Artificial intelligence for calculating and predicting building carbon emissions: a review

Environmental Chemistry Letters
https://doi.org/10.1007/s10311-024-01799-z

REVIEW ARTICLE

Artificial intelligence for calculating and predicting building carbon emissions: a review

Jianmin Hua[1,2] · Ruiyi Wang[1] · Ying Hu[1] · Zimeng Chen[1] · Lin Chen[1,3] · Ahmed I. Osman[4,5] · Mohamed Farghali[6,7] · Lepeng Huang[1,2] · Ji Feng[8] · Jun Wang[8] · Xiang Zhang[9] · Xingyang Zhou[10] · Pow-Seng Yap[11]

Received: 15 October 2024 / Accepted: 1 November 2024

Abstract

The construction industry, being responsible for a large share of global carbon emissions, needs to reduce its high carbon output to meet carbon reduction goals. Artificial intelligence can provide efficient support for carbon emission calculation and prediction. Here, we review the use of artificial intelligence techniques in forecasting, management and real-time monitoring of carbon emissions, focusing on how they are applied, their impacts, and challenges. Compared to traditional methods, the prediction accuracy of artificial intelligence models has increased by 20%. Artificial intelligence-driven systems could reduce carbon emissions by up to 15% through real-time monitoring and adaptive management strategies. Artificial intelligence applications improve energy efficiency in buildings by up to 25%, while reducing operational costs by up to 10%. Artificial intelligence supports the establishment of a digital carbon management system and contributes to the development of the carbon trading market.

Keywords Artificial intelligence · Building carbon emissions · Calculation and prediction · Real-time monitoring · Sustainable development

✉ Lin Chen
chnlinchen@gmail.com

✉ Ahmed I. Osman
aosmanahmed01@qub.ac.uk;
ahmed.osman@canterbury.ac.uk

✉ Lepeng Huang
huang_lepeng@cqu.edu.cn

✉ Pow-Seng Yap
PowSeng.Yap@xjtlu.edu.cn

1 School of Civil Engineering, Chongqing University, Chongqing 400045, China

2 Key Laboratory of New Technology for Construction of Cities in Mountain Area, Ministry of Education, Chongqing University, Chongqing 400045, China

3 Department of Engineering, University of Cambridge, Trumpington Street, Cambridge CB2 1PZ, UK

4 School of Chemistry and Chemical Engineering, Queen's University Belfast, David Keir Building, Stranmillis Road, Northern Ireland, Belfast BT9 5AG, UK

5 School of Engineering, Technology, and Design, Canterbury Christ Church University, Canterbury CT1 1QU, UK

6 Department of Agricultural Engineering and Socio-Economics, Kobe University, Kobe 657-8501, Japan

7 Department of Animal and Poultry Hygiene and Environmental Sanitation, Faculty of Veterinary Medicine, Assiut University, Assiut 71526, Egypt

8 China Construction Third Engineering Bureau Group Co., Ltd, Wuhan City 430073, Hubei Province, China

9 Undergraduate School, Chongqing University, Chongqing 400044, China

10 Department of the Built Environment, National University of Singapore, Singapore 117566, Singapore

11 Department of Civil Engineering, Xi'an Jiaotong-Liverpool University, Suzhou 215123, China

Published online: 21 March 2025

Introduction

With 40% of global energy consumption and nearly 30% of energy-related emissions attributed to it, the construction industry stands as a significant driver of global carbon emissions [1–4]. The design and construction phases significantly impact the carbon footprint of buildings, with material selection, construction methods, and energy systems playing a pivotal role [5–7]. Building construction and operation contribute significantly to global energy consumption and carbon dioxide emissions, primarily due to the production of energy-demanding materials like cement and steel [8, 9]. In addition, much of the sustained energy required to heat, cool, and light buildings is derived from fossil fuels, thus exacerbating carbon emissions and amplifying adverse environmental impacts [10, 11]. Greenhouse gases generated by the building sector significantly affect the local environment and are instrumental in the degradation of the global climate [12–14]. Greenhouse gases destabilize the climate system and are a major driver of rising global temperatures and the heightened incidence of extreme weather phenomena [15, 16]. Accordingly, the urgency of tackling carbon dioxide output from the building industry is closely connected to efforts to curb global warming and meet international environmental targets [17, 18].

Artificial intelligence is becoming a transformative tool to combat climate change, especially in predicting and lowering carbon output [19, 20]. Through advanced machine learning algorithms and big data analytics, artificial intelligence technologies can accurately monitor and predict carbon emissions throughout the building lifecycle, contributing to more efficient building decision-making and resulting in more efficient and eco-friendly building implementation programs [21, 22]. Furthermore, artificial intelligence-driven tools such as neural networks and deep learning are being used to optimize energy consumption and resource utilization in real time, greatly minimizing the ecological footprint of construction activities [23]. Existing research utilizes machine learning algorithms to analyze large-scale datasets, accurately identifying carbon emission patterns in construction activities and forecasting emissions for future buildings, thereby optimizing energy and material usage to significantly reduce the construction domain's environmental footprint [24]. The use of artificial intelligence, including the integration of Internet of Things devices for continuous environmental monitoring and artificial intelligence-driven simulations to assess the ecological impacts of various construction materials and technologies, has significantly enhanced the efficiency of sustainability efforts and provided valuable insights for future planning and development [25, 26]. Thus, artificial intelligence is poised to be instrumental in meeting global carbon reduction objectives and fostering a greener, more sustainable construction industry.

This review systematically analyzes the scope and objectives of artificial intelligence applications for carbon output in the construction sector; Fig. 1 shows the framework for writing this review. This review examines specific artificial intelligence techniques such as artificial neural networks, convolutional neural networks, recursive neural networks, random forests, and support vector regression and their relevance to the latest developments in the construction field, with an emphasis on the analysis of cutting-edge artificial intelligence models, data management techniques, and applications in real-time monitoring and carbon emissions management. At the same time, this review discusses the improvements brought by artificial intelligence techniques in terms of predictive power and accuracy of the carbon emissions management process through specific case studies. In addition, this review discusses the challenges faced regarding data quality, artificial intelligence implementation, economic factors, and emerging technologies and makes recommendations for future interdisciplinary collaborations. This review aims to highlight the groundbreaking potential of artificial intelligence in achieving sustainable building practices and reducing global carbon emissions.

Advancements in artificial intelligence models for emission calculation

In recent years, artificial intelligence, as a digital technology, has seen extensive application in industries such as manufacturing, retail, and telecommunications. Compared to traditional technologies, the implementation of artificial intelligence has notably enhanced automation, not only optimizing production processes but also significantly increasing efficiency and accuracy [27]. Similarly, this revolutionary technology initially penetrated into the field of construction in the 1960s and was accompanied by the concept of "intelligent building" [28]. The implementation of artificial intelligence architecture predominantly emphasizes the convergence and advancement of machine learning, the Internet of Things, blockchain, and other technologies. Machine learning algorithms are used for building design optimization, project cost estimation, and construction risk management to achieve higher accuracy and cost efficiency [29]. In addition, through smart sensors and real-time data analysis, artificial intelligence technology can also execute real-time monitoring of structural health in buildings, predict maintenance needs, and ensure the prolonged safety and durability of buildings [30].

As artificial intelligence technology continues to evolve, its application in the construction sector has grown

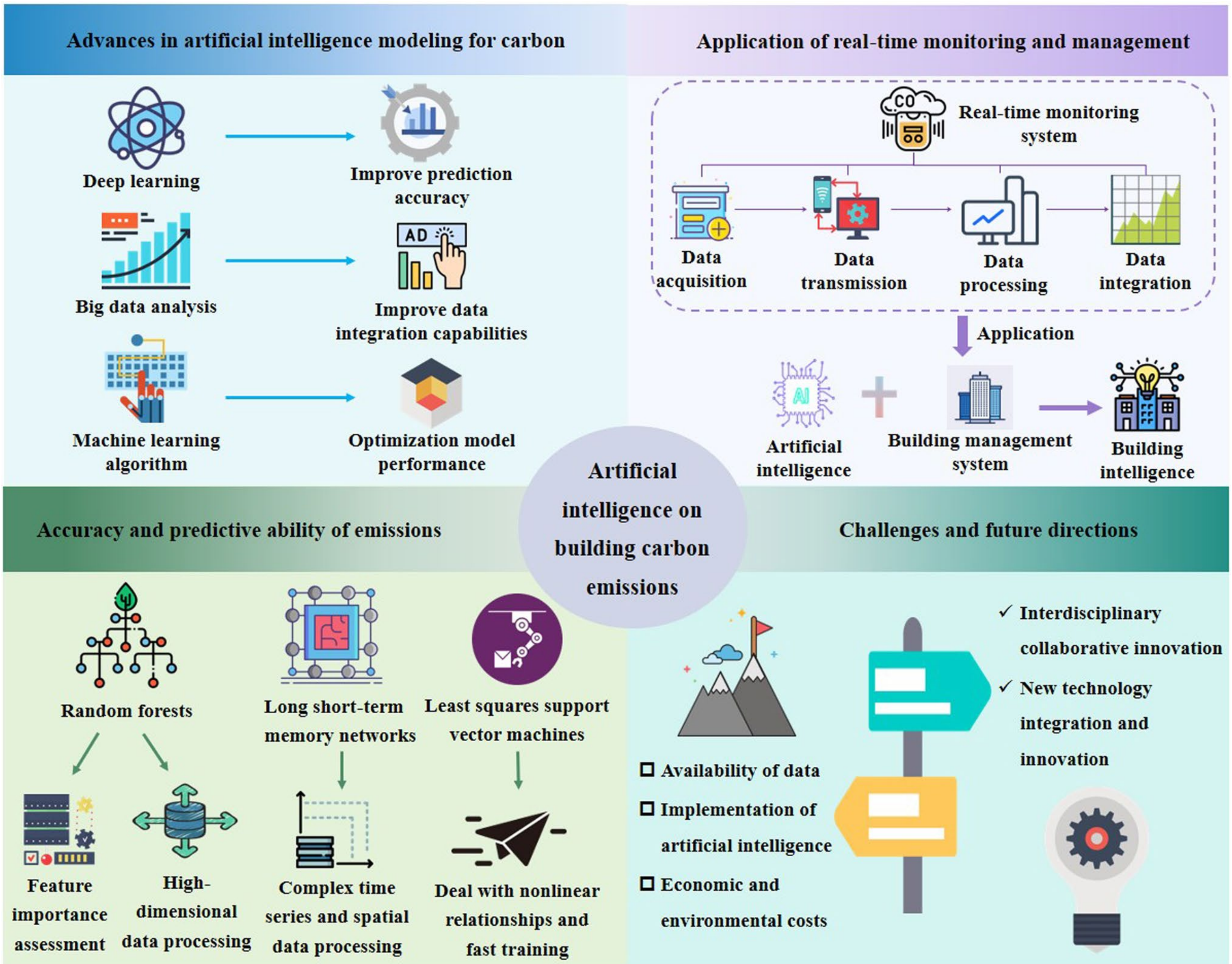

Fig. 1 Application of artificial intelligence in managing carbon emissions of buildings. This figure highlights four key areas of research advancements in artificial intelligence technologies related to building carbon emissions: applications in real-time monitoring systems, capabilities for enhancing emissions management and forecasting accuracy, and the challenges and future directions for further development. Through an overview of the deployment of artificial intelligence in carbon emissions management, the advantages of artificial intelligence technology in areas such as processing and analyzing data are highlighted, thus paving the way for the later description of the potential of artificial intelligence in improving emissions management and forecasting accuracy. This figure clearly shows the full picture of artificial intelligence technology in building carbon emissions, from research progress to practical applications to future challenges and directions

increasingly advanced, particularly in the calculation and forecasting of building carbon emissions. Artificial intelligence technology shows great potential. By analyzing building energy consumption data, the artificial intelligence system can accurately calculate carbon emissions and predict future emission trends, providing a scientific basis for optimizing energy use and cutting emissions in buildings [31]. Simultaneously, the optimization algorithm based on artificial intelligence can also provide personalized energy-saving suggestions and programs based on building characteristics and usage requirements, helping buildings achieve sustainable and carbon-efficient development [32].

Influence of artificial intelligence modeling on building carbon emissions

The building sector is rapidly advancing its shift towards digitalization, and pioneering technologies such as building information modeling, artificial intelligence, Internet of Things technologies, and smart vision have become the main driving forces [33]. From the whole building lifecycle, such as building design, construction, and operation, advanced technologies such as artificial intelligence and building information modeling synergize with each other to enhance building efficiency [34]. As the core driving force of this transformation, artificial intelligence can realize data processing, analysis, decision-making, and automated control through computational methods and algorithms that simulate human intelligence, including subfields such as machine learning, deep learning, natural language processing, and computer vision, enabling efficient extraction of key insights from extensive data [35]. Through autonomous learning and improved algorithms, artificial intelligence can achieve optimal processing of building energy consumption data and automated oversight and regulation of the building construction procedure, maximize the efficiency of energy use, and provide a basis for optimizing construction plans and decision-making [36, 37]. To this end, researchers are actively exploring innovative uses of artificial intelligence in managing building carbon emissions. Table 1 shows five commonly used artificial intelligence technologies in the construction field and summarizes their advantages and the challenges linked to them. Through deep learning and big data analysis, the potential of energy usage information can be explored, and the carbon emission calculation model can be optimized to provide technical support for targeted carbon mitigation and long-term sustainability in the architectural and engineering sectors.

Table 1 demonstrates that applying artificial intelligence modeling to building carbon emissions offers a novel and effective approach to tackling environmental issues and advancing sustainability. However, several challenges hinder the broad adoption of artificial intelligence models in the industry. One important barrier is the high demand for computational resources and data for artificial intelligence models, which increases the cost and difficulty of application [43]. To tackle this issue, more efficient algorithms and optimized data processing workflows must be created to minimize resource consumption and enhance model performance. In addition, another key challenge is the overfitting problem, which can aptitude for generalization exhibited by the model and the effectuality of practical applications [44]. To overcome this problem, appropriate regularization techniques and model validation methods must be employed to ensure model robustness and reliability. Nonetheless, artificial intelligence techniques possess substantial capacity to enhance energy utilization efficiency, foster sustainable building practices, and provide strong evidence for accurate carbon reduction.

Artificial intelligence can quantify carbon emissions with high precision through advanced algorithms and large data sets, which greatly enhances the precision of carbon emission calculations. Wang et al. [45] used You Only Look Once framework based on convolutional neural networks to detect targets of marine carbon emissions, which can identify key targets in real time and efficiently and offer data support for the swift forecasting of carbon emissions. The study also achieved highly precise forecasting of carbon emissions with an error of only 5% by using the long short-term memory algorithm. Through real-time monitoring of the building environment, artificial intelligence technology can continuously gather and evaluate data from multiple sources, such as sensors and Internet of Things devices, to provide the most up-to-date information on emission levels and respond quickly to changes in emission patterns in response to differences in the monitoring information. In addition, a study by Choi et al. [46] showed that the random forest model could optimize the exactness of the carbon emission computation model by evaluating and identifying critical variables associated with carbon emissions, such as hydrosulfide and ammonia, thereby improving the efficiency of carbon emission calculation.

In summary, pioneering technologies such as deep learning, big data analytics, and computer vision can significantly improve building efficiency and sustainability. Despite their many advantages, artificial intelligence technologies still face the challenges of high computational resource requirements, potential overfitting problems, and complex algorithms and data processing. To ensure model robustness and widespread adoption, collaboration is essential to address these obstacles. By overcoming these challenges, artificial intelligence is poised to assume a pivotal role in precise carbon emission calculations and advancing sustainable development in the construction sector.

