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Artificial intelligence in achieving carbon-neutral buildings: a critical analysis of the emerging techniques, their applications and challenges

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ABSTRACT

Given the increasing energy consumption and carbon emissions within the building sector, developing carbon-neutral buildings (CNB) has become essential in recent times. To further advance the development of CNB, the use of Artificial Intelligence (AI) technologies has been considered beneficial. This paper aims to explore the application of AI in achieving CNB by focusing on emerging techniques, their applications/functions in achieving CNB, and their associated challenges. The current study employs a mixed method of literature review using both bibliometric and systematic reviews. Based on the 77 selected journal articles analysed, the results show 35 emerging AI tools for delivering CNB. Further, 30 barriers to AI adoption in delivering CNB were explored using the Technological-Organizational-Environmental framework. Major barriers include lengthy computational times, high operational complexity, large datasets, limited human resource skills, and high costs. The outputs of this study will inform practitioners on the key AI tools to consider when developing CNB. More importantly, the findings will serve as a basis for formulating relevant hypotheses for further empirical investigations.

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Carbon reduction goals; carbon neutral buildings; net zero carbon; artificial intelligence; project management

Introduction

Climate change has become one of the world's environmental challenges in the last two decades, with an increase in the occurrence of floods, fires, and droughts (Dorr, Goldstein, Aubry, Gabrielle, & Horvath, 2023; Muhammad, Ibrahim, & Dalibi, 2020). Climate change is driven by the increased concentration of greenhouse gases in the atmosphere, predominantly resulting from the combustion of fossil fuels and associated human activities (Carlander & Thollander, 2023). These greenhouse gases, mainly carbon dioxide and methane, block the sun's heat, thereby raising global temperatures (United Nations Climate Action Plan, 2025). It has been projected that global warming would exceed 1.5 and 2 °C, and carbon emissions would increase by 25%–90% in the next couple of decades, unless carbon emissions and other greenhouse gases are reduced to net zero (IPCC, 2021).

The building sector has been considered a significant contributor to carbon emissions (Falana, Osei-Kyei, & Tam, 2025). The building sector accounts for approximately 40% of global carbon emissions. It is estimated that building energy consumption will grow by 15% between 2013 and 2035 (Yang, Ghahramani, & Becerik-Gerber, 2016). Consequently, it is imperative that all new buildings achieve climate

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neutrality by 2030 and that all buildings transition to carbon neutrality by 2050. Thus, attaining climate neutrality by 2050 in the building sector is paramount in realizing the emission targets set by the Paris Agreement. In this context, a carbon-neutral building (CNB) is considered an effective strategy to reduce the carbon footprint generated by the building to net zero or less than zero.

CNBs are healthy buildings that have the potential to positively influence the natural environment and mitigate the adverse effects of carbon generated by the building throughout its lifecycle (Falana, Osei-Kyei, & Tam, 2024b; World Green Building Council, 2022). CNBs are buildings that can conserve resources (energy, land, water, and materials) and the environment, significantly reducing pollution to the bare minimum over their life cycle (World Green Building Council, 2022). Due to the benefits of CNB, it has become essential for practitioners and stakeholders to consider adopting innovative approaches towards achieving carbon neutrality goals in the building sector. One of the innovative approaches identified in the literature for achieving CNB is the use of artificial intelligence (AI). Artificial Intelligence (AI) has emerged as a promising technique to mitigate climate change and can help achieve the goal of carbon neutrality (Akomea-Frimpong et al., 2025; Tao, Weng, Chen, ALHussan, & Song, 2024). More specifically, Artificial Intelligence (AI) could reduce building energy consumption and carbon emissions by 8% to 19% in 2050 if properly utilized (Ding, Ke, Levine, & Zhou, 2024). AI has played a crucial role in the building sector by advancing building materials, technologies and structural design to mitigate carbon emissions (Attia, Hamdy, O'Brien, & Carlucci, 2013). Several studies highlight the profound impact of integrating AI with CNB to ensure significant structural stability and mitigate negative ecological effects on the environment and society (Chen, Ge, Liang, Jin, & Du, 2024; Liu, Liu, Qian, & Song, 2022). Countries and organizations have advocated for, invested in, and implemented several initiatives to encourage the use of AI in achieving carbon neutrality in the building sector. Despite governments' and stakeholders' efforts towards achieving CNB through AI, there are still reported challenges that affect the effective and efficient use of AI in achieving CNB (Akomea-Frimpong et al., 2025). Therefore, it has become imperative for the barriers to adopting AI for CNB to be thoroughly examined to enable practitioners to adopt proper measures for future implementations.

Although past studies, including Lee, Avelina, Rim, Chi, and Ahn (2023), Chen et al. (2022), Liang, Zheng, Wang, Liang, and Hu (2023) and Tushar et al. (2023), have attempted to conduct a review of CNB, and their findings are useful, these studies focused on the general strategies and methods for achieving CNB. Notably, the past studies failed to holistically explore the specific AI tools and the barriers to their usage in achieving CNB. Considering that the use of AI has become essential in modern construction practices, particularly towards CNB, it is necessary for a holistic approach to be adopted to explore the AI tools, their applications and barriers to their usage towards achieving CNB. Such a review study is critical during this period to inform future research directions and policy practices towards AI adoption in CNB.

Against this background, this study critically analyses the extant literature to unravel the new and emerging AI tools and their applications/functions for achieving CNB. Further, the barriers/challenges to using AI in delivering CNB are also explored using the Technology-Organizational-Environment model.

The results of this study will facilitate the successful implementation of CNB and align with the global sustainability 2030 and 2050 goals. Most importantly, they will serve as a theoretical foundation for future research directions.

Methodological approach

This study aims to review the existing studies and trends related to the application of AI in achieving CNB. A mixed-methods literature review was employed in this study, combining a systematic literature review (qualitative) using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol and a quantitative review (bibliometric analysis) to achieve the study aim.

To achieve the aim of this study, this research methodology is in three stages: (1)exploring the chosen database, (2) application of exclusion criteria stage for screening the important articles, and (3) data mining stage (Debrah, Chan, and Darko 2022). Figure 1 illustrates the overall research framework.

Search and identification of existing studies process and criteria

The Scopus database was adopted in this research work to search for and capture relevant studies related to the research theme. Several studies have utilized only Scopus to locate important literature relevant to the study field. Scopus is a multidisciplinary database that extracts literature related to a field of study from several reputable journals. Moreover, Scopus is the largest and most recognized academic data source for systematic and bibliometric review analysis (Qin, Xu, Wang, & Škare,

