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Mapping Two Decades of AI in Construction Research: A Scientometric Analysis from the Sustainability and Construction Phases Lenses

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Abstract: The construction industry plays a vital role in the urbanization process and global economy, and there is a growing interest in utilizing artificial intelligence (AI) technologies to improve sustainability, productivity, and efficiency. However, there is a lack of comprehensive analysis regarding the progression of AI in the construction context, particularly from the sustainability angle. This study aims to fill this gap by conducting a scientometric analysis of AI research in construction by focusing on historical clusters, emerging trends, research clusters, and the correlation between sustainability pillars and key project stages. A Scopus search, between January 2000 and July 2023, was conducted that used 25 construction industry-related keywords, resulting in a total of 9564 publications. After evaluating practical AI applications in construction, 3710 publications were selected for further analysis using VOSviewer for visual diagrams and to further understand connections and patterns between literature. The findings revealed that: (a) Literature on AI in construction has experienced steady growth over the past two decades; (b) Machine learning, deep learning, and big data are seen as the key enabling digital technologies in the construction sector's performance; (c) Economic and governance pillars of sustainability exhibit the highest potential for AI adoption; (d) Design and construction phases demonstrate substantial advantages for AI adoption; (e) AI technologies have become, despite adoption challenges, a strong driver of construction industry modernization, and; (f) By incorporating AI, the construction industry can advance towards a more sustainable future by consolidating its processes and practices.

Keywords: urbanization; artificial intelligence; construction technologies; construction phases; Industry 4.0; sustainability; machine learning; deep learning; robotics

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1. Introduction and Background

In our increasingly urbanizing world, the construction industry is not only vital for the development of cities but also for the global economy, accounting for approximately 13% of the world's gross domestic product (GDP) [1]. This estimate is based on a combination of economic data, industry reports, and various sources of information to estimate the percentage. Despite its urbanization and economic significance, the industry faces a range of challenges that undermine productivity and efficiency, including cost overruns, project delays, and quality issues. This is evident in a Mckinsey 2020 report that indicated that large construction projects tend to exceed their schedules by 20% and exceed their budgets by 80% [1]. This is compounded by a lack of digitalization, and the manual nature of the industry makes projects more complex and tedious [2]. To combat these challenges and transform the construction sector, particularly in a sustainable way, the integration of artificial intelligence (AI) has emerged as a promising solution [2–4].

The widely accepted definition of AI states that "AI is the study of how to make machines do things, which at the moment, people do better" [5]. However, the industry has experienced sluggish productivity growth, falling behind other sectors with an annual rate of only 1% over the past two decades [6,7]. This slow growth can be attributed to inherent characteristics of the industry, such as cyclical demand, limited capital investment, and a lack of standardization. Furthermore, the industry's inadequate investment in construction innovation and the prevalence of small, specialized subcontractors with limited technological advancements have hindered the widespread adoption of automation and constrained its overall growth potential [7–9]. This is apparent in a recent study conducted by KPMG that indicated only 8% of construction companies are identified as highly innovative, with the remaining 92% categorized as moderate or low innovators [4].

The history of AI in construction dates back several decades, with the concept evolving alongside advancements in technology and computing power [10]. In the initial phases of AI integration in construction, three significant applications emerged. First, AI optimizes project schedules and planning for enhanced efficiency. Second, AI-enhanced risk management identifies and mitigates potential issues proactively. Finally, AI's precise cost estimation helps prevent budget overruns, contributing to improved financial control [5,11].

The application of AI in construction involves the use of intelligent machines and programs that mimic human cognitive functions, such as learning, problem-solving, and decision-making. Furthermore, the major components of AI include leaning, knowledge representation, perception, planning, action, and communication [5]. In the early stages, AI in construction focused primarily on automation, aiming to enhance efficiency and productivity on construction sites [12]. As computing power increased and data analysis capabilities improved, the concept of AI expanded to include machine learning and data-driven decision-making. Machine-learning algorithms allow systems to analyze large amounts of data, recognize patterns, and make predictions or recommendations based on past experiences [13]. This capability has been applied to various aspects of construction, including project planning, design optimization, risk management, and resource allocation [14,15].

In recent years, AI in construction has further evolved around the following major subfields; machine learning, computer vision, natural language processing, knowledge-based systems, optimization, robotics, and automated planning and scheduling [5,16]. These emerging technologies have enabled real-time data collection, optimized decision-making, and improved project management [17,18]. Today, deep learning, a subset of AI has gained significant attention in the construction industry due to its potential to address complex technical challenges. It involves training artificial neural networks with multiple layers to learn patterns and make accurate predictions based on large datasets [13,19,20]. Deep learning offers a crucial advantage to the construction industry as it gives the ability to process intricate data, allowing for informed decisions, improved efficiency, and enhanced project outcomes [2]. Furthermore, by analyzing data, deep learning models can predict hazards, identify defects, optimize scheduling, and enhance design decisions. Overall, deep learning has the potential to revolutionize construction processes [10,21,22].

AI continues to emerge as a powerful tool to tackle productivity challenges in the construction industry and drive improvements in performance, efficiency, and innovation [7,23]. By simulating human cognitive functions, AI technologies offer opportunities to transform business models within construction [24,25]. Through AI adoption, construction operators can optimize resource allocation, automate tasks to address skill shortages and unlock higher levels of productivity and efficiency [26]. Nonetheless, the practical implementation of AI in construction faces several obstacles. One key challenge is the need for accurate and comprehensive data to train AI algorithms, which can be costly and time-consuming for many construction companies [27]. The dynamic outdoor environmental conditions and the non-standardized nature of building designs pose further complexities in effectively applying AI. As a result, while larger construction companies may reap some benefits from AI technologies, there remains a lack of widespread knowledge and established frameworks within the industry. This has led to ongoing debates regarding the future of the construction workforce and the potential impact of AI on jobs [8,28].

Although there have been numerous studies examining the application of AI in construction, it is important to note that many of these studies have been limited in their scope. These include small sample sizes, theoretical focus, limited long-term analysis, data quality issues, and concerns about bias. Addressing these constraints through interdisciplinary research is essential to gain a comprehensive understanding of AI's potential in construction. They have focused on specific aspects of AI implementation in construction, often neglecting to comprehensively review research clusters related to the four pillars of sustainability and the different stages of construction projects [11]. Sustainability in construction involves creating built environments that meet present needs without compromising the ability of future generations to meet their own needs. It combines environmental responsibility, social equity, economic viability, and responsible governance to create balanced and positive outcomes for society and the environment [28]. The four pillars of sustainability are the following.

- *Economic sustainability:* The ability of construction projects to create long-term economic value while considering the needs of both present and future generations. It involves ensuring the financial viability of construction projects, promoting fair trade practices, supporting local economies, and optimizing resource allocation [5]. This pillar emphasizes the importance of cost-effectiveness, profitability, and the long-term economic benefits derived from sustainable construction practices [29,30].
- *Social sustainability*: Meeting the needs and improving the quality of life for individuals and communities affected by construction projects. It encompasses factors such as social equity, inclusivity, health, safety, and well-being. Socially sustainable construction practices involve providing safe working conditions, promoting diversity and equal opportunities, respecting local cultures and traditions, and enhancing community engagement throughout the project lifecycle [28].
- *Environmental sustainability*: Minimizing the negative impact of construction activities on the natural environment. It involves practices that conserve resources, reduce pollution, promote energy efficiency, and mitigate climate change [31]. Examples include using renewable energy sources, employing sustainable construction materials, reducing waste generation, and implementing effective water and land management strategies [32].
- *Governance sustainability:* Promoting transparency, accountability, and ethical decision-making in construction projects. It emphasizes the importance of effective governance structures, policies, and regulations to ensure compliance with environmental, social, and economic standards. This pillar focuses on promoting responsible practices, preventing corruption, establishing clear frameworks for decision-making, and fostering collaboration between stakeholders to achieve sustainable outcomes [33].

The use of AI is evident across all four pillars and plays a vital role in achieving sustainability. Economically, AI leverages historical data for precise cost estimates, optimized resource allocation, and waste reduction [34]. Socially, AI's predominant applications lie in safety monitoring, community engagement, and workforce development, fostering safer sites, inclusive feedback analysis, and efficient training [5]. Environmentally, AI optimizes energy use, promotes sustainability, and reduces waste through consumption analysis, improved systems, material evaluation, and waste reduction efforts [34]. In governance, AI ensures compliance, transparency, and oversight by monitoring data for regulations, enhancing accountability, and refining project management and risk mitigation [22].

Each of these pillars plays a crucial role in ensuring sustainable construction practices. However, previous studies often tend to focus on a subset of these dimensions or overlook their interconnectedness [2]. By taking a holistic approach and considering all four pillars, a more comprehensive understanding of the potential impact of AI on sustainable construction can be achieved. Additionally, construction projects consist of various phases, including planning, design, construction, and operation and maintenance. Each phase presents unique challenges and opportunities for implementing AI. However, many studies have focused on specific phases or failed to consider the entire project lifecycle.

Understanding the potential of AI across all phases of construction is vital for developing effective strategies and harnessing its full potential [29,35].

This study adopts a scientometric approach to analyze scholarly research published in the last two decades. It aims to bridge gaps in the existing literature by conducting a comprehensive analysis that encompasses the four pillars of sustainability and considers the complete lifecycle of construction projects. The study has the objectives to uncover historical and emerging trends, identify research clusters, and present a summary of influential authors, publications, countries, universities, and publishing sources in the domain of AI in construction. The primary contribution of this research lies in improving our understanding of the potential opportunities and challenges associated with AI in construction and providing practical insights for its application from commencement to completion of a project. Overcoming AI implementation challenges in construction involves education and training for professionals, collaboration with experts, and robust data management. Regulatory frameworks should also be established to ensure ethical deployment. These solutions enable effective AI adoption and innovation in the industry. By undertaking such research, the construction industry can develop more robust frameworks and strategies to effectively leverage the capabilities of AI and achieve sustainable and efficient construction practices.

Following this introduction, the paper is organized as follows. Section 2 outlines the research methodology employed in the study. Section 3 presents the results that cover a range of aspects including general observations, academic influence analysis, research clusters in AI in construction literature, historical clusters, and emerging trends in AI research specific to construction and, along with the analysis findings of research trends and clusters, considers both the four pillars of sustainability and the four construction phases (planning, design, construction, and operation and maintenance). Section 4 offers a detailed discussion of the results, providing insights and interpretations. Section 5 concludes the paper.

2. Methodology

This study undertakes a scientometric analysis of existing AI and construction literature to address the following research questions: (a) What are the different areas of focus in AI in construction research? (b) What are the historical clusters, emerging trends, research clusters, and the correlation between sustainability pillars and project phases in AI in construction? With the guidance of the key literature—e.g., [36–38]—and using scientometric techniques, the study creates a knowledge connection map that visually represents qualitative data and helps to provide a clearer understanding of the research clusters [39]. This approach can provide valuable insights and a deeper understanding of the topic under investigation [40].

An extensive literature review was conducted to identify the existing applications of AI in the construction industry. The primary database search was performed on Scopus and was then validated by data from other databased such as the Institute of Electrical and Electronics Engineers (IEEE), Association for Computing Machinery (ACM), and Science Direct were used for validation. These databases were selected for their collection of high-impact publications in construction, engineering, and computer science. Scopus, being the largest citation database was chosen as the primary data source, while the others were utilized for downloading full articles and validating the data. Furthermore, Scopus provides the added advantage of allowing files to be exported in multiple formats that are compatible with mainstream scientometric analysis software—e.g., VOSviewer 1.6.19.

The search was performed using 25 keywords of the subfields and the construction industry: ("Artificial Intelligence*" OR "AI") AND ("Construction Industry" OR "Building") AND ("Sustainable" OR "Sustainability") OR "Urban Environment" OR "Construction Projects" OR "Automation" OR "Machine Learning" OR "Deep Learning" OR "Robotics" OR "Industry 4.0" OR "Building 4.0" OR "Urban Development" OR "AI Application" OR "Construction Projects" OR "Green Buildings" OR "Building Information Modeling" OR

"BIM" OR "Smart Cities" OR "Smart Buildings" OR "Technology" OR "Lifecycle" OR "Civil Construction" using advanced search to achieve the focus of this study.

The search task of literature data was conducted in July 2023 by covering the publication between 1 January 2000 to 8 July 2023—covering over two decades of publications on the topic. Excluding the small number of publications with information absence—i.e., undefined document type and authors—the search resulted in selected a total of 9564 publications from Scopus repositories, including conference papers, articles, conference reviews, book chapters, and gray literature. It is noted that journal papers are extended, structured pieces published in journals, while a conference paper is a concise, focused work presented at conferences. After extracting the papers from the database, they were carefully checked for completeness and screened to remove any publications that did not meet the inclusion criteria. The primary criteria for inclusion in this study were articles that described or evaluated practical applications of AI subfields and techniques in the construction industry, based on information from the abstract, title, or full-text article when needed. Data extracted from each article included the application area in construction, the methodology/techniques used, and the findings.

As a result of this screening process, a final selection of 3710 publications was considered relevant and included for further investigation. From these screened papers, the publications were sorted based on the author keywords and abstract into the four pillars of sustainability, namely: (a) economic; (b) social; (c) environmental; and (d) governance, as well as into different project phases, such as: (a) planning; (b) design; (c) construction; and (d) operation and maintenance. After the search task was completed, full records of the resulting publications, including citation and bibliographical information, abstracts, keywords, funding details, and other relevant data were exported in CSV format. This format was chosen to ensure compatibility with the selected data analysis software, namely VOSviewer [3].

VOSviewer is a widely used software tool designed to visualize and analyze bibliometric networks. Allowing researchers to comprehend intricate relationships and trends within the extensive scholarly literature. By processing bibliographic data encompassing publication records, citations, and keywords, VOSviewer creates visual representations that unveil connections and patterns among different elements in the dataset [3]. It achieves this by constructing networks of nodes (authors, keywords, journals) and edges (co-citation or co-occurrence relationships), arranging them in the visualization space based on their associations. This interactive visual map facilitates the identification of key authors, influential papers, collaboration trends, and emerging research areas [4]. VOSviewer has become a popular tool for scientometric research in various fields, including thermal comfort and building control [41], sustainable urban development [42], circularity in construction [43], autonomous vehicles [44], and smart homes [45]—just to name a few. In this study, VOSviewer was used to analyze AI in construction literature and create a range of visual diagrams, such as co-authorship network maps, citation-based network maps, and co-occurrence network maps, to help visualize and qualitatively analyze the literature data [39].

To ensure the reliability and validity of the analysis, repeated validations of the results were conducted, including duplicate screening of initial data, retesting of the software, and random selective tests of outputs. Scientometric analysis, while valuable for assessing research trends and patterns, comes with inherent limitations that should be considered [40]. One significant constraint is its heavy reliance on bibliometric data, primarily citations and publication counts. Such data might not provide a comprehensive picture of research quality, impact, or context. Another limitation is not accounting for qualitative aspects of research [41]. Consequently, this may lead to the inclusion of studies that have garnered citations due to factors other than their genuine impact or contributions. Lastly, scientometric analysis focuses on academic impacts and may overlook non-academic impacts un which have significant real-world implications or application. In essence, these limitations can lead to a distorted view of research trends, impact, and relevance. To mitigate these effects, it is crucial to acknowledge these limitations and complement scientometric analyses with qualitative evaluations and a broader consideration of research context and influence [2].

3. Results

3.1. General Observations

The dataset used in this study consisted of 3710 scholarly publications published between 1 January 2000 and 8 July 2023. These publications were sourced from 148 countries and involved 9567 authors, 1214 organizations, and 937 publishing sources (Table 1).

Table 1. Statistical information on the data.

Domain	Specifics
Data source	Scopus bibliographic repository
Covered period	From 1 January 2000 to 8 July 2023
Number of publications	3710
Covered country contexts	148
Number of authors	9567
Number of universities	1214
Number of publishing sources	937
Number of papers in each sustainability pillar	Economic: 1973 (53.2%) Environmental: 430 (11.6%) Social: 462 (112.4%) Governance: 845 (22.8%)
Number of papers in each project stage	Design: 1161 (31.3%) Panning: 876 (23.6%) Construction: 1366 (36.8%) Operation and maintenance: 307 (8.3%)

As seen in Figure 1, the amount of AI in construction-related publications increased over time, where exponential growth was observed from 2019 (n = 347) and almost doubled in 2021 (n = 640). The number of publications between 2018 to 2023 accounts for 75.1% of the total publications in the database. The surge in interest surrounding AI in the construction sector is the result of a convergence of influential factors in recent years. Technological advancements, particularly in machine learning and deep learning, have unlocked more sophisticated applications for construction. This progress aligns with the increasing availability of data generated throughout the project lifecycle, offering a foundation for AI-driven insights. Notably, AI's capacity to enhance cost and time efficiency, mitigate risks through predictive analytics, and address labor shortages has increased attention. The complexity of modern projects, coupled with client demand for innovative solutions, has positioned AI to manage intricacies effectively. Moreover, the success of AI in other industries, government initiatives, research developments, and the pursuit of competitive advantages have collectively propelled the construction industry's embrace of AI as a transformative tool for advancement [33].

