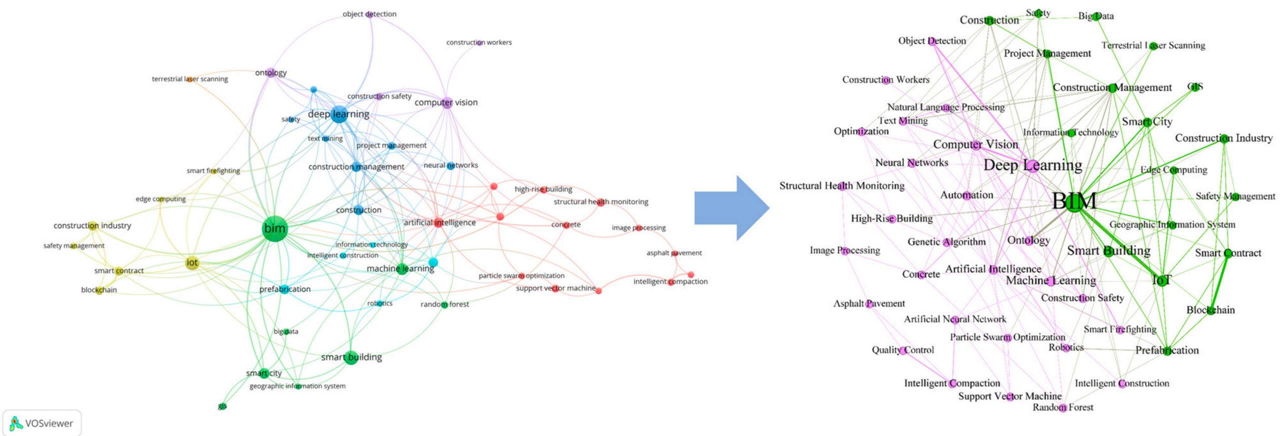

Figure 6. Network of co-occurrences of author keywords in the Chinese literature.

4.1.1. Information Integration and Digital Twins

BIM technology is a typical application of IT in the AEC industry. BIM provides excellent 3D visualization and rich semantic information, making it an important tool for collaborative management and design throughout the life cycle of a construction project [68]. Therefore, the BIM model has become an indispensable element in the area of IC. However, BIM has its limitations. The information in a BIM model is usually static and cannot be automatically updated without additional data sources. In recent years, the integration of semantic technology, the IoT, geographic information systems (GISs), and other technologies with the AEC field has become more in-depth. More scholars focus on how to use these technologies to complement and organize BIM information. For instance, Lin et al. proposed a BIM intelligent retrieval and representation method based on natural language processing for large-scale BIM. By mapping keywords and constraints to entities in Industrial Foundation Classes (IFC) standards or properties through the International Framework for Dictionaries (IFD), they achieved an effective arrangement of BIM information and further enhanced the value of BIM data [69]. Wu et al. achieved the extraction of mechanical, electrical, and plumbing (MEP) information by utilizing a suffix-based matching algorithm for named entity recognition (NER) on text segments and a dependency-path-based matching algorithm on dependency trees for relationship extraction (RE) [70]. Li et al. designed an IoT platform to obtain real-time data on the on-site assembly process of prefabricated components via radio frequency identification (RFID). After integrating these data into the BIM model, they realized the efficient operation, decision making, collaboration, and supervision of prefabricated buildings [68]. Tang et al. combined GIS and BIM to perform an integrated analysis of aboveground and underground buildings and the surrounding environment. They also realized the real-time monitoring and efficient management of underground pipelines via the monitoring data [71]. Many scholars also use BIM to carry out the quality assessment and defect detection of components, such as combination and laser scanning, storing the detailed dimensions of concrete in BIM, and conducting a quality assessment in combination with relevant specifications [72]. Chen et al. matched the aerial images with BIM to retrieve material information, thereby realizing the monitoring of concrete defects [73].

Additional sources of information can break down information barriers between different disciplines and the physical world and support the realization of digital twins. For example, Zheng et al. proposed a digital-twin-based building-collapse investigation method that integrates BIM, a finite element model (FEM), and a physical engine model to simulate the whole life cycle of structures [74]. Zhao et al. monitored the movement state of prefabricated components (PCs) using long-range radio (LoRa) technology, integrated this information into the BIM model, established a digital twin model of the hoisting process of PCs, and realized the intelligent control of PCs [75]. Lin et al. proposed an integrated framework for the closed-loop management of structural safety that relies on integrating data from multiple sources. The framework's bridge safety information model (BrSIM) integrates information from the BIM model, schedule information, structural analysis model, structural simulation results, and bridge-monitoring data. An on-site implementation of the framework for a large-scale bridge demonstrated that it could enable the secure and automated management of structures [76]. To better achieve the digital twin, efficient collaboration among construction project participants is necessary. Therefore, Lin et al. proposed a framework for twinning and mining collaborative networks which included twinning a fine-grained collaborative network of a construction project, detecting key players involved in the collaboration, and discovering frequently collaborating users and associations between information flows and task levels. The framework's effectiveness was validated by collected collaborative data related to the on-site inspection of a construction project [77].