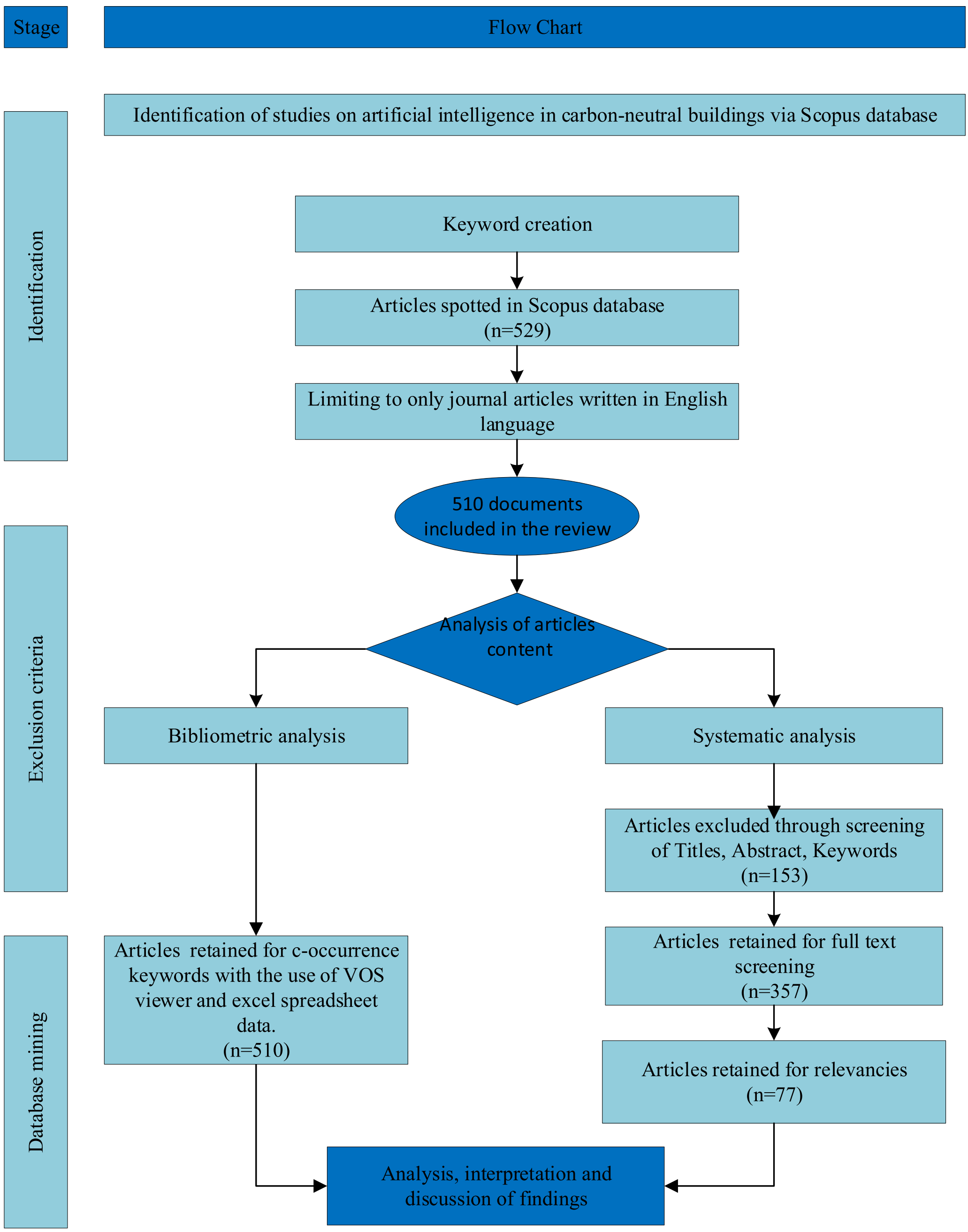

Figure 1. Research framework.

2022; Tijani, Nwaeze, Jin, & Osei-Kyei, 2023). Compared to Web of Science, Google Scholar and PubMed databases, Scopus has been deemed to have better search accuracy and performance (Falana et al., 2025; Osei-Kyei, Tam, Ma, & Mashiri, 2021). The preliminary search was conducted using a keyword search string as listed in Table 1. Multiple keywords were used.

To avoid being restrictive and to keep the data up to date, the title, abstract, and keywords publication search were not constrained to a defined time frame. Following the search, 529 papers related to AI in CNB were identified in this stage, with a citation frequency of 20,000.

Exclusion criteria

The 529 papers generated in the identification stage were further screened by limiting them to English-written peer-reviewed journal articles only. The reason is that peer-reviewed journal articles portray research studies that are most reputable and recognized (Santos, Costa, & Grilo, 2017). Overall, 510 papers met the criteria, following the elimination of documents published in books, book chapters, conference reviews, conference proceedings, editorials, and notes categories.

Content analysis

Bibliometric analysis

This study conducts a bibliometric analysis to comprehensively assess the knowledge domain. The VOSviewer 1.6.20, a bibliometric data technique, was chosen to analyse and visualize the bibliometric data from Scopus (Opoku, Perera, Osei-Kyei, & Rashidi, 2021; Osei-Kyei et al., 2021). 510 journal articles retained in the second stage were downloaded in CSV (comma-separated value) files from Scopus, which cover the author's data, published article data, and article source data. The sample size of 510 was considered adequate for the bibliometric analysis compared to other studies that adopted this approach (E.g. (Geng, Ma, Osei-Kyei, Jin, & Shrestha, 2025) (96 papers)). More importantly, AI in CNB is still emerging; therefore, having a small number of papers in this area for bibliometric analysis is reasonable. VOSviewer is an open-source software tool that offers sufficient features for visualizing bibliometric networks and scientifically mapping literature through clustering and density maps (Salihu, Hussein, Mohandes, & Zayed, 2022). The data were uploaded to the VOSviewer software to create spatial representations that assist in generating, understanding, and interpreting the co-occurrence networks of keywords.

Systematic analysis

To conduct a systematic analysis for this study, 510 documents obtained in stage 2 were subjected to abstract screening to filter out journal articles that did not conform to the research theme and could not provide important information concerning the research theme. 153 articles were excluded, and 357 journal articles were reserved for the complete text assessment. The 357 journal articles were subjected to a thorough screening of the full text. Most of the articles were dismissed after full-text screening because they did not adequately explore the study's focus. Overall, 280 journal articles were eliminated after the full-text examination. The remaining 77 journal articles (see Appendix 1)

Table 1. Search string adopted for this study.

Search Engine	Search String	Results
Scopus	TITLE-ABS-KEY ('AI' OR 'computational intelligence' OR 'robotics' OR 'artificial intelligence' OR 'expert systems' OR 'machine learning' OR 'machine intelligence' OR 'computer vision' OR 'neutral networks' OR 'genetic algorithms' OR 'data mining' OR 'deep learning' OR 'transfer learning') AND TITLE-ABS-KEY ('carbon neutral' OR 'net zero energy' OR 'zero energy' OR 'zero carbon' OR 'low energy' OR 'net zero carbon' OR 'nearly zero carbon' OR 'energy neutral' OR 'low carbon' OR 'energy positive' OR 'carbon positive' OR 'nearly zero energy' OR 'zero emission' OR 'net zero emission' OR 'climate neutral') AND TITLE-ABS-KEY ('housing' OR 'building')	529

were deemed significant for this study and were selected for data extraction and further investigation. It should be emphasized that, despite a thorough search of the database, some relevant journal articles may have been missed. However, this does not invalidate the authenticity of the research findings because this paper aims only to explore the trend in the use of AI in achieving CNB but does not assess the entire population of journal articles in CNB. Notwithstanding, the selected 77 articles are considered adequate for further analysis when compared to many past review papers in construction management, such as (Osei-Kyei et al., 2021) (35 papers), (Falana et al., 2025) (37 papers) and (Kukah, Jin, Osei Kyei, & Perera, 2025) (68 papers). Two structural dimensions were identified and will be further explored in the discussion section based on the arrangement below:

1. AI techniques and their applications/functions towards achieving CNB.
2. Critical barriers to the use of AI in achieving CNB.

Results and discussion

This section is classified into two parts. The first part discusses the findings of the bibliometric analyses, while the second emphasizes the findings of the systematic analysis.

Bibliometric analysis results

Active countries in the research on the use of AI in achieving CNB.

Analysing the active countries in the research on the use of AI in achieving CNB revealed a chain of authors collaborating to broaden the field of study. The collaboration of active countries focusing on the study theme is demonstrated in Figure 2. As shown in the figure, some countries contribute more than others in using AI to achieve CNB research discourse. The node size reflects the country's weight based on its participation in the research domain. The larger the node of each country, the greater the country's research participation. Figure 2 was produced by establishing 5 and 20, respectively, as the least number of documents and citations of a country. Among the 72 countries generated in the VOSviewer, only 33 meet the thresholds. This implies that approximately 45% of all countries globally have the strongest link strength in co-authorship research on AI for achieving CNB. As shown in the figure, China, the United States, Italy, the United Kingdom, and Hong Kong are the leading countries/regions producing quality research focusing on this study theme. This aligns with the study by Darko et al. and Wuni et al. (2019), which found that the United States, Italy, China, the United Kingdom, and Hong Kong are the leading countries/regions in CNB research on zero-carbon buildings. Moreover, five clusters of the most effective countries in AI research for achieving CNB are shown in the figure. China, Hong Kong, Singapore, and Japan form one cluster, characterized by yellow, while

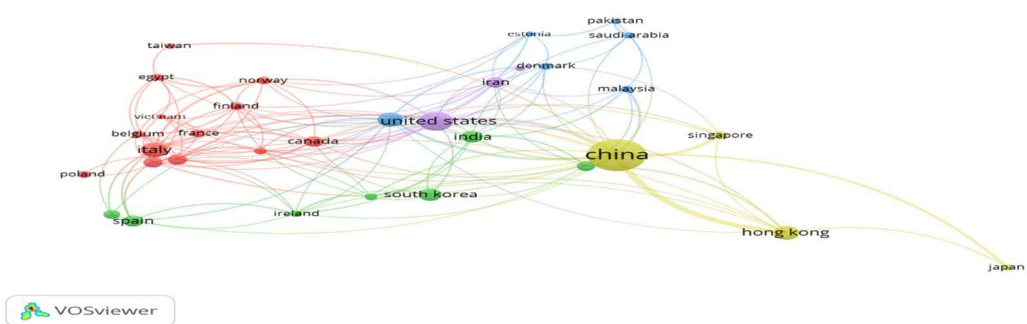

Figure 2. Active countries contributing to the research of using AI in achieving CNB.

separate colours denote other clusters. It is important to note that these clusters are produced based on authors' collaboration in different countries, considering their co-citations and interest in related research areas.

