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Review

Artificial Intelligence in Net-Zero Carbon Emissions for Sustainable Building Projects: A Systematic Literature and Science Mapping Review

Yanxue Li [1], Maxwell Fordjour Antwi-Afari [2], Shahnawaz Anwer [3,*], Imran Mehmood [3], Waleed Umer [4], Saeed Reza Mohandes [1], Ibrahim Yahaya Wuni [5], Mohammed Abdul-Rahman [3] and Heng Li [3]

[1] Department of Mechanical, Aerospace and Civil Engineering, Faculty of Science and Engineering, University of Manchester, Manchester M13 9PL, UK; l782290131@163.com (Y.L.); saeedreza.mohandes@manchester.ac.uk (S.R.M.)
[2] Department of Civil Engineering, College of Engineering and Physical Sciences, Aston University, Birmingham B4 7ET, UK; m.antwiafari@aston.ac.uk
[3] Department of Building and Real Estate, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong SAR, China; imran.mehmood@connect.polyu.hk (I.M.); 18042561r@connect.polyu.hk (M.A.-R.); heng.li@polyu.edu.hk (H.L.)
[4] Department of Architecture and Built Environment, Northumbria University, Newcastle upon Tyne NE1 8ST, UK; waleed.umer@northumbria.ac.uk
[5] Department of Architectural Engineering and Construction Management, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia; ibrahim.wuni@kfupm.edu.sa
* Correspondence: shah-nawaz.anwer@polyu.edu.hk

Abstract: Artificial intelligence (AI) has emerged as an effective solution to alleviate excessive carbon emissions in sustainable building projects. Although there are numerous applications of AI, there is no state-of-the-art review of how AI applications can reduce net-zero carbon emissions (NZCEs) for sustainable building projects. Therefore, this review study aims to conduct a systematic literature and science mapping review of AI applications in NZCEs for sustainable building projects, thereby expediting the realization of NZCEs in building projects. A mixed-method approach (i.e., systematic literature review and science mapping) consisting of four comprehensive stages was used to retrieve relevant published articles from the Scopus database. A total of 154 published articles were retrieved and used to conduct science mapping analyses and qualitative discussions, including mainstream research topics, gaps, and future research directions. Six mainstream research topics were identified and discussed. These include (1) life cycle assessment and carbon footprint, (2) practical applications of AI technology, (3) multi-objective optimization, (4) energy management and energy efficiency, (5) carbon emissions from buildings, and (6) decision support systems and sustainability. In addition, this review suggests six research gaps and develops a framework depicting future research directions. The findings contribute to advancing AI applications in reducing carbon emissions in sustainable building projects and can help researchers and practitioners to realize its economic and environmental benefits.

Keywords: artificial intelligence; net-zero carbon emissions; science mapping approach; sustainable buildings; systematic literature review

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1. Introduction

Due to global warming (e.g., climate change), humans and other living organisms face severe crises; thus, proactive interventions are critically needed to mitigate these environmental issues [1] Many industries (e.g., manufacturing, automobile, and construction) have driven the expansion of the global economy and significantly impacted both the natural and built environments [2–4]. The built environment is a major source of most greenhouse gases worldwide [5–7]. Increases in global industrialization and development have led to the release of greenhouse gases, which may lead to high temperatures and environmental degradation [8–10]. Therefore, there is an urgent need to achieve net-zero carbon emissions (NZCEs) within industries and across the world.

NZCEs are greenhouse gases produced by human activities and can be reabsorbed by the atmosphere [11–13]. Achieving NZCEs would help to protect the ecological environment and reduce damage to the natural environment. To achieve sustainable development and industrialization, attaining NZCEs by 2050 is a global goal [14], which requires efforts from everyone, including government policies, individuals, and corporate bodies. Although it may seem challenging, continuous improvement, planned goals, long-term efforts, and persistence are of utmost priority. For instance, some countries have already set policies to achieve NZCEs [15–19] Italy's long-term strategy shows that deep decarbonization is achieved with the support of government policies and increased investment in technology, research, and development [20]. According to a comprehensive assessment model, Brazil and the United States achieved NZCEs earlier than the global average [16,17].

Sustainable construction processes help to promote economic justice while protecting the natural environment [21,22]. In other words, they help minimize damage to the natural environment during project development [23]. Sustainable construction, which is an advanced construction method, has an adverse impact on the harmonious development of humans and nature. Despite its global recognition and usefulness, it is still regarded as a complex process or method owing to financial constraints, non-economic construction projects, or sustainable resource management [16,24]. Three strategies and methods for achieving sustainable building projects have been reported: resource conservation, cost efficiency, and design for human adaptation [25]. Based on these strategies, the implementation of advanced digital technologies is crucial. However, the construction industry has a slow adoption rate compared with other industries in digital transformation [26].

Artificial intelligence (AI) refers to the theory and development of computer systems that can perform tasks that often require human intelligence, such as visual perception, speech recognition, decision-making, and language translation [27]. Within the architecture, engineering, and construction (AEC) sector, there are many AI applications, such as genetic programming, neural networks, fuzzy logic, heuristic search, and computer software [28–30]. Previous studies have explored how AI can improve practical projects in the AEC sector [31–33]. Building information modeling (BIM) can help manage a centralized database for the entire life cycle of a building and combining it with AI can also be used to estimate costs, identify product issues, and increase construction quality [34]. Darko et al. [35] reported on state-of-the-art research on AI in the AEC industry. They found that genetic algorithms, neural networks, fuzzy logic, fuzzy sets, and machine learning were the predominant AI techniques employed in the field of AEC. Similarly, Pan and Zhang [36] conducted an in-depth review of AI applications in construction engineering and management. They found that a variety of AI methods have greatly contributed to the transformation of the construction industry. In construction engineering and management, AI has been able to automate and expedite learning, reasoning, and perception processes using extensive data. This has significant promise for addressing various engineering projects based on their unique attributes. Moreover, unlike conventional computational approaches and expert judgments, highly promising AI excels in handling intricate and ever-changing situations amidst significant ambiguity and vast amounts of data. Consequently, they are more inclined to provide precise and persuasive outcomes for tactical decision-making. These studies have suggested that various AI-related techniques can ultimately accomplish three primary functions (model and pattern detection, prediction, and optimization) that are helpful to the AEC industry in terms of automation, risk reduction, digitalization, enhanced efficiency, and computer vision [35–37].

Artificial intelligence has revolutionized the management of carbon emissions in sustainable building projects. AI techniques, such as machine learning, neural networks, and genetic algorithms, are increasingly being employed to optimize energy efficiency, predict carbon footprints, and enhance decision-making processes in construction projects. The integration of AI in these processes not only accelerates the path toward achieving NZCEs but also significantly reduces the environmental impact of construction activities. This study highlights how AI-driven technologies can automate complex processes, providing more accurate and data-driven insights that were previously unattainable through traditional methods [32,35]. Thus, the application of AI represents a critical advancement in carbon emissions management, offering the potential to transform the construction industry into a more sustainable and environmentally conscious sector.