The construction industry has been grappling with the challenge of meeting higher productivity demands, leading to a significant research focus on optimization within the field of AI [5]. In recent years, machine learning has emerged as the primary area of interest, surpassing knowledge-based systems due to its adaptability to dynamic data and predictive capabilities. Unlike knowledge-based systems, machine learning handles complex scenarios effectively, and its adaptability suits construction's variable conditions [1]. This is evident as machine learning has demonstrated success in practical application areas such as project scheduling, cost estimation, and predictive maintenance. Although knowledge-based systems have benefits, machine learning's versatility with diverse construction data makes it a more promising choice for practical use on a construction site. Conversely, natural language processing (NLP) has received limited attention over the past decade compared to other AI subfields. Challenges in understanding construction-specific language and a historical focus on quantitative methods could explain this disparity [45]. Despite this, there is potential for NLP to provide insights in areas like text mining and sentiment analysis for construction project documents and communications. As the field evolves, NLP might find a more significant role in construction research.

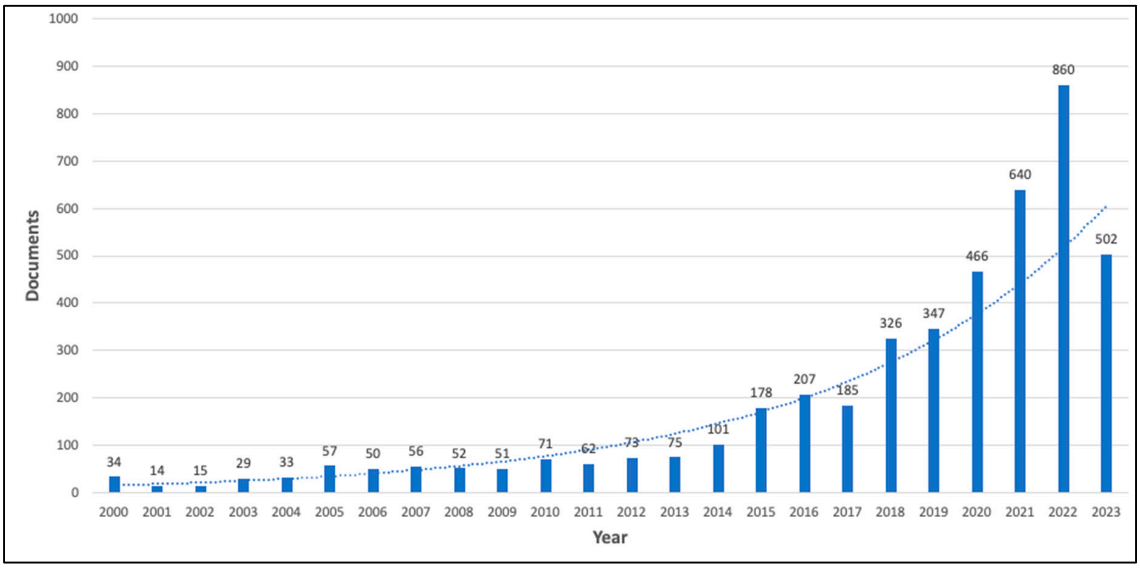


Figure 1. Publication growth trends.

The main types of selected publications are conference papers (47.8%) and articles (38.7%). Other gray literature such as reviews, book chapters, and others only account for 4% of the total number of publications (Figure 2). The major subject areas of selected publication are Engineering (n = 44.9%), Computer Science (n = 24.1%) and Mathematics (5.6%) (Figure 3). USA (n = 1791), China (n = 1289), and India (n = 794) are the top three productive countries, which, respectively, account for 39.9%, 28.7%, and 17.7% of the total publications (Figure 4). Despite excelling in AI across various sectors, Japan's absence from the top 10 AI research publishers in construction could stem from its broader AI focus, including robotics, electronics, and manufacturing. The construction sector's distinct challenges might have influenced Japan's research distribution despite its AI leadership.

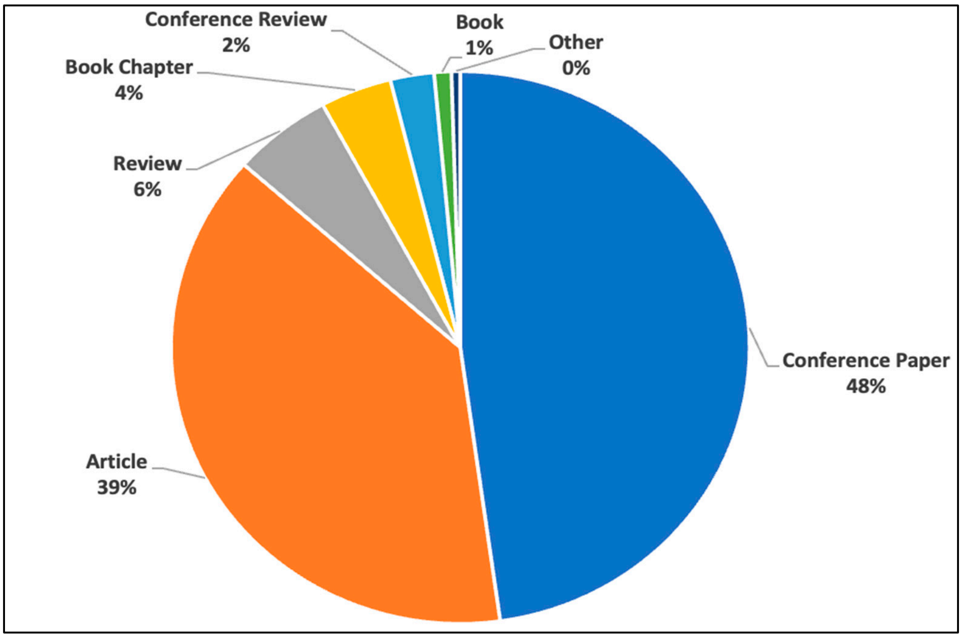


Figure 2. Document types.

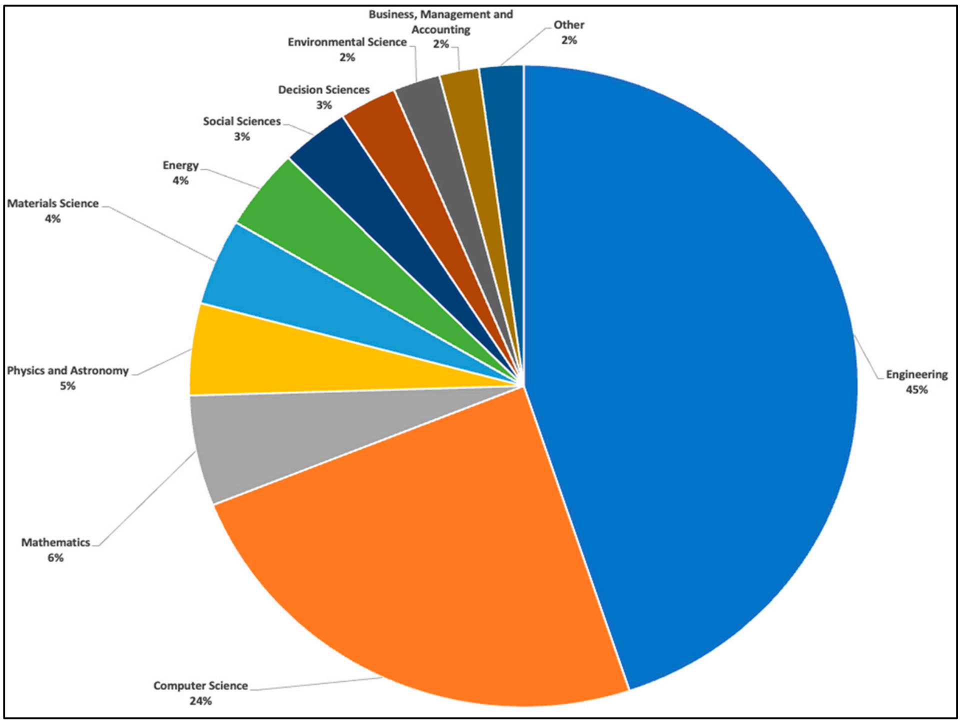


Figure 3. Documents by subject areas.

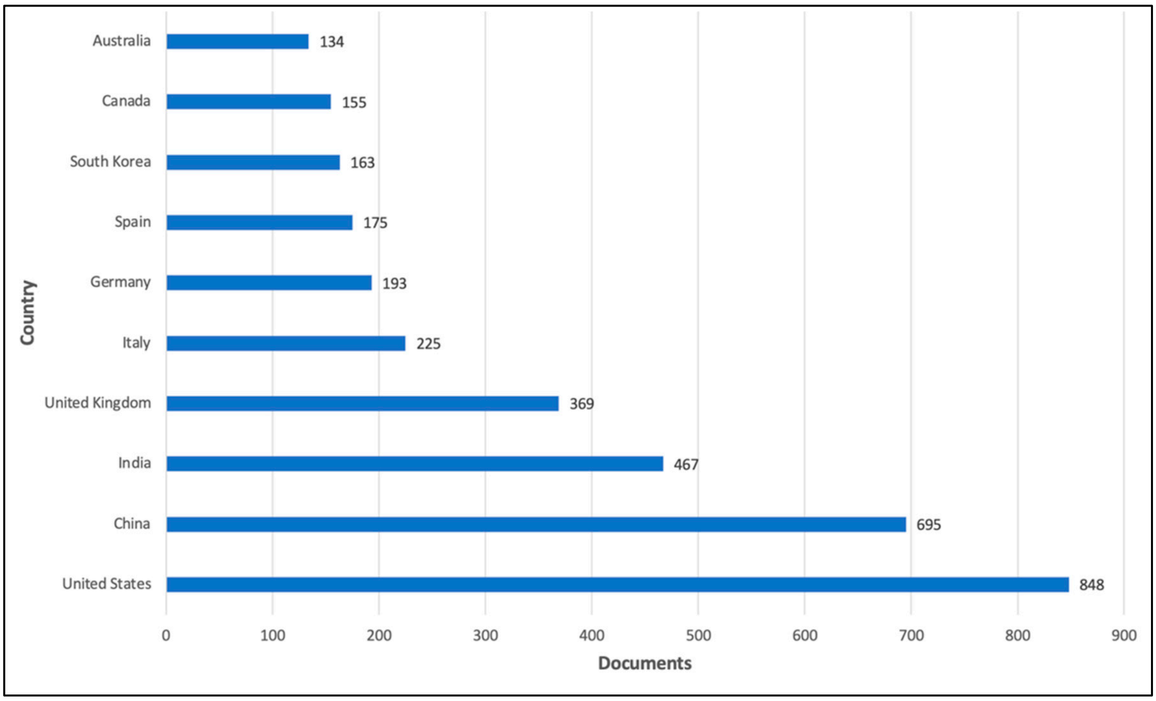


Figure 4. Top-10 highest publishing countries.

Based on the literature selected for AI in construction, Shuangyu Wei, Yacine Rezqui, and Paige Wenbin Tien emerge as the three most productive authors, with contributions of 2.2%, 2%, and 2%, respectively. Interestingly, these three authors are affiliated with the University of Nottingham and Cardiff University, which are based in England. Furthermore, these three authors' specific focus and expertise are in building technology and informatics.

Notably, among the top 10 most productive authors, there are from England and China and two are from Canada. For a comprehensive list of the top 10 most productive authors, their affiliated universities, and their respective contribution shares, refer to Table 2.

Table 2. Top-10 most published authors.

Rank	Author	Affiliation	Country	Count	Share
1	Suangyu Wei	University of Nottingham	England	10	2.23%
2	Yacine Rezqui	Cardiff University	England	9	2.01%
3	Paige Wenbin Tien	University of Nottingham	England	9	2.01%
4	Min-YuanCheng	National Taiwan University	China	8	1.79%
5	Bruno Bouchard	University of Quebec	Canada	7	1.56%
6	Calautit Kaiser	University of Nottingham	China	7	1.56%
7	Albert Chan	Hong Kong Polytechnic University	China	7	1.56%
8	Chimay Anumba,	University of Johannesburg	South Africa	6	1.34%
9	Mehrdad Arashpour	Monash University	Australia	6	1.34%
10	Abdenour Bououance	University du Quebec	Canada	6	1.34%

Among the top institutions, Hong Kong Polytechnic University from China leads with the highest contribution at (n = 34), followed by Politecnico di Milano from Italy at (n = 30), and Nanyang Technological University from Singapore and the Chinese Academy of Sciences both at (n = 28) as seen in Table 3. This demonstrates that various countries are actively participating in advancing AI technologies in construction. Furthermore, this global collaboration indicates a growing interest in leveraging AI's potential to enhance various aspects of construction, leading to innovative solutions and increased efficiency in the industry.

Table 3. Top-10 most published universities.

Rank	University	Country	Count	Share
1	Hong Kong Polytechnic University	China	43	0.96%
2	Politecnico di Milano	Italy	30	0.67%
3	Nanyang Technological University	Singapore	28	0.63%
4	Chinese Academy of Sciences	China	28	0.63%
5	Tsinghua University	China	27	0.60%
6	Carnegie Institute of technology	USA	27	0.60%
7	Georgia Institute of Technology	USA	26	0.58%
8	National Taiwan University	China	25	0.56%
9	Politecnico di Torino	Italy	24	0.54%
10	University of Florida	USA	24	0.54%

Prominently, Advances in Intelligent Systems and Computing stands out as the leading source, with 161 publications, representing 3.59% of the total publications in this paper (Table 4). This source focuses on research related to intelligent systems and computing, covering areas such as artificial intelligence, machine learning, robotics, and advanced computational techniques. Following closely is IEEE Access, a prominent journal with 114 publications, making up 2.54% of the overall output. Third, automation in construction published 79 papers, representing 1.76% of the total papers used in this paper. These three prolific publishing sources collectively highlight the strong research landscape in this field, as shown by their respective h-indices of 58, 204, and 157, respectively. Other journals, such as Automation in Construction (n = 79), Energy and Building (n = 67), Sensors (n = 65), and Energies (n = 58), demonstrate significant contributions to AI research in the construction domain.

Table 4. Top-10 publication outlets.

Rank	Publishing Source	Subject Area	Type	Count	Citations	H-Index	Share
1	Advances in Intelligent systems and Computing	Computer Science and Engineering	Book Series	161	525	58	3.59%
2	IEEE Access	Computer Science, Engineering, and Materials Science	Journal	114	2237	204	2.54%
3	Automation in Construction	Engineering	Journal	79	4197	157	1.76%
4	Energy and Building	Engineering	Journal	67	3986	214	1.49%
5	Sensors	Computer Science and Engineering	Journal	65	371	219	1.45%
6	Energies	Energy and Engineering	Journal	58	791	132	1.29%
7	Building and Environment	Engineering, Environmental Science, and Social Science	Journal	41	1589	189	0.92%
8	Journal of Building Engineering	Engineering	Journal	33	765	129	0.74%
9	Journal of Construction Engineering and Management	Business, Management and Accounting and Engineering	Journal	32	942	189	0.71%
10	Sustainable Cities and Society	Energy, Engineering, and Social Science	Journal	27	1249	103	0.60%

Most of the publishing sources (n = 6) focus on specific engineering disciplines. This indicates a strong emphasis on applying AI in various engineering within the construction industry. Computer science and engineering is also a prominent subject area (n = 3), which indicates a significant interest in utilizing AI technologies in computer science and engineering applications related to construction. Lastly, subject areas such as Environmental Science, social science, energy, and social science are represented by single publishing sources. This indicates a growing trend of integrating AI with broader social and environmental aspects of construction and urban planning.

3.2. Academic Influence Analysis

3.2.1. Citation Analysis by Publication

As shown in Table 5, Boje et al.'s (2020) [46] review paper examines the impact of digital technologies on the AEC sector, focusing on design, construction, and operation processes. It highlights the role of sensor networks, semantic models, and engineering system simulation in enhancing efficiency and minimizing lifecycle impacts. The study also introduces the concept of a Construction Digital Twin and identifies areas for future research. Overall, it underscores the transformative potential of digital technologies in achieving sustainable and efficient construction practices.