Artificial intelligence data management techniques for carbon emission projections

Given the major strengths of artificial intelligence models in data processing, accurate prediction, and powerful modeling capabilities, their application in building carbon emission prediction shows strong potential. Artificial intelligence techniques provide sophisticated methods to analyze complex datasets, identify patterns, and accurately predict carbon emissions from buildings [47]. Through machine learning algorithms and deep learning, artificial intelligence can model various factors affecting carbon emissions. Wen and Yuan [48] integrated random forest, particle swarm optimization algorithms, and backpropagation neural networks to develop an innovative prediction model for estimating carbon dioxide output from China's commercial industries. Yan et al. [49] put forward a convolutional neural network-based method for real-time operational carbon emissions prediction and predicted the carbon emissions throughout the operational phase of a building by training a model based on data from 2000 actual residential units in Beijing. By comparing with the Energy Plus model, although there are some deviations in the predicted values, the results of the two methods have the same trend of change, which proves the responsiveness of convolutional neural networks in terms of layout changes. It is evident that the present studies have fully proved the feasibility and effectiveness of artificial

Table 1 Benefits and challenges of applying artificial intelligence technology in buildings

Types of artificial intelligence technology	Benefits of applying artificial intelligence technology in buildings	Challenges of applying artificial intelligence technology in buildings	Key findings	References
Artificial neural networks		High computational complexity Risk of overfitting Lack of transparent operational processes	The artificial neural network can effectively learn building energy-related outputs required for simulation through a comprehensive training process, delivering accurate analytical results. It remains operational even in the presence of structural damage or data noise, showcasing robust tolerance to degradation and incomplete data	[38]
Convolutional neural network	Efficient processing of image and spatiotemporal data Powerful modeling capabilities Automatic feature extraction	High demand for computing resources High data requirements Lack of interpretability	By combining the convolutional neural network model, real-time monitoring and prediction of energy usage and carbon output in buildings can be realized, supporting intelligent building management systems and improving energy utilization efficiency and carbon emission control levels	[39]
Recursive neural networks	Efficient processing of time series data Dynamic feature extraction	High computational resource requirements Easy to overfitting Poor model interpretability	The grey prediction model, integrated with recurrent neural networks, harnesses their dynamic capabilities to accurately capture and forecast the intricate patterns of building carbon emissions over time	[40]
Random forest	Handling high-dimensional data and nonlinear relationships Preventing overfitting	High computational complexity Poor model interpretation High data dependency	Utilizing random forests to identify factors influencing building carbon emissions and optimize key indicators, such as floor area and average number of buildings, can effectively reduce carbon output, making the overall building design more eco-friendly and sustainable	[41]
Support vector regression	Handling high-dimensional data High prediction accuracy	High computational complexity Difficult parameter selection High data demand	The support vector regression model enables the detection of anomalies in energy utilization, uncovers inefficiencies by examining disparities between projected and actual data, and facilitates the implementation of targeted energy conservation tactics	[42]

The table presents five artificial intelligence models implemented for building carbon emissions analysis, including artificial neural networks, convolutional neural networks, recurrent neural networks, random forests, and support vector regression. These artificial intelligence models have many advantages, such as handling complex data and images, dynamic feature extraction, and high-precision prediction. However, the challenges of applying these artificial intelligence models to building carbon emissions, including the need for greater computational resources, extensive data, and the risk of overfitting, must be addressed. These artificial intelligence techniques can enhance energy efficiency and promote sustainable building development while offering solid evidence for precise carbon emission reduction intelligence technologies, such as machine learning algorithms in carbon emission prediction, and the related technology system is maturing.

Although artificial intelligence technology, with its intelligent and automated features, has provided an opportunity to elevate the precision of carbon emission forecasting in buildings, the process of its realization is not a straight-line advancement without challenges. Actually, the prediction process entails a complex workflow, spanning from data collection and pre-processing to model development and validation, and each step is crucial to forming an efficient and accurate prediction system. Yeasmin et al. [50] presented a carbon dioxide emission prediction system for smart cities, detailing the whole process of carbon dioxide prediction for trucks under different driving distances and fuel consumption conditions. Boateng et al. [51] evaluated six machine learning models and emphasized the process of selecting the optimal hyperparameters through cross-validation to accurately predict carbon emissions associated with building-related activities. Also, machine learning models for predicting carbon dioxide emissions from buildings have been evaluated and should focus on hyperparameter tuning and cross-validation to guarantee precise and reliable prediction results [52]. Figure 2 depicts the key stages of a building carbon emission prediction system, highlighting the central role of data quality, model selection and optimization, and validation aspects in improving prediction accuracy.

As depicted in Fig. 2, the key aspect of predicting carbon outputs is the application and optimization of artificial intelligence model adjustments, which is due to the fact that

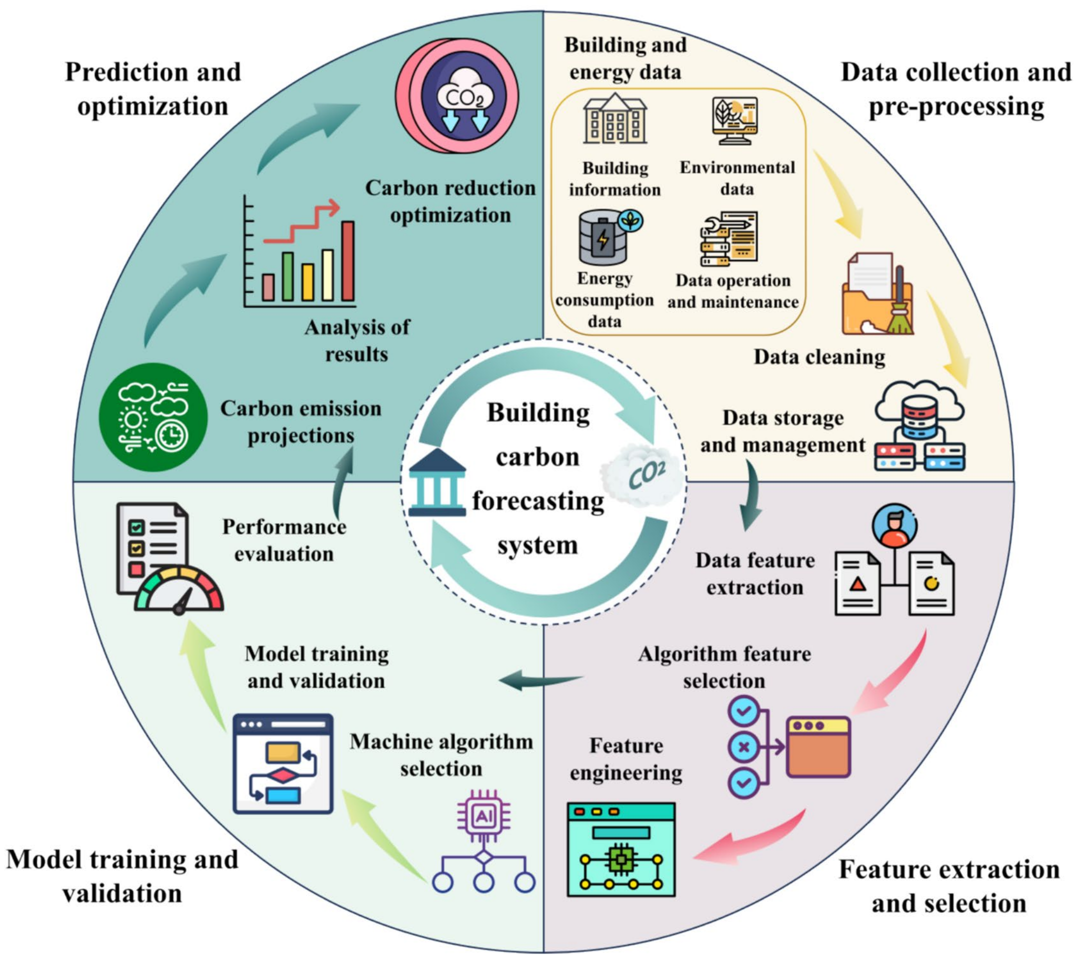

Fig. 2 Artificial intelligence for predicting carbon emissions of buildings. This figure shows the key steps and process of building carbon emission prediction, which mainly contains four stages: data collection and preprocessing, feature extraction and selection, model training and validation, and prediction optimization. This diagram starts by collecting detailed data on the building project, covering all aspects of the building, energy consumption, and environment, and realizing the training of the data through suitable machine learning algorithms to ensure precise forecasting of carbon emissions for the building project. In addition, this figure highlights the optimization and adjustment of the prediction results in actual project applications to continuously increase the precision of the prediction. The whole process of predicting building carbon emissions is not only beneficial to assessing the environmental effects of building projects but also of great significance to promoting sustainable construction practices and technological progress

the ability of machine learning, deep learning, and other artificial intelligence technologies to process and analyze large data sets is directly tied to the precision of emission predictions. Historical data collected are typically vast and unstructured, necessitating advanced preprocessing techniques for proper analysis. Through processes such as data cleaning and data normalization, they are converted into a format suitable for in-depth analysis [53]. In addition, advanced machine learning algorithms such as support vector machine models, random forests, principal component analysis, and cluster analysis can manage high-dimensional data and identify complex nonlinear relationships between variables [54]. Jansson et al. [55] illustrated the effectiveness of principal component analysis and K-mean clustering in lowering the dimensionality of the data and the significant advantages of multivariate data for classification. By constructing predictive models, these algorithms can predict future carbon emission trends based on historical data, providing a scientific basis for policymakers.

However, when addressing long-term patterns and complex dynamics in time series data, deep learning methods like convolutional neural networks and recurrent neural networks demonstrate outstanding performance. Convolutional neural networks can extract local features about carbon emission data through convolutional operations and construct higher-level representations based on the features to identify complex patterns in both time and space [56]. Traditional machine learning algorithms, focused on extracting local data features, may face limitations with time series data and struggle to address long-term dependencies [57]. Recurrent neural networks have the capacity to handle sequence data of arbitrary length and capture extended dependencies and time-based patterns within the data through recursive computation of internal states [58]. Fang and He [59] showed that recurrent neural networks can capture the dynamic properties of nonlinear systems when dealing with energy consumption data, which enables them to effectively model and predict complex data affected by multiple factors, with a mere 0.78% mean forecast error. At the same time, the model is also able to efficiently utilize limited data samples, reduce the overfitting problem, and enhance the interpretability of the model through the visualization of hidden state functions.

In addition, artificial intelligence models based on big data platforms have demonstrated significant advantages in accurate carbon emission forecasting. Big data platforms such as the Internet of Things, Hadoop, and Spark use their powerful data collection and processing capabilities to be able to integrate sensor data, historical emission data, and building-related information for prediction, sourced from diverse origins, while simultaneously performing data screening, standardization, and integration to ensure data quality [60, 61]. In contrast, artificial intelligence models can leverage high-quality data processed by the big data platform for advanced machine learning and deep learning training, allowing for the identification of essential patterns in multimodal data and providing highly accurate carbon emission predictions.

With the incorporation of big data and artificial intelligence technologies, along with an increasing depth of application in the area of environmental protection, Peng et al. [62] combined genetic algorithm and particle swarm optimization support vector regression to construct a vehicle emission model based on predicting traffic conditions and fuel usage, which is capable of accurately estimating the emission level under different traffic scenarios and selecting the optimal route to reduce carbon emission. Validated by actual traffic data, the results show that this intelligent navigation system can significantly reduce fuel consumption and emissions compared with traditional navigation methods, which helps to build a sustainable and environmentally friendly intelligent transportation system. Fu et al. [63] proposed a model combining the adaptive noise-whale optimization algorithm with an extreme learning machine and a deep learning-based temporal–spatial meteorological model for air quality prediction. The results elucidate that the enhanced model greatly surpasses individual artificial intelligence models in predicting air quality, demonstrating superior accuracy and robustness across different environmental conditions. Therefore, the parallel computing capability of the big data platform improves model iteration and optimization efficiency, ultimately offering technical support for real-time oversight and decision-making, thus enabling intelligent and dynamic carbon management.

The validation and optimization of the prediction model are critical to ensuring precise carbon emission forecasts, requiring a combination of cross-validation and independent validation sets for evaluation, with performance assessed using metrics such as mean squared error, root-mean-squared error, mean absolute error, and the coefficient of determination. The study by Hou et al. [64] focused on a shallow learning approach for estimating China's carbon dioxide emissions, converting temporal data into a supervised learning task with the sliding window technique, and optimizing parameters using K-fold cross-validation and network search. Following optimization, the random forest model demonstrated exceptional predictive accuracy, attaining R^2 values of 0.94 on the validation set and 0.88 on the test set, thereby substantially improving the exactness of the carbon dioxide emission forecasting model. The study of Vu et al. [65] also mentioned that the K-fold cross-validation reduced the uncertainty of the dataset and the overfitting problem. Meanwhile, hyper-parameter tuning, regularization techniques, and integrated learning methods could optimize the model, and Bouktif et al. [66] emphasized the role of selecting important features to elevate the exactness of the model, and the optimized machine learning model has higher prediction accuracy. In addition, predictive model robustness can be further enhanced by techniques such as model smoothing and outlier correction [67].

In conclusion, the artificial intelligence data management technology for carbon emissions prediction realizes high-precision prediction of carbon emissions by integrating big data, machine learning, and deep learning algorithms. Methodologies involving data preprocessing, big data platform application, model validation, and optimization work in unison to guarantee precise carbon emissions predictions. The application of artificial intelligence technology enhances data collection accuracy and completeness while resolving the complexity of multi-source data integration.

This section outlines the progress of research on artificial intelligence modeling related to building carbon emissions. High-precision carbon emission prediction is achieved by deep learning models, data integration capability is enhanced by big data analysis, and machine learning algorithms optimize the performance of carbon emission models. Meanwhile, advanced artificial intelligence technologies can process and analyze large datasets to achieve high-precision predictions of carbon emissions. Despite their many advantages, artificial intelligence technologies still face challenges in terms of high computational resource requirements, potential overfitting problems, and data processing complexity. Through collaborative efforts and novel strategies, artificial intelligence will serve as a cornerstone in advancing sustainable development and guaranteeing precise carbon emissions calculations within the construction domain.

Artificial intelligence applications in real-time emission monitoring and management

Artificial intelligence-driven real-time monitoring systems

Currently, the quantification of carbon emissions from buildings predominantly concentrates on post-construction phases, utilizing procedural analyses or input–output methodologies, among others [68, 69]. These approaches rely heavily on empirical approximations of carbon outputs stemming from construction materials, transportation, and associated activities, inherently introducing inaccuracies within the collected data. Consequently, the significance of implementing real-time monitoring systems for tracking building carbon emissions throughout the entire construction lifecycle cannot be overstated. Such systems not only enhance accuracy but also furnish vital insights to building administrators, enabling them to adopt more effective strategies for carbon emission management during the process [70].

The attainment of real-time emission monitoring in buildings via artificial intelligence technology is primarily facilitated by advanced sensing mechanisms, robust data handling capabilities, and sophisticated intelligent algorithms. This process can be systematically delineated into three pivotal stages: Firstly, the acquisition of comprehensive data, followed by its efficient transmission and secure storage, and finally, the intricate process of data processing and in-depth analysis. The primary means of acquiring data involves strategically deploying diverse sensor types. Subsequently, the seamless integration of the Internet of Things technology facilitates data transmission and storage, ensuring efficient data management. Furthermore, the employment of artificial intelligence techniques for data processing, analysis, and the automated orchestration of these three sequential stages culminates in a highly sophisticated system that operates independently and autonomously, devoid of direct human intervention, thereby enhancing its intelligence quotient.