Previous review studies have focused on NZCEs and the application of AI in other sectors [34,38–40]. Using decision-making and prediction algorithms, Ahmed et al. [41] presented a state-of-the-art review application of artificial neural networks (ANNs) for promoting sustainable construction projects within three sustainable development aspects: environmental, economic, and social. Additionally, Chen et al. [42] conducted a comprehensive literature review to analyze AI-based solutions for climate change. They discovered that the life cycle assessment is widely employed in the construction industry to evaluate environmental effects, with carbon emissions as the primary assessment indication. Owing to the continual advancement of computer technology and big data technology, random forests and neural networks have been utilized in recent years to quantify and estimate the carbon emissions of the construction industry [43]. The progression of green construction to attain net-zero carbon emissions aligns with worldwide sustainability goals. Manzoor et al. [34] conducted a systematic review based on a case study to develop techniques for incorporating BIM into sustainable building projects. The findings indicated that workshops, lectures, and conference events are employed to augment public consciousness, while improved information on the expenses and advantages of sustainable materials and reinforced sustainable development were identified as the most crucial tactics to enhance sustainable progress in construction projects. Moreover, Adunadepo and Sunday [44] conducted a review to explore novel methods to facilitate the implementation of AI to attain the sustainable development of intelligent buildings. Their recommendation involves utilizing integrated project delivery and creative green architecture to effectively execute these concepts and to promote the sustainable growth of artificial intelligence in buildings. Their suggestions could aid in mitigating adverse effects such as the degradation of the built environment and the exacerbation of global warming resulting from the mounting pressures of fast-expanding worldwide populations. Despite the relevance of previous review studies, they have limited applications of AI in reducing carbon emissions in sustainable building projects. Owing to the challenges of global warming, it is crucial to identify mainstream research topics on how to apply AI (especially machine learning) in combating NZCEs for sustainable building projects. In recent times, versatile applications of machine learning have extended far beyond energy efficiency, impacting various scientific and engineering challenges. Recent studies in the construction industry have highlighted its role in predicting energy consumption and optimizing building performance. For example, research such as "Machine learning as a surrogate to building performance simulation: Predicting energy consumption under different operational settings" emphasizes the ability of ML models to accurately forecast energy needs, thereby enabling better resource management [45]. Additionally, the study "Machine Learning Method Based on Symbiotic Organism Search Algorithm for Thermal Load Prediction in Buildings" explores advanced algorithms to predict thermal loads, ensuring optimal energy use and comfort in buildings [46,47]. These examples demonstrate the multifaceted potential of ML in revolutionizing the construction industry, making it an indispensable tool in modern engineering problem-solving.

In addition, none of the previous review studies adopted a mixed-method approach consisting of a systematic literature review (i.e., qualitative method) and a science mapping approach (i.e., quantitative method) on the application of AI in NZCEs for sustainable building projects. This review research paper distinguishes itself from the existing academic literature by adopting a mixed-method approach that integrates both a systematic literature review and science mapping analysis, which is not commonly found in prior studies. While previous research has extensively examined artificial intelligence (AI) applications in various sectors, including construction and environmental management, this study specifically focuses on the role of AI in achieving net-zero carbon emissions (NZCEs) in sustainable building projects. By identifying mainstream research topics, research gaps, and future research directions, this study provides a comprehensive framework that has largely been absent from the current literature. The novelty lies in its dual methodological approach and targeted exploration of AI's potential to mitigate carbon emissions in the construction industry, making it a valuable resource for both academics and practitioners in this evolving field [39,48].

In summary, this study aims to conduct a systematic literature and science mapping review of published articles related to the application of AI in NZCEs for sustainable building projects and to discuss mainstream research topics, research gaps, and future research directions. To achieve this aim, the specific research objectives of this review are as follows:

1. Analyze the annual publication trends of published articles and select peer-reviewed journals on AI in NZCEs for sustainable building projects.
2. Apply a science mapping approach to analyze influential keywords and document analyses of AI in NZCEs for sustainable building projects.
3. Identify and discuss mainstream research topics related to AI in NZCEs for sustainable building projects.
4. Develop a framework for depicting research gaps and future research directions on AI in NZCEs for sustainable building projects.

This study is significant to both researchers and professionals in the sense that analyzing the annual publication trends and selecting peer-reviewed journals will provide insights into the field's evolution and identify key journals, aiding in strategic publishing and funding acquisition for researchers [49]. A science mapping approach to influential keywords and document analyses also helps researchers and professionals understand critical terminologies and research interconnections, thus enabling strategic research planning [50]. On the other hand, identifying mainstream research topics helps narrow the focus to impactful areas, aiding benchmarking and curriculum development [51]. Developing a framework for depicting research gaps and future research directions highlights under-researched areas and emerging trends, fostering innovation and informing policies and strategies [52]. Consequently, this review acts as a comprehensive resource, guiding research, professional practices, and collaboration at the intersection of AI and sustainable building projects.

The remainder of this paper is organized as follows. The rationale for using a systematic literature review and science mapping approach and the methodological steps are discussed in Section 2. Section 3 presents the results of this review based on annual publication trends, the selection of relevant peer-reviewed journals, the co-occurrence analysis of keywords, and document analysis. Moreover, Section 4 discusses the mainstream research themes, gaps, and future research directions in the research domain. Lastly, conclusions, contributions, limitations, and further studies are presented in Section 5.

2. Research Methods

This review study aims to conduct a systematic literature and science mapping review of AI applications in NZCEs for sustainable building projects, thereby discussing mainstream research topics and identifying research gaps and future research directions. As such, this study adopted a mixed-method approach, consisting of a systematic literature review (i.e., a qualitative approach based on PRISMA guidelines) and a science mapping review (i.e., a quantitative approach based on VOSviewer, version 1.6.17). A systematic literature review can collect a significant number of articles from various perspectives and provide literature references on a particular domain [53]. The goal of a systematic literature review is to minimize the diverse results of published articles through a thorough literature search [54]. By providing a comprehensive process for identifying literature samples, precise bibliographic information and novel contributions to specific research domains can be obtained [55,56]. On the other hand, science mapping reviews are characterized by their ability to manage vast volumes of measurement data while serving as descriptive and diagnostic tools [57]. Adopting a mixed-method approach can combine the benefits of qualitative and quantitative research methods by focusing on the relevance and value of the study object, data analysis, and objective connections [58]. Specifically, the proposed mixed-method approach allows for the use of simultaneous datasets and thorough analyses using relevant tools [59]. Figure 1 provides an overview of the research methods used in this study. As shown in Figure 1, the review was conducted in four main stages: search strategy, selection criteria, science mapping analysis, and qualitative discussion.