Ranked second among the top-10 most cited publications is Pan et al.'s (2019) [39] paper on the roles of artificial intelligence in construction engineering and management. This publication explores the rapid digital transformation of construction engineering and management (CEM) due to extensive AI adoption. It presents a systematic review, revealing the surge in relevant papers and highlighting six key research topics leveraging AI advantages in CEM. Additionally, it outlines six promising directions for future research to further enhance automation and intelligence in the field. Overall, the paper provides valuable insights into AI's transformative impact on CEM.

Golparvar-Far et al. (2011) [22] present an automated approach for tracking and visualizing as-built progress in construction using unordered daily photographs and building information models (BIMs). The system utilizes structure-from-motion, Multiview stereo, and machine-learning techniques to achieve accurate and efficient progress monitoring, making it a significant advancement in the field. Experimental results demonstrate its potential for transformative impact in construction project management.

Table 5 displays the top 10 highly cited research publications, including information on the authors, year of publication, research focus, and citation count. The results reveal that the most influential publications primarily center on technology algorithms and the practical implementation of AI in construction sites. Out of the research focus areas, BIM, Construction Safety, Machine Learning, and Automation were each mentioned twice, while the other research keywords were mentioned once. This analysis highlights the diversity of research focus areas in the field of AI in construction, ranging from specific technologies and applications (e.g., BIM, 3D reconstruction) to broader concepts and methodologies (e.g., Digital Transformation and Machine Learning).

Table 5. Top-10 most cited publications.

Rank	Publication Title	Author	Research Focus	Year	Citation
1	Towards a semantic Construction Digital Twin: Directions for future research	Boje C.; Guerriero A.; Kubicki S.; Rezgui Y.	Big data, BIM, and construction safety.	2020	359
2	Roles of artificial intelligence in construction engineering and management: A critical review and future trends	Pan Y.; Zhang L.	Construction engineering and management.	2019	269
3	Automated progress monitoring using unordered daily construction photographs and IFC-based building information models	Golparvar-Fard M.; Peña-Mora F.; Savarese S.	3D reconstruction, Automation, and Computer vision.	2011	250
4	A review of rotorcraft unmanned aerial vehicle (UAV) developments and applications in civil engineering	Liu P.; Chen A.Y.; Huang Y.N.; Han J.Y.; Lai J.S.; Kang S.C.; Wu T.H.; Wen M.C.; Tsai M.H.	Image processing and analysis and Unmanned aerial vehicle.	2014	248
5	An Internet of Things-enabled BIM platform for on-site assembly services in prefabricated construction	Li C.Z.; Xue F.; Li X.; Hong J.; Shen G.Q.	BIM, Decision-support system, Internet of Things, and Prefabricated construction.	2018	235
6	Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities	Darko A.; Chan A.P.C.; Adabre M.A.; Edwards D.J.; Hosseini M.R.; Ameyaw E.E.	Automation, Digital transformation, Industry 4.0, and Machine intelligence.	2020	214
7	Application of machine learning to construction injury prediction	Tixier A.J.P.; Hallowell M.R.; Rajagopalan B.; Bowman D.	Construction safety, Machine learning, Predictive modeling, and Random Forest.	2016	192
8	Smartphone-based construction workers' activity recognition and classification	Akhavian R.; Behzadan A.H.	Machine learning, Neural networks, and Smartphone sensors.	2016	172
9	Developing a Digital Twin at Building and City Levels: Case Study of West Cambridge Campus	Lu Q.; Parlikad A.K.; Woodall P.; Don Ranasinghe G.; Xie X.; Liang Z.; Konstantinou E.; Heaton J.; Schooling J.	Asset management, Digital twin (DT), and Operation and maintenance (O&M).	2020	159
10	Predicting concrete compressive strength using hybrid ensembling of surrogate machine-learning models	Asteris P.G.; Skentou A.D.; Bardhan A.; Samui P.; Pilakoutas K.	Hybrid modeling and Soft computing.	2021	157

3.2.2. Citation Analysis by University

According to Table 6, universities from the USA and China dominate the list ($n = 7$), with Carnegie Institute of Technology and National Taiwan University holding the top two positions, respectively. Nanyang Technological University from Singapore ranks third. Notably, Hong Kong Polytechnic University, also from China, holds the fourth position and has the highest number of documents published ($n = 43$), indicating significant research impact. Universities from Italy, such as Politecnico di Milano and Politecnico di Torino, are also represented in the top 10, showcasing their contributions to the research in the given field. These findings suggest that the USA and China have made a significant contribution to the research on AI in construction and have exerted a substantial influence on research in other countries. In addition, the inclusion of Italian universities (*n* = 2) further adds to the international collaboration and research efforts in AI in construction.

Table 6. Top-10 most cited universities.

Rank	University	Country	Count	Citations	Share
1	Carnegie Institute of technology	USA	27	1282	0.60%
2	National Taiwan University	China	25	1259	0.56%
3	Nanyang Technological University	Singapore	28	1235	0.63%
4	Hong Kong Polytechnic University	China	43	1135	0.96%
5	Georgia Institute of Technology	USA	26	1031	0.58%
6	Tsinghua University	China	27	673	0.60%
7	Chinese Academy of Sciences	China	28	556	0.63%
8	University of Florida	USA	24	318	0.54%
9	Politecnico di Milano	Italy	30	242	0.67%
10	Politecnico di Torino	Italy	24	194	0.54%

3.2.3. Citation Analysis by Country

Table 7 presents a comparison of the top 10 most cited countries in AI in construction research in terms of citations, total link strength, and publication year. The USA emerges are the most influential country with a significantly higher citation count than any other country. England and China are ranked second and third, respectively, with similar citation numbers. The total link strength indicates the strength of a country's academic relationships with other countries. For instance, China has a total link strength of 284, which signifies a wider academic network (in terms of citation) with other countries compared to Germany (*n* = 142). Figure 5 illustrates the citation network by country, where each circle denotes a country, and the size of the circles indicates the citation count of that country's publications. The line between each circle signifies the academic relationship between pairs of countries, and a shorter line implies a closer academic relationship. The color of the circles indicates the scientific communities to which they belong, with countries belonging to the same community being deeply connected in terms of citation [3].

Table 7. Top-10 most cited countries.

Rank	Country	Citation	Totally Strength	Year
1	USA	17,143	343	2014
2	England	10,971	291	2016
3	China	9289	284	2019
4	Italy	4062	151	2011
5	India	3311	129	2022
6	Australia	3202	111	2019
7	Germany	2870	142	2018
8	Taiwan	2608	23	2017
9	South Korea	2604	65	2018
10	Spain	2590	130	2017

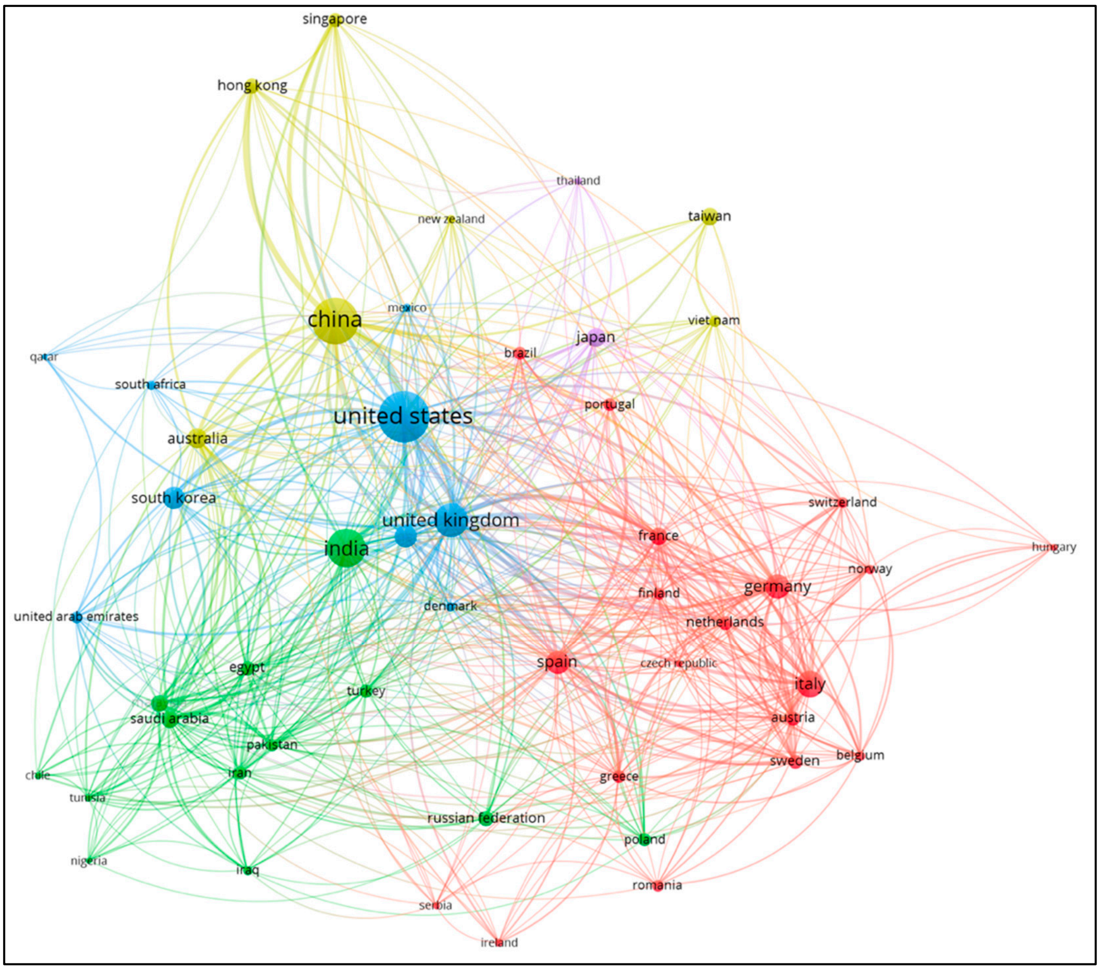


Figure 5. Citation network map by country.

Based on the citation network visualized in Figure 5, it can be discerned that the top three highly cited countries are from different citation communities but are closely interlinked through citations. Additionally, the citation communities comprising the network do not show any discernible regional patterns, such as being from the same continent. These observations imply that over the past two decades, research on AI in construction has not been dominated by any subject or group, and academia globally has sustained a level of interest and scholarly exchange in this area. These findings have significant implications for researchers, policymakers, and industry practitioners, as they suggest that AI in construction is a topic of interest for the academic community worldwide, and international collaboration is crucial for advancing the field.

Figure 6 depicts a citation network map visualizing the publication year by country in the field of AI in construction, which is an emerging area of research. The color-coded circles on the map represent the chronological order of the average publication year, with darker colors indicating earlier years and lighter colors representing more recent years. The network map analysis reveals the USA as the primary contributor to the field, showcasing a significant research presence and laying the groundwork for future studies. Notably, India has exhibited a considerable and noteworthy enhancement in its contributions in recent times, demonstrating promising advancements in the field. These findings offer valuable insights for researchers, policymakers, and industry practitioners, providing a comprehensive view of the global trends and the evolving landscape of AI applications in the construction sector. Understanding the key players and emerging contributors can help stakeholders make informed decisions and foster collaborations to further advance the integration of AI technologies in construction practices.

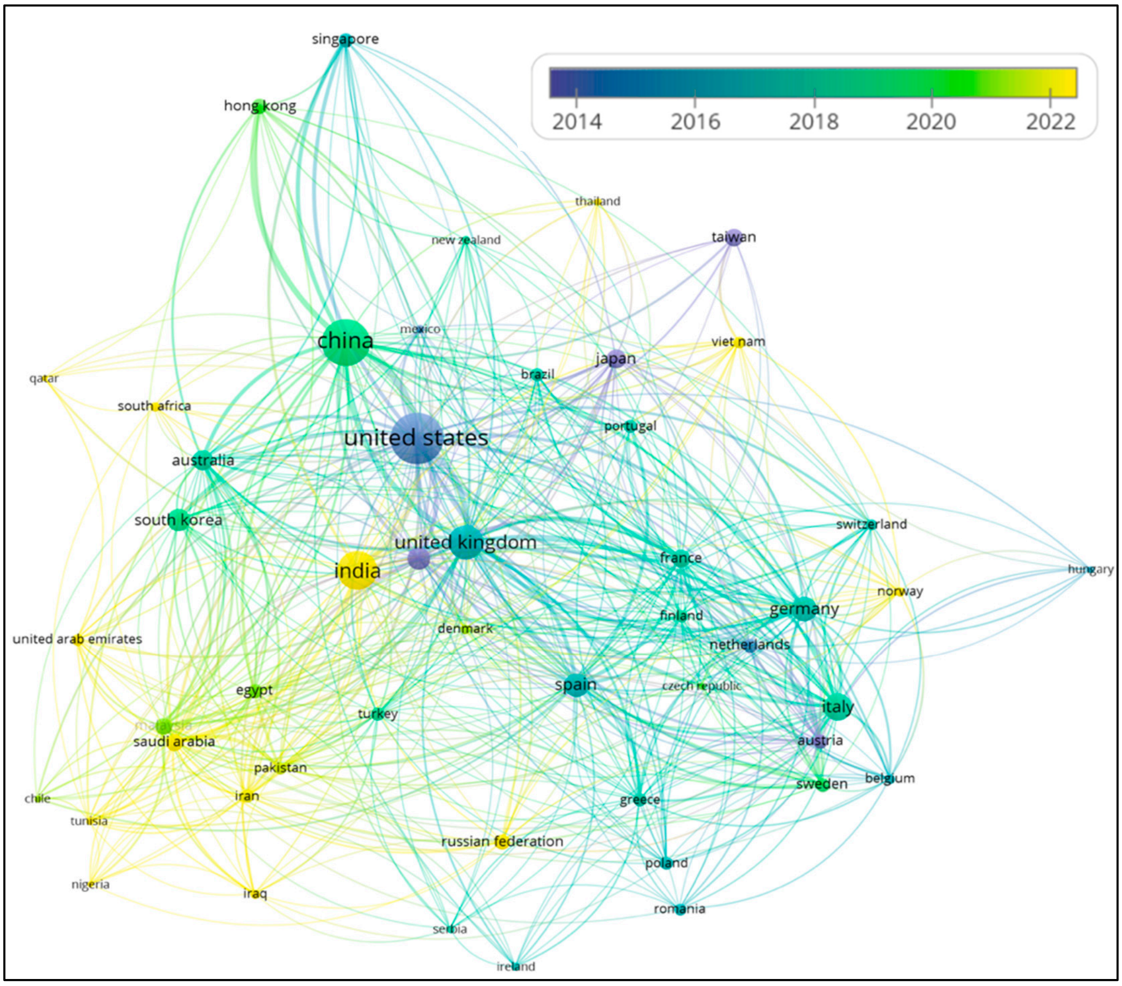


Figure 6. Citation network by country and publication year.

3.3. Research Clusters of AI in the Construction Literature

Referring to Figure 7, by utilizing frequency and link strength analysis of 8165 extracted keywords from AI in the construction database. The keywords were then filtered to meet a minimum threshold of five occurrences, resulting in a total of 260 keywords. The analysis identified six distinct clusters in the existing AI in construction research. The following outlines these clusters:

- *Cluster 1 (Automation):* Using technology to automate repetitive tasks and improve efficiency and safety.
- *Cluster 2 (Big data):* Analyzing large volumes of data to improve decision-making.
- *Cluster 3 (Digital twin):* Creation of a virtual replica of a physical asset such as a building or infrastructure project, allowing for optimized designs and improved collaboration between stakeholders.
- *Cluster 4 (Deep learning):* Uses artificial neural networks to analyze data and make predictions in construction, including quality control for materials such as concrete and steel.
- *Cluster 5 (Machine learning):* Using data and algorithms to make predictions and identify hazards.
- *Cluster 6 (Information systems):* Software and hardware used to manage and process project data.
- *Cluster 7 (Simulation):* Using software to model materials, structures, and construction processes to identify potential issues before construction begins.