Sensor network integration for data acquisition

By installing various types of sensors (e.g., sensors for temperature, humidity, light, gas concentration, and others), energy consumption and emission data of the building are collected in real time. These sensors can accurately measure various parameters inside and outside the building, providing raw data for artificial intelligence analysis. The gas sensor used to monitor carbon emissions from buildings is a high-precision electronic device that detects and quantifies greenhouse gas levels, including carbon dioxide and methane, in the air in real time. The sensor captures changes in gas molecules through a sensing element, converts these changes into electrical signals, and then analyzes them through the data processing system. These highly sensitive and quick-responding sensors are ubiquitous in the realm of environmental monitoring and building energy management, significantly contributing to lowering carbon outputs and elevating energy efficiency. Several prevalent technologies are employed in gas sensing, including electrochemical sensors, infrared-based detectors, semiconductor-type sensors, and photoionization sensors, each tailored to specific applications and offering distinct advantages. Among them, infrared gas sensors are generally used for building carbon emission monitoring mainly because of their ability to distinguish between the specific absorption wavelengths of different gases, thus effectively detecting the target gas and reducing the interference of other gases with high sensitivity and accuracy [71].

A single gas sensor can only measure the carbon emissions of a space at a given time. The assessment of carbon emissions coming from individual buildings or entire districts necessitates the deployment of multiple gas sensors. Integrating and organizing the data streams generated by these sensors necessitates a networking technology capable of interlinking them. Among the viable solutions, the wireless sensor network stands out, typically structured as an ensemble of interconnected wireless monitoring nodes, each furnished with an array of sensors and either physically wired or remotely linked to a centralized control unit, fostering efficient data consolidation and analysis [72]. Wireless monitoring nodes are constructed by integrating carbon dioxide sensors with radio communication modules. These integrated sensor nodes persistently observe their immediate surroundings, subsequently compiling the acquired data into packets that are then conveyed through the radio interface to the centralized control platform. This process ensures continuous, remote monitoring of carbon dioxide levels, facilitating real-time analysis and decision-making capabilities. Many wireless sensor network systems are derived from wireless sensor networks. The implementation of a real-time cognitive wireless sensor network system constitutes an innovative approach for continuous carbon dioxide monitoring, leveraging the principles of cognition within a wireless sensor network framework [73]. This system constructs a unique network architecture, wherein each node is equipped with dual antennas, employing cognitive networking strategies to mitigate potential interference affecting coexisting systems within the surveillance area. The transmission of data packets from the origination point to the control center adheres to the tenets of opportunistic routing, wherein relay nodes are crucial in ensuring the smooth transmission of real-time sensorial information from diverse sources. These relay nodes, in accordance with a pre-determined routing protocol, ensure the efficient forwarding of received packets to the control room [74].

Internet of things for data transmission and storage

The data pertaining to carbon emissions, amassed by sensors, necessitates transmission to a cloud-hosted data repository for centralized archiving. To ensure the expeditiousness and fidelity of this information, the integration of Internet of Things technology becomes paramount. The Internet of Things encompasses the interconnection of physical devices, sensors, software, and diverse technologies over the internet, facilitating data gathering and sharing. These interconnected devices are equipped with the capability to engage in autonomous communication, analysis, and decision-making, thereby offering advanced intelligence and enhanced functionalities in service delivery [75]. Using Internet of Things technology, gas sensors can similarly be networked within buildings to enable continuous monitoring of carbon emissions. The building's infrastructure incorporates infrared gas sensors strategically positioned in various zones, which are interconnected to a central control system leveraging diverse wireless network technologies (inclusive of Wi-Fi, Zigbee, LoRa, among others). This connectivity enables the seamless transmission of collected data over the network to a cloud-based platform, ensuring centralized data storage and thorough analysis. Utilizing the capabilities of this cloud platform, facility managers are equipped to undertake real-time monitoring of carbon dioxide and additional greenhouse gas concentrations within the building's confines. This real-time visibility enables the generation of insightful reports and prompt alerts, which serve as pivotal tools in optimizing ventilation systems and energy resource utilization strategies. Ultimately, such optimizations contribute to the mitigation of carbon emissions and the enhancement of overall energy efficiency within the building ecosystem. This Internet of Things-based monitoring system enables efficient, accurate, and intelligent environmental management, providing important support for the greening and sustainable development of buildings [76].

Over the past few years, a multitude of Internet of Things-driven smart carbon monitoring platforms have surfaced as viable solutions. Zhang et al. [77] introduced a pioneering platform that integrates conventional carbon management strategies with Internet of Things technology, enabling dynamic oversight and administration of low-carbon initiatives within small municipalities. This comprehensive system encompasses three pivotal subsystems: an intelligent thermoelectric management system, an industrial energy monitoring framework, and an intelligent transportation network. Moreover, an innovative methodology for quantifying carbon emissions is introduced, which ingeniously integrates sample-driven monitoring, extensive data analytics spanning over prolonged periods, and real-time data refinement strategies. This innovative framework adeptly tackles the intricacies of inter-scale inconsistencies in carbon emission measurements, thereby bolstering the precision and credibility of the monitoring outcomes, ensuring a more robust and reliable assessment process. Xu et al. [78], through integrating Internet of Things technology and building information modeling, an advanced implied carbon monitoring system for buildings was devised, encompassing an infrastructure tier, a computation tier, and an application tier. This comprehensive system facilitates the continuous tracking and visualization of the embedded carbon footprint of constructed edifices across various spatial and temporal dimensions, thereby empowering stakeholders to devise rational and timely carbon mitigation strategies with enhanced efficacy.

Similarly, Mao et al. [79] devised an Internet of Things-centric system architecture, incorporating a decentralized sensor network to gather continuous emission information. This data is subsequently stored and extracted into a comprehensive database, facilitating efficient retrieval and analysis.

An online building information modeling platform was also established, utilizing building information modeling virtual representations to display the emission status of diverse construction activities. This platform empowers project teams with a visual understanding of emissions, enabling them to adopt timely corrective actions to mitigate potential emissions and enhance environmental sustainability. Ming et al. [80] introduced an innovative approach to carbon dioxide environmental monitoring that harmoniously integrates the Internet of Things paradigm with cloud computing advancements. This solution employs the MQ135 carbon dioxide sensor for precise measurements, the ESP8266 WIFI module for seamless connectivity, and the firebase cloud storage service for scalable data management. Furthermore, it leverages the android platform to develop a comprehensive monitoring framework that encompasses data generation, aggregation, storage, and visualization of carbon dioxide concentrations. This architecture offers unparalleled accessibility to real-time, visually rich data, significantly expediting the process of analyzing carbon emissions in real time and facilitating the prompt deployment of effective countermeasures.

Artificial intelligence algorithms to realize data processing and analysis

Employing artificial intelligence algorithms, a robust approach is undertaken to process, intricately analyze, and meticulously mine gathered data, thereby enhancing the effectiveness of dynamic monitoring of building carbon emissions and furnishing decision-making insights. Artificial intelligence technology, renowned for its proficiency in managing vast quantities of intricate data, encompasses diverse sources such as satellite imagery, sensor outputs, traffic patterns, and myriad others. The real-time aggregation and processing of these multifaceted datasets facilitate the delivery of more precise and prompt information on carbon emissions, underpinning informed decision-making and mitigation strategies.

A large amount of data collected by sensors may contain some measurements that are abnormal for various reasons, and bringing these abnormal values into the analysis may lead to biased results, so artificial intelligence techniques are needed to preprocess the collected data firstly. Data preprocessing is the cleaning, formatting, conversion, and feature engineering of raw data for subsequent more rational analysis and more effective learning of models. Data cleaning refers to the processing of missing values, outliers, and duplicate data, which may be done by leveraging tools like Pandas and NumPy. After data cleaning is completed, the data need to be formatted, i.e., converted into the format required by the model, so as to facilitate normalization, standardization, feature selection, and feature extraction of these data. Once the data preprocessing is completed, the data analysis must be carried out using artificial intelligence. Data analysis is mainly divided into the following steps:

(1) Statistical analysis, i.e., calculating statistical quantities such as mean, standard deviation, and quartile, describing the basic characteristics of the data; (2) Machine learning, i.e., through the linear regression, decision trees, support vector machines, neural networks, digital twins, and other techniques used for the establishment of data classification and regression modeling, and through the K-mean clustering, principal component analysis, t-SNE and other techniques to achieve data in clustering and dimensionality reduction, and data-based decision-making and control through Q-learning, deep Q-network, and other techniques; (3) Deep learning, i.e., processing of complex unstructured data, such as images, audio, and textual information through techniques such as convolutional neural networks, recurrent neural networks, and generative adversarial networks; (4) Data visualization, for exploring the data and presenting analysis results; and (5) Time series analysis involves the construction of models, such as the autoregressive integrated moving average and long short-term memory networks, for the purpose of predicting future trends and identifying enduring patterns within temporal data [81]. Throughout this work, artificial intelligence technologies, bolstered by machine learning and deep learning methodologies, empower management personnel to formulate decisions or directives grounded in the insights derived from data analysis, or even to execute these actions fully autonomously. This underscores the potential for seamless integration of artificial intelligence technologies within management systems, a facet that will be delved into at length in the ensuing chapters.

Employing the sophisticated analytical prowess of artificial intelligence, a myriad of researchers have achieved noteworthy advancements in the realm of real-time carbon emission monitoring and forecasting, spanning diverse sectors, and applications. Their efforts exemplify the transformative capabilities of artificial intelligence in deepening our comprehension and refining the management of environmental pollutants, specifically with regard to real-time monitoring and assessment. For instance, Rolnick et al. [82] used machine learning to realize automated video monitoring of transportation systems through computer vision, support vector machines, and neural networks to accurately detect vehicle traffic in high-resolution satellite imagery to precisely calculate the transportation system's gas emissions. In addition, Yevu et al. [83] used the practicality of leveraging digital twin technology for the real-time tracking of carbon emissions emanating from intelligent and prefabricated structures. Their findings underscored the efficacy of integrating digital twins with cutting-edge technologies, including radio frequency identification, global positioning systems, laser scanning sensors, and other smart technologies, in monitoring carbon emissions throughout the building's production, transportation, and on-site assembly stages. Xikai et al. [84] utilized a comprehensive methodology suite comprising principal component analysis, multilayer perceptron neural networks, support vector machines, and random forest algorithms to devise a predictive regression model, to accurately estimate the lifecycle carbon dioxide emissions associated with a given building. Subsequently, these developed models underwent rigorous process analysis and comparative evaluation. The findings revealed that the support vector machine model outperformed the other three approaches, achieving the highest level of predictive accuracy, as evidenced by a coefficient of determination value of 0.8, underscoring its efficacy in this context.

Further advancing the predictive capabilities of artificial intelligence, Chen et al. [85] introduced a robust and interpretable encoder–decoder deep learning framework tailored for the forecasting of multiscale short-period carbon emissions. This innovative approach incorporates a feature importance analysis mechanism, enabling it to precisely forecast emission patterns within a diverse, multiscale carbon emission dataset sourced from a university setting. The model's robustness was validated, achieving R^2 values higher than 0.93 across various application scenarios, indicating its potential for broader application in environmental monitoring.

Artificial intelligence algorithms for automated integration of prelude steps

To streamline and automate the entire process, the construction of an "end-to-end" system facilitated by artificial intelligence technology is paramount. This system should encompass every facet of data collection, seamless transmission, and secure storage alongside proficient processing and insightful analysis, ultimately fostering seamless integration and autonomous operation. The system needs to be composed of three core components: integration platform, automated workflow, and adaptive optimization. The integration platform is a comprehensive artificial intelligence platform for connecting various data sources (sensors, remote sensing imagery devices, and others) and unifying the management of data acquisition, transmission, storage and processing. An automated workflow entails the implementation of an artificial intelligence-powered management system that orchestrates and regulates each procedural stage, ensuring expeditious data transmission and storage post-acquisition, alongside automatic processing and analysis as necessitated. Furthermore, adaptive optimization becomes indispensable, entailing the employment of continuous machine learning models to dynamically adjust and refine the data processing and transmission procedures, thereby enhancing the system's overall efficiency and dependability.

In recent years, domestic and international scholars have proposed a proliferation of solutions for the establishment of an artificial intelligence-driven, comprehensive, and automated system encompassing data acquisition, processing, and analysis. Among the notable exemplars are systems that leverage innovative technologies. One such instance is the google earth engine, a scalable, cloud-hosted geospatial platform created to facilitate remote sensing and geospatial data analysis by harnessing cloud computing resources. Incorporating artificial intelligence methodologies into this platform has emerged as a promising strategy, enabling the automation of monitoring processes reliant on remote sensing techniques. Remote sensing technology is paramount in data gathering across vital domains, such as global climate change mitigation, natural disaster risk assessment and resilience enhancement, ecosystem conservation, and urban planning. Consequently, the retrieval, curation, and analysis of voluminous remotely sensed imagery pose a formidable challenge, necessitating advanced systems capable of addressing these complexities.

Artificial intelligence technology stands as a pivotal force in automating remote sensing, significantly contributing to data gathering in vital domains such as global climate change monitoring, natural disaster risk assessment and mitigation, ecosystem resilience enhancement, and urban planning. However, the retrieval, administration, and analysis of vast quantities of remotely sensed imagery pose a formidable challenge. In this context, the fusion of artificial intelligence with the Google Earth Engine, particularly in object-oriented image interpretation, offers a promising avenue for streamlining automated data collection, processing, and analysis [86]. Gharibi et al. [87] introduced ModelKB, a comprehensive software system tailored for end-to-end automation. This innovative platform streamlines the monitoring and tracing of data, enhances the visualization of both models and their associated data, facilitates seamless deployment of models across local environments and cloud infrastructures, and promotes the dissemination or publication of trained models, thereby bolstering collaboration and efficiency. ModelKB was validated to have good efficiency and feasibility in automating the monitoring of model data, data processing and analysis, as well as significantly facilitating the reproducibility of models. Maddireddy and Maddireddy [88] devised a comprehensive monitoring and management framework that integrates artificial intelligence with real-time data analytics, enabling anomaly detection, predictive modeling, and automated incident response mechanisms. This system leverages machine learning algorithms and big data technologies to achieve its objectives. Additionally, incorporating advanced deep learning and reinforcement learning models enhances the system's predictive prowess and adaptability. The illustration of the real-time carbon emissions monitoring pathway, grounded in the fusion of artificial intelligence techniques, is depicted in Fig. 3, offering a visual representation of the system's capabilities.

This section discusses the mechanisms by which artificial intelligence technology facilitates real-time monitoring of carbon emissions emanating from buildings. Sensor networks serve as the cornerstone for gathering carbon emission data, while the Internet of Things facilitates the seamless, real-time transmission, and storage of this data. Subsequently, artificial intelligence algorithms process and analyze the data, offering decision-making insights and automating the integration of these processes. Presently, this holistic "end-to-end" artificial intelligence monitoring system has found application across diverse domains, enabling real-time monitoring and predictive analysis of carbon emissions. Looking ahead, research works will prioritize enhancing the system's interoperability and refining the accuracy of its predictive capabilities.