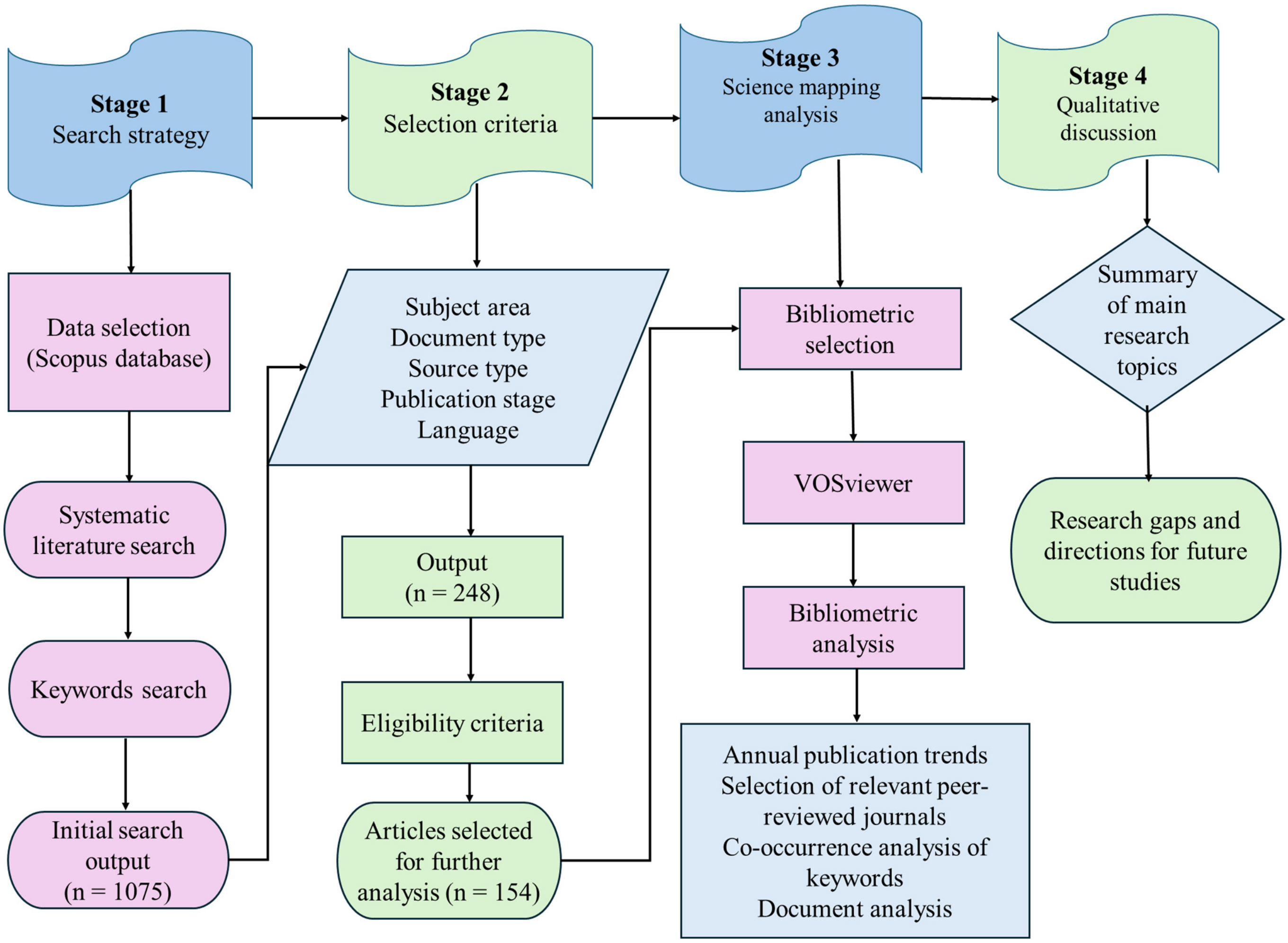

Figure 1. An overview of research methods.

2.1. Search Strategy

Many online bibliographic databases are used as storage platforms for literature samples (e.g., published articles, conferences, and books). Examples of these databases include the Web of Science (WoS), Scopus, Google Scholar and Science Direct, PubMed, and CINAHL. Although these databases overlap, the Scopus database provides wider coverage of publications and improves the efficiency of the indexing process [60]. Therefore, the Scopus database was selected to retrieve literature samples in this study. First, a systematic literature search was performed under the "title/abstract/keywords" section in the Scopus database. Based on the purpose of this review study, the main search terms used are "AI", "net-zero carbon emissions", and "sustainable building projects". The full search string was (TITLE-ABS-KEY (artificial OR intelligence OR AI) AND TITLE-ABS-KEY (net-zero OR carbon OR emissions) AND TITLE-ABS-KEY (sustainable OR building OR project) DOCTYPE (all) AND ACCTYPE (all). A total of 1075 bibliographic records, including articles, books, and reviews, were identified. It is worth noting that the search was conducted on 25 July 2023.

2.2. Selection Criteria

The second step of the proposed mixed-method approach is the selection of relevant bibliographic records using the following criteria: First, the subject category was limited to “engineering”, and 624 other subject areas (e.g., business, economics, etc.) were excluded. Second, bibliographic records related to reviews, conference papers, and book chapters were excluded. In other words, only articles were included in this review. Consequently, 179 bibliographic records were excluded. In the third criterion, the source of publication type was limited to journals. Five articles from trade journals and book series were excluded from the analysis. According to Smith and Johnson [61], scientific journals focus on rigorous, peer-reviewed academic research, whereas trade journals provide practical, industry-specific information for professionals. Next, the fourth criterion was to limit the publication stage to “final”, meaning online published journal articles. Four articles were excluded after meeting the fourth criterion. Finally, the fifth criterion was limiting published journal articles to only those written in English. Thus, 15 articles written in other languages, such as Chinese and Spanish, were excluded. After applying the selection criteria, 248 articles were obtained. The 248 articles were then comprehensively screened by reading each article’s title, abstract, and full text to identify relevant articles related to the studied domain. For example, some articles were removed during the screening process because they did not focus on emission reductions in the construction industry. Moreover, some articles were excluded because they did not focus on the role of AI in reducing carbon emissions. Two independent reviewers (YL and MFAA) screened the titles, abstracts, and full texts of 248 articles based on the selection criteria. Any disagreements between them were resolved via meeting and consensus. As of 25 July 2023, 94 articles were excluded, and 154 were used for further analysis. All the included articles were exported and stored using a CSV file. Next, the two reviewers extracted relevant data from the 154 included articles. These include publication year, author keywords, authors’ full names, affiliations, article titles, and source titles.

2.3. Science Mapping Analysis

In the third step of the proposed mixed-method approach, the science mapping approach was used to analyze 154 articles related to AI applications in NZCEs for sustainable building projects. Bibliometrics plays an important role in evaluating and analyzing scientific production [62] and is specifically divided into two analytical methods: performance analysis and science mapping analysis [63]. The former mainly uses literature data and documentary indicators [64], whereas the latter focuses on the correlation between various field parts while considering the time factor [65,66]. Therefore, this study used science mapping analysis to analyze influential AI articles in NZCEs for sustainable building projects. Many tools have been used for science mapping analysis, including Bibexcel (version 1.0.3), CiteSpace (version 6.2.R4), CoPalRed (version 1.7.5), Science of Science (Sci 2) Tool, Gephi, and VOSviewer (version 1.6.17). Choosing a suitable science-mapping tool can help achieve relevant study results. For instance, CiteSpace can analyze trends in scientific literature and provide visualization functions. Gephi is a tool for gaining insight into networks [14]. VOSviewer can build and visualize any co-occurrence data using a mapping technique that is divided into different views, such as network visualization, overlay visualization, and density visualization. In addition, these tools are freely available and easy to use. Therefore, this review adopted the VOSviewer tool for science mapping analysis for the reasons listed. In this study, four science-mapping analyses were performed using VOSviewer. These include (1) annual publication trends, (2) selection of relevant peer-reviewed journals, (3) co-occurrence analysis of keywords, and (4) document analysis.

2.4. Qualitative Discussion

The final step after the science mapping analysis was a qualitative discussion. In this step, an in-depth systematic review was carried out on the included articles to identify the mainstream research topics, gaps, and future research directions using methods recommended by [67]. Moreover, the theoretical and practical contributions of this study are summarized.

3. Results

3.1. Annual Publication Trend

Figure 2 shows the number of annual publications of the 154 included articles. As shown in Figure 2, the number of published articles within the study domain was very small from 2006 to 2018. From 2006 to 2018 (years inclusive), only 32 articles were published, with less than five articles in other years, except 2010. Between 2019 and July 2023, the number of published articles increased significantly, reaching its highest value of 28 articles in 2021. This significant growth may be linked to the recent research interest in AI and carbon emissions among scholars from different disciplines. It is worth mentioning that there was a decrease in the number of publications by 2022. However, 26 articles were published in 2023 (as of 25 July 2023). These findings indicate that AI plays a critical role in reducing carbon emissions from sustainable buildings; thus, more relevant research articles are expected to be published before the end of 2023.