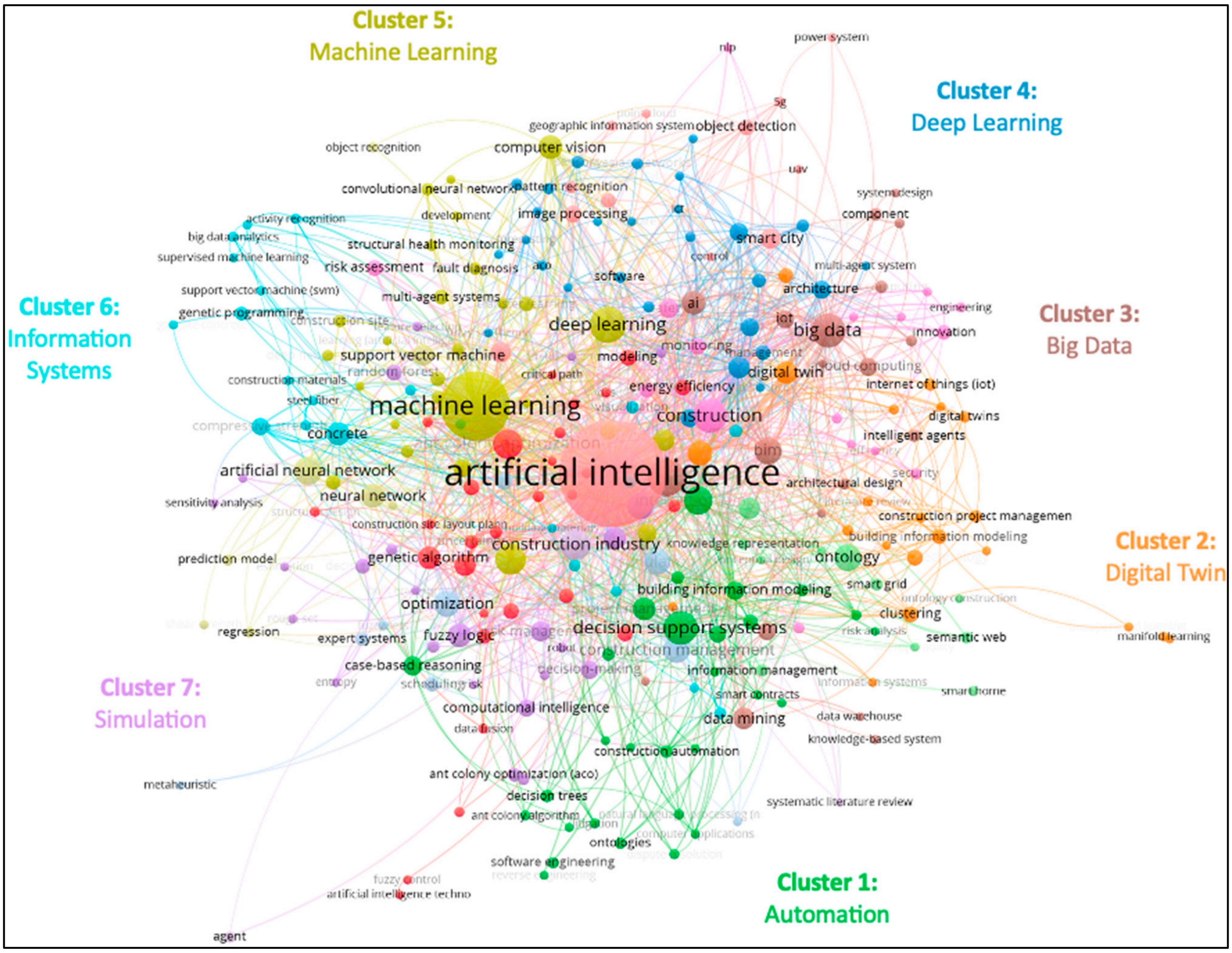


Figure 7. Research cluster network map by keyword occurrences.

The research clusters network map presented in Figure 7 exhibits valuable insights regarding the relationships and interactions between the various research clusters. Each circle within the map represents a distinct keyword, and its size is proportional to its frequency of occurrence, while the color reflects its research cluster affiliation. The proximity of the circles to each other indicates the strength of correlation and similarity between the corresponding keywords.

The network map reveals several noteworthy findings, including Clusters 1 and 5 are located centrally within the network, serving as pivotal points for connecting various clusters. Additionally, the high degree of overlap between Clusters 2 and 3 suggests a close interconnection between these two clusters. Furthermore, the circles within Clusters 4, 5, and 7 display an assortment of colors from different clusters, indicative of their diverse and extensive connections with other clusters. Conversely, Cluster 1 appears to be relatively independent in its distribution, signifying weaker connections with other clusters. These clusters provide a comprehensive overview of the relationships and interdependencies between various research clusters, allowing for deeper insights into the underlying patterns and connections within the research domain.

Table 8 provides a list of the top-10 occurrence keywords and shows the average publication year, occurrences, link, total link strength, and subordinate clusters. The list excludes the search keywords and other alternative keywords—e.g., "Artificial Intelligence", "Construction", and "Modeling". A set of exclusion criteria can reduce the redundancy on the list and help identify the research trends of AI in construction research, i.e., identify the specific research clusters or extended research orientations. The most frequent keyword

"Machine Learning" has the strongest total link strength, indicating that machine learning has emerged in construction and has been the most popular trend that has attracted significant interest from various universities and researchers. Three of the top-10 occurrences keywords (the 1st, 3rd, and 9th ranked keywords) are categorized as Cluster 5. The sum of the total link strength of these 3 keywords ranks first on the list (n = 557) from the total list of (n = 1140). This shows that existing AI in construction research has kept a strong connection with Machine learning. Furthermore, no keywords categorized to Cluster 6 are on the list, which means that Information Systems clusters are not a popular extended research orientation for AI in construction research.

Table 8. Top-10 occurrence keywords.

Rank	Keyword	Occurrences	Total Strength	Year	Cluster
1	Machine Learning	238	410	2019	5
2	Deep Learning	68	120	2021	4
3	Neural Networks	47	98	2017	5
4	Big Data	60	94	2019	3
5	Internet of Things	42	92	2020	2
6	Decision-Support Systems	72	89	2014	1
7	Digital Twin	26	72	2021	2
8	Automation	25	67	2015	4
9	Computer Vision	28	49	2017	5
10	Fuzzy Logic	30	49	2012	7

3.4. Historical Research Clusters of AI in the Construction Research

This subsection identifies historical research-based keyword occurrences on a density map in the context of AI in construction. The keyword selection process excluded redundant keywords and alternative keywords to provide a more explicit understanding of the specific research clusters and extended research orientation of AI in construction.

The outputs are interpreted as follows: First, on the density map of 2000–2005, the keywords of Clusters 1 and 6 are distributed in the areas as seen in Figure 8a. These keywords are closely linked to each other, which assemble the largest aggregation on the map. On the other hand, the keyword for Cluster 7 is in an area relatively far away from the aggregation of Clusters 1 and 6, having a weak connection with them. In this period, the most frequent keyword is from Cluster 1 (n = 7) and occupies most of the top-10 occurrence keyword list. The remaining keywords on the list are from Clusters 6 and 7 as seen in Table 9.

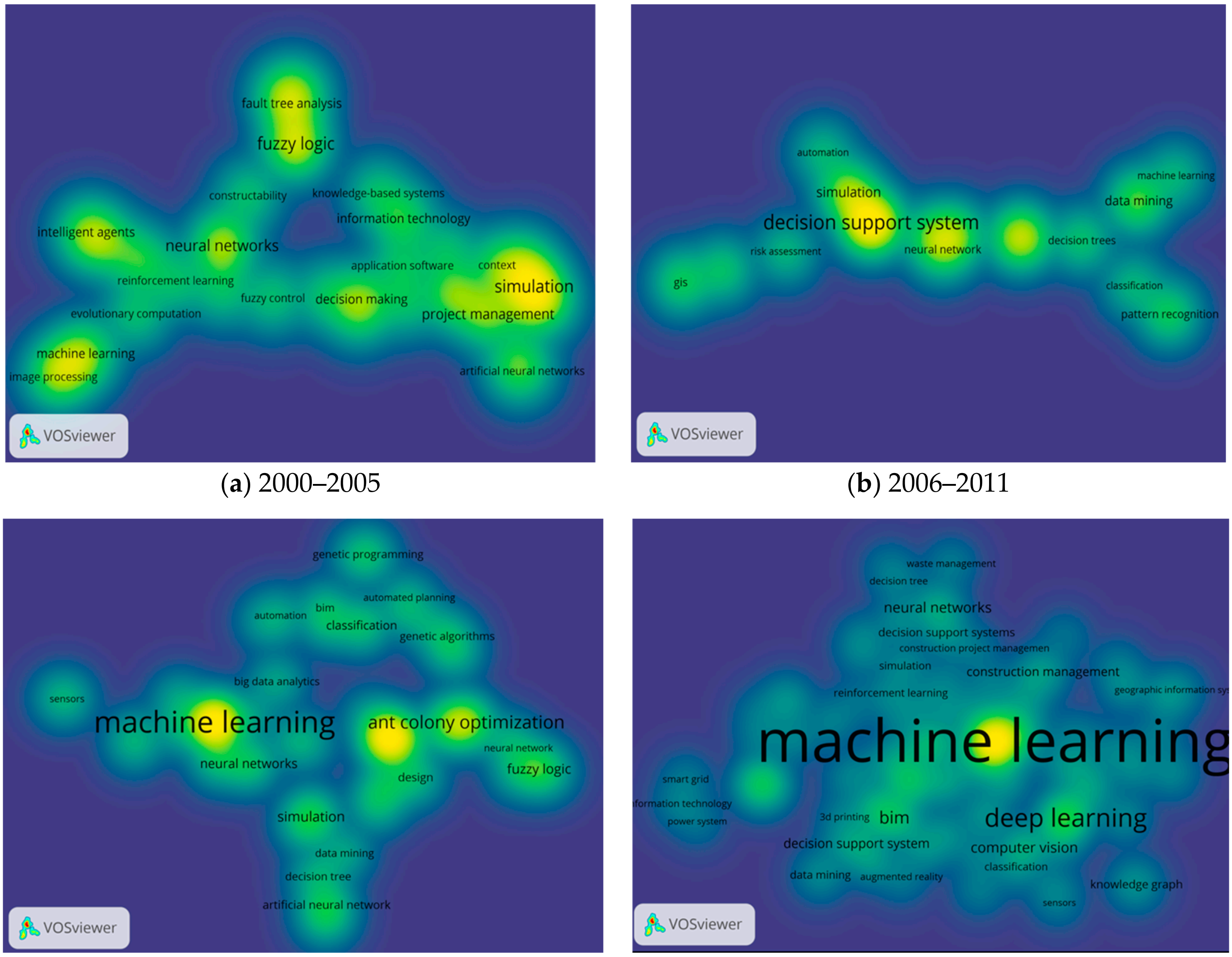
Second, on the density map of 2006 to 2011, the largest aggregation is composed of Cluster 3 (Big Data) and Cluster 7 (Simulation) (Figure 8b). Furthermore, some keywords from Clusters 3 and 5 first appear on the map with higher density, i.e., neural networks, data mining, and machine learning. In this period, Cluster 1 (n = 4), Cluster 2 (n = 1), Cluster 3 (n = 1), Cluster 5 (n = 1), and Cluster 7 (n = 3) occupy the top-10 occurrence keywords list as seen in Table 9.

Thirdly, on the density map of 2012 to 2017, the keyword of Cluster 5 appears to be the most predominant research cluster as seen in Figure 8c. The keywords of Cluster 7 (Simulation) form a separate and individual aggregation. So far, five clusters are displayed on the density map: Cluster 1 (n = 4), Cluster 3 (n = 1), Cluster 5 (n = 2), Cluster 6 (n = 1), and Cluster 7 (n = 2).

Finally, on the density map of 2016 to 2023, the keyword density distribution is completely different from previous layouts (Figure 8d) as it presents a spreading layout with keywords of Clusters 4 and 5. This is the first appearance of Clusters 2 and 4 with higher density and are in close aggregation with Cluster 5. Furthermore, Clusters 1, 6, and 7 are diminishing in aggregation and are being replaced with Clusters 4 and 5. The results of keyword occurrence density (by period) revealed that:

- The earliest research clusters in AI in construction were Automation (Cluster 1) and Information systems (Cluster 6), which laid the groundwork for the field.

- Simulation (Cluster 7) was the first extended research orientation of AI in construction, but it had a relatively weak link to other clusters.
- The earliest research clusters that started to reduce the aggregation of Clusters 6 and 7 were Machine learning (Cluster 5) and big data (Cluster 3).
- Automation (Cluster 1) has been the most popular extended research orientation of AI in construction over the past two decades (2000 to 2023).
- Deep learning (Cluster 4) has recently emerged as a significant cluster in AI in construction, driven by advances in technology from Digital twin (Cluster 2) and big data (Cluster 3). It has strong links with other relevant research clusters. In the past 6 years, Deep learning (Cluster 4) has replaced Automation (Cluster 1) and Information systems (Cluster 6) as the most popular cluster in AI in construction (excluding AI).



(**a**) 2000–2005 (**b**) 2006–2011

(**c**) 2012–2017 (**d**) 2018–2023

Figure 8. Keyword occurrences density by period.

Table 9. Top 10 keyword occurrences per 5-year period.

		Occurrence per Period				Ranks per Period			
Cluster	**Keyword**	**2000–2005**	**2006–2010**	**2011–2015**	**2016–2023**	**2000–2005**	**2006–2010**	**2011–2015**	**2016–2023**
7	Fuzzy Logic	6	7	9	-	1	4	7	-
7	Simulation	6	9	-	-	2	3	-	-
5	Neural Networks	5	11	8	-	3	2	6	-
1	Decision-Support Systems	4	37	57	18	4	1	1	1
7	Genetic Algorithms	4	4	9	-	5	7	4	-
2	Reinforced Learning	2	-	-	-	7	-	-	-
6	Image Processing	2	-	-	-	8	-	-	-
3	Building Information Systems	-	3	10	-	-	10	3	-
3	Data Mining	2	7	4	-	9	5	5	-
1	Automation	-	3	-	-	-	8	-	-
5	Machine Learning	3	3	37	195	6	9	2	2
4	Deep Learning	-	-	-	66	-	-	-	3
3	Big Data	-	-	7	53	-	-	8	4
2	Internet of Things	-	-	-	40	-	-	-	5
1	Robotics	2	6	6	28	10	6	9	6
2	Digital Twin	-	-	-	26	-	-	-	7
6	Computer vision	-	-	-	23	-	-	-	8
5	Support Vector Machine	-	-	-	16	-	-	-	9
5	Natural Language Processing	-	-	4	14	-	-	10	10

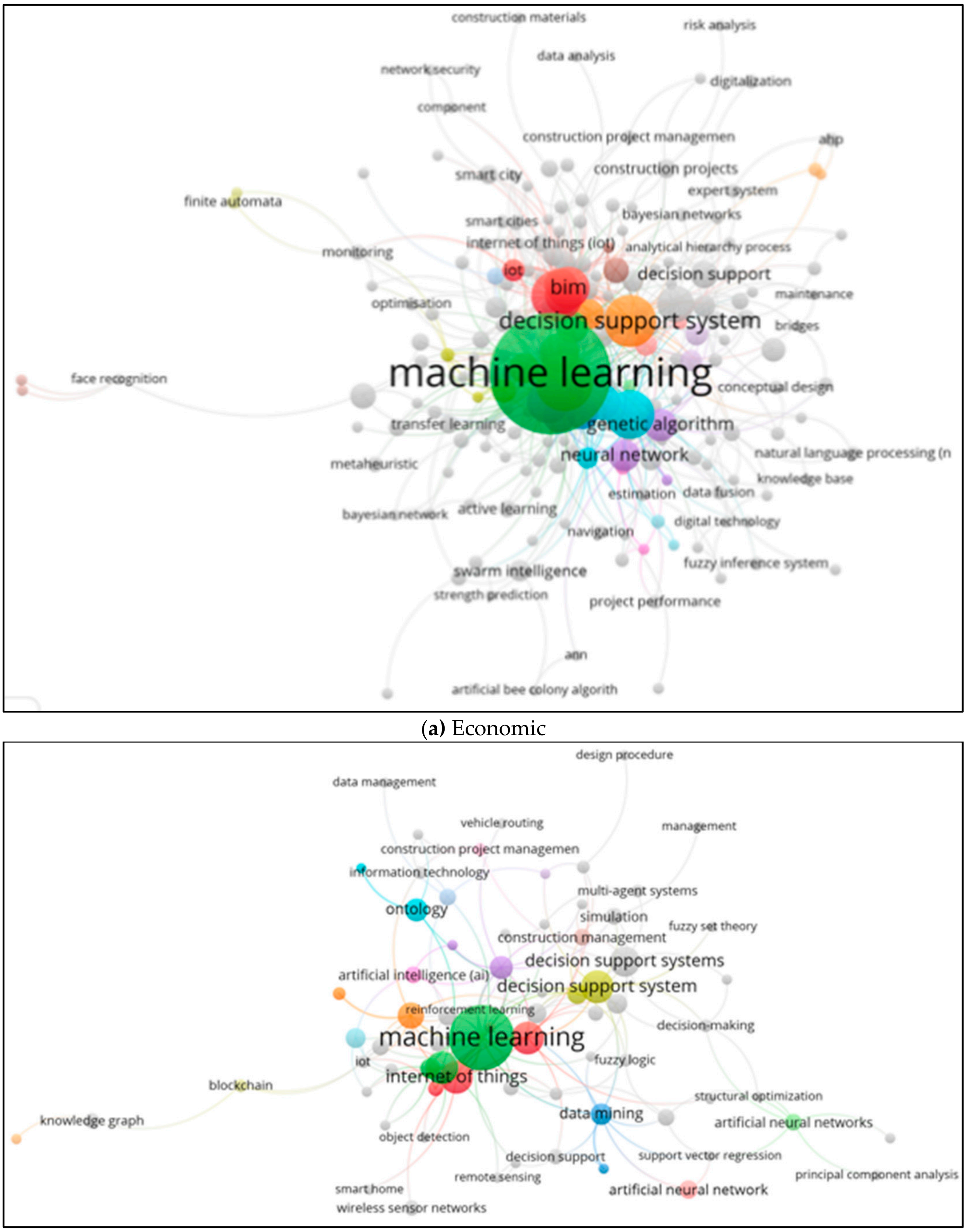
3.5. Research Clusters in the Context of AI and Sustainability

The network map in Figure 9 outlines the research clusters through sustainability pillars and the frequency of keyword occurrences. Figure 9a revealed that machine learning emerged as the most significant keyword associated with improving economic efficiency. As a subfield of AI, machine learning utilizes algorithms and statistical models to enable computers to learn from data and make predictions without being explicitly programmed. This technology has immense potential to optimize resource allocation, predict project outcomes, and identify potential risks, leading to better project outcomes. Moreover, the close association between machine learning and other technologies such as building information modeling (BIM), decision-support systems (DSS), genetic algorithms, and the IoT further highlights the potential of these technologies to improve economic efficiency in project management.