Systematic analysis results

AI techniques and their application/functions toward achieving CNB.

CNB has been considered an important strategy for reducing greenhouse gas emissions in the building sector, but the development status of CNBs is unsatisfactory (Falana, Osei-Kyei, & Tam, 2024a; Liu et al., 2023). AI has attracted much attention in the building sector as one of the effective approaches towards realizing carbon neutrality throughout the building lifecycle (Farzaneh et al., 2021). AI is a technology or programme that utilizes computer algorithms capable of executing tasks that require human cognitive functions, whether by mimicking human cognitive functions or intelligence (Shang, Low, & Lim, 2023). Most specifically, AI techniques and algorithms have the potential to revolutionize the building sector, making it intelligent, more effective, and secure (Ferdaus, Dam, Anavatti, & Das, 2024). However, the concept of AI is underpinned by the belief that the process of human thinking can be programmed (Mehmood et al., 2019). That implies AI can sense, understand, take actions, and learn during data processing. AI has prospects in climate change mitigation, and several AI techniques with their algorithms mentioned in existing studies can be used to achieve CNB. The AI techniques and algorithms identified in this study are inherent in making a building more energy-efficient and environmentally friendly. The list of emerging and recent AI techniques/algorithms in achieving CNB is presented in Table 2. The number of times a technique has been reported is shown in the last column in Table 2. Furthermore, the definitions of the techniques and algorithms are provided in the table for clarity. As shown in the table, the top five AI techniques/algorithms for achieving CNB are Genetic Optimization Algorithm (GOA), Random Forests (RF), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN) and Decision Trees (DT).

A further analysis was conducted to derive the applications/functions of the AI techniques listed in Table 2. Seventeen applications/functions were derived, and these are presented in Table 3. Table 3 also includes the required data set, the domain of applications in the construction process, and the number of times each application/function was identified in these studies.

Critical barriers to the use of AI in achieving CNB

This section examines the barriers to the use of AI in CNB. Examining the barriers to AI in CNB is important because it enables practitioners and stakeholders to understand the fundamental problems associated with AI usage in CNB. This will offer an opportunity for more informed policy strategies to be developed for future implementations. Table 4 presents the most reported barriers associated with the use of AI in achieving CNB as identified from the 77 selected articles. Further, the strength of evidence of each barrier is also presented in the table. The strength of evidence is classified as high, medium and low. Any barrier identified through more than two research methods, such as case studies, interviews, surveys and experimental design, is classified as high. A barrier identified through only two methods is classified as medium, and any barrier identified through one method is classified as low. As shown in the table, 30 barriers were derived, and to further analyse these 30 barriers, the Technology-organization-environment (TOE) framework was adopted. The TOE framework explains how the use of AI in achieving carbon neutrality in the building sector could be influenced from a technological, organizational, and environmental perspective. Thus, it provides valuable insight into formulating detailed strategies to facilitate the successful adoption of AI towards achieving CNBs. Although extant studies have adopted several frameworks and theories when investigating the acceptance and implementation of innovations and technology within the building sector, these frameworks (including the Diffusion of Innovation Theory and the Technology Acceptance Model (TAM)) do not accommodate organizational or environmental perspectives (Álvarez-Sanz et al., 2024; Ullah, Qayyum, Thaheem, Al-Turjman, & Sepasgozar, 2021).

Table 2. Most reported and emerging AI techniques in CNB.

AI techniques/algorithms.	Descriptions	References.	No.
Genetic Optimization Algorithm (GOA)	It is used for decision-making and optimization in building and engineering design. It functions by evolving a population of possible solutions over multiple generations. It also is used to search for near optimal or optimal solutions to complex problems in achieving CNB.	(Kim et al., 2024), (Yu et al., 2024), (Zhou & Liu, 2024), (Ntafalias et al., 2024), (Zhang et al., 2024), (Wang et al., 2024), (Luna-Romero et al., 2024), (Salihu et al., 2022), (Ntafalias et al., 2024), (Cen and Lim, 2024), (Mohammadi et al., 2024), (Chen et al., 2024), (Ruggeri et al., 2023), (Cui et al., 2024), (Sadeghibakhtiar et al., 2024), (Liu et al., 2023), Weng et al. (2015).	17
Random Forests (RF)	It uses decision trees to forecast carbon emissions in buildings and projects. Its predictions could provide an accurate estimate of carbon emissions, drawing on data	(Kim et al., 2024), (Yu et al., 2024), (Cao et al., 2024), (Ntafalias et al., 2024), (Zhang et al., 2024), (Wang et al., 2024), (Álvarez-Sanz et al., 2024), (Cen and Lim, 2024), (Zhang et al., 2024), (Chen et al., 2024), (Liu et al., 2023), (Dan et al., 2024), (Zhou & Liu, 2024), (Zhao, Wu, Hao, Wang, & Zhou, 2024).	14
Long Short-Term Memory (LSTM)	It is an enhanced version of RNN, which uses gates to retain long-term and short-term memory. This technique is used in CNB to forecast building energy demands and generation	(Das et al., 2024), (Zhou & Liu, 2024), (Salehi et al., 2024), (Cen and Lim, 2024), (Liu et al., 2024), (Wang et al., 2024), (Salehi et al., 2024), (Chen et al., 2024), (Sadeghibakhtiar et al., 2024), (Liu et al., 2024).	10
Recurrent Neural Networks (RNN)	It is a deep neural network model that possesses a memory of previous data, which can be used to predict environmental assessment, carbon emissions and energy usage of buildings	(Kim et al., 2024), (Cen and Lim, 2024), (Liu et al., 2024), (Wang et al., 2024), (Salehi et al., 2024), (Cen and Lim, 2024), (Chen et al., 2024), (Sadeghibakhtiar et al., 2024), (Liu et al., 2024).	9
Decision Trees (DT)	It uses a divide-and-conquer approach to solve complex problems. It is in the form of a tree-like structure that can predict or forecast carbon emissions, energy usage or generation in buildings based on predefined data sets	(Kim et al., 2024)., (Yu et al., 2024), (Zhang et al., 2024), (Liu et al., 2023), (Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	7
Generative Adversarial Network (GAN)	This AI tool is used to solve the generative modelling problem. It derives backpropagation signals through a competitive process from network signals. GAN is used to predict the energy consumption of buildings in construction	(Liu et al., 2023), (Wang et al., 2024), (Salehi et al., 2024), (Cen and Lim, 2024), (Chen et al., 2024), (Sadeghibakhtiar et al., 2024), (Liu, Zhang, Sun, & Zhou, 2023).	7
Backpropagation (BP) neural network based on particle swarm optimization	This is a multilayer feed-forward network which uses an error-back propagation algorithm for data training. It can be used to estimate or predict carbon dioxide emissions from CNB	(Liu et al., 2023)., (Salehi et al., 2024), (Cen and Lim, 2024), (Chen et al., 2024), (Sadeghibakhtiar et al., 2024), (Liu et al., 2023).	6
Genetic Algorithm (GA) (non-dominated sorting genetic algorithm (NSGA)-III and NSGA – II)	This tool is used for multi-objective optimization. This can be used to develop optimization model to reduce carbon emissions in CNB	(Kiavarz et al., 2023), (Cao et al., 2024),(Liu et al., 2023), (Cui et al., 2024), (Song et al., 2024), Coley and Schukat (2002)	6
Support Vector Machines (SVM)	This technique is used for classification and pattern recognition. It can handle both linear and nonlinear data set segregation. This tool can be used to predict thermal comfort in CNB. It can also predict the carbon emissions and energy consumption in CNB.	(Cao et al., 2024), (Zhang et al., 2024), (Liu et al., 2023), (Zhang et al., 2024), (Zhou & Liu, 2024), (Wang et al., 2024).	6
Extreme Gradient Boosting (XGBoost) model	This tool works based on a gradient boosted decision tree. It uses a new tree learning algorithm to handle less data. It can be used to accurately predict life-cycle carbon emissions in CNB. Also, it can be used to predict the cost of CNB.	(Yu et al., 2024), (Zhang et al., 2024), (Chen et al., 2024), (Álvarez-Sanz et al., 2024), (Du & Gou, 2023)	5

(*Continued*)

Table 2. Continued.