After the sorting of semantic information and the fusion of GIS, the IoT, and other information, BIM using information from multiple data sources can realize a digital twin. However, the simple fusion of information cannot achieve the intelligence and automation of the AEC industry. Therefore, there is a need to develop a decision-making system based on the combined information, achieve the industrial IoT, and achieve the goal of IC. Sun et al. proposed a hybrid model of Digital Twin-BIM which is supported by AI and can identify resource shortages, analyze requirements, make decisions, dispatch resources, and update all processes in the database [78]. While this model realizes the management and decision making of construction resources based on digital twins, it lacks the fusion and analysis of additional data source information. Therefore, developing a framework for a multi-source data analysis to achieve intelligent decision making could be a research direction that requires attention in the future.

While integrating multi-source data supports the intelligent decision making of digital twins, it also creates some challenges, such as information imbalances and disputes among multiple stakeholders. To address these issues, Zhong et al. proposed a blockchain-based framework that leverages the characteristics of decentralization, immutability, transparency, and the autonomous enforcement of agreements offered by blockchain technology [79]. In this framework, data collected by sensors are uploaded to the blockchain network, and an on-chained information flow is introduced to enable the traceable evaluation of sensor data. While this framework provides promising ideas for addressing these issues, few studies have explored the combination of blockchain and the AEC industry in China, and most of the existing research is theoretical in nature and lacks engineering applications [80,81]. Therefore, exploring the application of blockchain in digital twins is a valuable research direction.

4.1.2. Intelligent Algorithms in the Whole Life Cycle of Construction Projects

According to the definition of IC mentioned above, it can be inferred that IC includes intelligence throughout the entire life cycle of construction projects. However, the AEC (architecture, engineering, and construction) industry is facing high-risk and low-automation issues worldwide, resulting in a shortage of labor [22]. Intelligent algorithms can address these challenges by using data to enable perception, knowledge representation, and reasoning [21]. Consequently, intelligent algorithms have become a research hotspot in IC.

The structural design process heavily relies on the knowledge and experience of the designer, leading to inefficiency in the design process. To address this issue, Liao et al. proposed a shear wall design method based on generative adversarial networks (GANs) to enable the rapid and effective generation of design schemes [82]. On this basis, Lu et al. introduced the physics estimator to enhance the objectivity of the training process, further improving the efficiency and accuracy of the method [1]. After the design is completed, the drawings must be reviewed based on the specifications. However, manual review is extremely time-consuming and labor-intensive. Therefore, scholars have conducted research on automated compliance checking (ACC). ACC requires intelligent rule interpretation from regulatory texts, but there are still semantic gaps between design models and regulatory texts. To address this issue, Zheng et al. proposed an NLP-based knowledge information framework for automated compliance checking (ACC) [83]. The framework consists of four parts: ontology-based knowledge modeling, model preparation with semantic enrichment, enhanced rule interpretation, and inspection execution. The results show that the method has an accuracy rate of 90.1%, and its efficiency is five times higher than that of expert manual explanation. Zhou et al. utilized a combination of natural language processing (NLP) and context-free grammar (CFG) to analyze regulatory text, achieving a parsing accuracy of up to 99.6% for simple sentences—a result that surpasses the state of the art. They also released the first regulation dataset for further exploration in the ARC domain [84].

During the construction process, worker distribution is often fluid, and worker safety cannot be solely ensured by humans. Computer vision (CV) in intelligent algorithms can enable the automatic detection of targets. Therefore, recognizing worker behavior through computer vision has become a research focus. Fang et al. utilized two convolutional neural networks to determine whether workers wear safety belts while working at heights, thereby identifying unsafe behaviors of workers and avoiding falls from heights. The method's accuracy and recall of 99% and 95%, respectively, demonstrate the feasibility of the approach [85]. The effective prediction of tunneling parameters during tunnel construction can greatly reduce the impact on the environment and ensure the safety of the construction process. To this end, Liu et al. used discrete wavelet transform (DWT), a one-dimensional convolution neural network (1DCNN), and long-short-term memory (LSTM) to predict the multipoint earth pressure variation trend. The results demonstrate that the model can provide a decision-making basis for the tunneling process of the shield machine. Combining denoising technology, Wang et al. used LSTM and two regression models, a temporal convolutional network and random forest, to predict the slurry pressure of the slurry pressure balance shield machine. The model's root mean square error (RMSE) and coefficient of determination (R^2) were 1.83 kPa and 0.9974, respectively, indicating its high accuracy [86]. The effective management of resources and cash flow during the construction phase can be a determining factor in the success or failure of a project. To optimize these aspects of construction projects, Jiang et al. modeled the complex interactions between construction work, resources, and cash flows, as well as the uncertainty and variability of various influencing factors, based on a partially observable Markov decision process. Additionally, they introduced a method based on deep reinforcement learning (DRL) to optimize work and cash flows. Through simulations, they demonstrated the superiority of this method [87].