On the other hand, in the context of governance sustainability as seen in Figure 9b, the network map reveals the significance of machine learning in promoting risk management and mitigation. The close association between machine learning and other technologies such as the IoT, reinforced learning, and DSS highlights the potential of these technologies to improve governance sustainability in construction projects. Data mining and artificial neural networks also form separate clusters that promote different types of research. By leveraging the power of these technologies, construction managers can identify and mitigate risks, optimize resource allocation, and make more informed decisions, leading to more sustainable outcomes.

Figure 9c presents a network map of keyword clusters in the field of social pillar of sustainability. One key finding is that big data and data mining emerged as prominent clusters and were strongly associated with computer vision. This indicates that researchers in the field of AI governance have recognized the importance of data analysis and visualization in improving decision-making processes and achieving better outcomes. Another interesting observation is that decision-support systems and automation formed separate keyword clusters, which had little correlation with machine learning. This suggests that research projects are exploring a variety of approaches to improving decision-making, including both automated systems and human decision-making aided by technology.

In the environmental sustainability context as shown in Figure 9d, machine learning remains a predominate keyword. However, deep learning emerges as a key cluster, indicating its potential to address sustainability challenges in construction. Overall, most of the keywords in the environmental sustainability context form separate clusters, pointing to a diverse range of research topics and approaches. Common research clusters include simulation, artificial neural networks, and decision-support systems, which may require different AI techniques and methods to address sustainability challenges.



(**a**) Economic

(**b**) Governance

Figure 9. *Cont.*

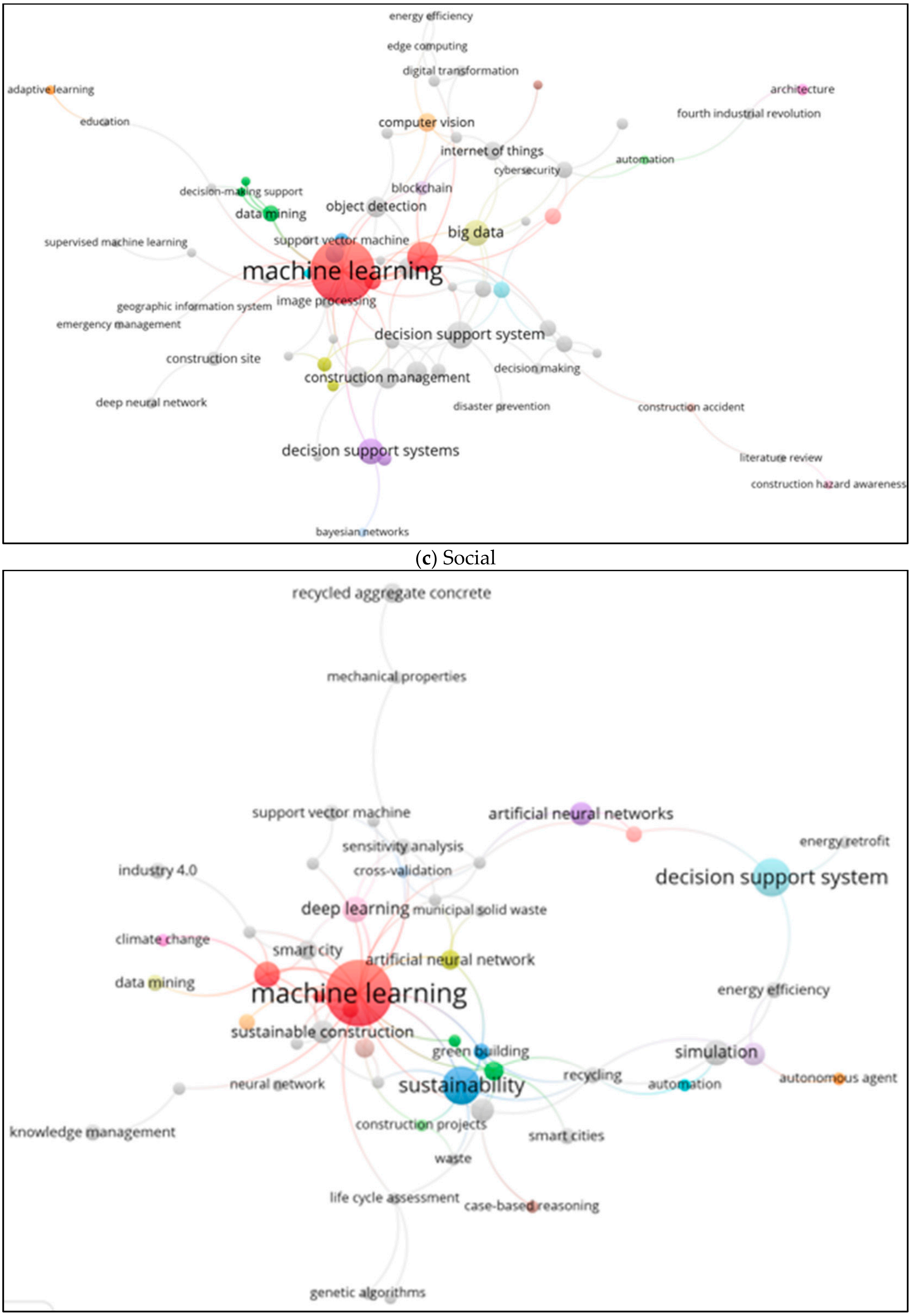


Figure 9. Research cluster map.

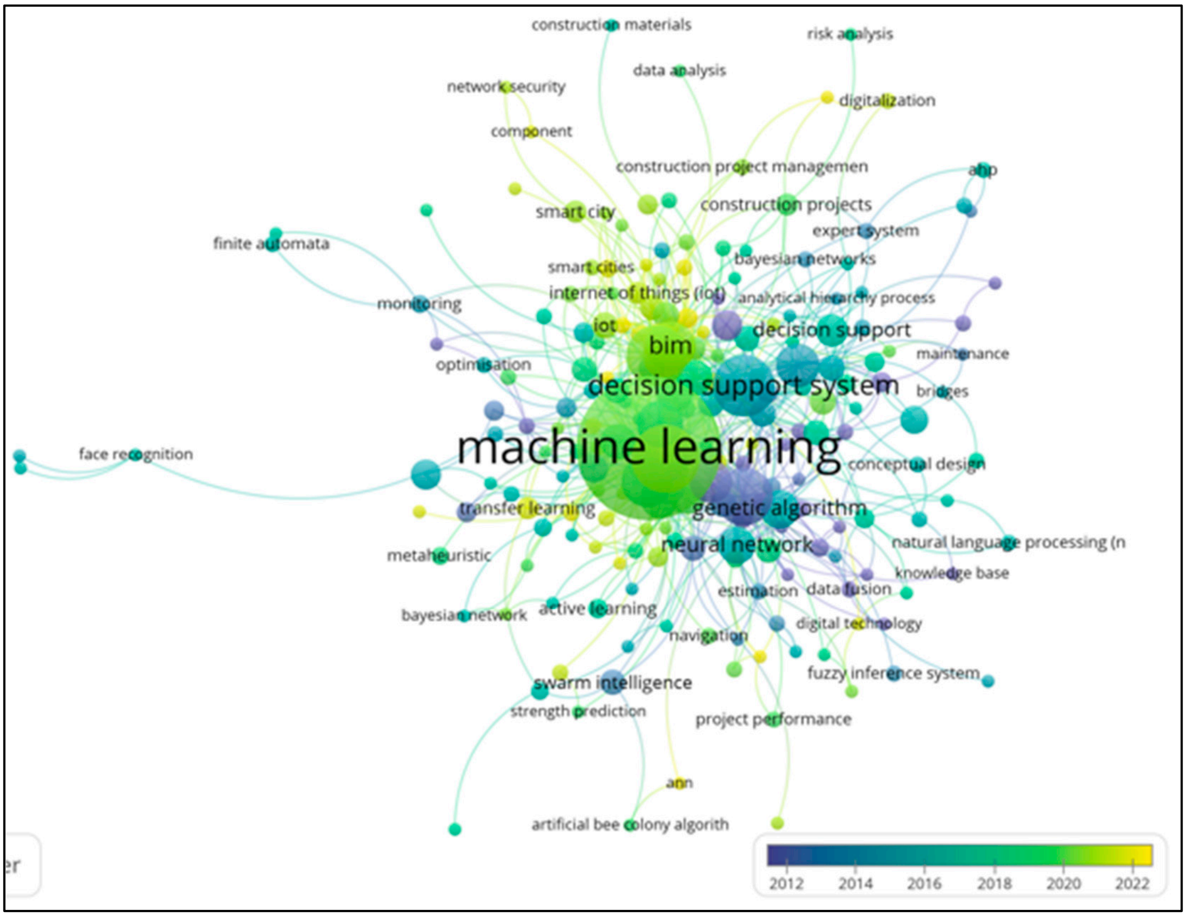
3.6. Historical Research Clusters of Sustainability in the Construction Domain

Figure 10 depicts a citation network map organized according to sustainability pillars. Earlier research in the economic pillar as shown in Figure 10a, identifies neural networks as a promising research cluster. Later, in 2016, DSS emerged as an area of focus in economic-related construction research. More recently, however, the focus has shifted to machine learning and building information modeling. Machine-learning algorithms have been applied to construction data to make predictions and learn from experience while building information modeling has been used to create virtual representations of buildings and construction projects. These technologies have expanded the scope of investigation into other advanced technologies, such as IoT, digital twins, and cloud computing, which have the potential to enhance the efficiency and effectiveness of construction processes.

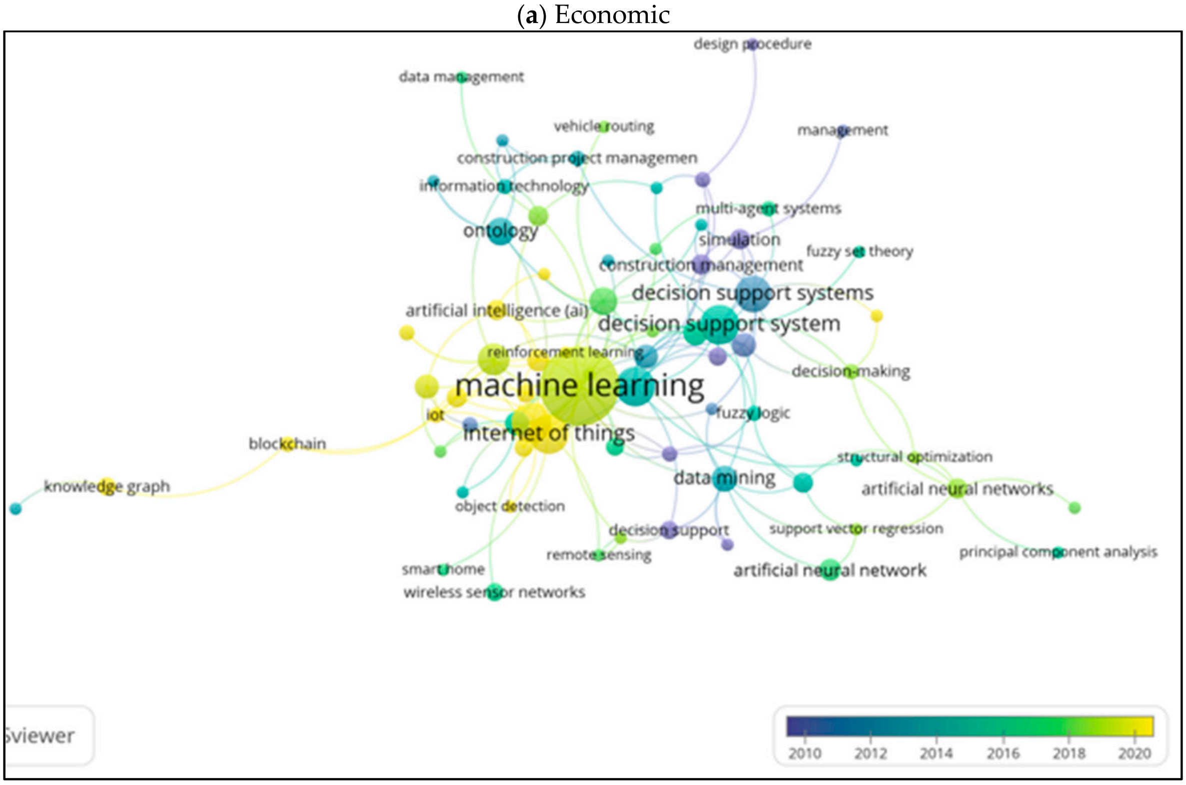
Governance research efforts as seen in Figure 10b have changed significantly over the past decade. Early research in 2010 placed a great emphasis on decision-support, simulation, and fuzzy logic. These technologies were seen as crucial for managing the complex and rapidly changing landscape of AI. However, by 2014, the focus began to shift towards data mining and reinforced learning. These approaches were seen as offering greater precision and flexibility in decision-making, as well as the ability to learn from experience and adapt to changing circumstances. More recently, the focus has shifted towards machine learning, which has emerged as a key area of research. This has led to further investigations into other advanced technologies such as IoT, blockchain, and object detection. These technologies have the potential to revolutionize the way that AI systems are governed, offering greater transparency, accountability, and security.

On the other hand, the early social pillar as shown in Figure 10c focused on DSS, data mining, and adaptive learning. These technologies were seen as critical for addressing the social implications of AI in construction. By 2018, the focus of research had shifted towards cyber security, automation, and support vector machine technology. As AI systems became more widespread and complex, the need to ensure their security and reliability became increasingly important. Automation was also seen as an important area of research, as it offered the potential to improve the efficiency and effectiveness of site safety. In the following years, machine learning emerged as the predominant cluster in social pillar research. However, more recently, the focus has shifted towards other advanced technologies such as big data, IoT, computer vision, and deep neural networks. These technologies can help to improve the accessibility and effectiveness of construction services, enhance worker safety, and promote social equity.

In the context of the environmental pillar (Figure 10d), research has evolved to explore the potential of AI and other advanced technologies to address environmental challenges. In the early stages of research, DSS, simulation, and artificial neural networks were identified as key areas of investigation [47]. These approaches were seen as potential solutions to address challenges related to energy efficiency, carbon footprint, and waste management. As the research progressed, the focus shifted towards automation and genetic algorithms in 2016. These techniques were explored as potential solutions to optimize building designs and reduce environmental impacts. However, in the following years, deep learning emerged as a predominant research cluster in the context of environmental sustainability.