AI techniques/algorithms.	Descriptions	References.	No.
Support Vector Regression (SVR)-supervised model	The model is used to evaluate energy usage of buildings to enhance their energy consumption characteristics. It is also used to forecast future energy consumptions in buildings through modelling non-linear relationships factors such as energy consumption and carbon emissions.	(Kim et al., 2024), (Yu et al., 2024), (Zhou & Liu, 2024), (Luna-Romero et al., 2024), (Liu et al., 2023).	5
Gaussian Regression (GR)	This probabilistic technique is used to estimate building's heating/cooling power demand and carbon emissions. assess factors such as weather and occupancy. As a probabilistic approach it generates accurate estimates considering uncertainty in factors such as weather and occupancy.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024), (Cao et al., 2024).	4
Light Gradient Boosting Machine (LightGBM)	This machine learning tool is based on decision tree algorithms. It is used for identification and classification of the most critical factors which impact the carbon footprint.	(Zhang et al., 2024), (Yu et al., 2024), (Du & Gou, 2023).	3
AdaBoost Regression (ABR)	This tool works based on decision trees principles. It estimates carbon emissions in buildings based on various scenarios (e.g. energy-saving) and is used to develop more effective policies in the field.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
Back-Propagation Artificial Neural Network	This algorithm uses a multi-layer feedforward neural network to predict energy consumption, building cost, thermal comfort and other aspects of CNB. It is often used to develop design and renovation strategies to balance conflicting CNB aspects.	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3
Bagging Regression (BR)	This machine learning model uses predictions from multiple regression algorithms and combines them to improve accuracy in estimations. It is used to estimate carbon emissions of buildings considering factors related to weather conditions, building design, and occupancy.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
Bayesian Regularized Neural Network (BRNN)	This neural network is based on Bayesian statistics. It is often used to detect overfitting issues in estimations, and it more precisely develops nonlinear energy-use patterns. It predicts building performance under different operational or environmental conditions	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024)	3
Bayesian Ridge Regression (BR)	This linear regression tool uses probabilistic data (such as related to environmental and building conditions) and generates more robust forecasts of energy consumption and carbon emissions. It works well with noisy or small datasets.	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3
Decision Tree Regression (DTR)	This algorithm divides dataset into smaller distinct decision trees based on input thresholds. It is used to define the most critical factors which affect the energy consumption and carbon footprint.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
Elastic Net Regression (EN)	It is a linear model which is used to test the impact of key factors on CNB	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3

(*Continued*)

Table 2. Continued.

AI techniques/algorithms.	Descriptions	References.	No.
	performance. It uses such factors as energy consumption, temperature, humidity, and occupancy to model CNB performance avoiding overfitting in estimates.		
Extremely Randomized Trees (ET)	This AI algorithm is used in highly random environments when there is lack or uncertainty in data. It is used to detect nonlinear relationships between CNB conditions (factors) and its carbon performance.	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3
Extremely Randomized Trees Regression (ETR)	It uses regression principles to model energy consumption and carbon intensity. It well handles variability and noise in input factors including those related to daily energy use, outdoor climate, and ventilation rates.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
Histogram-Based Gradient Boosting (HGB)	This technique is used in modelling complex nonlinear relationships. It uses factors related to weather, occupancy, equipment, and temperature to create high-precision estimates of energy consumption and emission in CNB.	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3
Kemel-Based Nonlinear Regressor (KNR)	This AI tool is used to model nonlinear relationships in CNB analysis with flexibility in its functional form. It uses outdoor temperature, solar irradiance, and occupancy levels to predict energy demand and thermal loads.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
K-Nearest neighbours (KNN)	This AI tool predicts CNB performance by averaging values from the k-most similar past data points. It is used to estimate energy consumption, cooling or heating loads, and renewable generation in the short term.	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3
Model Predictive Control (MPC)	It is an optimization algorithm which estimates performance of building operations by minimizing energy use and carbon emissions.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
Multi-Layer Perceptron (MLP)	It is a feedforward neural network algorithm which examines the relationships between historical building data and its performance. It is used to estimate energy demand and comfort levels in CNB.	(Dan et al., 2024), (Zhou & Liu, 2024), (Zhao et al., 2024).	3
Ridge Regression (RD)	This linear regression AI model uses its regularization algorithm and prevents overfitting in CNB performance predictions. It helps to identify the patterns between CNB features and its carbon performance.	(Liu et al., 2023a), (Cui et al., 2024), (Zhang et al., 2024).	3
BIM blockchain	This technique creates a digital representation of physical and functional characteristics of a building. Its blockchain feature uses a secure and decentralized system. This tool helps to analyse and track carbon emissions in a more transparent way.	(Kiavarz et al., 2023), (Zhou & Liu, 2024).	2
Cuckoo Search Optimization Algorithm (CSOA)	The algorithm optimizes CNB design parameters to minimize energy use and carbon emissions based on brood parasitism behaviour.	(Wang et al., 2024), (Cen and Lim, 2024).	2
Gated Recurrent Unit (GRU) Networks	This tool employs advanced recurrent neural networks and learns temporal	(Wang et al., 2024), (Cen and Lim, 2024).	2

(*Continued*)

Table 2. Continued.

AI techniques/algorithms.	Descriptions	References.	No.
	sudden patterns. It is used to model the relationship between CNB input and output features considering their time-dependency specifically.		
Gradient-boosting decision trees (GBDT)	This machine learning technique can develop multiple decision trees sequentially. In CNB research, it is used for high-accuracy prediction of building performance indicators where each tree improves the predictions of the previous one.	(Cao et al., 2024), (Zhang et al., 2024).	2
K – Nearest Neighbour (KNN)	This non-parametric algorithm is commonly used for energy use prediction and benchmarking CNB performance. It uses time-series data of related to energy consumption and building performance.	(Zhang et al., 2024), (Chen et al., 2024).	2
Linear regression	This traditional AI tools models the relationship between independent factors and building performance using a linear function. Factors used for CNB analysis are related to building design and mechanical system configurations.	(Chen et al., 2024), (Du & Gou, 2023).	2
Particle swarm optimization algorithm	As CSOA, it is a nature-inspired tool which is used to solve optimization problems. It is used to optimize features related to CNB configurations and operational strategies to minimize carbon emissions, energy use, and their cost.	(Liu et al., 2023a), (Cui et al., 2024).	2

In this regard, TOE is considered more practical as it considers the organizational perspectives of technology adoption. It is worth noting that limited or no studies have yet adopted TOE in the context of implementing AI for achieving CNB.

The top three prominent barriers inhibiting the use of AI in achieving CNB include lengthy computational time, high operational and computational complexity, and big data sets with 26, 15, and 13 articles, respectively (Table 4). Table 4 shows that technological barriers were the most frequently cited compared to other barriers affecting the adoption of AI in the delivery of CNB. This outcome supports the study by Rjab et al. (2023), which identified technological barriers as the most prevalent among the three categories of barriers (technological, organizational, and environmental) to the use of AI in achieving CNB. However, in pursuing growth and increased efficiency through AI, understanding the general barriers to AI adoption is crucial for achieving CNBs and other sustainable buildings.

Technological-related barriers

Technological barriers are the issues regarding the functionality, techniques and use of AI in achieving CNB (Tornatzky, 1990). Nineteen barriers were identified in this group. The most recorded technological barriers that could impede the use of AI in achieving CNB include lengthy computational time, operational and large computational complexity, big data or large data sets required, model uncertainty, compatibility and complexity barriers. These findings align with Elsisi, Amer, Dababat, and Su (2023), who elucidated how long computational time could hinder the adoption of AI in achieving CNB due to the need to upload extensive data into the database. It is an arduous task to obtain and amalgamate large, high-quality data sets that are complete and heterogeneous (Wu, Li, Qin, Xu, & Liu, 2023). Fully leveraging the impacts of the multitude of parameters input into the database increases the computational burden while leading to computational complexity.