Integration of artificial intelligence with building management systems

The optimization of building energy control and operational strategies presents substantial prospects for mitigating carbon emissions from the built environment. According to projections by the National Energy Technology Laboratory, a substantial portion exceeding a quarter of the total US' electricity demand of 713 gigawatts in 2010 could have potentially been managed more efficiently had buildings been equipped with advanced energy control and operational strategies in conjunction with smart grid infrastructures [89]. Consequently, the implementation of a comprehensive building management system tasked with monitoring energy consumption and suggesting tailored operational strategies offers a novel avenue for innovating solutions aimed at reducing the carbon footprint of buildings.

A building management system is an integrated computerized system designed to monitor and control a range of infrastructure and devices within a building. The primary objective of a building management system revolves around enhancing operational efficacy, fostering occupant comfort, and ensuring safety, all while minimizing energy usage and operational expenditures. This is accomplished by integrating crucial subsystems such as heating, ventilation, and air conditioning, lighting, electrical infrastructure, security, fire protection, and additional subsystems, facilitating centralized oversight and management of all pivotal facilities within the building's confines. The holistic approach ensures optimal performance and efficient utilization of resources. The components of this system mainly include sensors, controllers, communication networks, central management systems, and actuators. As mentioned above, sensors are the sensing part of the building management system,

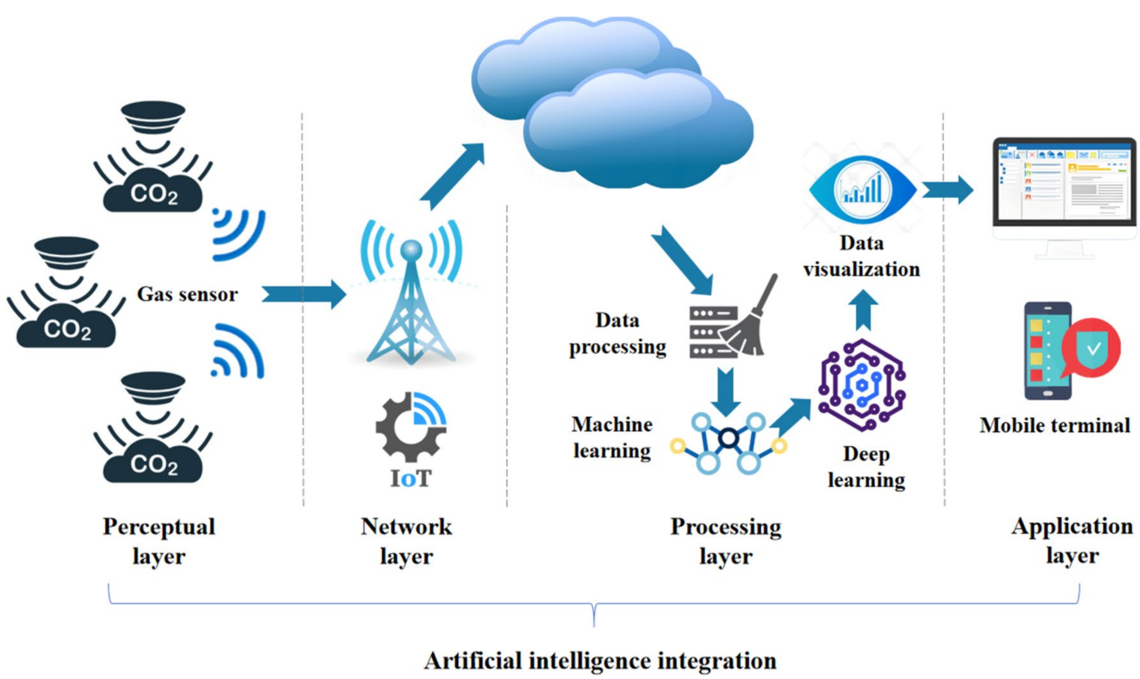

Fig. 3 Artificial intelligence integration applied to building carbon emissions. This diagram shows the path of real-time carbon emission monitoring integrated with artificial intelligence. It starts with a network of sensors, using gas sensors to collect carbon dioxide data, which is then networked, transmitted, and stored using the Internet of Things. The data is processed and analyzed through technologies such as machine learning and deep learning, and the analysis results are transmitted to the mobile terminal through data visualization, demonstrating the full integration of artificial intelligence technology in the system

responsible for collecting various data inside and outside the building. The controller is the decision-making part of the system, which receives the data from the sensors, analyzes and judges accordingly according to the pre-set control logic and algorithms, and finally sends out the control commands.

The communication network is the nervous system of the building management system, which is used to connect the sensors, the controller, and the central management system to ensure the real-time transmission of data and the accurate execution of instructions. The communication network usually adopts standardized communication protocols, such as BACnet and Modbus, to ensure compatibility and interoperability between different devices. The central management system is the "brain" of the system, which is a computer system equipped with specialized management software. It is responsible for centrally processing and displaying all data, as well as issuing control commands to coordinate the operation of each subsystem. Finally, the actuator is the execution part of the building management system, which receives instructions from the controller and performs specific operations, such as adjusting the valve opening to start or stopping the equipment [90].

The integration of artificial intelligence technology within building management systems has garnered substantial momentum, with notable advancements spanning diverse domains such as energy optimization, intelligent automation, and predictive analysis for anomaly detection and maintenance. This technological infusion empowers building management systems to substantially enhance operational efficacy, bolster energy conservation and emission mitigation efforts, and elevate user comfort levels. Illustrative case studies, encapsulated in Table 2, showcase the functionalities, merits, and challenges that necessitate addressing in the context of artificial intelligence-integrated building management systems, thereby providing valuable insights into their implementation and optimization.

(1) Energy utilization optimization: Utilizing artificial intelligence technologies, we can unlock substantial energy-saving potential by scrutinizing data pertaining to building energy usage and carbon emissions. These technologies dynamically adjust system configurations to achieve optimal energy consumption profiles. Illustratively, artificial intelligence algorithms, fueled by both historical and real-time information, can intricately modulate heating, ventilation, and air conditioning systems, ensuring reduced energy expenditure and emissions without compromising indoor comfort levels. Within the realm of artificial intelligence, machine learning and deep learning methodologies have been pervasively employed to forecast building energy consumption. Classical neural networks, support vector machines, and recurrent neural networks stand as prominent players, while emerging algorithms like continuous restricted boltzmann machines, recurrent long short-term memory networks, autoregressive integrated moving average models, seasonal autoregressive integrated moving averages, extreme gradient boosting, radial basis functions, and others have been validated as cutting-edge computational intelligence approaches, capable of delivering even more precise predictions of building energy consumption [36, 97].

(2) Intelligent control: Artificial intelligence technology enables the realization of intelligent oversight and regulation across diverse equipment and systems within the ambit of building management systems. Using the Internet of Things technology and sophisticated artificial intelligence algorithms, these systems dynamically adjust lighting intensities, temperatures, ventilation rates, and other pertinent parameters, thereby ensuring optimal comfort and operational efficiency. As an illustrative instance, the intelligent temperature control subsystem autonomously modulates the indoor temperature in harmony with external climatic conditions and occupant activities, fostering a balanced environment that aligns with both comfort and energy-saving objectives [98, 99]. With the development of 5G technology, intelligent control will become more real time and efficient and will be able to realize more complex scene control, further enhancing the intelligence level of the building.

(3) Anomaly detection advancement: The utilization of artificial intelligence technology in anomaly detection has reached a sophisticated level, enabling real-time identification of irregularities within buildings by analyzing vast amounts of sensor data and equipment operational metrics. For instance, leveraging image recognition capabilities, artificial intelligence systems facilitate real-time surveillance of buildings, promptly pinpointing safety hazards and deviations from normalcy. In the context of energy consumption anomaly monitoring, artificial intelligence primarily employs recurrent neural network models to anticipate future energy usage, subsequently computing the deviation between actual and predicted consumption as a metric of "anomaly severity" [100]. As deep learning algorithms evolve, the capacity of artificial intelligence to decipher anomaly signals from intricate data patterns intensifies, refining detection precision and quickening response times. Furthermore, multimodal data fusion methodologies empower artificial intelligence to integrate video, audio, and environmental sensor inputs for a holistic analysis, thereby enhancing anomaly detection's comprehensiveness and effectiveness.

(4) Predictive maintenance optimization: The integration of artificial intelligence technology into predictive main-

Table 2 Case studies of artificial intelligence-integrated building management system

System type	Technology	Functionality				Benefits	Challenges	References
		Real-time monitoring	Energy projections	Anomaly warning	Intelligent control			
Intelligent energy management system	ZigBee wireless sensor networks	√	Not applicable	Not applicable	√	Ability to adapt to any problem that may arise while controlling the heat load	Control is based on contracted power only, with limited intelligence	Nguyen et al. [91]
Advanced building management system	Internet of Things + Big data	√	Not applicable	Not applicable	Not applicable	Already in mass production, scalable to multiple buildings	Limited flexibility, interoperability, privacy, and failure to achieve prediction and early warning	Linder et al. [92]
Intelligent green energy management system	Internet of Things + Deep learning	√	√	Not applicable	Not applicable	Optimized performance in balancing power availability and demand	Monitoring and control only for electricity, not extended to other energy sources	Zhang et al. [93]
Heating, ventilation, and air conditioning intelligent control system	Artificial neural network	Not applicable	√	Not applicable	√	High prediction accuracy can be achieved, and operating modes can be adjusted in real-time according to the prediction	For heating, ventilation, and air conditioning systems only and not connected to real-time monitoring	Yayla et al. [94]
End-to-end intelligent energy monitoring and control management system	Internet of Things + Machine learning + Edge computing	√	√	Not applicable	√	Enables low-cost, simple, transparent and explainable building energy management	Dependent on human factors at the margins, human intervention has not been fully eliminated	Kök et al. [95]
Building automation and management systems	Internet of Things + Big data + Machine learning	√	√	√	√	Excels in energy detection, fault and anomaly monitoring, water monitoring, indoor environmental quality monitoring, etc.	Dependent on the presence of labeled data and the precision of its annotations	Himeur et al. [96]

The table lists several representative cases of artificial intelligence-integrated building management systems. With the growth of the year, the building management system used technology gradually diversified, the use of Internet of Things technology and artificial intelligence technology gradually increased, and the realization of the function became no longer single. Particularly in the past three years, the rapid progress of artificial intelligence technology has accelerated the intelligent update and upgrade of the building management system, which has been able to realize the whole stage of intelligent management from real-time monitoring, energy prediction, and anomaly early warning to intelligent control, resulting in increasingly noticeable effects on building energy conservation and output mitigation. The √ in the table indicates that the technology is capable of this function tenance practices has imparted substantial advantages to the realm of building management. By meticulously examining equipment operational data, artificial intelligence algorithms anticipate impending equipment failures and maintenance requirements, thereby mitigating the detrimental impacts of unexpected breakdowns [101, 102]. As an illustration, through the analysis of vibration signatures and thermal profiles, artificial intelligence can forecast failures within air conditioning systems, thereby enabling the proactive scheduling of maintenance activities. Looking ahead, the advent of digital twin technology will empower artificial intelligence to emulate equipment behavior within a virtual realm, allowing for the preemptive identification of latent issues and, consequently, enhancing maintenance efficiency and precision.

This section underscores the pivotal role of amalgamating artificial intelligence with building management systems, presenting a paramount opportunity to refine building energy control mechanisms and facilitate energy conservation as well as emission reduction efforts. By incorporating artificial intelligence, building management systems are endowed with the capability to seamlessly integrate disparate subsystems, including heating, ventilation, air conditioning, lighting, electrical, and security networks, yielding tangible advantages in realms of energy optimization, anomaly detection, automated control, and predictive maintenance. Over the past decade, numerous domestic and international cases have exemplified the triumphant incorporation of artificial intelligence within building management systems, marking notable progress in this field. Anticipating future advancements, the proliferation of advanced 5G technologies and digital twin methodologies will foster continuous innovation and enhancements, ultimately enhancing the competence and proficiency of building management systems, thereby ushering in an era of intelligent and environmentally sustainable building management.

Artificial intelligence-enhanced accuracy and predictive capabilities in emission management

Influence of artificial intelligence on enhancing building carbon emission prediction accuracy

With the widespread attention on climate change driven by excessive greenhouse gas emissions worldwide, cutting carbon dioxide emissions and promoting low-carbon growth are now recognized as a global mission and consensus for future sustainable development. Carbon emission prediction can not only evaluate the current emission situation and help us comprehend the environmental effects of energy consumption but also further offer a scientific foundation for future emission mitigation policies [103]. Research has shown that accurate prediction of carbon emissions is vital for crafting regulations that support environmental conservation and green economic growth [104]. Additionally, predicting carbon emissions from buildings is equally necessary to reach the carbon neutrality goal in the construction sector [105]. Nevertheless, developing a reliable model capable of forecasting future values using historical data is demanding. The traditional carbon emission prediction models commonly used in many previous studies mainly include grey prediction models, time series models, multiple linear regression models, and system dynamics models. Although these models can provide prediction results to a certain extent, their accuracy and efficiency are relatively low, which makes it challenging to meet the goal of accurately assessing and predicting carbon emissions [106]. In this context, artificial intelligence and machine learning technologies have significant advantages and are considered the best approach to handling the task of data modeling and prediction, which has great potential to contribute to environmental governance concerning various environmental challenges [107]. As a result, artificial intelligence has become an ever more crucial tool for organizations wishing to lower their carbon dioxide footprint.

Artificial intelligence modeling relies on data and algorithmic improvements to increase the efficiency and accuracy of model fitting. Several novel algorithms have been implemented for carbon output prediction, demonstrating significant potential. In particular, techniques, including machine learning and deep learning, have emerged as key research hotspots in the field of carbon emission prediction. Examples include various neural network models, including convolutional neural networks, recurrent neural networks and backpropagation neural networks, as well as prediction models like support vector machines, random forest and decision trees. By comprehensively analyzing extensive historical data and various influencing factors, these models can considerably enhance the precision and dependability of carbon emission forecasts, thus providing strong support for more accurate carbon emission reduction strategies.

Case studies of artificial intelligence applications in carbon emission prediction

Currently, research related to carbon output forecasting primarily concentrates on the factors influencing carbon outputs and the development of prediction models. Acheampong and Boateng [108] selected nine input variables influencing carbon emission intensity and utilized a multilevel perceptron to estimate the carbon emission intensity across six countries, including China, the USA, and Australia, and compared them with the actual values, which proved that artificial neural networks can overcome the limitations of the traditional prediction models and exhibit higher prediction performance. In another study [109], to consider the impact of the decrease in carbon outputs caused by the COVID-19 blockade on carbon emissions prediction in 2019, the researchers utilized a time series-based machine learning algorithm to predict global carbon dioxide emissions by incorporating data on the decline in carbon emissions during the epidemic. The findings indicate that the machine learning algorithm powered by artificial intelligence can help reasonably predict carbon emissions in future years during the late epidemic period, with a mean absolute percentage error of 9%, which is a more accurate prediction. We categorize the current widely used artificial intelligence models into the following three groups to explore how each technique contributes to improving the precision of carbon emission prediction: artificial neural network models, integrated learning models, and support vector machine models.

Artificial neural networks are usually applied to forecast carbon emissions at the macro level, including national and industry scales. Artificial neural networks can generally be divided into two categories according to their structure and function: feedforward neural networks and recurrent neural networks. A Canadian study [110] utilized convolutional neural networks and multiple regression models to predict carbon emissions associated with fuel consumption in light-duty vehicles. The findings revealed that the one-variable polynomial regression model attained a prediction accuracy of 98.6%, the highest recorded when using a single feature input for prediction. Compared with other traditional regression models, the convolutional neural networks model did not achieve the highest R^2 value, but it consistently provided stable and high values of the coefficient of determination for all scenarios, which proved that the convolutional neural networks model excelled in prediction stability and had high prediction performance.