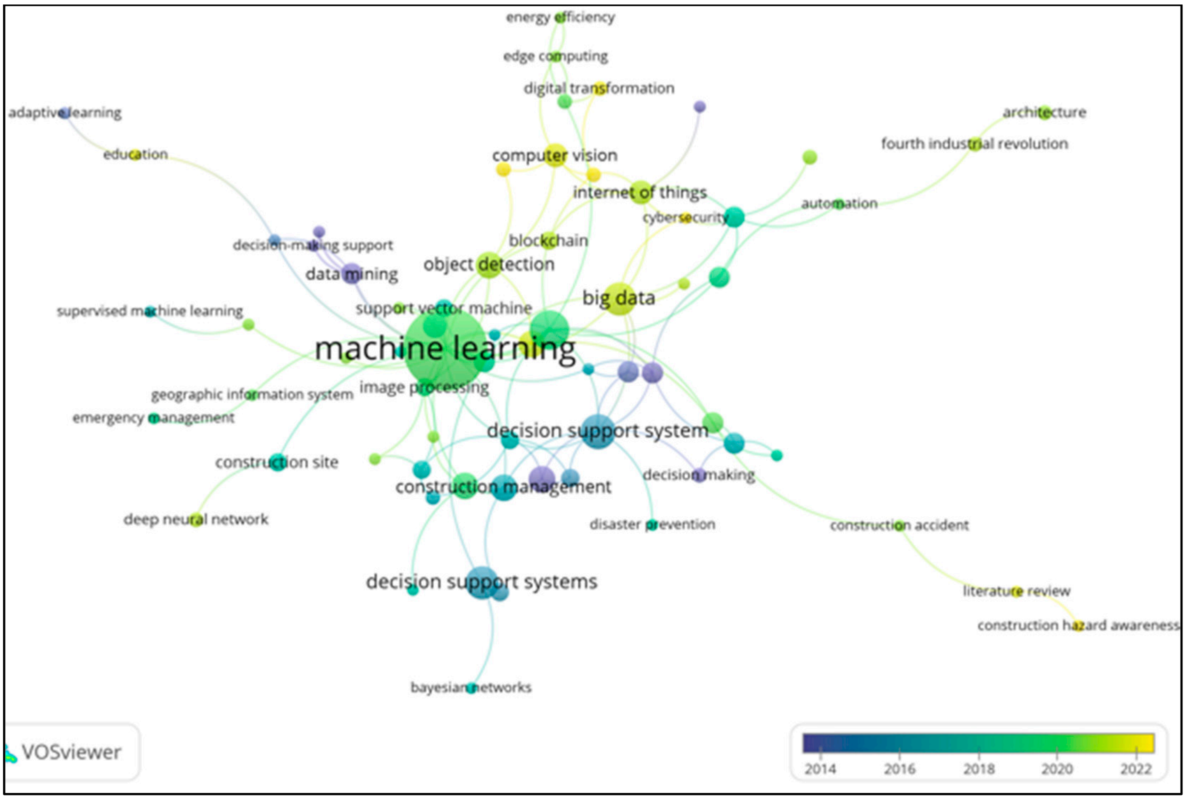


(**a**) Economic

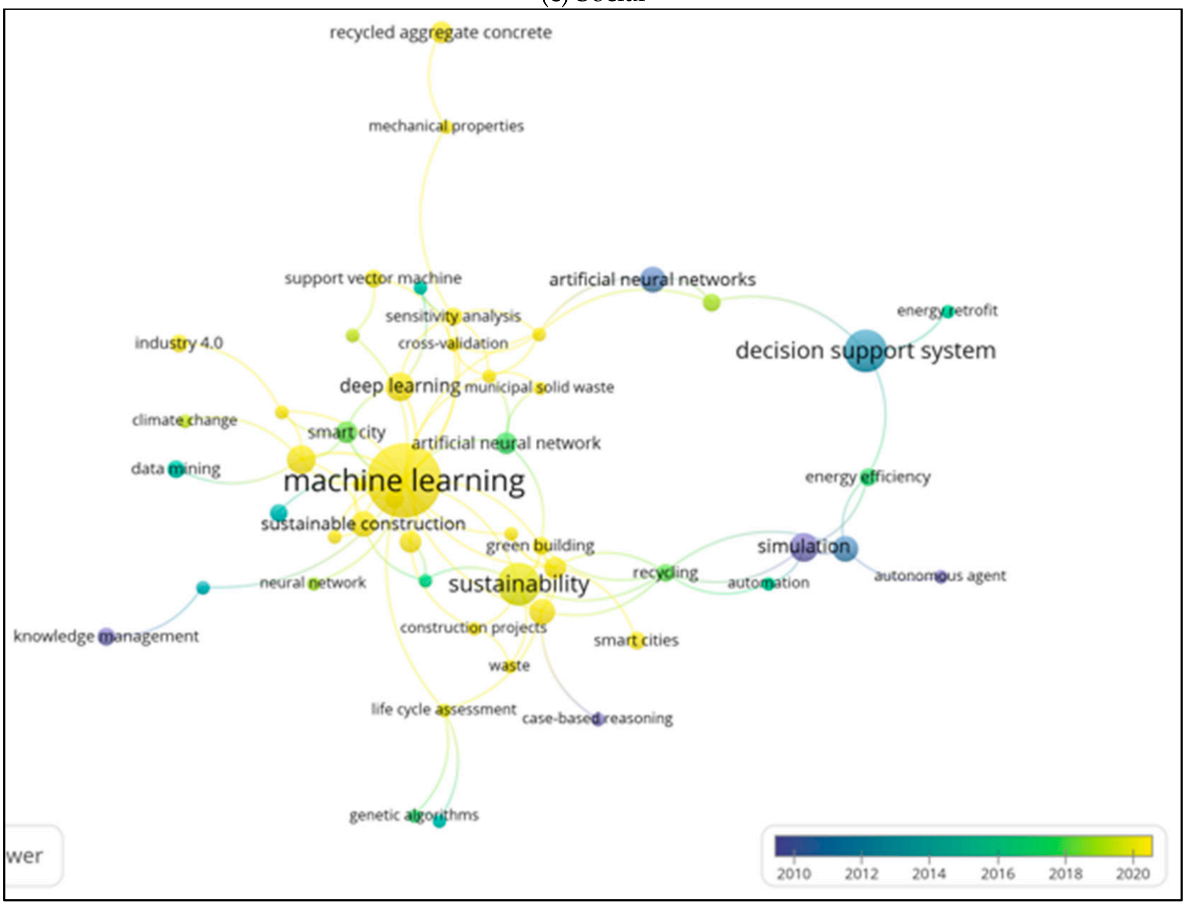


(**b**) Governance

Figure 10. *Cont.*



(**c**) Social



(**d**) Environmental

Figure 10. Citation network map.

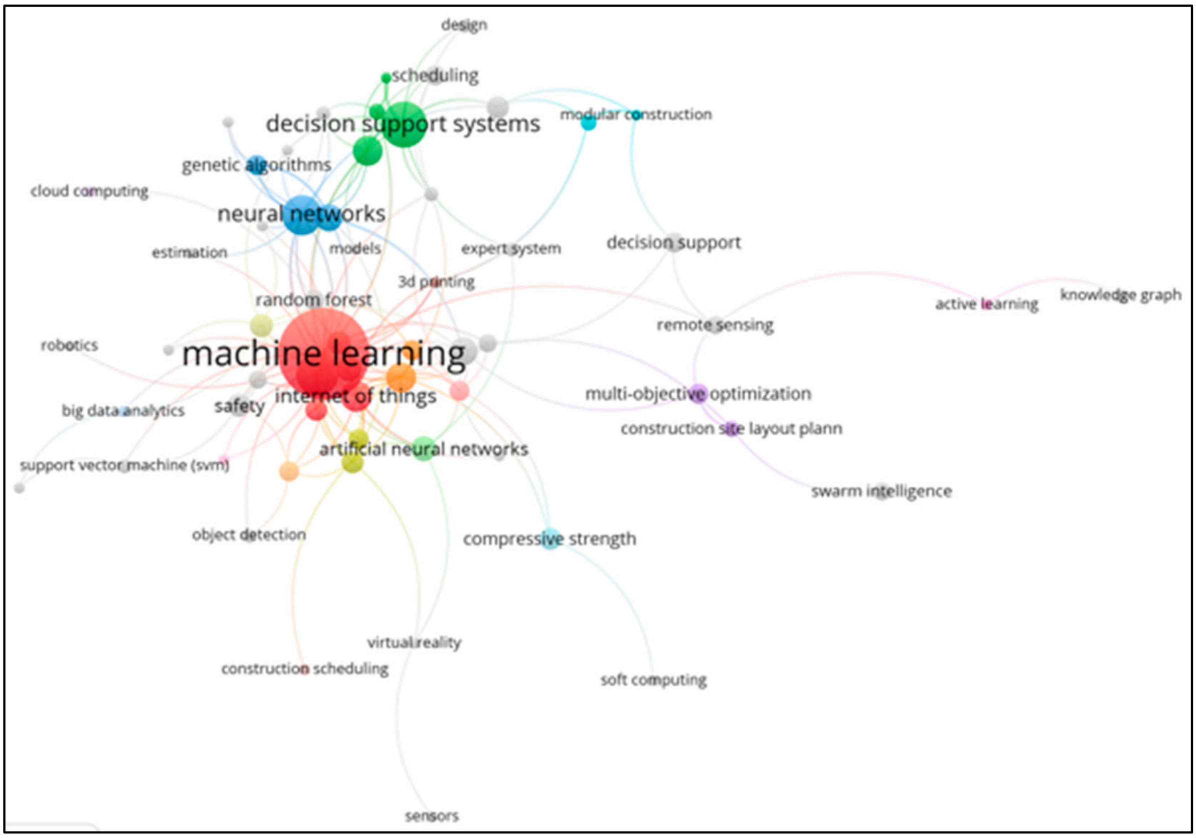
3.7. Research Clusters in the Context of AI in Construction Phases

The network map in Figure 9 depicts research clusters based on construction phases and the frequency of keyword occurrences. Figure 11a revealed that machine learning is the most significant keyword during the planning phase, with a cluster of related keywords emerging around it. This cluster includes neural networks, big data analytics, and genetic algorithms, which have been identified as key research areas in the construction industry in recent years. Another key research cluster that emerged is decision-support systems which focuses on developing systems that can support decision-making processes in construction by providing real-time information, forecasting capabilities, and optimizing algorithms. This cluster includes keywords related to scheduling, modular construction, and multi-agent optimization, which reflect the potential of decision-support systems to improve project planning and execution, reduce costs, and enhance project sustainability.

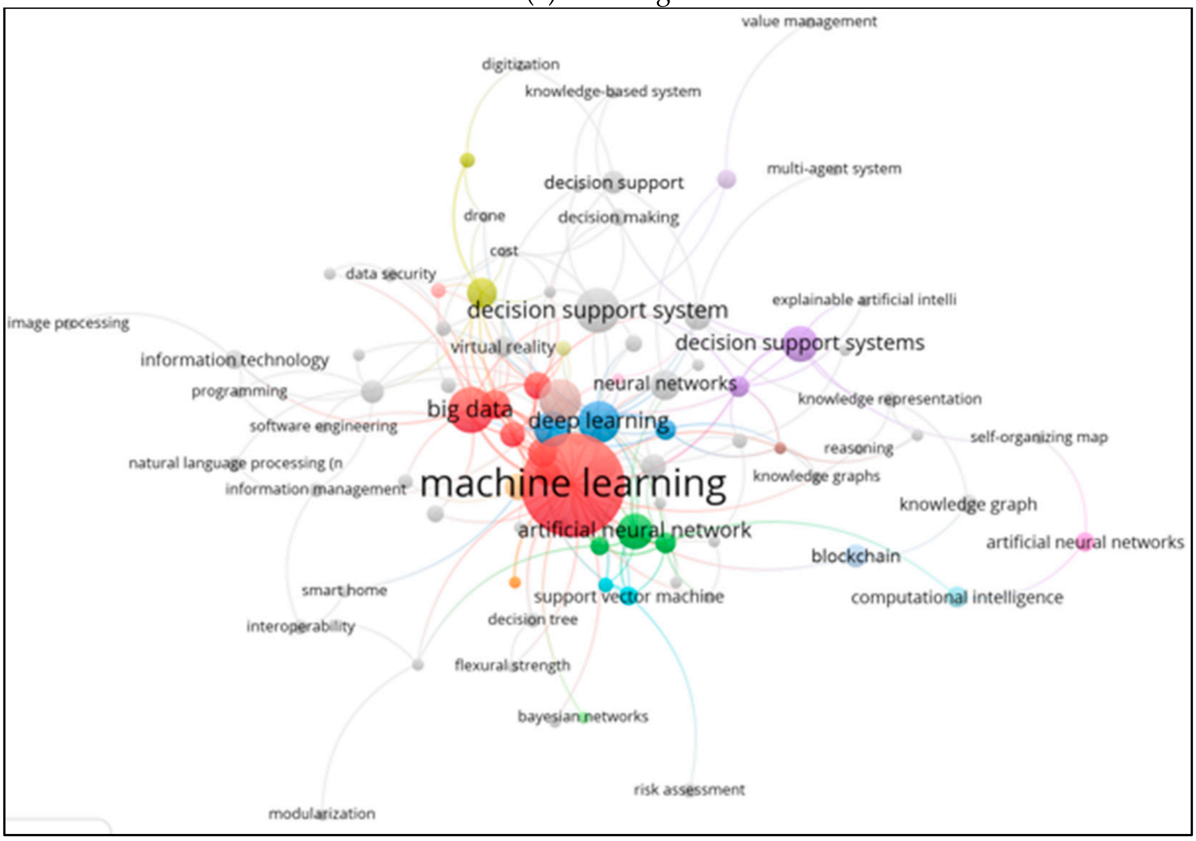
In the context of the design phase, as shown in Figure 11b, machine learning has emerged as the predominant keyword cluster, with a focus on big data, deep learning, and neural networks. This reflects the potential of these techniques to improve design processes, reduce errors, and increase efficiency. In addition, decision-support systems have formed a separate cluster that focuses on risk assessment, value management, and image processing. DSS can assist in the design process by providing real-time feedback and analysis, identifying potential risks and opportunities, and enabling collaboration between different stakeholders.

As shown in Figure 11c, machine learning has emerged as a predominant keyword in the construction phase. Big data is another important cluster of keywords, and it reflects the growing use of data analytics in construction, particularly in areas such as simulation, geographic information systems (GIS), and advanced monitoring. Furthermore, robotics and automation are separate clusters of keywords in the construction phase network map. These technologies are increasingly being used in construction to perform repetitive or dangerous tasks, such as bricklaying, welding, and demolition. By automating these tasks, construction companies can improve safety, reduce labor costs, and increase efficiency.

In the operation and maintenance (O&M) phase, which is the final phase of a construction project, the network map in Figure 11d revealed that the predominant keyword shifted from machine learning to risk management. Risk management is a crucial aspect of the O&M phase, as it involves identifying and mitigating any potential risks or issues that may arise during the project O&M process. The network map was spread out and formed three separate clusters. The first cluster was decision-support systems, which can be used to assist in identifying and assessing potential risks. The second cluster was fuzzy logic, which can be used in the O&M phase to evaluate the level of risk associated with various decisions or actions, even when the information is not fully clear or precise. The third cluster was knowledge-based systems, which can be used to assess the potential impact of various decisions and actions on the project, as well as to provide recommendations for mitigating risks and resolving issues. Overall, the use of these advanced technologies in the O&M phase can help to ensure that construction projects are completed on time, within budget, and with minimal risk or issues.