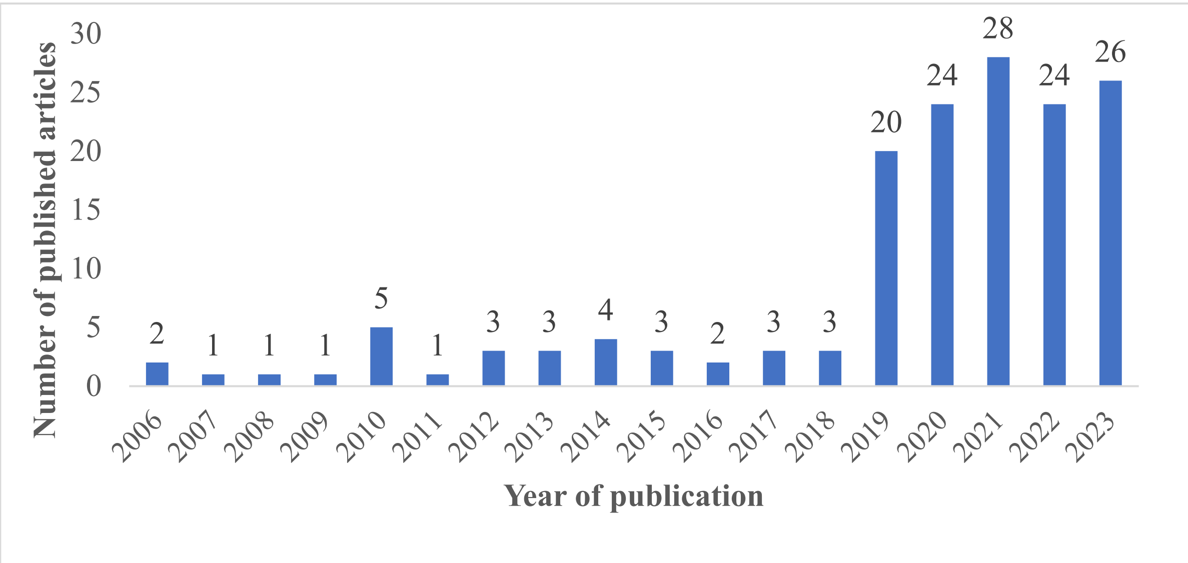

Figure 2. Number of publications from 2006 to July 2023.

3.2. Selection of Relevant Peer-Reviewed Journals

Table 1 lists the selection of relevant peer-reviewed journals during the study period. The peer-reviewed journals listed in Table 1 are those with two or more published articles focusing on AI in NZCEs for sustainable building projects during the study period. As shown in Table 1, only 15 peer-reviewed journals were selected. The top three peer-reviewed journals, according to their number of published articles, were the *Journal of Cleaner Production*, *Applied Energy*, and *Energy and Buildings*, representing 35.06% of the total published articles on AI in NZCEs for sustainable building projects. The *Journal of Cleaner Production* had the highest number of published articles (i.e., 24), indicating its impact on AI in NZCEs for sustainable buildings. The were two relevant articles published in *Computers and Industrial Engineering*, the *International Journal of Low-Carbon Technologies*, and the *Journal of Building Engineering*. Other peer-reviewed journals that published a single article constituted 29.87% of the included articles.

Table 1. Selection of relevant peer-reviewed journals from 2006 to 2023 (26 July 2023).

Journal Name	Number of Relevant Articles	% Total Publications
Journal of Cleaner Production	24	15.58
Applied Energy	17	11.04
Energy and Buildings	13	8.44
Energy	10	6.49
Sustainability (Switzerland)	9	5.84
Building and Environment	5	3.25
Buildings	5	3.25
Energies	5	3.25
Sustainable Cities and Society	5	3.25
Construction and Building Materials	3	1.95
Engineering Applications of Artificial Intelligence	3	1.95
Sensors	3	1.95
Computers and Industrial Engineering	2	1.30
International Journal of Low-Carbon Technologies	2	1.30
Journal of Building Engineering	2	1.30
Others	46	29.87
Total	**154**	

3.3. Co-Occurrence Analysis of Keywords

This review conducted a co-occurrence analysis of keywords to construct a network diagram and map the scientific knowledge domain of AI in NZCEs for sustainable building projects. By using "author keywords" as the unit of analysis, "full counting" as the counting method, and choosing the minimum number of occurrences of a keyword to be 3, 33 keywords met the threshold out of 655.

The second round of text mining of the selected keywords was conducted to eliminate general keywords. For example, "ann" and "ghg emissions" were excluded. Some other keywords with the same semantic meaning such as "artificial neural networks" and "artificial neural network", were combined. Finally, 23 items, six clusters, 51 links, and 57 link strengths were generated in the network of co-occurrence of keywords, as shown in Figure 3.

As presented in Figure 3, the font sizes of "artificial neural network", "carbon emission", "artificial intelligence", and "machine learning" are larger than other keywords, indicating that these keywords occur more frequently in the studied domain. The connecting lines in the figure indicate the interrelationships between two or more keywords. For example, "machine learning" and "building energy performance" are closely related. Through the presentation of different colors, it was found that the keywords in this review study could be categorized into six main clusters of keywords, representing mainstream research topics in the field of AI in NZCEs for sustainable building projects.

Table 2 summarizes the list of selected keywords and relevant network data, such as occurrences, average publication year, links, average citations, average normalized citation, and total link strength. The selected keywords in Table 2 are ranked according to their total link strengths. It was found that "artificial intelligence", "machine learning", "artificial neural network", and "energy efficiency" were the most frequently used keywords, indicating that they have been widely researched in the field of AI in NZCEs for sustainable building projects. The total link strength indicates the total strength linked to a specific keyword [68]. The results revealed that keywords such as "machine learning", "artificial intelligence", "life cycle assessment", and "sustainability" are the four keywords with the highest total link strength. The findings show that keywords with the highest occurrences do not necessarily have the highest total link strength. Keywords such as "building energy performance", "energy consumption", and "decision support system" had the highest average normalized citations, and "multi-objective optimization", "artificial intelligence", and "renewable energy" were the most recently used keywords according to the average publication year. These studies have focused on using ML to rate the energy performance of buildings. For instance, ML algorithms were used to analyze building energy data and perform prediction functions to reduce energy consumption [69–72].

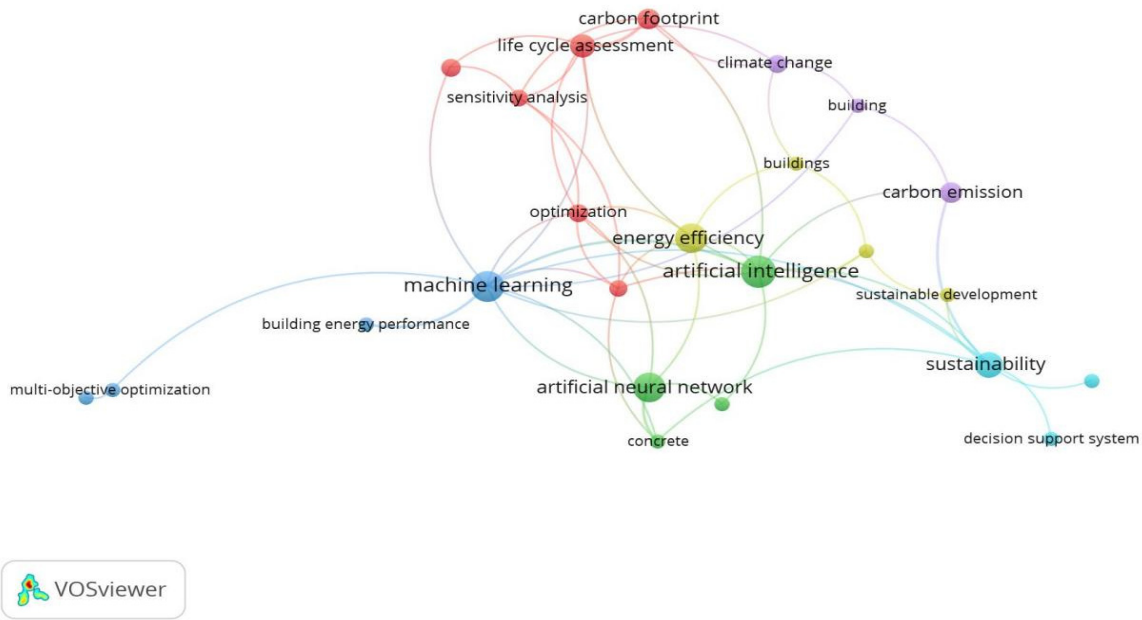

Figure 3. A network of co-occurrence of keywords related to AI in NZCEs for sustainable building projects.

Table 2. List of selected keywords and relevant network data.