As the demand for higher prediction accuracy grows, more scholars have begun to explore integrating multiple models for prediction to enhance prediction accuracy. Luo et al. [111] predicted the carbon emissions of Xian for the period 2020–2030 by constructing a hybrid multi-objective planning–principal component analysis–backpropagation neural network prediction model, using Xian City, China, as a case study. They demonstrated that the prediction precision of the model achieved 90%, greatly improving both the training rate and the prediction accuracy of the neural network with this hybrid modeling approach. In addition, there are some combinations of optimization algorithms, such as particle swarm optimization algorithm, genetic algorithm, and whale optimization algorithm, which are mainly used to finetune the parameters of neural network models to improve their predictive performance. In Sun and Huang [112]'s study, after screening the key variables influencing carbon emission intensity using stochastic frontier analysis, the whale optimization algorithm was employed to adjust the input weights and hidden layer bias of the extreme learning machine model to forecast the carbon emission intensity in China's manufacturing industry. Their results highlighted that the optimized extreme learning machine has higher prediction accuracy compared to single machine learning methods in this area.

Integrated learning models are machine learning methods that improve overall predictive performance by combining multiple base learners, comprising random forest, gradient boosting decision tree and extreme gradient boosting [113]. At present, random forest-based carbon emission prediction models are extensively applied at the individual building level. Fang et al. [114] conducted a case study using 38 traditional residential units from the Pearl River Delta region in China to forecast the carbon emissions throughout the construction phase using the random forest algorithm. The random forest model outperformed traditional multiple linear regression models, achieving a higher coefficient of determination R^2 value (0.6403) and lower mean square error (0.7649), effectively avoiding overfitting problems in the model. The results have shown that the random forest model's predictive performance considerably surpasses that of traditional prediction models, not only saving computation time, but also improving the precision and dependability of the model.

Although the random forest model reduces the need for feature selection to some extent, the model performance relies on good feature engineering and parameter tuning, and thus, the prediction accuracy of the random forest model may be lower compared to other prediction models. Ahmad et al. [115] compared the predictive performance of artificial neural networks and random forests for heating, ventilation, and air conditioning energy consumption, using a hotel in Madrid, Spain, as an example. The study revealed that the artificial neural network model had a root-mean-square error of 4.97, greatly lower than that of the random forest model, and a coefficient of determination R^2 value of 0.95, slightly higher than that of the random forest model. Overall, the artificial neural networks model is better than the random forest model in predicting heating, ventilation, and air conditioning energy consumption. Additionally, the random forest algorithm excels at identifying key influencing factors, and the importance of overall features is determined by the random forest's multi-decision tree structure, which combines the contributions of categorical features from each decision tree. This makes the random forest model effective in identifying the factors that impact carbon emissions and thus serves the prediction model well [116]. Some researchers integrated random forest, particle swarm optimization algorithm, and backpropagation neural network to propose an innovative combined prediction model aimed at forecasting carbon emissions in China's business sector [48]. Finally, the horizontal comparison with the prediction model without random forest revealed that the hybrid model could predict carbon emissions more accurately, demonstrating that screening good predictors through random forests may contribute more than the combination of algorithmic optimization and modeling to enhance the forecasting accuracy of the model.

Gradient boosting decision tree is an ensemble algorithm built on decision trees. The method employs classification and regression trees as base learner and is capable of addressing most regression problems by combining multiple weak predictive models and iterating step by step to eventually generate an optimal performance model [117]. Cui et al. [118] improved the whale optimization algorithm using composite chaotic mapping, nonlinear convergence factor, local domain perturbation, and inverse learning and established a gradient boosting decision tree model, refined using the enhanced whale optimization algorithm to forecast China's carbon outputs in the near future. The findings show that the relative errors of all the prediction points of the model do not exceed 1%, and the hybrid model has the best fit to the actual carbon emission values and the best prediction accuracy compared with the single gradient boosting decision tree and the gradient boosting decision tree based on other optimization algorithms.

Support vector machine models can be divided into least squares support vector machine and standard support vector machine models, distinguished by their rapid learning rate and strong generalization capability [106]. Wang et al. [119] evaluated the precision of backpropagation neural networks, Gaussian process regression, and support vector machine models in forecasting carbon emissions within the transportation sector. The results indicated that the support vector machine model outperformed traditional regression and neural network models in predictive performance. Another study introduced an integrated least squares support vector machine model using a combined kernel function to predict how China should adjust its industrial and energy structure to meet the carbon intensity target through scenario analysis [120]. It was also demonstrated that the model attains greater precision in forecasting energy consumption compared to traditional statistical models and single support vector machine models.

In addition, different prediction models have their unique advantages and characteristics. To maximize the benefits of each prediction model, an increasing number of scholars get the optimal prediction results by constructing hybrid prediction models, including the hybrid of traditional and intelligent models and the hybrid of intelligent and smart models. Among them, traditional and intelligent hybrid models usually combine classical statistical prediction models with artificial intelligence models, leveraging the transparency of statistical methods with the capacity of artificial intelligence models to deal with nonlinear and high-dimensional data, thereby enhancing prediction accuracy and stability effectively. Fenton et al. [121] employed various machine learning models, including support vector regression, decision trees, and random forests, to predict implied greenhouse gas emissions using attribute characteristics of buildings for two sets of building cases. Case 1 covers 319 typical French residences, and case 2 extends to 524 French and Belgian residential and non-residential buildings. To enhance the accuracy and robustness of the prediction models, this study established two hybrid prediction models utilizing the above machine learning models: linear ridge regression hybrid model and radial basis kernel support vector regression hybrid model. The results indicate that the accuracy of these two hybrid prediction models reached 92.3% in case 1 and 93.3% in case 2, respectively, and the root-mean-square error is considerably lower compared to the single machine learning model, with notable improvements in both prediction stability and accuracy.

This kind of hybrid model is not only applied to the prediction of carbon emissions of individual buildings at the microlevel but can also be successfully utilized to predict carbon emission-related indicators at the macro level. Moreover, many studies have combined the improved traditional prediction models with artificial intelligence algorithms to construct hybrid prediction models with higher prediction accuracy. For example, the results of a study in the Yangtze River Delta region reveal that the use of kernel principal component analysis for forecast data preprocessing and the enhanced butterfly optimization algorithm combined with the least squares support vector machine hybrid model for the prediction of carbon emissions achieved better performance than the ordinary hybrid forecasting model [122]. In addition, Hu and Lv [123] employed the grey prediction model and the generalized vector machine to forecast carbon transfer across various industries within China. They optimized the parameters of the generalized vector machine using the artificial fish swarm algorithm to obtain the artificial fish swarm algorithm-generalized vector machine model, which improved the convergence speed and prediction performance of the generalized vector machine. Then, the grey model of stochastic oscillatory sequence was established based on the classical grey model, and finally, a hybrid prediction model was formed, and the model was applied to establish the carbon emission transfer network of 28 industries in China in 2017. Intelligent and intelligent hybrid models, on the other hand, combine multiple artificial intelligence models to take advantage of their respective strengths. The main advantage of this approach lies in its ability to handle nonlinear, high-dimensional data and capture complex relationships, but it can potentially lead to overfitting problems.

In conclusion, in the area of carbon emission forecasting, artificial intelligence techniques have demonstrated higher accuracy and reliability than traditional forecasting models. Techniques such as artificial neural networks, support vector machines, random forests, and gradient-enhanced decision trees have shown their strengths and great potential in handling complex datasets and providing accurate predictions. In addition, these artificial intelligence models have been enhanced with optimization algorithms and hybrid modeling approaches to provide even more powerful tools for accurately predicting carbon emissions. These techniques boost both the accuracy and efficiency of carbon emission forecasting, while also offering more effective solutions for dealing with complex environmental factors, providing solid data backing for future carbon assessment and the formulation of emission reduction measures.

Comparison of artificial intelligence techniques in carbon emission prediction

Over the past few years, significant progress has been made in applying artificial intelligence technology to carbon emission prediction, and different artificial intelligence algorithms have shown their respective advantages and characteristics. By comparing and analyzing these techniques, we can better understand their performance and applicable scenarios in practical applications. Table 3 summarizes the main features, performance indicators, advantages and disadvantages, and application scenarios of several widely used artificial intelligence techniques and hybrid models in carbon emission prediction. Comparing and analyzing artificial intelligence-related prediction methods helps us identify the most appropriate algorithm for specific requirements and enhances the accuracy and efficiency of forecasting. In addition, the detailed comparative analysis can also promote further optimization and innovation of the technology to achieve carbon management and emission reduction goals more effectively.

Overall, the implementation of artificial intelligence technology in the realm of carbon emissions forecasting has made significant progress in model development, improvement and the combination of hybrid models. Through continuous improvement and innovation, artificial intelligence techniques have been able to address problems in forecasting accuracy and efficiency and fully utilize the strengths of different algorithms. These techniques not only provide more accurate and reliable carbon emission forecasting tools, but also serve as a vital foundation for decision-making by researchers and policymakers. As artificial intelligence technology continues to advance, more breakthroughs are expected to be realized related to carbon emission forecasting, facilitating a deeper integration of artificial intelligence systems into environmental management, thereby creating more opportunities for achieving carbon reduction and promoting sustainable development.

Impact of artificial intelligence on carbon emission management

As a key component of digitalization, artificial intelligence technology offers innovative tools and new directions for carbon emissions management and low-carbon development of enterprises [132]. It has been shown that artificial intelligence plays a key role in reducing carbon emissions, improving energy efficiency and promoting sustainable development, and that it can effectively reduce carbon emissions and improve green innovation in enterprises [133]. The implementation of artificial intelligence technology in carbon emissions management has become an important force in driving global efforts toward achieving carbon peaking and carbon neutrality goals. Artificial intelligence technologies provide innovative solutions for monitoring, managing and reducing carbon emissions through functions such as data analysis, pattern recognition, and predictive optimization. Below are specific examples of artificial intelligence technologies in different application areas and how they can achieve emission reduction targets.

Accurate data monitoring is fundamental in carbon emissions management. Artificial intelligence technologies can collect real-time data through sensor networks and Internet of Things devices and analyze it using machine learning algorithms to monitor and report on carbon emissions. For example, to precisely track the carbon emissions of enterprises, Gao et al. [134] proposed a novel approach for monitoring both direct and indirect carbon emissions using external big data, artificial intelligence and data privacy protection techniques—a vertical federated long short-term memory network model with self-attention mechanism, which can precisely monitor the hourly carbon emissions of an enterprise and ultimately transmit the monitoring data to carbon market regulatory agencies. In an Australian study [135], an artificial intelligence predictive model with strong interpretability was built to measure and validate energy-efficient infrastructure with net-zero carbon emissions. The model utilized the XGBoost algorithm to enhance its robustness of the model, which is suitable for monitoring building energy consumption and evaluating the energy-saving effect in multi-scenarios, providing a more accurate and efficient tool for carbon emission management and helping to better formulate and implement carbon reduction strategies.

Furthermore, the comprehensive implementation of artificial intelligence technology can realize cross-domain carbon emissions management by aggregating data from various sources and applications to provide comprehensive

Table 3 Performance of different artificial intelligence techniques in carbon emission prediction

Artificial intelligence technology	Characteristic	Performance indicators	Advantages and disadvantages	Application scenario	References
Convolutional neural networks	Using floor plan images as the primary input, the model can effectively grasp the detailed spatial layout of a residential unit and provide real-time predictions of carbon emissions during the operational phase, which is particularly useful for architects to anticipate potential carbon emissions in the early design phase	$R^2=0.91$ to 0.98	Pros: The convolutional neural network model is not only adaptable and fast, but also shows strong predictive ability Cons: The model demands extensive high-quality time series and spatial data, and the training process may require significant time	The model is suitable for the forecast of carbon emissions from single buildings, such as single-story residential units with minimal cross-sectional variation, which is common in regions such as Beijing, China	Yan et al. [49]
Random forest	Random forests have strong resistance to overfitting and can identify the key factors affecting carbon emissions more stably without being affected by data collinearity when selecting variables	Mean absolute difference	Pros: The prediction results are relatively stable and can effectively reduce the overfitting problem of a single model Cons: Since random forest contains many decision trees, its internal structure is more complex, making it more challenging to explain the results and in some cases more sensitive to noisy data	It is suitable for scenarios involving complex, high-dimensional datasets, particularly excelling in carbon emission impact factor analysis, large-scale data processing, and feature importance assessment. For example, the processing of urban carbon emission data and environmental monitoring data, as well as research on carbon emission driver analysis and environmental impact assessment	Wang et al. [124]
Gradient boosting decision tree	The model optimizes the prediction by minimizing the loss function using gradient descent and performs best in both its test and training sets for the prediction of nitrogen oxide emissions compared to support vector regression and long short-term memory models	$RMSE_{Train}=1.85$, $RMSE_{Test}=3.59$, $MAPE_{Train}=0.09$, $MAPE_{Test}=0.19$, $ACC_{Train}=0.79$, $ACC_{Test}=0.62$	Pros: By combining multiple decision trees, gradient boosting decision tree reduces overfitting, improve prediction accuracy, and offer high flexibility in different prediction scenarios Cons: Model complexity increases with the number of trees and is less interpretable than simpler models; gradient boosting decision trees require careful tuning of hyperparameters to achieve optimal performance, which is often a challenging iterative process	It is suitable for scenarios that require large-scale nonlinear data processing and feature importance assessment, such as the prediction of environmental monitoring-related emissions such as urban carbon emission data and the analysis of carbon emission drivers	Ding et al. [125]

Table 3 (continued)

Artificial intelligence technology	Characteristic	Performance indicators	Advantages and disadvantages	Application scenario	References
Least squares support vector machine	Least squares support vector machine can efficiently handle nonlinear relationships in data through kernel functions and has a fast training and prediction speed	MAPE = 0.16, RMSE = 0.001, MdAPE = 0.19, MaxAPE = 0.21	Pros: Compared with the backpropagation neural network and the traditional grey prediction model, this model can provide highly accurate prediction results with good robustness when dealing with complex datasets Cons: Model performance is sensitive to the choice of kernel function and parameters and needs to be optimized by methods such as cross-validation	It is suitable for systems with complex nonlinear relationships, such as the relationship between different economic activities and energy consumption, as well as long-term or large-scale industrial production carbon emission forecasting	Sun and Liu [126]
Extreme learning machine	It has high computational efficiency during training and prediction, and can process large-scale datasets quickly and reduce computational complexity	RMSE = 3494.46, MAPE = 2013.43, MASE = 0.93	Pros: Fast and accurate calculation, strong generalization ability, able to perform well in complex data environments Cons: High-quality requirements for input data, poor model robustness, if there is noise or outliers in the data, it may affect the predictive performance of the model	It is especially suitable for carbon emission forecasting scenarios that require efficient processing and fast forecasting, such as carbon emissions generated by gas-powered plants in the power industry, as well as energy consumption and carbon emission forecasting in industrial manufacturing	Rahman et al. [127]
Long short-term memory network	The model can capture both long-run and short-run dependencies while handling multiple input variables for multifaceted forecasting, such as labor force, capital stock, total energy consumption, and carbon emissions, and both the training and test sets of the model show a good fit	$R^2_{Train} = 0.95$, $R^2_{Test} = 0.96$, $MAE_{Train} = 0.03$, $MAE_{Test} = 0.03$, $MSE_{Train} = 0.002$, $MSE_{Test} = 0.002$	Pros: The model excels in handling complex nonlinear relationships, efficiently predicting dynamic trends, delivering accurate forecasting results, and maintaining good performance even in the presence of noisy data due to its high robustness Cons: The model structure is complex, the training time is long, and the requirement for computational resources is high	It is particularly well-suited for handling time series data with long periods, such as predicting future economic indicators and monitoring and predicting carbon emission trends over a long time	Niu et al. [128]