Table 3. Application/functions of AI in reducing carbon emissions in buildings

Application/functions of AI in reducing carbon emissions in buildings	Dataset required	Domain of application	References	No.
Monitoring, calculating, and forecasting energy use and carbon generated by the building.	Medium to Large dataset on carbon emissions and energy usage	Building maintenance	(Kiavarz et al., 2023), (Attia et al., 2013), (Dan et al., 2024), (Ntafalias et al., 2024), (Wang et al., 2024), (Lan et al., 2024), (Liu et al., 2024), (Zhao et al., 2024), (Lan et al., 2024), (Moraliyage et al., 2022), (Álvarez-Sanz et al., 2024).	11
Ability to enhance energy efficiency and create smart energy networks while lowering energy usage and surplus.	Large dataset on the energy usage of buildings	Energy optimization of building	(Kiavarz et al., 2023), (Zhao et al., 2024), (Zhang et al., 2024), (Ntafalias et al., 2024), (Liu et al., 2024), (Zhao et al., 2024), (Lan et al., 2024), (Moraliyage et al., 2022), (Álvarez-Sanz et al., 2024).	9
Ability to quantify and reduce life cycle costs, including price prediction in the building sector.	Large dataset on carbon emission costs and operational costs	Lifecycle cost and operational cost estimation	(Kiavarz et al., 2023), (García Kerdan & Morillón Gálvez, 2020), (Cao et al., 2024), (Ntafalias et al., 2024), (Cui et al., 2024), (Lan et al., 2024), (Sun, Qaisar, Khan, Xing, & Zhao, 2023), (Khan et al., 2023),	8
Could improve the architectural, electrical, mechanical and layout design of the building.	Large dataset of available drawings and specifications of the project	Design and planning analysis	(Kiavarz et al., 2023), (Lan et al., 2024),(Álvarez-Sanz et al., 2024), (Attia et al., 2013), (Liu et al., 2024), (Moraliyage et al., 2022).	6
Optimization of building design and energy-intensive building systems.	Large dataset of available drawings and specifications of the project	Design and planning analysis	(Zhao et al., 2024), (Moraliyage et al., 2022), (Wang et al., 2024), (Álvarez-Sanz et al., 2024), Weng et al. 2015)	5
Improves air quality, health, thermal comfort, well-being, and occupant satisfaction.	Medium to large data set of humidity, temperature and pollutants	Air quality estimation and occupancy comfort prediction	(Zhang et al., 2024), (Attia et al., 2013), (Liu et al., 2024), (Álvarez-Sanz et al., 2024).	4
The potential to find and forecast pollution with significant precision to facilitate carbon trading.	Medium to large dataset of pollutants and carbon emissions	Carbon estimation for carbon trading	(Zhang et al., 2024), (Attia et al., 2013), (LI & AZMAN, 2022), (Li & Azman, 2023).	4
Improves the efficiency of building equipment and detects failures before they occur.	Medium to large dataset on plant and equipment usage	Plant and equipment maintenance	(Attia et al., 2013), (Liu et al., 2024), (Jiao, Kang, & Sun, 2024), (Liu et al., 2024)	4
Could facilitate the effective decision-making and implementation of environmental policies based on carbon emissions prediction.	Medium to large dataset of carbon emissions	Strategic project management decision-making	(Attia et al., 2013), (Moraliyage et al., 2022), (Álvarez-Sanz et al., 2024), (Zhao et al., 2024).	4
Ability to analyse the impact of the surrounding environment on building energy and carbon-neutral performance.	Medium to large dataset on environmental pollutants and related data metrics	Environmental assessment	(Zhang et al., 2024), (Jiao et al., 2024), (Lan et al., 2024), (Álvarez-Sanz et al., 2024).	4
Can improve the architectural, electrical, mechanical and layout design of the building.	Medium to large data set drawings and specifications of project	Design analysis and planning	(Moraliyage et al., 2022), (Jiao et al., 2024), Coley and Schukat (2002)	3
Ability to identify abnormal patterns in electricity consumption and reduce grid electricity consumption.	Medium and large dataset of energy consumption	Electricity consumption estimation	(Wang et al., 2024), (Luna-Romero et al., 2024), (Álvarez-Sanz et al., 2024).	3

(*Continued*)

Table 3. Continued.

Application/functions of AI in reducing carbon emissions in buildings	Dataset required	Domain of application	References	No.
For the selection of CNB material and retrofitting of energy systems.	Medium to large data set of building materials	Materials management and scheduling	(Zhao et al., 2024), (Kiavarz et al., 2023), (García Kerdan & Morillón Gálvez, 2020).	3
The transition to CNB using AI could drive economic growth and reduce dependence on fossil fuels.	Small to medium dataset of economic macro indicators	Cost estimation and scheduling	(LI & AZMAN, 2022), (Li & Azman, 2023), (Lan et al., 2024).	3
AI can improve market competitiveness.	Small to medium dataset on demand and supply of market	Market analysis and prediction	(Cao et al., 2024), (LI & AZMAN, 2022), (Li & Azman, 2023).	3
Can allows for a nuanced examination of the policy's effects, considering economic and environmental data's complex and multi-dimensional nature.	Small to medium dataset on policy compliance indicators and economic metrics	Economic and market analysis	(Zhao et al., 2024), (Moraliyage et al., 2022),(Álvarez-Sanz et al., 2024).	3
Ability to predict future urban climate.	Small to medium dataset of urban carbon emissions	Enviornmental assessment and review	(Zhang et al., 2024), (Jiao et al., 2024).	2

Organizational-related barriers

Organizational barriers are mostly issues related to the project organization or the firms involved in delivering CNB. Nine organizational barriers were identified within this category. Based on the number of citations, limited skills in human resources, high cost of AI techniques and technologies, public fears, lack of data integrity, and computational cost were the most prominent organizational barriers. The shortage of human resources with specialized technical backgrounds to understand AI techniques increases the difficulty of using AI in delivering CNB. The acceptance of AI requires skills in data management, data mining and programming (Elsisi et al., 2023). These skills exceed basic computer skills and require the skills of an AI expert. Thus, AI experts need technical skills to develop and deploy AI algorithms to achieve carbon neutrality in the building sector.

Environmental-related barriers

The environmental barriers identified in this study relate to a lack of a legal framework, ethical concerns, data integrity issues, the negative impact of AI on sustainability, limited awareness and understanding of AI techniques, and the absence of user confidence. Several studies have emphasized the need for a comprehensive legal framework, including government policies and regulations, to aid decision-making when using AI in achieving CNB (S, B, & Appathurai, 2023). As mentioned by Elsisi et al. (2023), the absence of a standard legal framework on AI usage in CNB can result in unethical practices, which could affect personal privacy issues and companies' data security. Ji and Huang (2022) have added that regulations should be established to ensure that data is stored anonymously. Therefore, to ensure AI techniques are applied fairly and align with societal values and sustainability principles, governments should aim to establish a comprehensive legal and ethical framework for the usage of AI in achieving CNB.

Practical implications and future research directions

The findings of this study could provide policymakers with insights into developing and implementing effective policies that drive the adoption of AI in achieving CNB. Most importantly, ranking the barriers identified in this study would assist practitioners and decision-makers in focusing on the most significant barriers to AI adoption in CNB.

Below are some key recommended practice strategies. These strategies are believed to enhance the adoption of AI in achieving CNB.

Table 4. Critical barriers to the use of AI towards achieving CNB.

Category	Barriers	Descriptions	Strength of evidence (Based on research design)	References	Total
Technological	Lengthy computational time.	Training with big data and overloading the database will require a large amount of time. The training time is the time taken by a model to train on a dataset,	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (Batres, Dadras, Mostafazadeh, & Kavgic, 2023), (D'Agostino, Minelli, & Minichiello, 2023), (Abdou et al., 2022), (Ji & Huang, 2022), (Cordeiro-Costas, Villanueva, Eguía-Oller, & Granada-Álvarez, 2022), (Chegari, Tabaa, Simeu, Moutaouakkil, & Medromi, 2022), (Zhu, Ma, Zhang, & Xiang, 2021), (Ferrara et al., 2021), (Wu et al., 2023), (García Kerdan & Morillón Gálvez, 2020), (Camporeale & Mercader-Moyano, 2019), (Wu, Shen, & Cui, 2018), (Gilles, Bernard, Ioannis, & Simon, 2017), (Attia et al., 2013),(Park et al., 2013), (Caldas & Norford, 2002), (Z. Liu et al., 2023), (Elsisi et al., 2023), (Xu, Zhang, Yu, & Dong, 2023),(Tsai, 2024), (Du & Gou, 2023), (Elsisi et al., 2023), (Batres et al., 2023), (Khan et al., 2023), (Roth, Martin, Miller, & Jain, 2020).	26
	High operational and computational complexity.	The optimization approach and the process of inputting a multitude of parameters could result in a computational burden.	Medium – Multiple case studies	(Du & Gou, 2023),(Zhou, Xue, Du, & Ma, 2023), (Elsisi et al., 2023), (Wu et al., 2023), (Ferrara et al., 2021),(Pittarello, Scarpa, Ruggeri, Gabrielli, & Schibuola, 2021), (Roth et al., 2020), (Wu et al., 2018), (Gilles et al., 2017), (Zhao et al., 2024), (Batres et al., 2023), (Hongn, Bre, Valdez, & Flores Larsen, 2022), (Zhao et al., 2024), (Paudel et al., 2017).	15
	Requires large data set.	Problems may arise while obtaining flawless time-series datasets because of the massive dataset.	High – Multiple case studies, Experimental studies and interviews	(Zhang et al., 2024), (Du & Gou, 2023), (Z. Liu et al., 2023), (Elsisi et al., 2023), (Khan et al., 2023), (Cordeiro-Costas et al., 2022), (Garlik, 2022), (Ferrara et al., 2021), (Jalilzadehazhari, Johansson, Johansson, & Mahapatra, 2019), (Bäcklund, Lundqvist, & Molinari, 2024), (Das et al., 2024), (Kim et al., 2024), (Wu et al., 2023).	13
	Model uncertainty.	Difficulty in reusing AI models for different problems and comprehending how AI	High – Multiple case studies, Experimental	(Z. Liu et al., 2023), (Wu et al., 2023), (Roth et al., 2020),(Cheng & Ma, 2015),	8

(*Continued*)

Table 4. Continued.