Keywords	Occurrences	Average Publication Year	Links	Average Citations	Average Normalized Citations	Total Link Strength
Machine learning	14	2021	12	29.79	1.08	14
Artificial intelligence	15	2022	9	16.40	0.67	10
Life cycle assessment	8	2019	7	28.25	0.79	9
Sustainability	9	2020	8	32.78	1.31	9
Optimization	5	2020	7	19.00	1.65	7
Carbon footprint	6	2019	4	28.00	0.78	6
Energy consumption	4	2019	6	55.00	1.96	6
Artificial neural network	12	2021	5	28.25	1.47	6
Sensitivity analysis	4	2021	5	29.25	1.46	5
Concrete	3	2021	4	33.67	1.78	5
Energy efficiency	12	2020	5	19.83	0.69	5
Renewable energy	3	2023	4	0.67	0.54	4

Table 2. *Cont.*

Keywords	Occurrences	Average Publication Year	Links	Average Citations	Average Normalized Citations	Total Link Strength
Carbon emission	6	2021	3	14.83	1.45	4
Climate change	5	2016	4	36.40	0.88	4
Embodied carbon	5	2021	3	16.60	0.70	3
Buildings	3	2018	3	25.67	0.71	3
Building energy performance	3	2020	1	58.00	2.19	2
Sustainable development	3	2018	2	8.33	0.94	2
Energy conservation	3	2020	2	14.33	0.86	2
Multi-objective optimization	3	2023	2	0.67	0.54	2
Decision support system	3	2012	1	118.00	1.80	1
Thermal energy storage	3	2017	1	11.00	1.18	1
Compressive strength	3	2020	1	19.33	0.78	1

The observations in Figure 3 and Table 2 may lead to the following keyword clusters, which represent the dominant mainstream research topics related to AI in NZCEs for sustainable building projects:

1. Building eco-friendly, efficient, and energy-efficient structures can significantly reduce the problems associated with excessive carbon emissions. It has been shown that quantifying and analyzing the carbon footprint of public buildings over their life cycle can reduce negative environmental impacts [73]. Tushar et al. [74] applied sensitivity analysis to reduce the carbon footprint, thus improving energy efficiency. Developing implicit databases is also a good way to reduce carbon emissions and can be combined with machine and deep learning algorithms to combat climate change and resource scarcity [75]. It has also been reported that embodied carbon can be used throughout the life cycle of a building to improve the safety and environmental impact of a building project [76–79]. Additionally, the heating and cooling aspects of buildings consume more energy; therefore, the development of intelligent control systems is necessary. To reduce emissions, scalability should be the focus [69].
2. The use of AI to minimize carbon emissions in construction projects is the second cluster of research. AI can be used to create smart energy networks and reduce energy costs [80]. By applying AI techniques, building energy and carbon footprints can be used to predict energy consumption and CO_2 emissions [81–83]. Deep learning and ML are branches of AI techniques that are widely used as data analytics techniques for reducing NZCEs for sustainable building projects. For example, ANN has been used to quantify environmental costs in residential buildings and optimize commercial building design [84,85]. To achieve this goal, Palladino [86] studied the use of ANN in specific energy strategies in the Umbria Region. It has been reported that the application of ML can reduce the power consumption of buildings and help optimize building performance in the design and development of smart buildings [87,88].
3. A multi-objective optimization technique is proposed to reduce residential construction carbon emissions, accomplishing the dual goals of economic development and environmental conservation, and conforming to the sustainable development principle [89]. Multi-objective optimization combined with AI technology, can contribute to the development of sustainable buildings in terms of building material selection, retrofitting energy systems, and decision-making in building construction [90]. For example, the combination of an ANN with a multi-objective genetic algorithm can optimize the design of residential buildings [91,92]. Clustering techniques are integrated

with multi-objective optimization to identify urban structures based on their energy performance. This strategy can be replicated in other cities to increase energy efficiency and execute carbon-cutting initiatives [70]. Multiple goals can help sustainable buildings achieve NZCEs.

4. Improving energy consumption efficiency and strengthening building energy management are critical for mitigating the greenhouse effect and global warming trend [93]. Reduced carbon emissions, green buildings, and sustainable development have emerged as major concerns worldwide [2,94]. On the one hand, renewable energy-driven building systems based on solar and wind resources can reduce environmental effects and costs [95,96]. Building carbon emissions must be minimized to achieve energy sustainability [97]. However, focusing on building carbon emissions throughout their life cycle, including the design, transportation, construction, and operation stages, and quantifying them as environmental and carbon costs, can contribute to the long-term development of the construction industry [98]. In summary, reducing energy consumption can contribute to economic benefits and achieve sustainable development [77,99].
5. In the face of serious problems posed by climate change, efficient ways to minimize carbon emissions in the construction sector are receiving considerable attention. China is attempting to assess the feasibility of NZCEs, provide a path to reduce emissions, adjust and optimize the industrial structure, and achieve the policy goals of green development and carbon neutrality [1,100]. The prediction of carbon emission intensity in different countries can help policymakers devise environmental policies to address the adverse environmental effects of climate change [101,102]. Enhancing building management systems and promoting smart buildings will also help reduce the energy footprint and continuously optimize building performance [88]. Carbon capture and storage technologies currently play an essential role in lowering carbon dioxide emissions; however, they face problems such as high costs and regulatory issues, and related technologies still need to be developed [103].
6. Consider a structural design scheme for upgrading a building based on the decision support system (DSS). Carbon capture and storage technologies have been demonstrated in previous studies [104]. On the other hand, environmental considerations can be evaluated to assess building sustainability. As a result, the entire decision-making process can be optimized [105]. Simultaneously, DSS, combined with the predictive capabilities of ML to investigate the proper concrete mix proportions, can aid in assessing the impact of a building over its full life cycle, both in terms of environmental and financial expenses [72,106].

3.4. Document Analysis

Document analysis describes the most captivating research topics in a particular field, allowing researchers and practitioners to understand the specific findings and references cited in published articles. VOSviewer was used as a scientific mapping tool to generate a document analysis of the included articles retrieved from the Scopus database. Using "citation" as the type of analysis and "documents" as the unit of analysis in VOSviewer, and by setting the minimum number of citations of a document to 40, 24 documents met the thresholds out of the total 154 documents [68]. Table 3 summarizes the highly cited published articles related to AI in NZCEs for sustainable building projects. Although 24 documents met the threshold, the articles listed in Table 3 only included those with a normalized citation greater than one [107]. As such, 22 articles were listed and arranged based on normalized citations, whereas other articles (for example, Jiang et al. [108]; and Roaf et al. [109]) were manually excluded. As shown in Table 3, the top three articles with the highest total citations during the study period were Juan et al. [110] (238 citations), Acheampong and Boateng [101] (125 citations), and Çay et al. [111] (115 citations). A study by Fraga-lamas et al. [112], which focused on green IoT and edge AI toward a smart circular economy, received the highest normalized citations during the study period.

Most of the influential articles listed in Table 3 focus on the impacts of AI techniques on sustainable development [101,111–114]. Specifically, AI techniques, such as ML algorithms, were most applied in this studied research field [90,93,101,113,114]. Articles with fewer normalized citations during the study period included those by Petrovic et al. [115] (1.08) and Gobakis et al. [116] (1.00) were excluded.

Table 3. Summary of highly cited published articles related to AI in NZCEs for sustainable building projects.