Table 3 (continued)

Artificial intelligence technology	Characteristic	Performance indicators	Advantages and disadvantages	Application scenario	References
Hybrid model: long short-term memory network-convolutional neural networks	The hybrid prediction model can capture both time-dependence and spatial correlation simultaneously, and can account for spatial autocorrelation between different regions, thus improving the accuracy and reliability of predictions	MAE = 8.02, RMSE = 11.16, R^2 = 0.97	Pros: The hybrid model exhibits higher prediction accuracy compared to other common machine learning prediction models Cons: The model has a complex internal mechanism, making its judgment and inference results challenging to interpret, and it is only suitable for prediction; meanwhile, the model relies heavily on extensive time series and spatial data for support, and the training time is long	It is suitable for carbon emission forecasting tasks that need to consider inter-regional spatial correlation and deal with long-term time series data, such as carbon emission forecasting at provincial and national levels	Han et al. [129]
Hybrid model: random forest-sequence minimization algorithms	The model combines the strengths of random forest and sequence minimization algorithms and performs well when dealing with large-scale data, allowing for fast convergence and reduced training time	R^2_{Train} = 0.99, R^2_{Test} = 0.96, $MAPE_{Train}$ = 0.03, $MAPE_{Test}$ = 0.07 $RMSE_{Train}$ = 800, $RMSE_{Test}$ = 2374, $NMSE_{Train}$ = 0.003, $NMSE_{Test}$ = 0.02	Pros: The model has higher prediction accuracy on different datasets, can effectively identify intricate patterns in the data, and has strong generalization ability Cons: The model structure is complex, parameter tuning is more cumbersome and requires more computational resources, and the overall model is less interpretable	It is suitable for scenarios that require high accuracy, fast prediction and complex data processing, such as urban transportation planning, road transport carbon emission assessment and policy formulation	Khajavi and Rastgoo [130]

Table 3 (continued)

Artificial intelligence technology	Characteristic	Performance indicators	Advantages and disadvantages	Application scenario	References
Hybrid model: sparrow search algorithm-long short-term memory	This hybrid prediction model combines the powerful optimization potential of the sparrow search algorithm with the time series handling strengths of long short-term memory. The sparrow search algorithm enhances the efficiency of hyperparameter optimization for long short-term memory models by ensuring rapid convergence. This approach helps avoid issues such as overfitting and local optima, thus improving the fitting effect of the prediction model	MAE = 289.14, RMSE = 357.15, R^2 = 0.84, MAPE = 0.02	Pros: The sparrow search algorithm effectively simplifies the hyperparameter selection process of long short-term memory, preventing overfitting and local optima, thereby strengthening the general reliability and effectiveness of the prediction model. Accounting for the impact of the boiler feed water system greatly improves the accuracy of carbon emission predictions in coal-fired power plants Cons: The model training time is long, and the data requirements are high, and the cost of data collection and preprocessing is high	It is suitable for carbon emission prediction scenarios that deal with complex time series data. For example, the forecast of carbon outputs from coal-powered plants in the electric power industry; in environmental monitoring, the trend of carbon emissions at the city or national level can be monitored and predicted over a long period of time; in industrial production, energy consumption and emissions can be monitored and predicted in real time	Wang et al. [131]

The abbreviations in Table 3 are interpreted as follows:

R^2: Coefficient of determination; RMSE: Root-mean-square error; *MAPE*: Mean absolute percentage error; *MASE*: Mean absolute scaled error; *ACC*: Accuracy; *NMSE*: Normalized mean squared error; *MAE*: Mean absolute error; MSE: Mean squared error; *MdAPE*: Median absolute percentage error; and *MaxAPE*: Maximum absolute percentage error.

The table demonstrates the performance of different artificial intelligence techniques and their hybrid models utilized in the domain of carbon output forecasting. Long short-term memory networks and the hybrid prediction models combined with them excel in handling complex time series and spatial information and can significantly improve prediction accuracy. Random forests, on the other hand, excel in feature importance assessment and handling high-dimensional data, while least squares support vector machines are advantageous for handling nonlinear relationships and offering rapid training. Compared with traditional prediction models, these techniques not only strengthen the precision and dependability of carbon output forecasting but also reduce the time cost. In particular, hybrid prediction models, which combine the advantages of multiple artificial intelligence techniques, significantly improve the prediction performance of the models solutions. Amadi et al. [136] investigated the implementation of machine learning algorithms such as random forest, support vector regression, and artificial neural networks in carbon management. They applied these algorithms to forecast the instantaneous unconfined compressive strength of different lithologies through drilling parameters such as weight of bit, rate of penetration, and torque by utilizing the algorithms as mentioned above, in order to identify more effective methods and solutions to reduce drilling operations' carbon footprint, contributing to continuous improvements in drilling carbon emissions, performance monitoring, and overall drilling performance. Peng et al. [62] proposed an eco-friendly, low-carbon intelligent transportation system built on big data and machine learning techniques, utilizing a genetic algorithm combined with a particle swarm optimization-augmented support vector regression approach to predict traffic patterns, and constructing a carbon emission model for vehicles by considering predicted road conditions and fuel consumption rates. The results indicate that the method can significantly lower the total carbon outputs of vehicles across the road network, contributing to the development of a low-carbon transportation system and a smart city.

Overall, the implementation of artificial intelligence technology in carbon emissions management not only enables enterprises to attain long-term sustainability but also enhances their environmental and social performance, providing an effective tool for combating climate change and enhancing corporate competitiveness. The application of artificial intelligence technologies in carbon emissions management involves multiple aspects, from data monitoring to operations optimization to energy and transportation management, as shown in Fig. 4. Artificial intelligence technology provides companies and organizations with effective tools and solutions to achieve carbon reduction targets by improving energy efficiency, reducing energy waste, and optimizing production processes. With the continuous progress and in-depth application of artificial intelligence technology, its potential for carbon emission management will be even more significant in the future.

This section discusses the impact of artificial intelligence techniques on carbon emissions forecasting and management and the performance of different artificial intelligence techniques in carbon emissions forecasting. Implementing artificial intelligence techniques in carbon emission forecasting and management has made significant progress in model development, improvement, and combination of hybrid models. Compared with traditional carbon emission prediction models, artificial intelligence models such as artificial neural networks and integrated learning models, as well as related models enhanced by optimization algorithms and hybrid modeling approaches, have shown their unique advantages and great potential in handling large-scale and complex datasets, providing more accurate prediction accuracy, and improving prediction efficiency. In addition, the multifaceted application of artificial intelligence technologies in carbon emission management, such as real-time energy consumption monitoring, provides companies and organizations with effective solutions to achieve carbon reduction targets, which helps companies and the construction industry to meet long-term sustainable development, and provides a powerful tool for combating climate change and enhancing the competitiveness of companies.

Perspective

Data availability and the challenges of artificial intelligence implementation

The building sector is encountering efficiency and environmental hurdles tied to lowering carbon emissions, which are strongly connected to sustainable development goals. Big data plays a particularly important role in building energy and the environment [137]. In recent years, research and industry related to big data-driven smart energy and environmental management have developed rapidly. That said, several significant challenges remain to be tackled to fully harness the potential of big data and meet the objectives of smart energy and environmental management [138]. In the field of carbon emissions assessment, applications related to artificial intelligence modeling are still highly dependent on data quality and availability. High-quality, reliable data is essential for training accurate artificial intelligence models, ensuring the robustness of predictions and making informed decisions. Inconsistent data collection methods, gaps in data records, and the lack of standardized formats can seriously affect the effectiveness of artificial intelligence algorithms, and thus the accuracy of carbon emissions assessment and the efficiency of management.

High-quality, standardized and uniformly formatted data is a prerequisite for the effective assessment of carbon emissions and the realization of smart environmental management. It has been noted that data quality, integration, and sharing face many challenges in the energy and environment sectors. Although the volume of data is large and contains much valuable information, relatively little of it can be effectively utilized, and the quality of the data is poor, with timeliness, completeness, accuracy, and consistency needing to be improved [139]. Second, the lack of a unified data-sharing platform limits the accessibility of data, and different companies and institutional organizations use different standards for data definition, storage, and management, leading to data redundancy and inconsistency and making full data integration more difficult. For instance, within building carbon emissions, differences in data granularity, measurement

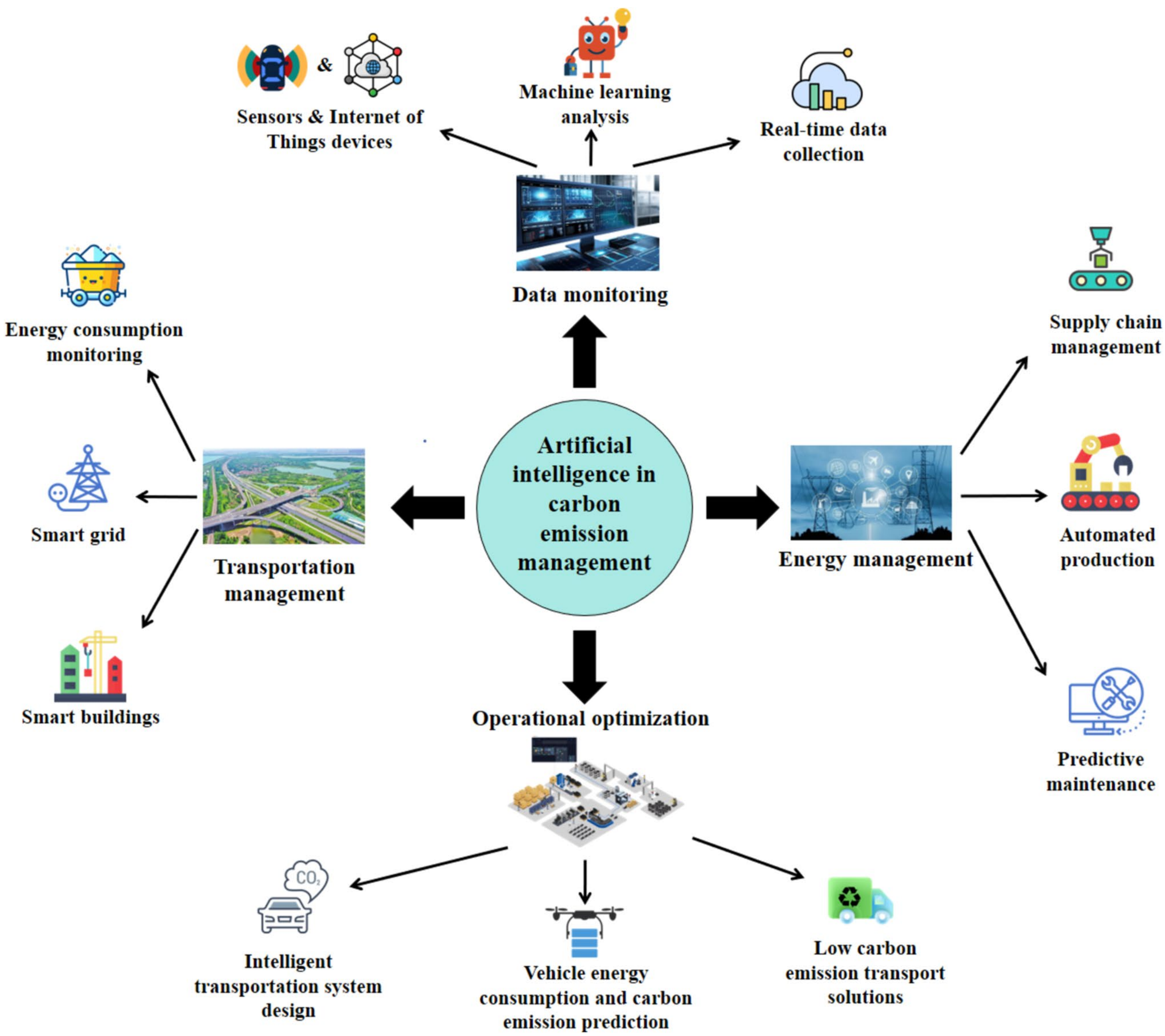

Fig. 4 Utilization of artificial intelligence in carbon emissions management. This figure demonstrates the multifaceted applications of artificial intelligence technology in carbon emissions management, including data monitoring, operations optimization, energy management, and transportation management. Artificial intelligence technology is able to achieve accurate carbon emissions monitoring and forecasting by collecting data in real time through sensors and Internet of Things devices and analyzing it using machine learning algorithms. Through supply chain management, automated production and predictive maintenance, companies can significantly reduce operational costs and improve productivity. In addition, the implementation of artificial intelligence in energy consumption monitoring, smart grids and smart green buildings improves energy use efficiency and reduces carbon emissions

techniques, and reporting standards across regions and building types can lead to significant biases that complicate the training and validation of artificial intelligence models. Meanwhile, the presence of noise and outliers in datasets further exacerbates the problem, requiring sophisticated data preprocessing and optimization techniques to ensure the reliability of artificial intelligence predictions. Without addressing issues related to data quality and accessibility, the potential for artificial intelligence to accurately predict and manage carbon emissions remains limited.

The first challenge that Cowls et al. [140] identified for artificial intelligence in addressing climate change was that of unwanted bias triggered by the way artificial intelligence models are designed and developed. Specifically, many artificial intelligence approaches that rely on data are supervised, meaning they are trained using labeled data. This process can introduce biases, potentially resulting in bias and unequal treatment of certain individuals or communities. Similarly, Nishant et al. [141]'s research also pointed out that artificial intelligence technology faced the problem of relying on historical data for training and prediction, balancing variance and bias in promoting sustainable development. Historical data may not fully reflect current and future climate conditions, models that overfit historical data may fail to accurately predict future dynamic climate change, and models that simplify overly biased models may perform poorly on training and test data. This issue is particularly prominent in applications related to climate prediction, such as carbon emissions, as the prediction results are easily influenced by political and social factors, thereby exacerbating the gap between science and policy.

Another risk is the invasion of privacy and cybersecurity issues, and the use of artificial intelligence technology to achieve environmental sustainability requires the integration of datasets from various data owners, formats, and structures. Although artificial intelligence systems typically rely on non-personal data, such as meteorological and geographic data, to assess the severity of the climate crisis, making privacy concerns less likely. Developing strategies to reduce carbon emissions may involve revealing data related to human behavior patterns, thereby posing privacy risks, for example, in the field of energy storage [142], industrial temperature control, and regulation [143]. In addition, increased cybersecurity and data management risks demand the capability to handle data standards and integration protocols. While isolated approaches decrease security risks, they are inefficient and arguably less effective. It is crucial to be carefully integrated to prevent hackers from accessing critical data [144].

Artificial intelligence technology is seen as a key driver for economic and social development, and nations place significant emphasis on advancing this technology. Empowering artificial intelligence technology to address climate change, including large-scale power generation from renewable energy sources and the assessment and management of carbon emissions, involves a cross-composite of industry-specific and artificial intelligence-specific knowledge. Liu et al. [145] pointed to the current shortage of relevant high-tech talent and a mature financial support system as one of the challenges limiting the wide-scale application of artificial intelligence technology. In addition, catastrophic disasters, major epidemics, such as COVID-19 pneumonia, and other emergencies have also brought increasing challenges to artificial intelligence prediction technology.