Intelligent algorithms also play a significant role in the operation and maintenance phase. For instance, Liu et al. utilized a convolutional neural network to identify pavement cracks and proposed a crack segmentation method based on an improved U-Net, enabling the monitoring and segmentation of pavement defects [88]. Additionally, Cheng et al. developed an automatic monitoring method for underwater pipeline defects based on faster R-CNN, leading to the rapid detection of sewer pipeline defects with high accuracy and precision [89]. These studies have significantly reduced the consumption of labor and material resources during the operation and maintenance stage while achieving intelligence in this phase.

Intelligent algorithms have achieved a high level of maturity in the stages of design, construction, operation, and maintenance. In the design stage, which requires creativity, reinforcement learning methods such as GAN have garnered attention from scholars.

Recently, the segment anything model (SAM) [90] and the generative pre-trained transformer (GPT) series models [91,92] have performed exceptionally well in the fields of computer vision (CV) and natural language processing (NLP). There are also some works similar to GPT and SAM in IC. For example, Zheng et al. proposed the first domain corpora for the AEC industry and established the first pre-trained language model, ARCBERT, for AEC. The results show that the domain corpora can significantly improve the performance of all deep learning models. Meanwhile, the pre-trained language model ARCBERT demonstrates state-of-the-art performance in all tested NLP tasks [93]. The model utilized for this task is based on the open-source language model BERT. While BERT is a popular choice for many NLP tasks, GPT is a larger language model with even better performance. With the application of transfer learning methods and AEC-specific corpora, it may be feasible to establish a customized and exclusive LLM for the AEC industry using GPT. In terms of CV, Duan et al. established a new, large-scale image dataset specifically collected and annotated for the construction site, called the Site Object Detection Dataset (SODA). The test results show that the deep learning model trained on this dataset has better performance in object detection in the AEC field. Moreover, the data set has more images and categories, which can further expand the scope of target detection [94]. Following the same path of reference [93], a feasible direction is to fine-tune the SAM based on SODA to establish a proprietary CV model in the AEC field.

4.2. Bibliometric Analysis of Documents from Developed Countries

The same method was used to conduct a keyword co-occurrence analysis of the literature on IC from developed countries (Figure 7). After merging synonyms and deleting unnecessary keywords, the fifty-six keywords with high frequencies were reclassified into six clusters. However, through the analysis, we found that the division of some clusters was unreasonable. For example, 3D reconstruction and structural health monitoring are both studies on structural components. The former focuses on the geometric characteristics of the structure, while the latter focuses on the dynamic characteristics of the structure. However, during the review process, no item in the literature was found to study both. Therefore, combined with the different research directions obtained in Section 3.3, this paper re-divided these clusters (Figure 7): Cluster 1 is knowledge representation, learning, and utilization; the related keywords include automated compliance checking, natural language processing, and IFC. Cluster 2 is construction industrialization and construction robots; the related keywords include robotics, automated construction, and deep learning. Cluster 3 is 3D reconstruction; the related keywords include CV, laser scanning, and point cloud. Cluster 4 is information integration; the related keywords include blockchain, digital twin, and construction industry. Cluster 5 is structure operation and maintenance; the related keywords include structural health monitoring, data collection, and damage detection.