Category	Barriers	Descriptions	Strength of evidence (Based on research design)	References	Total
		algorithms achieve a specific result. Moreover, AI operational features and user predisposition are most delineated by estimated unrealistic formulas encompassing constants, thus leading to untrustworthy data.	studies and interviews	(Attia et al., 2013), (Wu et al., 2023), (Ji & Huang, 2022), (Zhou & Liu, 2024).	
	Compatibility and complexity.	This relates to the difficulty in integrating AI with existing processes and workflows. Moreover, a multitude of parameters, and optimization techniques that encompass several decision variables could cause computational burden. Moreover, the hyperparameter adjustment procedure of some AI techniques such as SVM is a difficult process.	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (Garlik, 2022), (Álvarez-Sanz et al., 2024), (Zhao et al., 2024), (Khan et al., 2023), (Z. Liu et al., 2023), (Zhou & Liu, 2024), (Chen et al., 2024).	8
	Extensive computational effort and resources.	Difficult to use because of the tedious process and higher online computational demand.	High – Interviews, Experimental studies and Multiple case studies	(Hongn et al., 2022), (Camporeale & Mercader-Moyano, 2019), (Attia et al., 2013), (Caldas & Norford, 2002), (Z. Liu et al., 2023), (Elsisi et al., 2023), (Xu et al., 2023).	7
	Cyber or network security threats.	This is linked to the susceptibility of AI algorithms to cyber-attacks or other security dangers.	Medium – Multiple cases studies	(Z. Liu et al., 2023), (S et al., 2023), (Korkas et al., 2022), (Jiao et al., 2024), (Elsisi et al., 2023), (S et al., 2023), (Zhou & Liu, 2024),	7
	Complexity of AI use and implementation.	This indicates the arduousness of comprehending the use of AI techniques.	Medium – Multiple case studies	(Batres et al., 2023), (Ferrara et al., 2021), (Caldas & Norford, 2002).	3
	Lack of computing power and high volume of computing power.	Obtaining information from constantly updating databases for the application of AI requires continuous upgrading of processing power in data processing.	Medium – Experimental studies and Multiple case studies	(Kiavarz et al., 2023), (Xu et al., 2023), (Khan et al., 2023).	3
	Signal delay and long-term prediction.	Signal delay could occur when there is a time lag between the original data and the analysis platform, which may have an influence on its accuracy and efficiency.	Medium – Systematic Review and Multiple cases	(Elsisi et al., 2023), (Z. Liu et al., 2023).	2
	Lack of prediction accuracy	Prediction errors while using AI could result in a lack of prediction accuracy.	Low – Multiple cases only	(Ferrara et al., 2021), (Zhu et al., 2021).	2
	Bias and prejudice.	AI algorithms can collate biased data, indicating that AI systems could fortuitously deliver biased results. For example,	Low – Observational studies	(Srivastava, Mangla, Eachempati, & Tiwari, 2023), (Ji & Huang, 2022).	2

(*Continued*)

Table 4. Continued.

Category	Barriers	Descriptions	Strength of evidence (Based on research design)	References	Total
		computational black-box implementations are susceptible to user prejudice.			
	Lack of interpretability and transparency.	Relates to issues with accuracy and explainability around AI and when choosing a model. However, some models may be accurate but difficult to interpret. The reason is that some data-driven AI fails to show how they arrived at a decision when determining the output in a computational approach. However, the deficit of interpretability and transparency demonstrates the black box features of various AI methods, which are not favourable to authentication.	Medium – Observational and multiple case studies	(Kiavarz et al., 2023), (Jiao et al., 2024).	2
	Low interoperability and flexibility of models.	Relate to when two or more AI techniques, systems, and components find it difficult to exchange and integrate data when storing different data sources into different data formats.	Medium – Systematic Review and Multiple cases	(Attia et al., 2013).	1
	Deficit in structured method to carry out optimization.	In most scenarios, researchers adopt several approaches and ad-hoc methods without a standardized structure and categorization while using AI.	Medium – Systematic Review and Multiple cases	(Attia et al., 2013).	1
Organizational	Limited skills in human resources.	Relates to the skills necessary to operate and manage AI techniques. Limited availability of AI-ready talent and highly technical experts to handle data, data training time and maintenance issues.	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (LI & AZMAN, 2022), (Attia et al., 2013), (Camporeale & Mercader-Moyano, 2019), (Marin-Perez et al., 2019), (Xu et al., 2023), (Tsai, 2024), (Chen et al., 2024), (Feng et al., 2022).	10
	High cost of AI techniques and technologies.	The overall cost of investment in AI techniques and infrastructure is relatively weighty, and funds recoupling is slow, which escalates the opportunity cost of the building industry.	High – Multiple case studies, Experimental studies and interviews	(Z. Liu et al., 2023), (Elsisi et al., 2023), (Tsai, 2024), (Marin-Perez et al., 2019), (Zhou & Liu, 2024), (Bäcklund et al., 2024), (Ferrara et al., 2021), (LI & AZMAN, 2022), (S et al., 2023), (Deng, Zhang, Jiang, & Qi, 2024).	10
	Public fears.	This refers to the attitude, perceptions, and fear of the user towards AI techniques. This may be due to unawareness of the benefits and the techniques of using AI. The missing information	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (S et al., 2023), (Khan et al., 2023), (Attia et al., 2013), (Li & Azman, 2023), (Chen et al., 2024), (Srivastava et al., 2023).	7

(*Continued*)

Table 4. Continued.

Category	Barriers	Descriptions	Strength of evidence (Based on research design)	References	Total
		on the cost of AI techniques is a great concern. In addition, the fear that inputted data can be hacked.			
	Uncertainty of manual intervention.	Uncertainty in AI predictions due to working with big data sets.	Medium – Systematic Review and Multiple cases	(Jiao et al., 2024), (Rezaei Nasab, Tayefi Nasrabadi, Asadi, & Haj Seiyed Taghia, 2022), (Elsisi et al., 2023), (Das et al., 2024).	6
	Computational cost.	AI is highly computationally expensive due to increased implementation and maintenance costs.	High – Multiple case studies, Experimental studies and interviews	(Z. Liu et al., 2023), (Elsisi et al., 2023), (Batres et al., 2023), (Zhou & Liu, 2024), (Attia et al., 2013).	5
	Unemployment	Adopting AI in the building sector may lead to unemployment, social discrimination, and power inequality due to the substitution of human tasks and involvement with AI techniques.	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (S et al., 2023), (Khan et al., 2023), (Attia et al., 2013).	4
	The detrimental effect of AI on economic development.	Adopting AI may affect the economy because of replacing human tasks and the environment Moreover, there may be slow turnovers due to investing so much in AI infrastructure.	Medium – Experimental studies and Multiple case studies	(Elsisi et al., 2023), (S et al., 2023), (Khan et al., 2023), (Attia et al., 2013).	4
	Privacy issues.	Privacy issues refer to data breaches or unauthorized use of data saved in an individual's or a corporation's database or device.	Medium – Experimental studies and Multiple case studies	(Sun et al., 2023), (Khan et al., 2023), (Korkas et al., 2022).	3
	Inadequate AI infrastructure.	Inadequate AI infrastructure (AI systems such as software and technologies, buildings to support the effective use of AI.	Low – Multiple cases only	(Z. Liu et al., 2023).	1
Environmental	Lack of a legal framework.	Deficit of a legal framework on AI technologies, institutions and individuals' rights and obligations.	High – Multiple case studies, Experimental studies and interviews	(Ji & Huang, 2022), (Elsisi et al., 2023), (S et al., 2023), (Khan et al., 2023), (Attia et al., 2013).	5
	Ethical issues.	Issues related to algorithmic bias and mistakes accountability, which relate to the reliability of AI to make accurate and trustworthy decisions.	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (S et al., 2023), (Khan et al., 2023), (Attia et al., 2013), (Srivastava et al., 2023).	5
	Lack of data integrity	Lack of data integrity in case of transferring sensitive data, and most importantly, reliance on third-party AI providers and potential vendor lock-in.	High – Multiple case studies, Experimental studies and interviews	(Elsisi et al., 2023), (S et al., 2023), (Attia et al., 2013), (Jiao et al., 2024).	4
	Negative impact of AI on sustainability.	The more complex the datasets and models, the more energy is required to	Medium – Experimental studies and	(Elsisi et al., 2023), (S et al., 2023),	2

(*Continued*)

Table 4. Continued.