This subsection discusses the potential challenges that may be encountered in applying artificial intelligence to carbon emission assessment and advancing environmental sustainability, including data quality, security, and the shortage of highly skilled personnel and financial support in related professions. The government should maximize its policy guidance, further strengthen data governance, establish a unified data-sharing platform, and increase financial subsidies and tax incentives for various research institutions to guide the integration and innovation of smart technologies with traditional industries such as construction. It is also crucial to promote the training of interdisciplinary talents and to increase financial support. For enterprises and research institutions, they should work to optimize data collection and processing technologies, ensure data quality and standardization, and actively participate in data sharing and cooperation. Meanwhile, they should increase investment in artificial intelligence research and development, strengthen the independent research and development capability of green technology, and address key technological breakthroughs as soon as possible to provide technical support for accurate prediction and management of pollution emissions by artificial intelligence technology.

Economic considerations and cost-effectiveness

In recent years, hardware and technological advances have driven the computational level of artificial intelligence models trained on large amounts of data to new heights, leading to impressive advances in artificial intelligence in different application areas. However, the large-scale computation necessary to achieve these impressive results incurs significant economic and environmental costs. This is due to the expense associated with specialized hardware and power or cloud computing time, as well as the reliance on non-renewable energy sources to power the processing equipment [146]. While the positive impact of artificial intelligence technologies in carbon emissions prediction and management is significant, for example, optimizing production processes through machine learning algorithms that accurately predict energy usage and carbon emissions improves energy efficiency and reduces carbon emissions, thereby lowering long-term operating costs. In addition, maintenance and repair costs can be saved by reducing maintenance and downtime through real-time monitoring and prediction of system failures. In general, the implementation of artificial intelligence technology enables enterprises to attain long-term sustainability, and at the same time, enterprises can enhance their market competitiveness and brand value by adopting artificial intelligence technology to realize a green and sustainable mode of operation, thus obtaining higher economic returns.

But the fact is that artificial intelligence models themselves are expensive to train and develop, including hardware and personnel costs, as well as power and fuel costs [147]. Meanwhile, another study also pointed out that the environmental costs associated with training machine learning models increased directly with the size of the model. To put it differently, larger models necessitate increased computational resources, including time, hardware, and other resources, which leads to higher training costs and greater energy consumption [31]. This is especially pertinent to deep learning models, which are generally larger and more intricate compared to other machine learning models. The study additionally noted that applying various optimization and tuning techniques to improve a model's overall accuracy resulted in a rapid increase in the model's size, thereby amplifying its environmental impact. As a result, Delanoë et al. [148] proposed that assessing the environmental cost of artificial intelligence algorithms should be a necessary step in the model development process and that environmental cost should be used as one of the evaluation criteria for artificial intelligence models, along with other metrics such as accuracy and stability. If the algorithm's energy consumption is too high, some choices should also be made to reduce it, perhaps because the parameters are not well optimized or the accuracy goals are too high. Particularly if the artificial intelligence tool is designed for sustainable purposes, it does not make sense to implement it when the environmental costs are too high.

Gaur et al. [31]'s research indicated that artificial intelligence was a double-edged sword, and the overall carbon emissions related to economic costs during the training and development of artificial intelligence could not be ignored. If artificial intelligence algorithms will increase economic and environmental costs, the focus should be on balancing the performance and efficiency of the algorithm. This entails promoting the development and promotion of energy-efficient artificial intelligence methods. Generally, numerous prospects for future research are present where artificial intelligence and building sustainability converge. A crucial element for future research may involve examining how economic rationality influences the diverse responses of artificial intelligence applications to sustainability, an aspect that must not be overlooked. The operation and allocation of funds have always played a crucial role in the development and transformation of the construction sector. Therefore, economic and cost considerations will undoubtedly influence how the results of artificial intelligence-based models are interpreted and applied. Consequently, future studies need to integrate insights from environmental, behavioral, and traditional economics to comprehensively evaluate the benefits and challenges of artificial intelligence in tackling environmental sustainability issues.

Emerging technologies and interdisciplinary collaboration

In addition to artificial intelligence, emerging information and digital technologies, such as 5G networks, blockchain, and the Internet of Things, represent some of the most dynamic fields for industrial advancement and technological innovation. These technologies offer novel pathways for achieving low-carbon development within the construction sector. As a transformative technological advancement, digital technology depends heavily on data and broadband networks as novel production factors, integrating them into social economic activities [149]. The reliability and application validity of building life cycle assessment results depend on data collection. Employing cutting-edge technologies like the Internet of Things, artificial intelligence, and digital control systems during the material production and construction phases can enable precise monitoring, measurement, and forecasting of carbon emissions across multiple processes. Secondly, the 5G-enabled energy and carbon management system can autonomously gather data on the consumption and emissions of energy sources like water, electricity, heat, and gas within enterprises. The system intelligently detects and evaluates opportunities for improving energy efficiency in production, while regularly producing precise and intuitive charts to assess results, thereby aiding in the development of an optimized energy use plan and supporting direct or indirect reductions in carbon emissions. Woo et al. [150] highlighted the potential for the construction sector to leverage blockchain technology to significantly decrease fossil fuel consumption and boost the energy efficiency of buildings was huge and proposed an innovative carbon trading model based on blockchain technology, demonstrating how the construction industry is able to leverage blockchain to encourage more companies to join the carbon market.

In addition, quantum computing has enormous potential for reducing pollution and global warming. Ashwani [151] summarised a quantum network-based construction carbon footprint analysis model to accurately predict carbon emissions at the city block level, and concluded by stating that circular economy concepts were integral to the development of sustainable building construction using quantum networks for carbon footprint detection. Another study pointed to the promise of quantum optimization techniques to maximize grid allocation and thus reduce waste production within intricate supply chains [152]. While there have been some influential applications of the technology in areas such as carbon capture, energy optimization, and environmental monitoring, there is still a great deal of work to be done to translate the theoretical potential into practical solutions. In the future, addressing technical hurdles like scalability and error correction will be essential for unlocking the full potential of quantum computing to tackle environmental issues. In addition, ensuring equitable use of this technology is crucial, along with addressing any ethical and environmental concerns that may arise during its growth.

The use of artificial intelligence technologies in enhancing building and environmental sustainability currently still relies on the expertise of engineers or users, and in order to effectively utilize artificial intelligence technologies and thus gain a deeper understanding of a given system, researchers often need to have expertise in multiple disciplines such as physics, economics, computers, and environmental sciences, and therefore, the collaboration and advancement of training new artificial intelligence practitioners in each discipline is critical [153]. An interdisciplinary approach to collaboration is conducive to helping researchers understand and solve problems from multiple dimensions, thereby improving the comprehensiveness and scientific quality of research. At the same time, interdisciplinary cooperation can also promote knowledge sharing and technological innovation. Empirical research has indicated that the efficiency of artificial intelligence in lowing carbon emissions differs among various industries and regions [154], and therefore, local governments need to tailor their carbon emission reduction strategies to the specific characteristics of each industry and region, taking into account the distinct energy systems, industrial structures, and levels of artificial intelligence development present in different areas. For China, it is crucial to leverage the technological strengths of the eastern and northeastern regions to generate a positive influence on surrounding regions. Additionally, emphasis should be placed on upgrading artificial intelligence infrastructure in the central and western areas, while encouraging the expansion of low-carbon industries through strategic industrial support. To maximize the benefits of artificial intelligence, it is crucial to minimize administrative obstacles between regions, enhance the sharing and exchange of technology and skilled labor among enterprises and areas, and fully leverage the spillover effects of these advancements.

In summary, new-generation information technologies such as 5G networks, blockchain, quantum computing, and the Internet of Things provide new paths for low-carbon development in the construction industry and show great potential in addressing environmental challenges such as global warming. As shown in Fig. 5, the obstacles and future paths of artificial intelligence technologies in sustainable building development are summarized. Meanwhile, interdisciplinary collaboration is vital for enhancing the implementation of artificial intelligence technologies in promoting building and environmental sustainability. Although new technologies may face challenges such as scalability, economic costs, and policy ethics, the potential of artificial intelligence and other new technologies can be fully utilized through, for example, interdisciplinary collaborative innovation to help achieve the goal of more efficient and sustainable carbon emissions management.

Conclusion

Artificial intelligence is seen as an important tool in evaluating carbon emissions and improving building sustainability. Its strengths lie in efficient data processing, precise forecasting, and optimization capabilities, which are crucial in combating increasing climate change and promoting sustainable development. This review assesses the implementation and possible impact of artificial intelligence technologies in the estimation, forecasting, and management of carbon emissions, including a variety of machine learning algorithms, deep learning algorithms, and hybrid prediction methods. The application of artificial intelligence techniques in building carbon emissions considerably boosts model prediction accuracy and efficiency, while also increasing stability and preventing overfitting issues. In addition, this work discusses and analyzes the contribution of artificial intelligence to real-time carbon emissions monitoring systems, reviewing how artificial intelligence techniques facilitate the real-time tracking of carbon emissions in buildings and their integration with contemporary building management systems.

Different artificial intelligence technologies can play unique advantages and roles in carbon emissions forecasting and management, and we summarize and compare the effectiveness and performance of different artificial intelligence technologies in carbon emissions forecasting and explore the potential impacts of their multifaceted applications in carbon emissions management. The current application of artificial intelligence technologies still faces challenges such as data quality, sharing and security issues, and high time and economic costs. In the future, the combination and innovation of emerging technologies such as 5G networks and quantum computing with artificial intelligence technologies will emerge as a key area of research in the realm of building sustainability, offering new possibilities to meet the challenges posed by energy optimization and the development of carbon trading markets. Meanwhile, relevant policy support, such as intense financial subsidies and interdisciplinary cooperation, will be crucial for attaining sustainable development within the building sector.

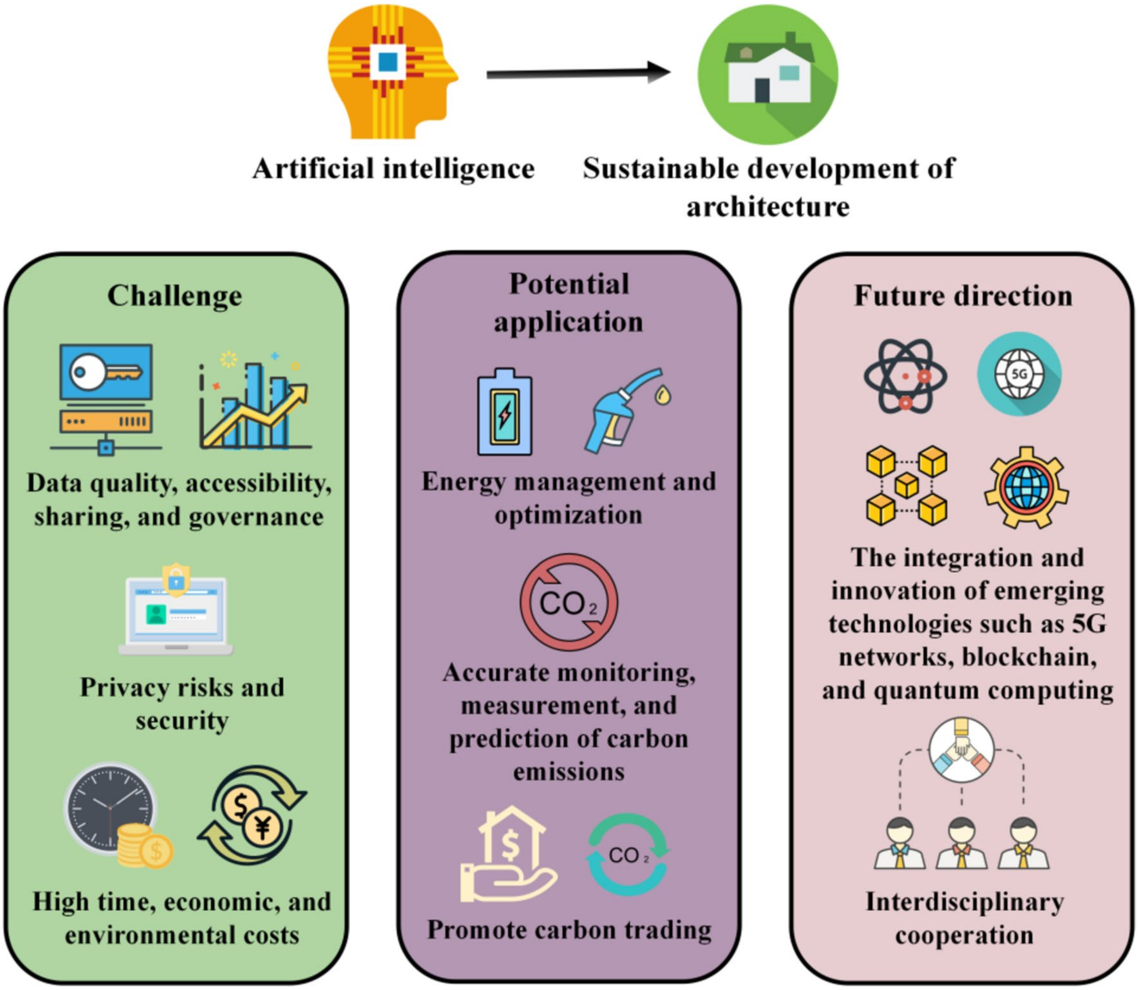

Fig. 5 Prospects of artificial intelligence technology in building sustainability. Artificial intelligence technologies can be used in the future sustainable development of the building industry for energy management and optimization, accurate monitoring and forecasting of carbon emissions, as well as creating a digital carbon management system and facilitating the development of a carbon trading market. However, the current application of artificial intelligence technologies still faces challenges such as data quality, sharing, and security issues as well as high time and economic costs. In the future, the integration and innovation of emerging technologies such as 5G networks, blockchain, quantum computing, and the Internet of Things need to be strengthened through interdisciplinary cooperation in order to maximize the positive role of artificial intelligence in sustainable development

Funding Dr. Ahmed I. Osman wishes to acknowledge the support of The Bryden Centre project (Project ID VA5048). The Bryden Centre project is supported by the European Union's INTERREG VA Programme, managed by the Special EU Programmes Body (SEUPB). Lin Chen and Ji Feng wish to acknowledge the funding support from China Construction Third Corporation's Science and Technology Research and Development Project (No. CSCEC3B-2023-08).

Data availability No data was used for the research described in the article.

Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. AIO declares that he is the Editor of Environmental Chemistry Letters.