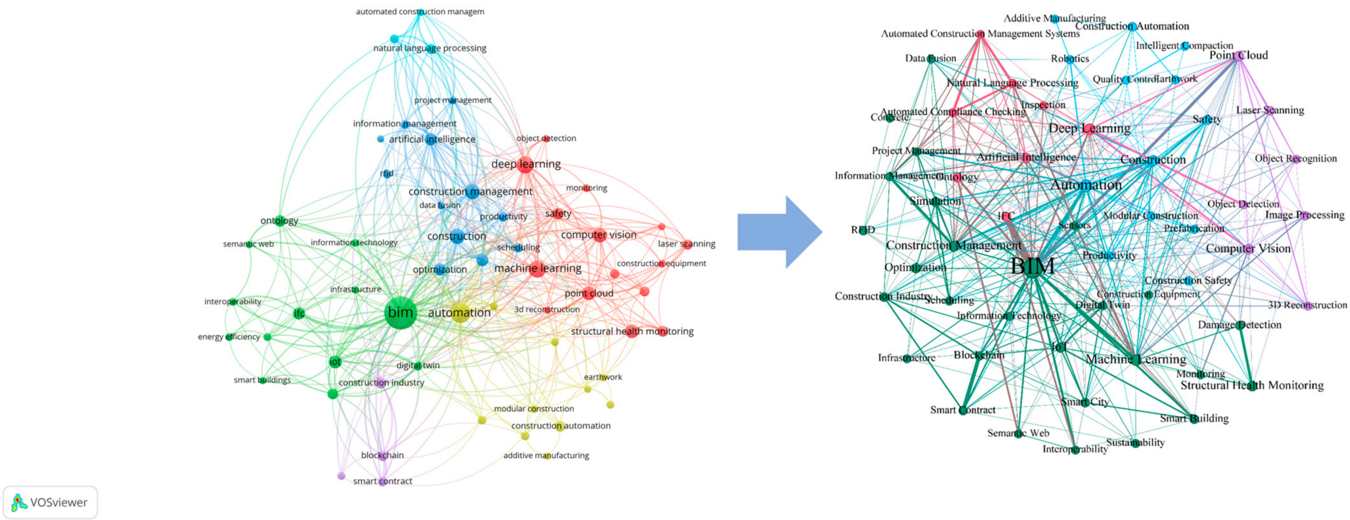

Figure 7. Network of the co-occurrences of author keywords in the literature from developed countries.

4.2.1. Knowledge Representation, Learning, and Utilization

There is a vast amount of data generated throughout the life cycle of construction projects, and the AEC industry is subject to a large number of regulatory provisions. This information can be mined for knowledge which, if not collated properly, can affect the efficiency of each stage of the construction process [1,5,95]. Efficiently processing domain knowledge is thus a crucial step toward achieving IC. It is time-consuming and resource-intensive to represent knowledge manually. To overcome this, some scholars are investigating ways to enable computers to learn, convert, and utilize domain knowledge.

Compared to images and audio, text data are easier to collect in construction projects. However, more than 80% of text data are unstructured, making it important to automatically extract and understand text data in a cost-effective manner [95]. Natural language processing (NLP) technology can analyze text structure and meaning, enabling machine learning or deep learning models to replace manual procedures and automate the extraction and analysis of text data [12]. Based on NLP technology, some scholars transform, store, and utilize AEC industry knowledge. For example, Zhang and EI-Gohary proposed a rule-based natural language processing method to automate information extraction (IE) and information transformation (ITr) in the AEC domain in 2015 [37,96]. In 2017, they integrated NLP technology with a representation based on semantic logic to achieve a high degree of automation of automated compliance checking (ACC) [36].

Zhang et al. proposed a construction safety ontology to address construction safety issues. By combining the construction product model, construction process model, construction safety model, and BIM, they were able to realize the prototype application of job hazard analysis and visualization [97]. Kebede et al. combined ontology semantics and BIM to represent product data, enabling the effective entry and query of products [98]. Akanbi et al. applied semantic modeling and NLP to match materials, construction projects, and material price information in building specifications, thus achieving the automatic processing of construction specifications and the automatic estimation of construction costs [95]. Ren et al. integrated NLP and sensing techniques to extract construction program text information and automate construction site management tasks [4].

While progress has been made in representing and learning knowledge in civil engineering, only a few studies have combined knowledge with sensing data or BIM. The ultimate goal of knowledge representation and learning is to enable automatic decision making and achieve the intelligence and automation of design, construction, operation, and maintenance. Therefore, future efforts should focus on combining different types of knowledge to make more informed decisions.

4.2.2. Construction Industrialization and Construction Robots

Construction robots have the potential to improve productivity and safety in the construction sector. In 2003, Kim et al. proposed a path-planning method for construction robots used in earthwork operations [99]. However, due to the low level of sensor integration, wireless communication, and other technologies in the AEC industry at that time, the algorithm could not be successfully applied. In recent years, numerous scholars have conducted cross-research on these technologies and the AEC industry. This renewed interest has led to several innovative advancements in the field of construction robots. For instance, Lublasser et al. developed a robot capable of applying foam concrete to exterior walls, which provided a new approach to automating building renovation [100]. Additionally, Hack et al. proposed a standardized construction system to address the shortcomings of traditional formwork and 3D printing. The system integrates design, planning, and construction nodes and ultimately facilitates automatic structure construction through a robot [101].

With the continuous development of AI, intelligent algorithms are increasingly being used in construction robots. For robots to achieve a high degree of automation, they must be capable of making efficient decisions independently. Lakshmanan et al. proposed a full-coverage path-planning model (CCPP) that uses deep reinforcement learning to achieve this goal. Their study found that this scheme has a low cost, high efficiency, and strong robustness, making it a promising approach for construction robot automation [102]. Similarly, Zhou et al. developed a scene reconstruction method based on deep learning and a corresponding robot teleoperation system. Their approach achieved the high-efficiency and high-quality reconstruction of 3D scenes, demonstrating the potential for deep-learning-based methods in construction robotics [103].