Article	Title	Total Citations	Normalized Citations
[112]	Green IoT and edge AI as key technological enablers for a sustainable digital transition toward a smart circular economy: An industry 5.0 use case	65	3.60
[110]	A hybrid decision support system for sustainable office building renovation and energy performance improvement	238	2.88
[101]	Modeling carbon emission intensity: Application of artificial neural network	125	2.82
[74]	An integrated approach of BIM-enabled LCA and energy simulation: The optimized solution toward sustainable development	48	2.66
[114]	Comparison of linear regression and artificial neural networks models to predict heating and cooling energy demand, energy consumption, and CO_2 emissions	100	2.63
[117]	Modeling heating and cooling energy demands for building stock using a hybrid approach	47	2.61
[90]	Machine learning modeling for predicting non-domestic buildings energy performance: A model to support deep energy retrofit decision-making	73	2.54
[118]	Designing sustainable concrete mixture by developing a new machine learning technique	66	2.29
[111]	Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network	115	2.25
[80]	Developing novel 5th generation district energy networks	63	2.19
[119]	Design and implementation of cloud analytics-assisted smart power meters considering advanced artificial intelligence as edge analytics in demand-side management for smart homes	97	2.19
[120]	Life cycle greenhouse gas emissions and energy use of polylactic acid, bio-derived polyethylene, and fossil-derived polyethylene	58	2.02
[113]	A machine-learning-based approach to predict residential annual space heating and cooling loads considering occupant behavior	55	1.91
[70]	Grading buildings on energy performance using city benchmarking data	84	1.9
[121]	Analyzing the influence factors of the carbon emissions from China's building and construction industry from 2000 to 2015	81	1.83
[122]	The hourly life cycle carbon footprint of electricity generation in Belgium, bringing a temporal resolution in life cycle assessment	84	1.76
[93]	Comparative study of machine learning-based multi-objective prediction framework for multiple building energy loads	47	1.63
[123]	Development of electrochromic evacuated advanced glazing	49	1.38
[124]	Low-carbon cold chain logistics using ribonucleic acid-ant colony optimization algorithm	61	1.38
[125]	Data-driven strategic planning of building energy retrofitting: The case of Stockholm	50	1.13

Table 3. *Cont.*

Article	Title	Total Citations	Normalized Citations
[115]	Life cycle assessment of a wooden single-family house in Sweden	48	1.08
[116]	Development of a model for urban heat island prediction using neural network techniques	69	1.00

4. Discussion

Following the science mapping analysis of the included articles, this section mainly focuses on discussing mainstream research topics, identifying research gaps, and summarizing future research directions in the field of AI in NZCEs for sustainable building projects.

4.1. Mainstream Research Topics on AI in NZCEs for Sustainable Building Projects

As shown in Figure 3, the clusters of keywords have many connections with each other, and the keywords from different clusters are also closely connected. Based on the keyword analysis, the mainstream research topics related to AI in NZCEs for sustainable building projects can be summarized as follows:

4.1.1. Life Cycle Assessment and Carbon Footprint

Owing to the complexity of building projects and the variety of construction materials, the environmental impacts of different phases need to be considered. The life cycle assessment (LCA) method can be used to investigate the total carbon footprint of a building and is a widely known environmental impact assessment method [75,126]. The LCA method can be combined with BIM to reduce energy consumption [74]. Yan et al. [127] examined the carbon footprint of building energy systems and the factors affecting carbon emissions using sensitivity analysis. The development of novel building materials with sustainable and energy-efficient qualities can reduce the carbon footprints of buildings [128,129]. Simultaneously, energy efficiency standards have been established, which contribute to improving the quality of life of the population [41,48,73]. Combining AI techniques with energy prediction models can improve the cost of the environmental impact of buildings at the design stage [84]. Intelligent control systems are being developed to address the issue of excessive energy use in the provision of heating and cooling in buildings [69]. Specifically, there are differences in the total carbon footprints of heating- and cooling-dominated buildings in terms of their economic, environmental, and operational aspects [130]. As a result, the selection of heat-carrying fluids should be based on actual building characteristics to avoid environmental impact and ensure system stability. When combined with a building energy simulation tool (EnergyPlus^{TM}, Department of Energy, Springfield, IL, USA), AI technology can predict the annual cooling energy consumption of a building in a shorter period, thereby enhancing the prediction efficiency [131]. In addition to the operational energy, buildings consume implicit energy. Thus, it is important to calculate the implicit carbon footprints of buildings. LCA methods can be used to provide data support for energy consumption throughout the life cycle of a building, to reduce carbon emissions during construction [132]. All the aforementioned studies can assist project practitioners in making decisions to reduce the total carbon footprint, thus improving the sustainability of the building's life cycle.

4.1.2. Practical Applications of AI Techniques in Sustainable Buildings

AI techniques are increasingly used in the construction sector, particularly in the design and operation phases of buildings, providing practical solutions in the construction industry [133]. AI techniques have been previously adopted in traditional industrial sectors, but their benefits have been widely recognized in recent years. Zhang and Zhu [134] examine the effects of industrial robots on carbon emissions in the three largest economies—China, Japan, and the United States. They employed the classical linear regression model, ordinary least squares (OLS), to analyze the relationship between robot installations and robot density, which is measured as ownership per thousand manufacturing individuals. They concluded that the growth of industrial intelligence not only enhanced the efficiency of the energy system but also enhanced environmental quality and contributed to the achievement of ecologically sustainable development. In the Stockholm case, a data-driven approach to building retrofitting was empirically tested to achieve deep decarbonization, energy efficiency, and sustainable development [125]. AI can analyze data from many perspectives to optimize energy-intensive building systems [135]. When applied to outdoor lighting, AI techniques can improve energy efficiency [136]. The implications of living density on energy and CO2 emissions can also be investigated using a robust deep learning technique of the long short-term memory (LSTM) model, as well as how to improve living quality [82]. In addition, AI plays an important predictive role in helping sustainable buildings save energy and reduce their carbon emissions. Combined with carbon capture and storage (CCS) technology, it can better fulfill its predictive role in contributing to CO2 storage and combating climate change [103]. In contrast to LCA, ANN focuses on developing predictive models through data analysis, dealing with complicated nonlinear interactions, and is appropriate for predicting building-specific carbon emissions. ANN in an environmental impact cost assessment model can be used to estimate a building's energy consumption and calculate the configuration that will result in NZCEs in a shorter period [85,100]. It is beneficial in helping construction practitioners estimate early costs and achieve sustainability goals using an ANN model [84]. Additionally, ML can forecast certain elements and the total carbon footprint of a structure during the early design phase, thereby assisting designers in making sustainable design decisions [133].

Beyond the broad application of machine-learning algorithms, the research corpus highlights several specific AI techniques that are instrumental in advancing sustainable building projects. One such technique involves the use of neural networks, which are employed for the predictive modeling of energy consumption and optimization of heating, ventilation, and air conditioning (HVAC) systems. These models learn from historical data to forecast energy needs under varying conditions, thereby enabling more efficient resource management [137]. Another AI technique gaining traction is genetic algorithms, which are utilized to optimize building designs to minimize energy consumption and maximize natural lighting and ventilation [138]. Furthermore, fuzzy logic systems have been applied to manage uncertainties in building performance simulations, providing more robust decision-making tools for sustainable construction practices [139]. These AI techniques are integral for achieving more efficient, cost-effective, and environmentally friendly building solutions.

4.1.3. Multi-Objective Optimization

Multi-objective optimization is a powerful decision-making tool in the field of sustainable construction. It is efficient and time-saving compared to single-objective forecasting and can reduce carbon emissions during building operations while maintaining comfort [93,95]. In recent years, the combination of multi-objective optimization and ML to evaluate construction cases has seen a gradual increase in interest in the construction industry. For example, it can provide energy optimization for non-residential buildings [90]. Innovative structural designs of buildings through environmental impact assessment to improve the sustainability of buildings [75]. The effect of changes in the insulation installation position on carbon emissions as the temperature changes, to reduce energy consumption [87].

4.1.4. Energy Management and Energy Efficiency

Energy efficiency has a significant effect on carbon emissions. Managers focusing on energy management and improving energy efficiency can contribute to the sustainable development of the built environment. Most importantly, AI contributes positively to ecological and social sustainability through energy efficiency [1,99]. By comparing data from nine countries, including China and the UK, it was found that energy consumption significantly impacts the environment [140]. They suggested that using renewable energy sources, smart energy modeling using AI, and raising public awareness of environmental protection could foster the implementation of sustainable development policies [141]. A holistic assessment is required to achieve the goal of net-zero energy consumption in buildings. For instance, appropriate emission reduction programs need to be formulated in the light of the actual situation, thereby aiding in effectively reducing the total carbon emissions [74,121]. Using AI techniques in energy modeling can be a smart way to investigate a building's carbon footprint and explain and manage the elements that influence energy consumption [142]. According to the above findings, improving energy efficiency is the foundation and key to the development of sustainable buildings. The building sector can achieve environmental and social sustainability through the implementation of innovative technologies and strategies using AI.