Category	Barriers	Descriptions	Strength of evidence (Based on research design)	References	Total
		train and run AI models. The increase in energy use affects carbon emissions in the operational stage of the building, thereby aggravating climate change.	Multiple case studies		
	Lack of awareness and understanding of AI techniques.	This relates to the situation where users in CNB resist AI adoption as a result of inadequate awareness and understanding of the use of AI in achieving CNB.	Low – Literature review only	(Zhou & Liu, 2024), (Das et al., 2024),	2
	Absence of user confidence.	Insufficient real-world demonstrations of AI applications and a lack of understanding of the training rules of AI techniques can sometimes be unclear.	Medium – Literature review and Multiple case studies	(Z. Liu et al., 2023), (Attia et al., 2013).	2

- Policies should be developed to govern ethical barriers to AI. This will ensure that AI use is trustworthy, based on human values, and maintains transparency. Moreover, it will keep AI data secure to protect users' privacy.
- Policymakers must implement economic policies (e.g. incentives, subsidies) as AI techniques and expert training are expensive.
- Government bodies and AI service providers should sponsor training to develop AI-related education programmes to educate users and improve the workforce on the use of AI. This would address incompetence and a lack of human resources. Moreover, new and improved AI techniques could also be developed to address technical issues such as lengthy computational times and high operational and computational complexity.
- Digital technology-related subjects must be added to tertiary institutions' construction management studies to enhance their AI literacy.
- A standard legal framework, including guidelines, should be developed to ensure that using AI is fully compatible with human values.
- Policymakers and decision-makers should exert more effort in investing in and improving the technical infrastructure to drive AI in the building sector.

For future research directions, conducting additional studies to develop ethical strategies and frameworks for utilizing AI to achieve CNB is crucial. Although AI presents functional benefits for achieving CNB, many ethical issues remain underexplored; therefore, more empirical studies should be conducted in this area. Lastly, AI training is required for construction workers and professionals. Therefore, more research studies should examine the critical AI skill sets required for project managers and construction workers towards delivering CNB.

Conclusion

Achieving carbon neutrality in the building sector is crucial for limiting the rise in global temperatures while mitigating the effects of climate change. An in-depth qualitative and quantitative review of 510 articles from Scopus was conducted to explore the use of AI in achieving CNB. Based on the quantitative analysis, the leading countries/regions in AI research in achieving CNB are China, the United States, Italy, the United Kingdom, and Hong Kong. Results from the comprehensive analysis of the 77 publications selected for systematic review indicate 35 emerging AI tools used in delivering CNB. Furthermore, using the Technological-Organizational-Environmental (TOE) framework, 30 barriers to AI adoption in delivering CNB were identified. According to the TOE framework, the use of AI in achieving CNB is more affected by technological barriers than organizational and environmental barriers. The top-ranked critical barriers identified in the literature include lengthy computational time (technological), high operational and computational complexity (technological), large data set (technological), limited skills of human resources (organizational), and high cost of AI techniques and technologies (organizational). To overcome these challenges, the study provides strategies to enhance the use of AI in delivering CNB.

The findings of this study provide valuable insights for both theory and practice. Theoretically, this study contributes to the growing body of research and the ongoing call for the use of AI to achieve CNB. This study has bridged the gap by conducting a comprehensive literature review to unearth emerging AI techniques, their applications/functionalities, and critical barriers to using AI in achieving CNB. Moreover, the TOE framework was adopted to categorize the barriers to a better comprehension of the research theme and to offer a sound theoretical foundation for advancing the study theme.

It is worth noting that the study has some limitations; the qualitative and quantitative data were obtained from Scopus databases, and the search string was restricted to journal articles only. It is possible that some journal articles may have been excluded despite the exhaustive search and thorough examination. Nonetheless, the outcomes are still helpful for future reference, considering that the number of articles is adequate compared to past studies.

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Zhu, S., Ma, C., Zhang, Y., & Xiang, K. (2021). A hybrid metamodel-based method for quick energy prediction in the early design stage. *Journal of Cleaner Production*, *320*, 128825. doi:10.1016/j.jclepro.2021.128825

Appendix 1 – List of selected papers for systematic review analysis

No.	Author and year	Title	Journal
1.	Kiavarz et al. (2024).	An Explainable & Prescriptive Solution for Space-based Energy Consumption Optimization Using BIM Data & Genetic Algorithm.	*Journal of Building Engineering.*
2.	Zhou and Liu (2024).	Advances in emerging digital technologies for energy efficiency and energy integration in smart cities.	*Energy and Buildings.*
3.	Y. Zhang et al. (2024b).	Data-driven optimization for mitigating energy consumption and GHG emissions in buildings.	*Environmental Impact Assessment Review.*
4.	Cao et al. (2024).	Enhancing mix proportion design of low carbon concrete for shield segment using a combination of Bayesian optimization-NGBoost and NSGA-III algorithm.	*Journal of Cleaner Production.*
5.	W. Liu et al. (2023).	Machine learning applications for photovoltaic system optimization in zero green energy buildings.	*Energy Reports.*
6.	Cui et al. (2024).	Study on the synergistic effects and eco-friendly performance of red mud-based quaternary cementitious materials.	*Construction and Building Materials.*
7.	Song et al. 2024).	Multi-objective capacity configuration optimization of the combined wind - Storage system considering ELCC and LCOE.	*Energy.*
8.	Kim et al. (2024).	Forecasting building energy demand and on-site power generation for residential buildings using long and short-term memory method with transfer learning.	*Applied Energy.*
9.	Cen and Lim (2024).	Multi-Task Learning of the PatchTCN-TST Model for Short-Term Multi-Load Energy Forecasting Considering Indoor Environments in a Smart Building.	*IEEE Access.*
10.	Yu et al. (2024).	A novel machine-learning based framework for calibrating micromechanical fracture model of ultra-low cycle fatigue in steel structures.	*Engineering Fracture Mechanics.*
11.	Ntafalias et al. (2024).	Smart buildings with legacy equipment: A case study on energy savings and cost reduction through an IoT platform in Ireland and Greece.	*Results in Engineering.*
12.	Wang et al. (2024).	Sustainable energy transition in cities: A deep statistical prediction model for renewable energy sources management for low-carbon urban development.	*Sustainable Cities and Society.*
13.	Luna-Romero et al. (2024).	Enhancing anomaly detection in electrical consumption profiles through computational intelligence.	*Energy Reports.*
14.	Salehi et al. (2024).	Comparative study of univariate and multivariate strategy for short-term forecasting of heat demand density: Exploring single and hybrid deep learning models.	*Energy and AI.*
15.	M. Zhang et al. (2024a).	Enhancing hourly heat demand prediction through artificial neural networks: A national level case study.	*Energy and AI.*
16.	Mohammadi et al. (2024).	Comparative transient assessment and optimization of battery and hydrogen energy storage systems for near-zero energy buildings.	*Renewable Energy.*
17.	Chen et al. (2024).	Lifelong learning with deep conditional generative replay for dynamic and adaptive modelling towards net zero emissions target in building energy system.	*Applied Energy.*
18.	Ruggeri et al. (2023).	Artificial Intelligence and Optimization Computing to Lead Energy Retrofit Programs in Complex Real Estate Investments.	*Engineering Proceedings.*
19.	Sadeghibakhtiar et al. (2024).	Size optimization of a stand-alone solar-wind-battery hybrid system for net zero energy buildings: A case study.	*Energy and Buildings.*