In some construction scenarios, robots must work collaboratively with humans. Therefore, human–machine collaboration is a major research focus in the field of construction robotics. For example, in hazardous work scenarios, Liu et al. proposed a brain–computer interface (BCI)-based system. This system can translate workers' brainwaves into robot commands with an accuracy of 90 percent, enabling the remote control of the robot and ensuring worker safety [104]. Similarly, Kim et al. used camera-mounted drones, computer vision, and deep neural networks to improve the efficiency of human–machine collaboration. Their approach demonstrated the potential for advanced technologies to enhance worker safety and productivity in construction [105].

4.2.3. Three-Dimensional Reconstruction

As mentioned in Section 4.1.1, BIM is often used as an integration center for multiple data sources. However, many existing structures were built using traditional methods without BIM, posing a challenge for modeling such structures in the construction process. Xiong et al. proposed an efficient solution to this problem by converting raw 3D point cloud data into a semantically rich information model. This method can effectively identify and model the main visible components of the indoor environment, allowing for the accurate modeling of existing structures [106]. Golparvar-Fard et al. compared image-based point cloud model creation with laser-scanning-based point cloud model creation. While image-based point cloud models may not be as accurate and dense as those obtained through laser scanning, they can provide more semantic information for structural division. They also added temporal attributes to point cloud models and proposed a machine learning method for automatic progress tracking. This approach allows for the synchronization of physical and virtual models, with deviations in the reconstructed point cloud model marked on the BIM [58,59].

In addition to identifying structural components, some scholars are also working on more detailed 3D reconstruction. For example, Park et al. proposed a framework for point cloud information modeling (PCIM). This framework can automatically recognize construction objects and their properties via deep learning approaches [107]. Pan et al. recognized small but important entities such as signs, sockets, switches, and smoke alarms, etc., from 2D images and mapped them to a 3D space. Then, the point cloud was divided into point clusters via semantic segmentation and geometric primitives were fit to the point clusters. Finally, they also incorporated some textual information into the model, resulting in an enriching geometric digital twin model [108]. In the process of data collection, data loss may occur due to instrument errors and algorithm precision problems. Therefore, Kim et al. [109] and Braun et al. [110] proposed a deep learning method which solved this problem to a large extent.

Based on the above studies, it can be concluded that 3D reconstruction research is relatively advanced. By using 3D reconstruction, the BIM of a constructed building can be established quickly. Furthermore, it is possible to integrate BIMs of specific structures with information from other data sources. This integration can lead to intelligent decisions that consider deep information. As discussed in Section 4.1.2, SAM is a leading technology in the current computer vision field. Some researchers have conducted studies on 3D reconstruction based on SAM. For example, Shen et al. combined SAM and 3DFuse [111] to realize the 3D reconstruction of an object after image semantic segmentation [112].

4.2.4. Information Integration

As the IoT continues to grow, an increasing number of sensors are being used in structures to ensure their safety. This massive amount of sensor data needs a carrier to transmit and reconstruct it. Moreover, planning and decision making in construction projects also require the integration of information from various data sources. Therefore, information integration is a crucial component of IC. Pan et al. proposed a digital twin framework that integrates BIM, the IoT, and data mining techniques. This framework can establish a 4D visual process model based on inspection data which simulates task execution and worker cooperation to optimize decision making in construction projects [113]. Chiachio et al. introduced a structural digital twin framework that operates at the technical integration level of software and hardware. A probabilistic Bayesian method is proposed based on real-time data from the structural health monitoring (SHM) system to update the model [6].

As mentioned in Section 4.1.1, after integrating multi-source data, solving the problem of data security and delivery between stages is essential to enable intelligent decision making. Elghaish et al. proposed a framework for using blockchain technology in integrated project delivery (IPD). They combined blockchain network components and smart contracts with BIM technology to improve the efficiency and security of transactions at different stages [114]. Ahmadisheykhsarmast and Sonmez presented a smart contract payment security system that provides a platform for the safe, efficient, timely, and transparent payment of construction projects [115].

4.2.5. Structure Operation and Maintenance

In real life, people spend far more time interacting with built structures than with structures that are being designed and constructed. Therefore, implementing intelligence in the operation and maintenance phase of the structure is an important aspect of IC. Structural health monitoring (SHM) can detect possible damage to the structure during its lifetime and assess its remaining life [116]. On one hand, SHM plays a sensing role by collecting data from various parts of the structure through sensors. On the other hand, researchers in the field of SHM use algorithms to mine monitoring data to infer the characteristics and status of the structure. For example, Kurata et al. studied the role of a smart sensor based on the Berkeley Mote platform in structural health monitoring and control [54]. Laflamme et al. achieved structural damage localization by detecting changes in strain with a capacitive sensor [117]. In terms of algorithms, Ying et al. comprehensively applied machine learning and signal processing techniques and built five machine learning classifiers based on adaptive boosting and support vector machines to predict structural damage. These models achieved an average accuracy of 98.5–99.8% during random testing and an average accuracy of 84.2–89% during systematic testing [118]. Civera et al. automated operational modal analysis (OMA) identifications in SHM using machine learning methods [116].