4.1.5. Carbon Emissions from Buildings

In recent years, industrialization has severely influenced the environment while encountering the economy, and the increase in carbon dioxide emissions has contributed to global warming [134]. As a major contributor to global carbon emissions, the construction industry is a key sector in meeting emissions reduction targets; therefore, optimizing building performance is vital to improving climate conditions [88]. Many countries have committed to carbon-neutral policies to address the excessive carbon dioxide emissions [1]. Carbon emissions from countries such as the United States and the United Kingdom decreased significantly in 2017. Asian countries such as China and India account for a larger share of global emissions [101]. The energy optimization of German building types is aimed at improving energy efficiency and reducing carbon emissions [135]. The UK has developed AI-driven green building practices to mitigate urban heat [143]. AI-enabled building control systems have also been developed in the USA to reduce energy consumption and carbon emissions [69].

4.1.6. Decision Support System (DSS) and Sustainability

The DSS can be used to assess carbon emissions, energy consumption, design decisions, and material selection for buildings, thereby improving the energy efficiency of buildings. DSS has been reported to play a role in design decisions for curtain walls in high-rise buildings, helping designers make environmentally friendly decisions [144]. Moreover, DSS has been applied to the design of retrofitted residential complexes in European cities [145]. Compared to traditional structural design solutions, sustainable structural design considers the impact of the building on the environment, and combining it with DSS can help to increase the flexibility of design decisions [105]. As a common material in construction, high-compressive strength concrete can lead to increased carbon emissions, so it is crucial to balance the need between compressive strength and other properties. Low-carbon concrete is a good option for optimizing the structural design of buildings. It can also reduce carbon emissions from construction and promote sustainable buildings [146].

4.2. Research Gaps of AI in NZCEs for Sustainable Buildings

4.2.1. Existing Problems of the Life Cycle Assessment Method

Studies based on LCA methods consider the contribution of sustainable materials and energy prediction modeling to the reduction of the carbon footprint [74,131,132]. Sensitivity analysis can be used as a decision-making tool for predicting energy consumption in future buildings and exploring the factors affecting carbon emissions [74,127]. However, only a few studies have been conducted on various climatic conditions and buildings of different sizes. For instance, distributed energy systems are limited in their use and are not suitable for analyzing the carbon footprint of cities or countries [127]. When evaluating a client's energy requirements, future research should evaluate the feasibility and cost considerations to optimize energy savings considering a limited global carbon budget [147].

4.2.2. Opportunities and Challenges Faced by AI Techniques in Sustainable Buildings

Previous studies applying AI techniques in the building sector have focused on predicting carbon emissions from buildings [85,103]. However, the approach of combining ANN with genetic algorithms can be extended to a wider range of building types [85]. Compared to traditional regression techniques, ANN can use multiple parameters in decision analyses with high reliability [114]. However, there is a lack of case or empirical studies on whether the application of AI techniques could promote economic growth while optimizing the environment [134]. The application of AI techniques also faces the challenges of international regulatory issues, military conflicts, and insufficient legal frameworks, which require international cooperation to innovate technologies and address opportunities and challenges [103].

4.2.3. Scope of Application of Multi-Objective Modeling

When using multi-objective modeling, because the costs of occupancy and carbon emissions are fixed for a particular building, its parameters remain constant and do not apply to other building types [89,127]. In the future, there is still a need to refine the ML framework and add more sophisticated algorithms to improve decision-making in building design and prediction during the construction phase [90]. The findings of future research can assist policymakers in balancing competing goals and developing more effective carbon reduction plans.

4.2.4. Improvements in Energy Management and Efficiency

In general, improvements in energy management and efficiency can effectively reduce carbon emissions from buildings. Research on energy efficiency to improve carbon emissions has been conducted in other sectors [148,149]. For instance, innovative production and consumption patterns have been developed in the chemical industry to reduce energy consumption and achieve sustainable development [148]. AI techniques have also been demonstrated to improve energy efficiency in the logistics industry [149]. However, in the building sector, few studies have been conducted on how to enhance the correlation of energy emissions among different project life cycle phases to ensure optimized energy efficiency. Moreover, the estimation of the development density and degree of urbanization should be studied in the future. These two important indicators for assessing carbon emissions are complex, and new models must be created for their application in sustainable buildings [121].

4.2.5. Raise Awareness of Reducing Carbon Emissions

The negative environmental impact of buildings is of great concern to professionals and stakeholders in the construction industry. Many countries and industries have focused on low-carbon developments, with government departments actively involved and providing policy support. However, the design and implementation of low-carbon buildings should also consider economic factors, occupant comfort, and material availability [150]. These factors should be considered in future studies to create awareness among other researchers, practitioners, policymakers, and the general public.

4.2.6. Sustainable Development of Buildings

Similar to research on multi-objective optimization, research on DSS and sustainability has focused on design decisions, energy optimization, and sustainable material selection [125,151]. Future research on eco-concrete should consider more environmental parameters, such as methane and sulfur dioxide, and focus on the environmental friendliness and sustainability of building materials [118]. The use of bio-composites can also effectively improve the thermal performance of buildings and reduce energy consumption and carbon emissions [152].

4.3. Research Trends of AI in NZCEs for Sustainable Building Projects

After discussing the mainstream research topics and research gaps in the studied research domain, this section highlights recommendations for future research direction in the field of AI in NZCEs for sustainable building projects. Figure 4 illustrates the proposed framework for future research directions on AI in NZCEs for sustainable building projects. Numerous recommendations for future research include the following:

1. Various factors, such as energy savings, emissions reduction, and the feasibility of financial costs, should be considered when adopting LCA methods.
2. Improving the legal framework and international regulatory regime for the application of AI techniques to reduce carbon emissions.
3. Balancing carbon emission reduction with other sustainability objectives in response to changes in building parameters.
4. Empirical research on energy optimization strategies for different building scenarios.
5. Construction industries and practitioners should actively implement carbon-neutral policies.
6. Countries can share their experiences and work together to promote the development of sustainable buildings.
7. Using DSS to provide data analyses and forecasts should incorporate more environmental parameters to enable decision-makers to make sustainable development decisions.
8. Increased attention to decision-making processes and the implementation of program design to reduce carbon emissions.