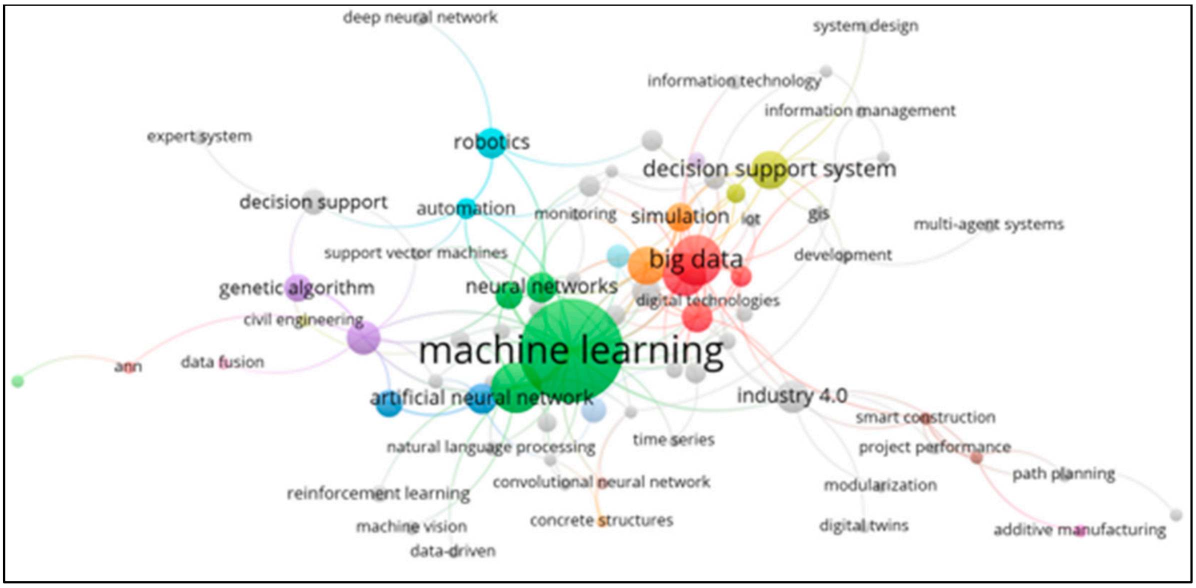


(**a**) Planning

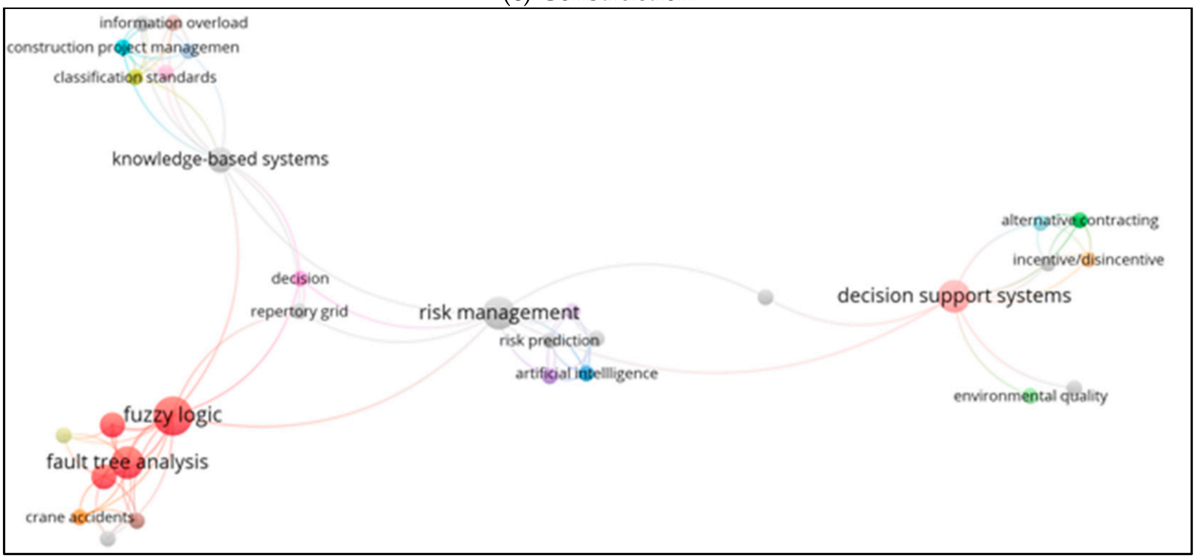


(**b**) Design

Figure 11. *Cont*.



(**c**) Construction

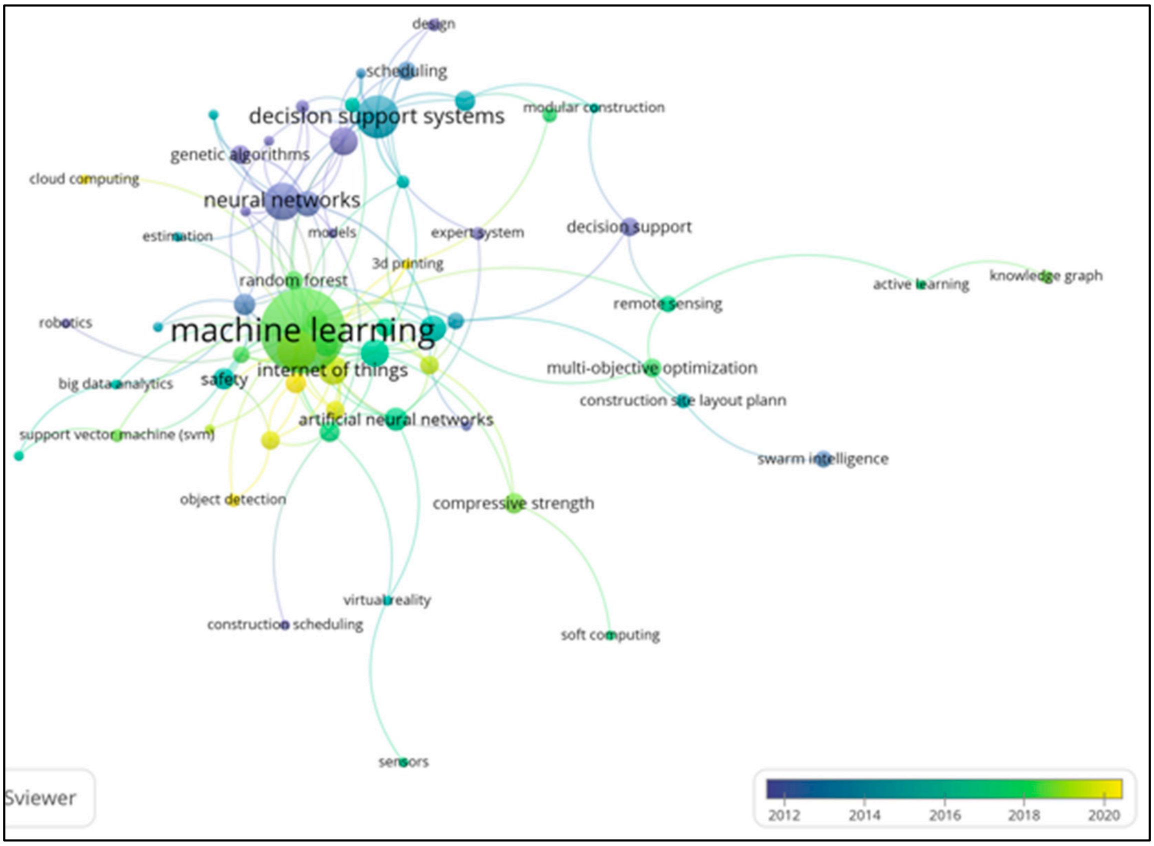


(**d**) Operation and maintenance

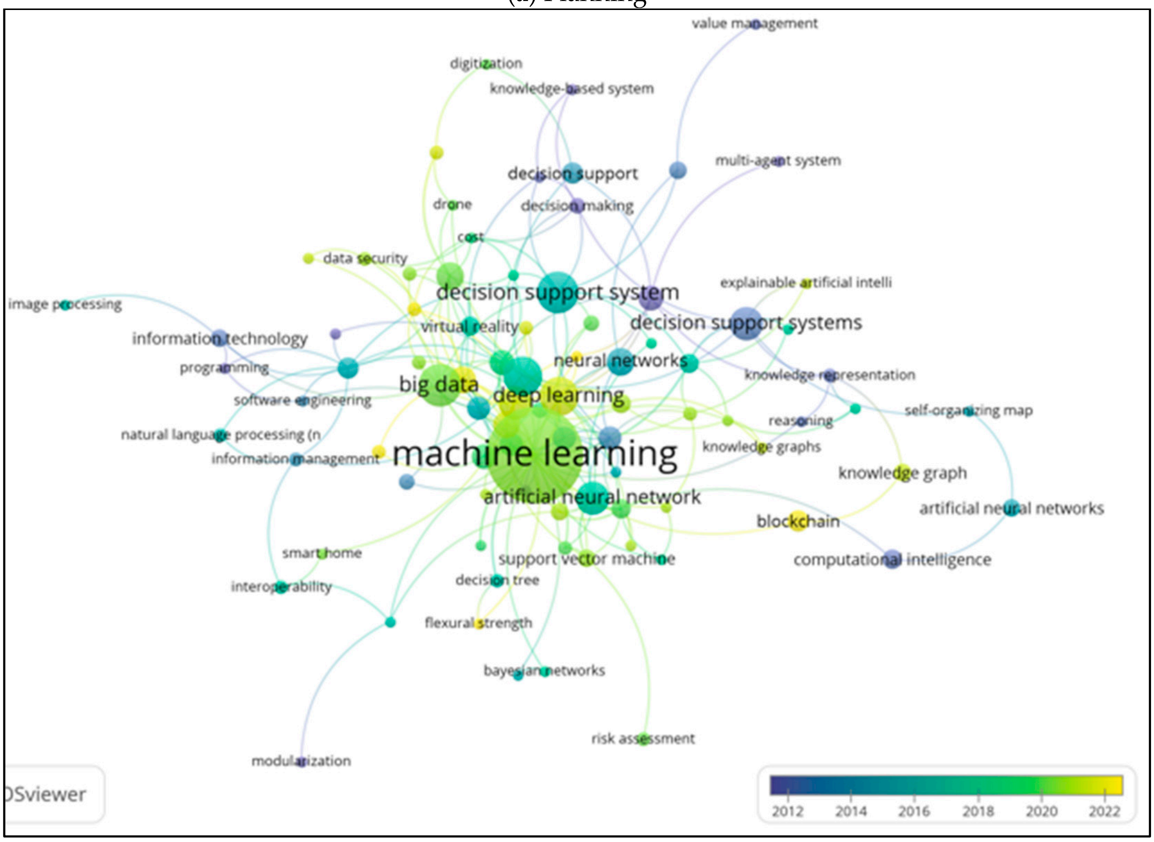
Figure 11. Research cluster map.

3.8. Historical Research Clusters of the Construction Phases

Figure 12 illustrates a citation network map based on construction phases. Figure 12a presents a network map that showcases the research trends in the planning phase of construction. In 2013, the research clusters were mainly focused on neural networks, genetic algorithms, and robotics. These technologies were applied to predict and optimize construction schedules, reduce costs, and improve safety. However, over time, the focus shifted to DSS which aimed to improve scheduling and modular construction. DSS can help determine the best sequence of activities, identify potential inefficiencies on site, and optimize resources. By 2019, the research clusters in the planning phase were dominated by machine learning, which highlighted the use of advanced technologies such as IoT, 3D printing, object detection, and computer vision [45]. This shift in research clusters indicates the growing interest and recognition of the potential opportunities of AI and advanced technologies in the construction industry.

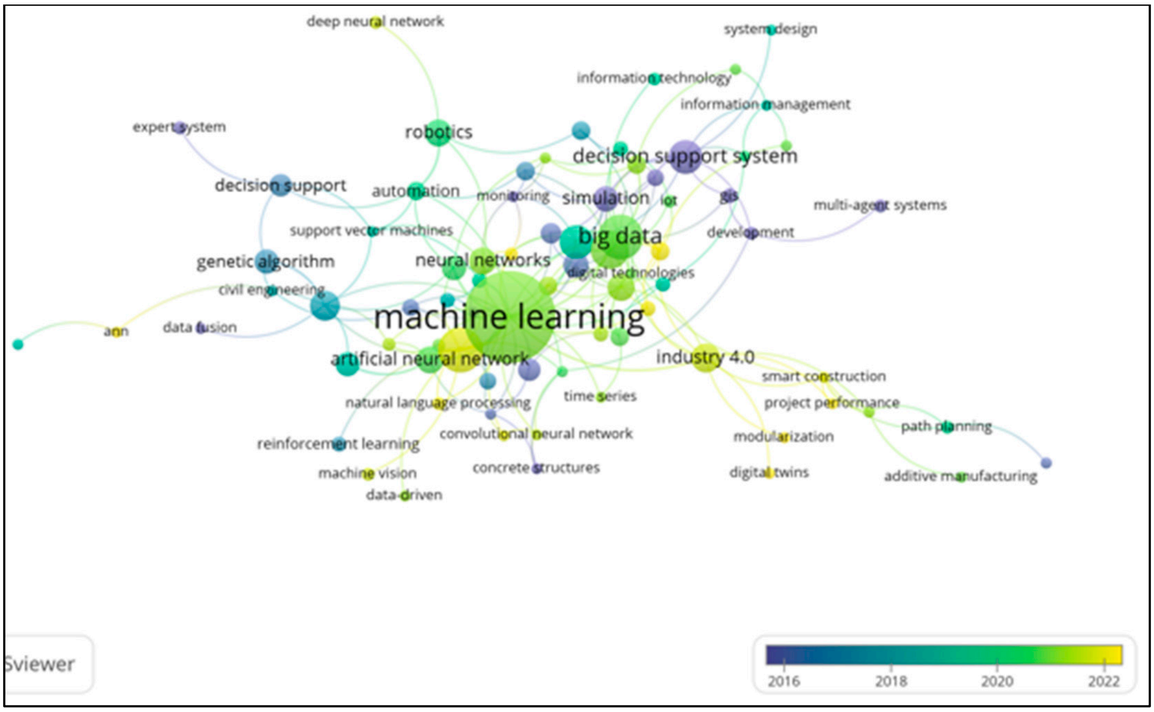


(**a**) Planning

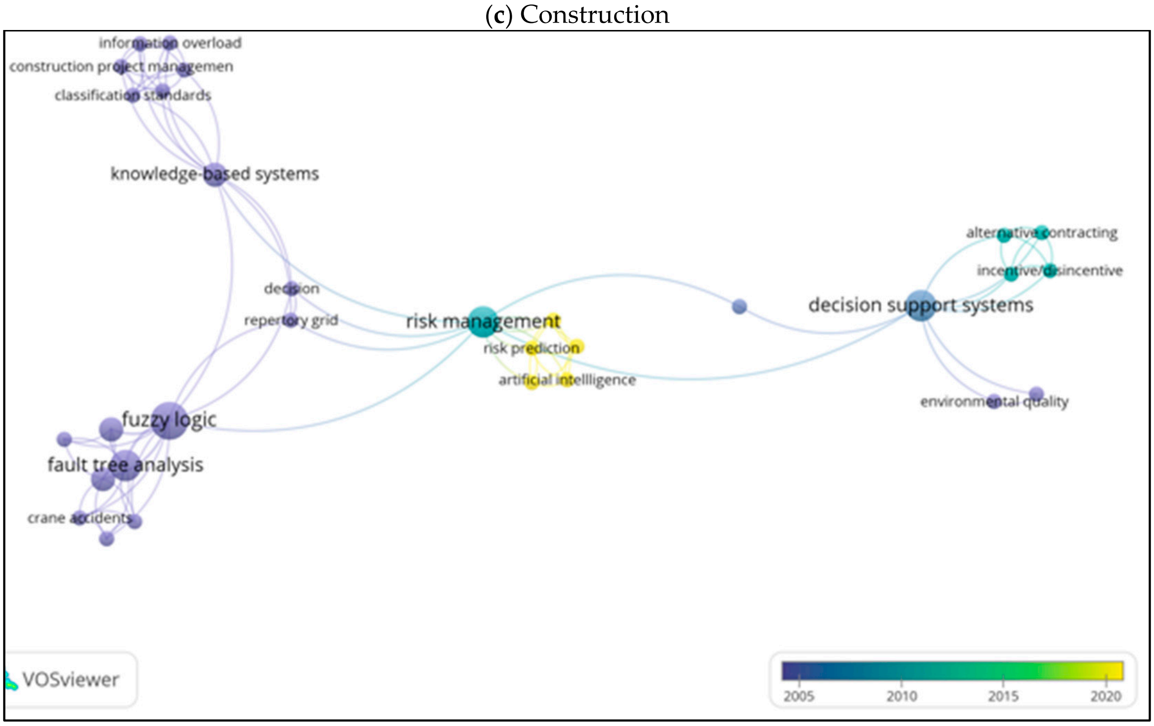


(**b**) Design

Figure 12. *Cont.*



(**c**) Construction



(**d**) Operation and maintenance

Figure 12. Citation network map.

In contrast to the planning phase, the design phase as seen in Figure 12b revealed a diverse range of early research clusters. In 2013, focused on exploring different approaches to decision-making, value management, and multi-agent systems, as these were seen as critical components of the design phase. However, as research progressed, the focus shifted toward decision-support systems and knowledge-based systems in 2014, as these approaches were believed to be more effective in addressing the challenges of the design phase. In recent years, machine learning has emerged as the predominant keyword and promoted deep learning and big data analytics that explored potential solutions to optimize design sequences and reduce unforeseen costs.

Figure 12c illustrates that the early research in the construction phase was focused on the use of simulation, decision-support systems, and data fusion as potential solutions to address challenges related to construction efficiency and productivity. However, in 2020, the research landscape shifted, and these keywords were replaced by simulation, genetic algorithms, reinforced learning, and natural language processing. These techniques were identified as key areas of investigation for optimizing building designs and improving construction processes. Furthermore, in 2021, machine learning emerged as the predominant research cluster in the construction phases, and it promoted the use of robotics, automation, and big data. For instance, machine learning can be used in conjunction with big data and IoT to improve construction scheduling, cost estimation, and quality control.