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No.	Author and year	Title	Journal
20.	Liu et al. (2024).	Performance of an Office Building in an Extremely Hot and Cold Region.	*Sustainability.*
21.	Liu et al. (2023b)	Towards the goal of zero-carbon building retrofitting with variant application degrees of low-carbon technologies: Mitigation potential and cost-benefit analysis for a kindergarten in Beijing	*Journal of Cleaner Production*
22.	Dan et al. (2024).	Electrification-driven circular economy with machine learning-based multi-scale and cross-scale modelling approach.	*Energy.*
23.	X. Zhao et al. (2024b)	Exploring the dynamics of urban energy efficiency in China: A double machine learning analysis of green finance influence.	*Environmental Technology & Innovation.*
24.	Luna-Romero et al. (2024).	Enhancing anomaly detection in electrical consumption profiles through computational intelligence	*Energy Reports.*
25.	Álvarez-Sanz et al. (2024).	Ranking building design and operation parameters for residential heating demand forecasting with machine learning.	*Journal of Building Engineering.*
26.	Du and Gou (2023).	Predicting Passivhaus certification of dwellings using machine learning: A comparative analysis of logistic regression and gradient boosting decision trees.	*Journal of Building Engineering.*
27.	Das et al. (2024)	Alkali-activated binder concrete strength prediction using hybrid-deep learning along with shapely additive explanations and uncertainty analysis.	*Construction and Building Materials.*
28.	Song et al. (2024).	Multi-objective capacity configuration optimization of the combined wind - Storage system considering ELCC and LCOE.	*Energy.*
29.	Lan et al. (2024).	Enhancing the performance of zero energy buildings with boosted coyote optimization and elman neural networks.	*Energy Reports.*
30.	Attia et al. (2013).	Assessing gaps and needs for integrating building performance optimization tools in net zero energy buildings design.	*Energy and Buildings.*
31.	Y. Zhao et al. (2024c).	Examining nonlinear effects of socioecological drivers on urban solar energy development in China using machine learning and high-dimensional data.	*Journal of Environmental Management.*
32.	Moraliyage et al. (2022).	A Robust Artificial Intelligence Approach with Explainability for Measurement and Verification of Energy Efficient Infrastructure for Net Zero Carbon Emissions.	*Sensors.*
33.	Khan et al. (2023).	Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting.	*Energy and Buildings.*
34.	Sun et al. (2023).	Building occupancy number prediction: A Transformer approach.	*Building and Environment.*
35.	Li and Azman (2022).	The Impact of Artificial Intelligence (AI) on the Low-Carbon Economy: A Prospective Study on the Long-Term Rental Housing Market in Guangxi, China.	*Chinese Journal of Urban and Environmental Studies.*
36.	Li and Azman (2023).	A review of the impact of artificial intelligence (AI) trust concerns on digital Chinese Yuan (E-CNY) to promote Chinese economic low-carbon sustainable development.	*Journal of Infrastructure, Policy and Development.*
37.	Jiao et al. (2024).	An intelligent landscaping framework for net-zero energy smart cities: A green infrastructure approach.	*Sustainable Energy Technologies and Assessments.*
38.	Elsisi et al. (2023).	A comprehensive review of machine learning and IoT solutions for demand side energy management, conservation, and resilient operation.	*Energy.*
39.	Batres et al. (2023).	A Metamodel-Based Evolutionary Optimizer for Building Energy Optimization.	*Energies.*
40.	D'Agostino et al. (2023).	New genetic algorithm-based workflow for multi-objective optimization of Net Zero Energy Buildings integrating robustness assessment.	*Energy and Buildings.*
41.	Abdou et al. (2022).	Prediction and optimization of heating and cooling loads for low energy buildings in Morocco: An application of hybrid machine learning methods.	*Journal of Building Engineering.*

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No.	Author and year	Title	Journal
42.	Ji and Huang (2022).	Analysis of social governance in energy-oriented cities based on artificial intelligence.	*Energy Reports.*
43.	Cordeiro-Costas et al. (2022).	Machine Learning and Deep Learning Models Applied to Photovoltaic Production Forecasting.	*Applied Sciences.*
44.	Chegari et al. (2022).	An optimal surrogate-model-based approach to support comfortable and nearly zero energy buildings design.	*Energy.*
45.	Zhu et al. (2021).	A hybrid metamodel-based method for quick energy prediction in the early design stage.	*Journal of Cleaner Production.*
46.	Ferrara et al. (2021).	Design optimization of renewable energy systems for NZEBs based on deep residual learning. Renewable	*Energy.*
47.	Wu et al. (2023).	Intelligent Mult objective optimization design for NZEBs in China: Four climatic regions.	*Applied Energy.*
48.	García Kerdan and Morillón Gálvez (2020).	Artificial neural network structure optimisation for accurately prediction of exergy, comfort and life cycle cost performance of a low energy building.	*Applied Energy.*
49.	Camporeale and Mercader-Moyano (2019).	Towards nearly Zero Energy Buildings: Shape optimization of typical housing typologies in Ibero-American temperate climate cities from a holistic perspective	*Solar Energy.*
50.	Wu et al. (2018).	Multi-Objective Flexible Flow Shop Scheduling Problem Considering Variable Processing Time due to Renewable Energy.	*Sustainability.*
51.	Gilles et al. (2017).	Decision-making based on network visualization applied to building life cycle optimization.	*Sustainable cities and society.*
52.	Park et al. (2013).	Cost and CO2 emission optimization of steel reinforced concrete columns in high-rise buildings.	*Energies.*
53.	Caldas and Norford (2002).	A design optimization tool based on a genetic algorithm.	*Automation in construction.*
54.	Z. Liu et al. (2023c).	Advanced controls on energy reliability, flexibility and occupant-centric control for smart and energy-efficient buildings.	*Energy and Buildings.*
55.	Xu et al. (2023).	Energy Saving Optimization of Commercial Complex Atrium Roof with Resilient Ventilation Using Machine Learning.	*Smart Cities.*
56.	Tsai (2024).	The Application of Design Thinking and Project-Based Learning in Human–Computer Interaction Courses for Construction Engineering Students.	*Journal of Civil Engineering Education.*
57.	Roth et al. (2020).	sing open data to create a synthetic city of hourly building energy estimates by integrating data-driven and physics-based methods.	*Applied Energy.*
58.	Zhou et al. (2023).	Optimization of building demand flexibility using reinforcement learning and rule-based expert systems.	*Applied Energy.*
59.	Pittarello et al. (2021).	Artificial Neural Networks to Optimize Zero Energy Building (ZEB) Projects from the Early Design Stages.	*Applied Sciences.*
60.	Wu et al. (2018).	Multi-Objective Flexible Flow Shop Scheduling Problem Considering Variable Processing Time due to Renewable Energy.	*Sustainability.*
61.	Hongn et al. (2022).	Two novel resistance-capacitance network models to predict the dynamic thermal behavior of active pipe-embedded structures in buildings.	*Journal of Building Engineering.*
62.	Paudel et al. (2017).	A relevant data selection method for energy consumption prediction of low energy building based on support vector machine.	*Energy and Buildings.*
63.	Zhao et al. (2024a).	Machine learning for optimal net-zero energy consumption in smart buildings	*Sustainable Energy Technologies and Assessments*
64.	Garlik (2022).	Energy Centers in a Smart City as a Platform for the Application of Artificial Intelligence and the Internet of Things.	*Applied Sciences.*
65.	Jalilzadehazhari et al. (2019).	Developing a decision-making framework for resolving conflicts when selecting windows and blinds. Architectural Engineering and Design Management,	*Architectural Engineering and Design Management.*
66.	Bäcklund et al. (2024).	Showcasing a digital twin for higher educational buildings: developing the concept toward human centricity.	*Frontiers in Built Environment.*

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No.	Author and year	Title	Journal
67.	Kim et al. (2024).	Forecasting building energy demand and on-site power generation for residential buildings using long and short-term memory method with transfer learning.	*Applied Energy.*
68.	Cheng and Ma (2015).	A data-driven study of important climate factors on the achievement of LEED-EB credits.	*Building and Environment.*
69.	Ji and Huang (2022).	Analysis of social governance in energy-oriented cities based on artificial intelligence.	*Energy Reports.*
70.	S, R., B, M. K., and Appathurai, A. (2023).	Energy aware Clustered blockchain data for IoT: An end-to-end lightweight secure & Enroute filtering approach.	*Computer Communications.*
71.	Korkas et al. (2022).	Integration and Verification of PLUG-N-HARVEST ICT Platform for Intelligent Management of Buildings.	*Energies.*
72.	Srivastava et al. (2023).	An explainable artificial intelligence approach to understanding drivers of economic energy consumption and sustainability.	*Energy Economics.*
73.	Feng et al. (2022).	Efficient creep prediction of recycled aggregate concrete via machine learning algorithms.	*Construction and Building Materials.*
74.	Deng et al. (2024).	A novel operation method for renewable building by combining distributed DC energy system and deep reinforcement learning.	*Applied Energy.*
75.	Rezaei Nasab et al. (2022).	Investigating the probability of designing net-zero energy buildings with consideration of electric vehicles and renewable energy.	*Engineering, Construction and Architectural Management.*
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