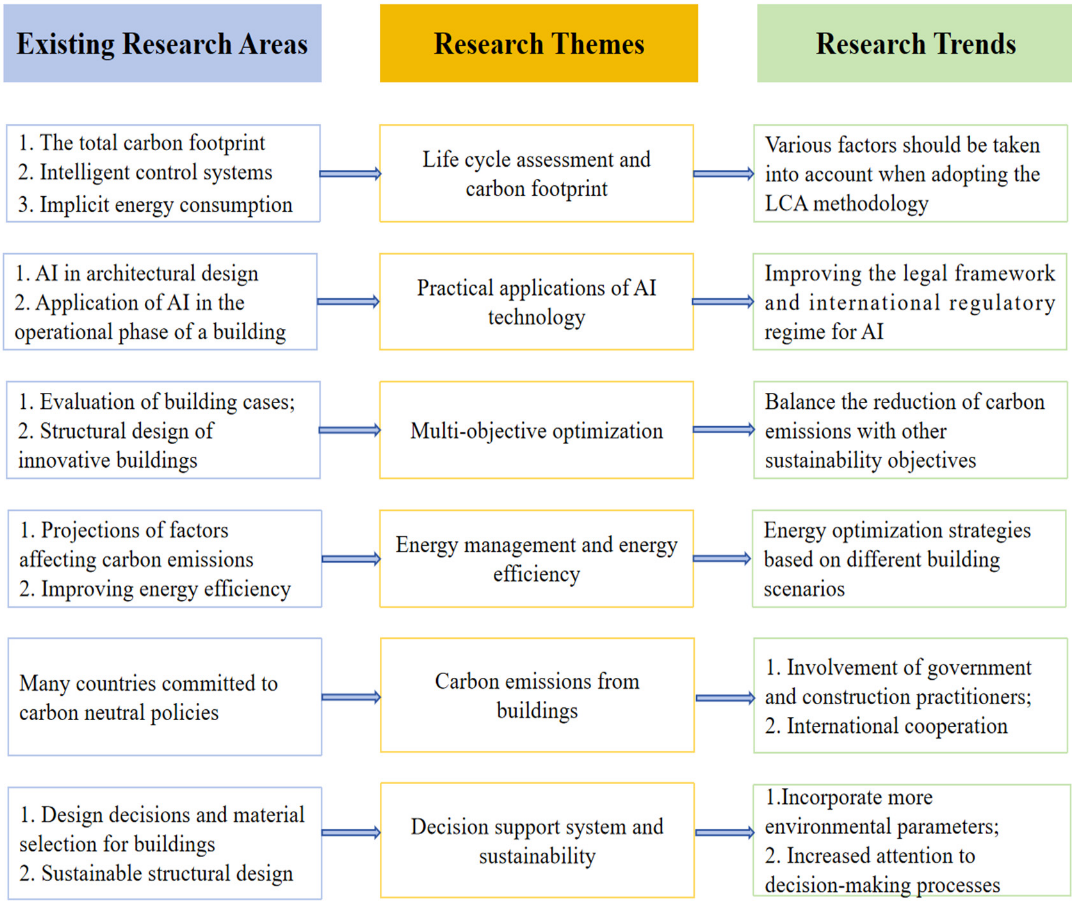

Figure 4. Proposed framework for the future research direction of AI in NZCEs for sustainable building projects.

5. Conclusions

In this review study, we conduct a systematic literature and science mapping review of AI applications in NZCEs for sustainable building projects. We employed a mixed-method approach (i.e., systematic literature review and science mapping) consisting of four comprehensive stages: search strategy, selection criteria, science mapping analysis, and qualitative discussion. The Scopus database was used to retrieve relevant articles, and 154 articles were included in further analysis. The results revealed a significant increase in relevant published articles in the studied research domain since 2019. Moreover, the most influential journals that published several articles during the study period were the *Journal of Cleaner Production*, *Applied Energy*, *and Energy and Buildings*. According to the keyword co-occurrence analysis, "building energy performance", "energy consumption", and "decision support system" had the highest average normalized citations, whereas "multi-objective optimization", "artificial intelligence", and "renewable energy" were the most recently used keywords. In addition, countries such as China, Australia, Malaysia, and the United Kingdom had the highest total link strength, suggesting strong connections with other countries in the studied research domain.

The qualitative discussion focuses on mainstream research topics and gaps and summarizes future research directions in AI in NZCEs for sustainable building projects. Six mainstream research topics were identified and discussed. Next, this review study discussed six main research gaps: (1) existing problems of the life cycle assessment method, (2) opportunities and challenges faced by AI techniques in sustainable buildings, (3) scope of application of multi-objective modeling, (4) improvements in energy management and efficiency, (5) raising awareness of reducing carbon emissions, and (6) sustainable development of buildings. Finally, this review study proposed a research framework for future research directions that could help researchers and practitioners advance related research areas in this domain.

5.1. Study Implications and Contributions

This study has several theoretical and practical implications. First, it emphasizes the reduction in carbon emissions through advanced technological innovations. The application of AI can effectively minimize the negative environmental impact of the construction industry, transition the construction industry toward low-carbon practices, and achieve sustainable development. Second, this review provides other scholars with new research methods and models to gain insights into the factors affecting carbon emissions. For example, it suggests potential areas that require attention to achieve NZCEs. Third, the findings of this review would assist local governments and project practitioners (e.g., project managers, workers, etc.) in raising awareness and actively participating in reducing carbon emissions. One potential initiative is to introduce stringent building codes that mandate the use of energy-efficient materials and technologies. These codes can be coupled with incentives such as tax breaks or grants for developers who exceed the minimum sustainability requirements [153]. Additionally, local governments could establish green certification programs that recognize and reward buildings to achieve high standards for energy efficiency and carbon footprint reduction. Another key policy could involve providing subsidies or low-interest loans to support the adoption of AI-based tools in building design and management, facilitating the transition toward more sustainable construction practices [119]. By enacting these policies, local governments can drive the adoption of the best practices identified in the literature and contribute significantly to reducing the environmental impact of the built environment.

The differences in building types in different regions are also considered, which provides managers in the construction industry with effective management solutions to improve existing energy management systems and focus on environmental sustainability indicators. One prominent management solution involves the use of AI-powered building energy modeling, which allows precise predictions of energy consumption under various operational conditions. This technology enables building managers to optimize energy use, reduce waste, and reduce overall carbon emissions [154]. Another solution involves the integration of smart sensors and IoT (Internet of Things) devices, which provide real-time data on building performance, enabling proactive adjustments to improve efficiency [155]. When implemented effectively, these technologies offer powerful tools for achieving and maintaining high energy efficiency in buildings. Achieving NZCEs is a focus of attention for construction projects and companies and practical action for the entire construction industry. As such, it would help the construction industry and other related industries (e.g., manufacturing, automobile) adopt smart and environmentally friendly approaches to improve project efficiency and achieve economic and environmental benefits.

Traditionally, life cycle assessment (LCA) has focused mainly on operational emissions; however, embodied carbon emissions in LCA are increasingly recognized as essential for a more comprehensive assessment of a building's environmental impact. Embodied carbon refers to greenhouse gas emissions associated with the extraction, production, transportation, and installation of building materials and their disposal at the end of a building's life. By integrating both embodied and operational emissions into LCA, stakeholders can better understand the total carbon footprint of a building across its entire life cycle. This holistic approach is crucial, especially in modern construction, where energy-intensive materials and processes significantly contribute to a building's overall carbon emissions [156,157]. Such an integrated assessment enables more informed decision-making and supports the development of strategies aimed at reducing both types of emissions, ultimately contributing to more sustainable building practices [158]. In addition, this research also calls for countries worldwide to learn from each other's successful experiences and work together to address the challenges of climate change.

5.2. Limitations and Future Research Directions

Although the application of AI in sustainable building projects offers substantial benefits, it also presents several challenges that need to be addressed. One significant challenge is the requirement for high-quality training data. AI models, particularly those based on machine learning, rely heavily on large datasets for learning and making accurate predictions. However, acquiring such datasets can be difficult, especially in the construction industry, where data collection is often inconsistent, and data quality can vary significantly [159]. Another challenge is the "black box" nature of some AI algorithms, particularly deep learning models. These models can produce highly accurate predictions; however, their internal workings are often opaque, making it difficult to understand how specific decisions are made. This lack of transparency can be problematic in the construction industry, where accountability and trust are critical [160]. Addressing these challenges requires ongoing research and development of methods to enhance the interpretability of AI models and improve data quality in the construction sector.

Despite the contributions of this study, it still has some limitations. This study only used one database (Scopus), and the search was limited to journal articles written in English only. It is recommended to utilize other databases in order to obtain more complete and comprehensive results. Moreover, the source publication type was limited to journals. Integrating multiple databases and document types in review studies presents significant challenges, particularly regarding data harmonization. Differences in data formats, metadata standards, and terminologies across databases can create inconsistencies that can complicate data analysis and interpretation. Harmonizing these data requires extensive preprocessing, which can be time-consuming and prone to errors if not meticulously performed [161]. Additionally, the variation in document types, ranging from structured databases to unstructured text, further complicates the integration process, as different approaches and tools are often needed to extract and standardize relevant information [162]. Addressing these challenges is critical for ensuring the accuracy and reliability of research findings in review studies that rely on diverse data sources. However, it is beneficial to incorporate multiple data sources if the risks mentioned here can be minimized to enhance the authenticity and usability of these findings; future research should consider more databases, document types, multiple languages, and source publication types. Future research could also use the PRISMA diagram format to summarize data from the extracted articles.

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