Finally, the research conducted in the operation and maintenance phase as seen in Figure 12d was heavily focused in 2004, with a focus on knowledge-based systems, fuzzy logic, and decision-support systems. However, in recent years, there has been limited research conducted in this area. Nevertheless, in 2021, there has been a renewed interest in this phase, with research clusters focusing on risk prediction. This has been facilitated using risk management techniques, which have helped to identify and mitigate potential risks associated with project completion and handover. As such, this research has the potential to make a significant contribution to improving the overall efficiency and effectiveness of a project operation and maintenance phase.

4. Findings and Discussion

This study conducted a scientometric analysis from the sustainability and construction phases lenses to map over two decades of AI in construction research. The study analyzed a total of 3710 literature pieces published between January 2000 and February 2023 (spanning over two decades), intending to gain a clearer understanding of the historical clusters and research clusters in construction, as well as in the context of the four pillars of sustainability and the four construction phases.

The scientometric analysis disclosed that: (a) Literature on AI in construction has experienced steady growth during the last two decades; (b) Machine learning, deep learning, and big data are seen as the key enabling digital technologies; (c) Economic and governance pillars of sustainability exhibit the highest potential for AI adoption; (d) Design and construction phases demonstrate substantial advantages for AI adoption; (e) AI is, despite adoption challenges, a strong driver of the construction industry modernization; (f) By incorporating AI, the construction industry can advance towards a more sustainable future by consolidating its processes.

The identified research clusters in AI within the construction domain encompass various areas, including automation, digital twin, big data, deep learning, machine learning, information systems, and simulation. These clusters have expanded the research scope beyond their primary focus and have led to the emergence of new directions in the field. The subsequent overview presents the key findings based on the key research clusters (see Tables 10–12).

Table 10. Research clusters associated with pillars of sustainability and construction phases.

Research Clusters	Affiliation with Pillars of Sustainability and Construction Phases
Automation	Automation was the most predominant keyword cluster which leverages AI technologies to automate construction processes. It benefits all four phases of construction and aligns with the four pillars of sustainability. Automation involves the use of machinery, software, and other technologies to perform tasks that were traditionally manual, such as bricklaying, painting, and welding [34,48]. Drones are also utilized for site surveying, progress monitoring, and structural inspection [41]. Digital technologies like BIM automate tasks such as clash detection and cost estimating. Automation is a central focus in the construction industry, with AI technologies continually evolving around this cluster [34,48,49]

Table 10. *Cont.*

Research Clusters	Affiliation with Pillars of Sustainability and Construction Phases
Digital Twin	The digital twin cluster is gaining significance in the construction industry, particularly in the economic and governance pillars and the planning and design phases. Digital twin involves creating virtual replicas of buildings or infrastructure systems using data from sensors and other sources. It enables simulation and testing of designs before construction, leading to cost reductions, improved performance, and increased efficiency [15]. Simulating and testing designs before construction is a key goal aligned with BIM. This model encompasses various dimensions of a construction project, allowing stakeholders to analyze aspects ranging from architectural design to structural integrity, systems integration, and operational efficiency [41]. AI enhances the capabilities of the digital twin by identifying patterns and anomalies and optimizing asset performance. However, the integration of digital twin technologies with other AI clusters remains relatively weak, indicating a need for further research in this area [2].
Big Data	Big data plays a vital role in the social pillar and the construction phases, aiming to improve project outcomes. Construction professionals leverage the vast amount of data generated by projects to enhance safety on construction sites. Analyzing data on accidents and near-misses enables the identification of patterns and the development of strategies to reduce risks. For instance, training programs and safety protocols can be designed based on the most frequently occurring accidents [49].
Information Systems	Information systems, frequently mentioned in the governance pillar and the planning, design, and operation and maintenance phases, involve AI-powered systems for efficient project management. These systems analyze data from multiple sources, including project schedules, personnel, equipment, and weather forecasts, to generate accurate schedules and optimize building design and performance [50]. The use of AI in information systems helps reduce energy consumption, improve building performance, and enhance occupant comfort [51].
Simulation	Simulation, relevant to the governance and environmental pillars, as well as the planning, design, and operation and maintenance phases, plays a crucial role in optimizing project outcomes. Simulation techniques provide insights into the impact of different factors on project performance and identify potential issues before construction begins testing materials, layouts, and construction techniques, construction professionals can determine the most effective approach for a project [52]. Furthermore, simulation can predict the long-term performance of buildings and infrastructure systems, allowing for maintenance planning and asset replacement [15].
Deep learning	Deep learning, a more recent research cluster, is mainly associated with the economic and social pillars and the construction phases. It has found application in quality control and defect detection, where AI models are trained to identify defects and anomalies in construction materials like concrete and steel [52]. Deep learning also improves resource management, reducing waste and improving efficiency on construction sites. Although the literature on deep learning in construction is relatively new, it has the potential to revolutionize the industry by enabling more accurate and cost-effective projects [41].

Table 11. AI adoption opportunities and challenges by construction phases.

Phases	Opportunities	Challenges
Planning	Optimized project schedule, accurate risk assessment and mitigation, selection of sustainable design alternatives, improved design making, enhanced project outcomes, identification and mitigation of risks, improved collaboration between stakeholders, resource optimization, efficient spatial planning, accurate feasibility by conducting simulations, assistance in ensuring compliance with regulatory requirements [41].	Integration complexity, data integration and collaboration, data availability and quality, gaining acceptance from all project stakeholders, significant cost and required allocation of resources, expertise and skill requirements, data privacy and security, legal and ethical considerations, change management, uncertainty, and risk [53].
Design	Parametric designs, design optimization and intelligent recommendations, cost, and time efficiency, facilitation of collaboration and data integration between stakeholders, design flaw identification, accurate simulation of design performance, and supporting the integration of sustainable practices and materials [32].	System integration and data interoperability, industry standards and regulatory compliances, data quality and availability, user acceptance and adoption, and bias in design algorithms, may lead to a limited design diversity, overcoming technical limitations, data security and privacy, and continuous learning and adaption [45].

Table 11. *Cont.*

Phases	Opportunities	Challenges
Construction	Real-time monitoring, automation of repetitive tasks, improved safety by identifying potential hazards, advanced inspection and defect detection, resource allocation, enhanced productivity by streamlining workflows, improved collaboration and communication between stakeholders, quality control and assurance, remote construction management and cost control and budget management [29,33].	Integration complexity with existing systems and workflows, interoperability with various equipment and data formats, communication between stakeholders, data accessibility and quality for up-to-date constriction data, change management to traditional construction practices, skill requirements and training, high initial investment and ongoing costs, limited industry adoption, system reliability and maintenance and legal and regulatory compliance [48,54].
Operation and maintenance	Digital twins for real-time monitoring, predictive maintenance, operation and maintenance schedule generation, energy efficiency optimization, occupant comfort management, enhanced facility management, accurate lifecycle cost analysis, improved compliance and regulatory analytics, enhanced building performance evaluation, and streamlined documentation and reporting [2].	Accurate capturing of data, data standardization and integration, privacy, and data governance, user-friendly and accessible to different stakeholders, skill requirements and training, seamless integration with current automated technologies, system reliability and maintenance, interdisciplinary collaboration, cost and resource allocation and change management [55].

Table 12. AI adoption opportunities and challenges by sustainability pillars.

Pillars	Opportunities	Challenges
Economic	Cost savings through improved project efficiency and resource management, enhanced project profitability through optimized schedules, improved cost estimation accuracy, enhanced decision-making, and risk assessment, streamlined procurement processes and supply chain management, improved financial transparency and long-term cost benefits through adopting sustainable practices [30].	Higher initial investment costs for implementing AI, balancing costs, and long-term economic benefits, ensuring accessibility between all stakeholders, addressing potential job displacement, overcoming resistance to change, ensuring data privacy and security, streamlined integration with existing technologies, limited availability of skilled AI professionals and ensuring compliance with legal and regulatory frameworks [56].
Governance	Improvement transparency and accountability, enhanced decision-making and risk assessment, streamlined project approvals and regulatory compliance processes, efficient collation and communication between stakeholders, effective project governance and project monitoring, enhanced contract management and dispute resolution, and enhanced project oversight [57].	Potential biases in the algorithms, compliance with data privacy and regulations, overcoming resistance to change, ensuring transparency and accountability, and ensuring compatibility with existing governance frameworks [58].
Social	Enhance worker safety through risk assessment and monitoring, improve labor conditions and welfare through optimizing resource allocation, enhanced worker productivity, and enhanced stakeholder involvement in projects [59].	Job displacement and workforce transition, ensuring equal access to AI technologies, overcoming resistance to change, ensuring stakeholder engagement, data privacy and protection, balancing automation, and human interaction, addressing potential social disruptions, and ensuring social acceptance [60].

Table 12. *Cont.*

Pillars	Opportunities	Challenges
Environmental	Reduce carbon footprint and emissions through AI-optimized construction processes, efficient use of resources and materials, enhanced resource management and waste reduction, enhanced energy efficiency and sustainable building designs through simulation and optimization, improved air and water quality through pollution monitoring and control systems, AI-informed environmental impact assessment and sustainable land use planning g, reduce environmental risk through AI risk assessment and mitigation strategies and promote adaptive and resilience infrastructure designs [32].	Ensuring accurate and reliable data for monitoring and assessment, overcoming technological limitations and construction for environmental solutions, Incorporate complex and dynamic environmental factors into AI models and simulations, balancing the trade-offs between environmental considerations and other project objectives, ensuring compliance with environmental regulations, addressing conflicts between economic consideration and environmental objective, integrating AI technologies with existing environmental management systems and ensuring long-term sustainable and maintenance of environmental solutions [16].

Based on these research clusters, the key opportunities and challenges of each construction phase and sustainability pillar can be identified.

The study's findings hold significant implications with actionable recommendations for the construction industry. First, it is imperative to recognize the steady growth of AI literature within the construction realm over the span of the last two decades. This awareness can serve as a vital starting point, prompting industry stakeholders to remain vigilant and responsive to the evolving landscape of AI advancements. By staying informed about the latest AI trends and research developments, the industry can proactively position itself for growth and innovation [7,8].

Second, an emphasis on prioritizing the integration of key enabling technologies is paramount. Machine learning, deep learning, and big data have emerged as foundational pillars for driving effective digital transformation. To navigate the complexities of modern construction challenges, embracing these technologies can empower the industry with data-driven insights, predictive capabilities, and enhanced decision-making [50]. The following are key opportunities that AI can provide to the construction industry:

- *Design Complexity and Optimization:* Modern construction projects involve complex designs that must be optimized for various factors, including structural stability, energy efficiency, and cost-effectiveness. AI-powered algorithms can analyze countless design variations to identify optimal solutions quickly, enhancing design efficiency and accuracy [41].
- *Project Planning and Scheduling:* The complexity of construction project schedules often leads to delays, resource conflicts, and cost overruns. AI can analyze historical project data, real-time progress, and external factors to generate dynamic and adaptable schedules that account for uncertainties and potential disruptions [45].
- *Risk Assessment and Management:* The construction industry has constant uncertainties that can lead to project risks. AI's predictive analytics can forecast potential risks by analyzing historical data and project parameters, enabling proactive risk mitigation strategies and better-informed decision-making [33].
- *Quality Control and Defect Detection:* Ensuring the quality of construction work is a persistent challenge. AI-powered visual recognition systems can detect defects, discrepancies, and deviations from design plans by comparing real-time construction progress to digital models, ensuring adherence to specifications and standards [48].
- *Resource Allocation and Management:* Efficiently allocating labor, materials, and equipment is vital for project success. AI can optimize resource allocation by analyzing project requirements, availability, and constraints, thus minimizing waste, and enhancing resource utilization [2].
- *Safety Monitoring and Compliance:* Safety concerns are paramount in construction. AI-driven sensors, cameras, and wearable devices can monitor work environments for

potential safety hazards in real time, alerting workers, and supervisors to risks and ensuring compliance with safety regulations [35].

- *Data Integration and Collaboration:* Construction projects involve multiple stakeholders, each contributing diverse data sources. AI can facilitate seamless data integration, enabling improved collaboration among project teams and decision-makers by providing a unified platform for information sharing and analysis [47].
- *Supply Chain Optimization:* Managing the supply chain efficiently to ensure timely delivery of materials and resources is a significant challenge. AI algorithms can predict demand, optimize procurement, and monitor logistics to prevent disruptions and delays [52].
- *Environmental Impact Mitigation:* Sustainable construction practices are essential for minimizing the industry's environmental footprint. AI can assess and model the environmental impact of construction activities, suggesting eco-friendly materials, energy-efficient designs, and waste reduction strategies [10].
- *Post-Construction Maintenance and Operations:* Maintaining and operating constructed assets efficiently is an ongoing challenge. AI-powered predictive maintenance algorithms can analyze real-time data from sensors to anticipate maintenance needs and optimize asset performance [26].

The third key recommendation centers on the strategic allocation of efforts toward the economic and governance pillars of sustainability. The study's findings underscore the substantial potential for AI adoption in these areas, showcasing its capacity to streamline operations, optimize resource allocation, and strengthen compliance measures. This strategic alignment between AI and sustainability objectives can foster improved economic outcomes while concurrently bolstering social and governance standards [52]. Furthermore, tapping into the substantial advantages outlined in AI adoption, particularly within the design and construction phases, can drive substantial performance improvements. Lastly, by leveraging AI-powered tools for efficient project planning, risk assessment, and real-time monitoring, the industry can elevate project execution while minimizing errors and delays.

Amid the challenges mentioned, the integration of AI into construction and the adoption of sustainable practices across the pillars of sustainability present noteworthy opportunities for the industry. Embracing these technologies and principles could catalyze transformative shifts in project planning, design, construction, and management [15]. The advantages of AI, encompassing automation, data-driven decision-making, and advanced analytics, could yield enhanced project efficiency, cost reduction, and heightened productivity. In parallel, the adoption of sustainable practices might drive resource optimization, minimize environmental impact, and improve social outcomes. By proactively addressing challenges and capitalizing on the potential of AI and sustainability, the construction industry can steer itself toward a more sustainable trajectory. This approach aligns projects not only with economic viability but also with environmental and social responsibility [5]. This cohesive strategy contributes to the broader goals of sustainable development, paving the way for more sustainable urban futures [29,61].

5. Conclusions

This study presents a comprehensive scientometric analysis of 3710 published papers on AI in construction over the past two decades with a particular angle from sustainability and construction phases. By examining the existing literature, this study provides an updated and concise overview of the field's knowledge structure and evolution. The findings reveal a progression from basic automation to more advanced neural network platforms, with a strong focus on machine learning, deep learning, big data, and IoT. The concept of AI in construction has expanded over time, encompassing emerging technologies such as natural language processing, virtual reality, and augmented reality [41]. The integration of intelligent systems and algorithms has shown great potential in improving productivity, efficiency, safety, and sustainability within the construction industry [62]. As technology continues to advance, AI is expected to play an even larger role in driving innovation and transforming traditional construction practices [5,29,46,63].

Additionally, this comprehensive analysis of the integration of the pillars of sustainability into the various construction phases highlights the benefits, challenges, and opportunities associated with each phase. By identifying the specific contributions and implications of AI technologies in conjunction with sustainability principles, this research provides valuable insights for industry professionals, policymakers, and researchers seeking to drive sustainable transformations in the construction industry. The synthesized information on the benefits, challenges, and opportunities serves as a foundation for informed decision-making and strategic planning in implementing AI-driven solutions while considering sustainability goals. This study provides valuable insights into the present state of AI in construction, paves the way for future research and development, and underscores the significance of sustainable practices in shaping the industry's future.

Although this research provides a sound foundation, several areas warrant further investigation. Future research can focus on addressing the identified challenges, such as the cost-effectiveness of implementing AI technologies in the construction industry, ensuring equitable access to AI-driven solutions, and resolving issues related to data integration and interoperability. Moreover, it should delve into the legal consequences that AI may introduce concerning intellectual property ownership, liability, data privacy, standards, ethics, contracts, cybersecurity, employment impact, transparency, and the evolving legal landscape. Additionally, it should investigate the potential societal and ethical impacts of AI adoption in construction, encompassing employment effects and the role of human workers in an increasingly automated setting. Further studies could focus on enhancing AI algorithms and models for more precise and streamlined decision-making in sustainability-related domains. Furthermore, the formulation of comprehensive frameworks and guidelines for seamlessly integrating AI technologies with sustainability principles throughout various construction phases would prove advantageous. By pursuing these research avenues, scholars can continue advancing the field, paving the way for future construction practices that are both sustainable and efficient.

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