Although these methods can monitor structural information, the cost is often related to the type and number of sensors [119,120]. Some scholars have begun to install sensors on mobile vehicles for data collection in order to reduce the cost of sensor installation [121–123]. These studies simplify the inspection process by passing the vehicles and reducing the cost of installing SHM systems. Recently, scholars have proposed a method of data collection based on smartphones, which further reduces the cost of data collection [124,125]. However, cars and trucks have non-negligible weights and suspension systems that may affect the collected vibration data [126]. Therefore, Quqa et al. combined smartphones with shared mobility vehicles for data collection. Meanwhile, a recognition procedure is also proposed to extract the dynamic parameters of bridges. This method enables the monitoring of structures without any sensors [126].

Currently, there have been significant advancements in information perception and processing during the operation and maintenance phase of structures. However, decision-making based on information still heavily relies on a single source of truth: surveillance data. By integrating these data into the BIM model and combining them with other sources of information, such as pictures of structural surface damage and relevant specifications, decision-making reliability can be greatly improved.

5. Comparison of Documents from China and Developed Countries

From a research perspective, other countries have accumulated a considerable amount of literature on IC in the early stages, which is why they have received more attention in this field. The number of documents published in China only began to take shape after 2018 (more than 50 documents) (Figure 1). This has resulted in a smaller number of citations for Chinese documents, even though the number of papers published in China is currently similar to that of the United States (Section 3.2).

According to the analysis results of Section 3, although the number of documents in China is relatively high, more attention has been paid to the documents in developed countries, and the highly cited authors are mainly from developed countries (the United States, Israel, South Korea, and Denmark). In the results of Section 4, the items in Figure 6 are less than those in Figure 7, and the items with strong correlations are far away and the distribution is scattered. This also led to unreasonable classification results of the co-occurrence analysis of Chinese literature in VOSviewer. Considering that the analysis results in Figure 7 come from multiple countries, it is not possible to obtain a fair evaluation of the current status of IC research in China based on this scale alone. Therefore, we analyzed the timeline-overlayed network of author keyword co-occurrences between China and developed countries through VOSviewer. Figure 8 illustrates that in 2014, developed countries had performed extensive research on IC, while relevant research in China only emerged in 2016 (Figure 9). This suggests that China's scholars have been influenced by scholars from developed countries to some extent.

In general, IC research in developed countries has progressed through stages such as "construction project information management and integration", "structural operation and maintenance", and "informatization and intelligence" and is currently exploring multi-source data such as the IoT and blockchain for integration and decision making. These studies are more structured, gradually solving problems according to needs. Research by Chinese scholars is influenced by both domestic demand and research by scholars from developed countries. This has resulted in more fragmented literature in China, making it difficult to construct a framework as a whole; therefore, the research cannot be as in-depth. For example, in 2016–2018, scholars in developed countries were studying "structural operation and maintenance" and semantic technologies such as "ontology". Affected by this, Chinese scholars were also studying "structural health monitoring" and "ontology" while also studying "support vector machine", "neural networks" and other machine learning (ML) algorithms, and "construction management". The fragmentation of research results in incomplete research. For this reason, after 2018, there is research on "project management".

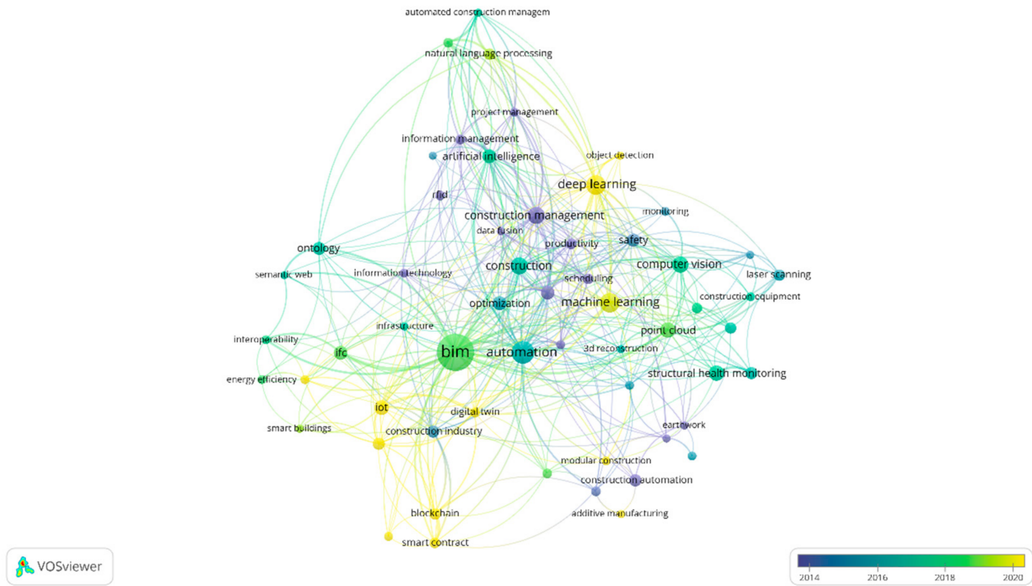

Figure 8. Timeline-overlayed network of author keyword co-occurrences in developed countries' documents.

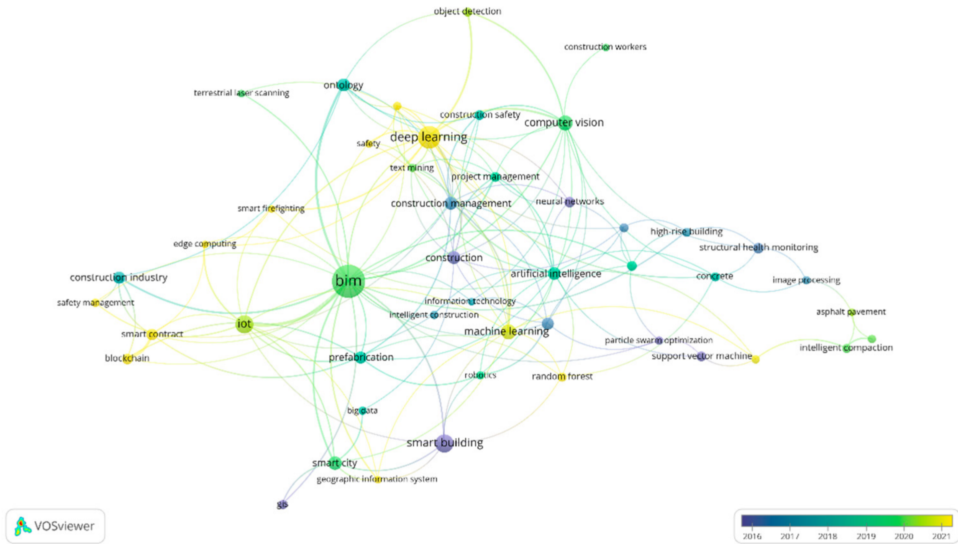

Figure 9. Timeline-overlayed network of author keyword co-occurrences in China's documents.

To compare the latest research in IC in China and developed countries, we summarize the research direction as follows:

IC aims to achieve the intellectualization and automation of the entire life cycle of construction projects. This requires both the real-time perception of external information to obtain the status of construction projects and the transformation of existing domain knowledge. The combined domain knowledge and perceived information allow for a comprehensive evaluation of the construction project status, which can then inform decision making. Finally, an embodied AI is needed to implement the decision.

Therefore, we summarized and compared the latest related literature between China and developed countries in terms of domain knowledge transformation, information perception, fusion, decision making, and embodied AI. A summary of the relevant literature is shown in Table 6.

Table 6. Some of the latest documents.

Research Direction	China		Developed Countries	
	Reference	Characteristics	Reference	Characteristics
Domain knowledge transformation	Lu et al., 2022 [1], Zhao et al., 2022 [2], and Zheng et al., 2022 [83]	Structural intelligence design and automated compliance checking	Ren et al., 2021 [4], Candas and Tokdemir, 2022 [127], and Tang et al., 2022 [128]	Economic disputes in the AEC industry
Information perception, fusion, and decision making	Zhong et al., 2022 [79], Zhao et al., 2022 [75], Chen et al., 2022 [73], and Zhang et al., 2022 [80]	Pairwise fusion between different data sources	Kebede et al., 2022 [98], Ren et al., 2021 [4], Ahmadisheykhsarmast et al., 2020 [115], and Elghaish et al., 2020 [114]	Fusion and decision making of multiple data sources
Embodied AI	Wu et al., 2022 [129] and Wang et al., 2022 [130]	Human–robot collaboration and on-site construction robotics (only two documents)	Zhu et al., 2021 [39], Lam et al., 2022 [131], Liu et al., 2021 [104], and Momeni, et al., 2022 [132]	Brain–computer interface; human–robot collaboration; on-site construction robotics

Combining Figures 8 and 9 and Table 6, it is apparent that the integration of multiple data sources through deep learning, blockchain, and other technologies represents a new trend in IC research worldwide. However, research in developed countries is more comprehensive than research in China. Scholars in these countries not only conduct research on information perception and fusion but also utilize the analysis of fused information to inform decision making [4]. Additionally, they have made significant advancements in the development of embodied AI. In Table 6, we can also find that there are some differences between China's research on domain knowledge transformation and that of developed countries. The recent achievements of China's scholars are to use domain knowledge for the intelligent design of structures, while scholars in developed countries pay more attention to economic research.

6. Conclusions

This paper presents a bibliometric analysis of the research on IC from 2001 to 2022. The analysis includes a study of the number of publications, co-citations, co-authorships, and co-occurrences of the literature from China and developed countries. Our findings show a rapid growth in the number of publications on IC, indicating its status as a significant research focus for the future. Additionally, we identified research hotspots for both China and developed countries.

The main concerns of the literature from China are as follows:

(1) Information integration and digital twins: at present, scholars mainly study how to integrate two data sources and solve the problem of information imbalance through blockchain.

(2) Intelligent algorithms in the whole life cycle of construction projects: research on intelligent algorithms at different stages has achieved certain results. Deep learning methods such as GAN are more popular during the design phase, where creativity is required.

The main research hotspots in developed countries are as follows:

(1) Knowledge representation, learning, and utilization: research on knowledge representation and learning has made significant strides in recent years, but more thorough research is needed on knowledge utilization.

(2) Construction industrialization and construction robots: the current research aims to solve the problems of high levels of risk, low levels of automation, and labor shortages in the AEC industry through brain–computer interfaces, human–computer collaboration, and other solutions. However, the accuracy and cost of these methods still need to be optimized.

(3) Three-dimensional reconstruction: existing studies have achieved accurate reconstructions of structures. At present, the efficiency of this process can be improved by combining the frontiers of CV fields such as SAM.

(4) The IoT and information integration: the integration of multi-source data has been supported by some documents. The next step is determining how to make decisions via integrated data.

(5) Structure operation and maintenance: sensor-based SHM systems have matured. Scholars are currently looking for monitoring methods that are less costly.

By comparing the results of the analysis of China's documents with those of developed countries, we have drawn the following conclusions:

(1) The research scale of IC in developed countries was established earlier than in China, which is one of the reasons why the literature from China has received less attention in this field and has been fragmented.

(2) In the latest literature, China's articles focus more on intelligence and automation in the design stage, emphasizing domain knowledge transformation. On the other hand, documents from developed countries concentrate on economic disputes in construction projects. Moreover, research on embodied AI is more extensive and the number of publications is higher in developed countries. Furthermore, developed countries have a more in-depth understanding of information perception, fusion, and decision making.

Combined with the development status of IC and the related bibliometric analysis, it becomes apparent that scholars worldwide could make innovative contributions in the future in the following areas:

(1) Exploring methods of integrating multi-dimensional information can improve information utilization and eliminate information silos. BIM can be combined with the IoT, physical engines, and other technologies to establish a digital twin model. This model can integrate various types of building information such as geometric attributes, materials, and real-time status. It can facilitate collaborative design and the comprehensive management of buildings throughout their life cycle, from design and construction to operation and maintenance.

(2) As mentioned in Section 4.2.1, there are a many unstructured data, especially text data, in construction projects. The method of processing unstructured text data currently relies heavily on humans. Future research may focus on automatically processing the unstructured text data into structured data based on NLP technology. The cost of processing will thereby be greatly reduced, and the efficiency of project management and information processing could be improved.

(3) Currently, there are remarkably large models, such as SAM and GPT series models, in the fields of computer vision (CV) and natural language processing (NLP). However, to achieve artificial general intelligence (AGI), their accuracy is often inferior to models trained with specific data. Therefore, based on pre-trained models or provided APIs, professional and customized improvements can be made using domain knowledge. This approach can enhance multi-source data decision-making and fusion, resulting in more intelligent models.

(4) IC has made significant progress in domain knowledge transformation, information perception, fusion, and decision making, and the development of embodied AI. However, there is a lack of communication between the outcomes of different directions and stages of the construction project. For instance, there is a need to transmit information perception and fuse decision making to embodied AI or to transform domain knowledge to enable an embodied AI to make decisions. These efforts can ultimately result in the intelligence of the entire life cycle of construction projects.

The paper makes three main contributions: (1) conducting a bibliometric analysis and review of the literature on IC; (2) comparing the differences in IC among countries at different levels of development, using China as a representative case study; (3) presenting the latest research findings and possible future research directions of IC. Overall, this article provides practitioners and academics in the AEC industry with a valuable overview of the current status of IC, highlighting the latest developments in the field.

However, there are still some limitations to this research. First, it is possible that some relevant documents were missed or overlooked during the literature search and filtering process, which could result in the exclusion of important journals, authors, or papers. Additionally, emerging fields may not have been fully considered due to the few publications available. Furthermore, the suggestions provided in this article are based on the authors' opinions to some extent. Therefore, future research can benefit from seeking expert opinions in related fields to gain a more professional and comprehensive understanding of this subject.

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