References

1. Chen L, Huang L, Hua J, Chen Z, Wei L, Osman AI, Fawzy S, Rooney DW, Dong L, Yap P-S (2023) Green construction for low-carbon cities: a review. Environ Chem Lett 21:1627–1657. https://doi.org/10.1007/s10311-022-01544-4
2. Lai KE, Abdul Rahiman N, Othman N, Ali KN, Lim YW, Moayedi F, Mat Dzahir MA (2023) Quantification process of carbon emissions in the construction industry. Energy Build 289:113025. https://doi.org/10.1016/j.enbuild.2023.113025
3. Li D, Huang G, Zhang G, Wang J (2020) Driving factors of total carbon emissions from the construction industry in Jiangsu Province. China J Clean Prod 276:123179. https://doi.org/10.1016/j.jclepro.2020.123179
4. Zhang Y, Teoh BK, Wu M, Chen J, Zhang L (2023) Data-driven estimation of building energy consumption and GHG emissions using explainable artificial intelligence. Energy 262:125468. https://doi.org/10.1016/j.energy.2022.125468
5. Li H, Yang J, Yang D, Zhang N, Nazar S, Wang L (2024) Fiber-reinforced polymer waste in the construction industry: a review. Environ Chem Lett. https://doi.org/10.1007/s10311-024-01769-5
6. Osman AI, Chen L, Yang M, Msigwa G, Farghali M, Fawzy S, Rooney DW, Yap P-S (2023) Cost, environmental impact, and resilience of renewable energy under a changing climate: a review. Environ Chem Lett 21:741–764. https://doi.org/10.1007/s10311-022-01532-8
7. Zhou Y, Ma M, Tam VWY, Le KN (2023) Design variables affecting the environmental impacts of buildings: a critical review. J Clean Prod 387:135921. https://doi.org/10.1016/j.jclepro.2023.135921
8. Chen L, Yang M, Chen Z, Xie Z, Huang L, Osman AI, Farghali M, Sandanayake M, Liu E, Ahn YH, AaH A-M, Rooney DW, Yap P-S (2024) Conversion of waste into sustainable construction materials: a review of recent developments and prospects. Mater Today Sustain 27:100930. https://doi.org/10.1016/j.mtsust.2024.100930
9. Chen W, Yang S, Zhang X, Jordan ND, Huang J (2022) Embodied energy and carbon emissions of building materials in China. Build Environ 207:108434. https://doi.org/10.1016/j.buildenv.2021.108434
10. Akram MW, Mohd Zublie MF, Hasanuzzaman M, Rahim NA (2022) Global prospects, advance technologies and policies of energy-saving and sustainable building systems: a review. Sustainability 14(3):1316. https://doi.org/10.3390/su14031316
11. Farghali M, Osman AI, Mohamed IMA, Chen Z, Chen L, Ihara I, Yap P-S, Rooney DW (2023) Strategies to save energy in the context of the energy crisis: a review. Environ Chem Lett 21:2003–2039. https://doi.org/10.1007/s10311-023-01591-5
12. Baena-Moreno FM, Leventaki E, Riddell A, Wojtasz-Mucha J, Bernin D (2023) Effluents and residues from industrial sites for carbon dioxide capture: a review. Environ Chem Lett 21:319–337. https://doi.org/10.1007/s10311-022-01513-x
13. Chen L, Hu Y, Wang R, Li X, Chen Z, Hua J, Osman AI, Farghali M, Huang L, Li J, Dong L, Rooney DW, Yap P-S (2024) Green building practices to integrate renewable energy in the construction sector: a review. Environ Chem Lett 22:751–784. https://doi.org/10.1007/s10311-023-01675-2
14. Sheppard SRJ (2015) Making climate change visible: a critical role for landscape professionals. Landsc Urban Plan 142:95–105. https://doi.org/10.1016/j.landurbplan.2015.07.006
15. Armstrong DI, McKay AS, Abrams JF, Winkelmann R, Sakschewski B, Loriani S, Fetzer I, Cornell SE, Rockström J, Lenton TM (2022) Exceeding 1.5°C global warming could trigger multiple climate tipping points. Science 377:6eabn7950. https://doi.org/10.1126/science.abn7950
16. Yang M, Chen L, Wang J, Msigwa G, Osman AI, Fawzy S, Rooney DW, Yap P-S (2023) Circular economy strategies for combating climate change and other environmental issues. Environ Chem Lett 21:55–80. https://doi.org/10.1007/s10311-022-01499-6
17. Chen L, Msigwa G, Yang M, Osman AI, Fawzy S, Rooney DW, Yap P-S (2022) Strategies to achieve a carbon neutral society: a review. Environ Chem Lett 20:2277–2310. https://doi.org/10.1007/s10311-022-01435-8
18. Hasan MA, Abubakar IR, Rahman SM, Aina YA, Islam Chowdhury MM, Khondaker AN (2020) The synergy between climate change policies and national development goals: Implications for sustainability. J Clean Prod 249:119369. https://doi.org/10.1016/j.jclepro.2019.119369
19. Bibri SE, Krogstie J, Kaboli A, Alahi A (2024) Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: a comprehensive systematic review. Environ Sci Ecotechnol 19:100330. https://doi.org/10.1016/j.ese.2023.100330
20. Chen L, Chen Z, Zhang Y, Liu Y, Osman AI, Farghali M, Hua J, Al-Fatesh A, Ihara I, Rooney DW, Yap P-S (2023) Artificial intelligence-based solutions for climate change: a review. Environ Chem Lett 21:2525–2557. https://doi.org/10.1007/s10311-023-01617-y
21. Arsiwala A, Elghaish F, Zoher M (2023) Digital twin with machine learning for predictive monitoring of CO_2 equivalent from existing buildings. Energy Build 284:112851. https://doi.org/10.1016/j.enbuild.2023.112851
22. Hong T, Wang Z, Luo X, Zhang W (2020) State-of-the-art on research and applications of machine learning in the building life cycle. Energy Build 212:109831. https://doi.org/10.1016/j.enbuild.2020.109831
23. Morariu C, Morariu O, Răileanu S, Borangiu T (2020) Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems. Comput Ind 120:103244. https://doi.org/10.1016/j.compind.2020.103244
24. Zheng L, Mueller M, Luo C, Yan X (2024) Predicting whole-life carbon emissions for buildings using different machine learning algorithms: a case study on typical residential properties in Cornwall, UK. Appl Energy 357:122472. https://doi.org/10.1016/j.apenergy.2023.122472
25. Peng X, Guan X, Zeng Y, Zhang J (2024) Artificial intelligence-driven multi-energy optimization: promoting green transition of rural energy planning and sustainable energy economy. Sustainability 16:4111. https://doi.org/10.3390/su16104111
26. Tanasiev V, Pătru GC, Rosner D, Sava G, Necula H, Badea A (2021) Enhancing environmental and energy monitoring of residential buildings through IoT. Autom Constr 126:103662. https://doi.org/10.1016/j.autcon.2021.103662
27. Abioye SO, Oyedele LO, Akanbi L, Ajayi A, Davila Delgado JM, Bilal M, Akinade OO, Ahmed A (2021) Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges. J Build Eng 44:103299. https://doi.org/10.1016/j.jobe.2021.103299
28. Alanne K, Sierla S (2022) An overview of machine learning applications for smart buildings. Sustain Cities Soc 76:103445. https://doi.org/10.1016/j.scs.2021.103445
29. Tayefeh Hashemi S, Ebadati OM, Kaur H (2020) Cost estimation and prediction in construction projects: a systematic review on machine learning techniques. SN Appl Sci 2:1703. https://doi.org/10.1007/s42452-020-03497-1
30. Sofi A, Jane Regita J, Rane B, Lau HH (2022) Structural health monitoring using wireless smart sensor network—an overview.

Mech Syst Signal Process 163:108113. https://doi.org/10.1016/j.ymssp.2021.108113

31. Gaur L, Afaq A, Arora GK, Khan N (2023) Artificial intelligence for carbon emissions using system of systems theory. Eco Inform 76:102165. https://doi.org/10.1016/j.ecoinf.2023.102165
32. Hu D, Sun H, Mehrabi P, Ali YA, Al-Razgan M (2023) Application of artificial intelligence technique in optimization and prediction of the stability of the walls against wind loads in building design. Mech Adv Mater Struct 2023:1–18. https://doi.org/10.1080/15376494.2023.2206208
33. Baduge SK, Thilakarathna S, Perera JS, Arashpour M, Sharafi P, Teodosio B, Shringi A, Mendis P (2022) Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications. Autom Constr 141:104440. https://doi.org/10.1016/j.autcon.2022.104440
34. Pan Y, Zhang L (2021) Roles of artificial intelligence in construction engineering and management: a critical review and future trends. Autom Constr 122:103517. https://doi.org/10.1016/j.autcon.2020.103517
35. Andronie M, Lăzăroiu G, Iatagan M, Uță C, Ștefănescu R, Cocoșatu M (2021) Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. Electronics 10:2497. https://doi.org/10.3390/electronics10202497
36. Aguilar J, Garces-Jimenez A, R-moreno MD, García R (2021) A systematic literature review on the use of artificial intelligence in energy self-management in smart buildings. Renew Sustain Energy Rev 151:111530. https://doi.org/10.1016/j.rser.2021.111530
37. Ahmed SF, Saha SC, Debnath JC, Liu G, Mofijur M, Baniyounes A, Chowdhury SMEK, Vo D-VN (2021) Data-driven modelling techniques for earth-air heat exchangers to reduce energy consumption in buildings: a review. Environ Chem Lett 19:4191–4210. https://doi.org/10.1007/s10311-021-01288-7
38. Mohandes SR, Zhang X, Mahdiyar A (2019) A comprehensive review on the application of artificial neural networks in building energy analysis. Neurocomputing 340:55-75. https://doi.org/10.1016/j.neucom.2019.02.040
39. Hu Y, Man Y (2023) Energy consumption and carbon emissions forecasting for industrial processes: status, challenges and perspectives. Renew Sustain Energy Rev 182:113405. https://doi.org/10.1016/j.rser.2023.113405
40. Duan H, He C, Pu S (2024) A new circular neural grey model and its application to CO_2 emissions in China. J Clean Prod 445:141318. https://doi.org/10.1016/j.jclepro.2024.141318
41. Lin J, Lu S, He X, Wang F (2021) Analyzing the impact of three-dimensional building structure on CO_2 emissions based on random forest regression. Energy 236:121502. https://doi.org/10.1016/j.energy.2021.121502
42. Liu Y, Chen H, Zhang L, Wu X, Wang X-j (2020) Energy consumption prediction and diagnosis of public buildings based on support vector machine learning: a case study in China. J Clean Prod 272:122542. https://doi.org/10.1016/j.jclepro.2020.122542
43. Shoaei M, Noorollahi Y, Hajinezhad A, Moosavian SF (2024) A review of the applications of artificial intelligence in renewable energy systems: an approach-based study. Energy Convers Manage 306:118207. https://doi.org/10.1016/j.enconman.2024.118207
44. Wang Q, Hussain A, Farooqi MU, Deifalla AF (2022) Artificial intelligence-based estimation of ultra-high-strength concrete's flexural property. Case Stud Constr Mater 17:e01243. https://doi.org/10.1016/j.cscm.2022.e01243
45. Wang B, Hua L, Al-Mohaimeed AM, Zhao N (2024) Ocean carbon emission prediction and management measures based on artificial intelligence remote sensing estimation in the context of carbon neutrality. Environ Res 251:118591. https://doi.org/10.1016/j.envres.2024.118591
46. Choi Y, Kim K, Kim S, Kim D (2022) Identification of odor emission sources in urban areas using machine learning-based classification models. Atmos Environ: X 13:100156. https://doi.org/10.1016/j.aeaoa.2022.100156
47. Mehmood MU, Chun D, Zeeshan HH, Jeon G, Chen K (2019) A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. Energy Build 202:109383. https://doi.org/10.1016/j.enbuild.2019.109383
48. Wen L, Yuan X (2020) Forecasting CO_2 emissions in Chinas commercial department, through BP neural network based on random forest and PSO. Sci Total Environ 718:137194. https://doi.org/10.1016/j.scitotenv.2020.137194
49. Yan S, Zhang Y, Sun H, Wang A (2023) A real-time operational carbon emission prediction method for the early design stage of residential units based on a convolutional neural network: a case study in Beijing, China. J Build Eng 75:106994. https://doi.org/10.1016/j.jobe.2023.106994
50. Yeasmin S, Syed SNJ, Shmais LA, Dubayyan RA (2020) Artificial intelligence-based CO_2 emission predictive analysis system. In: 2020 international conference on artificial intelligence and modern assistive technology (ICAIMAT), pp 1–6. https://doi.org/10.1109/ICAIMAT51101.2020.9307995
51. Boateng EB, Twumasi EA, Darko A, Tetteh MO, Chan APC (2021) Predicting building-related carbon emissions: a test of machine learning models. In: Hassanien A-E, Mohamed HN, Taha NE, Khalifa M (eds) Enabling AI applications in data science. Springer International Publishing, Cham, pp 247–266. https://doi.org/10.1007/978-3-030-52067-0_11
52. Wang P, Hu J, Chen W (2023) A hybrid machine learning model to optimize thermal comfort and carbon emissions of large-space public buildings. J Clean Prod 400:136538. https://doi.org/10.1016/j.jclepro.2023.136538
53. Pau M, Kapsalis P, Pan Z, Korbakis G, Pellegrino D, Monti A (2022) MATRYCS—a big data architecture for advanced services in the building domain. Energies 15:2568. https://doi.org/10.3390/en15072568
54. Kabir MF, Chen T, Ludwig SA (2023) A performance analysis of dimensionality reduction algorithms in machine learning models for cancer prediction. Healthcare Anal 3:100125. https://doi.org/10.1016/j.health.2022.100125
55. Jansson NF, Allen RL, Skogsmo G, Tavakoli S (2022) Principal component analysis and K-means clustering as tools during exploration for Zn skarn deposits and industrial carbonates, Sala area. Sweden J Geochem Expl 233:106909. https://doi.org/10.1016/j.gexplo.2021.106909
56. Saif-ul-Allah MW, Khan J, Ahmed F, Hussain A, Gillani Z, Bazmi AA, Khan AU (2023) Convolutional neural network approach for reduction of nitrogen oxides emissions from pulverized coal-fired boiler in a power plant for sustainable environment. Comput Chem Eng 176:108311. https://doi.org/10.1016/j.compchemeng.2023.108311
57. Liu H, Lang B (2019) Machine learning and deep learning methods for intrusion detection systems: a survey. Appl Sci 9:4396. https://doi.org/10.3390/app9204396
58. Das S, Tariq A, Santos T, Kantareddy SS, Banerjee I (2023) Recurrent neural networks (RNNs): architectures, training tricks, and introduction to influential research. In: Colliot O (ed) Machine Learning for Brain Disorders. Springer US, New York, NY, pp 117–138. https://doi.org/10.1007/978-1-0716-3195-9_4
59. Fang L, He B (2023) A deep learning framework using multi-feature fusion recurrent neural networks for energy consumption

forecasting. Appl Energy 348:121563. https://doi.org/10.1016/j.apenergy.2023.121563
60. Bibri SE (2018) The IoT for smart sustainable cities of the future: an analytical framework for sensor-based big data applications for environmental sustainability. Sustain Cities Soc 38:230–253. https://doi.org/10.1016/j.scs.2017.12.034
61. Zhang D, Pan SL, Yu J, Liu W (2022) Orchestrating big data analytics capability for sustainability: a study of air pollution management in China. Inf Management 59:103231. https://doi.org/10.1016/j.im.2019.103231
62. Peng T, Yang X, Xu Z, Liang Y (2020) Constructing an environmental friendly low-carbon-emission intelligent transportation system based on big data and machine learning methods. Sustainability 12:8118. https://doi.org/10.3390/su12198118
63. Fu L, Li J, Chen Y (2023) An innovative decision making method for air quality monitoring based on big data-assisted artificial intelligence technique. J Innov Knowl 8:100294. https://doi.org/10.1016/j.jik.2022.100294
64. Hou Y, Wang Q, Tan T (2022) Prediction of carbon dioxide emissions in China using shallow learning with cross validation. Energies 15:8642. https://doi.org/10.3390/en15228642
65. Vu HL, Ng KTW, Richter A, An C (2022) Analysis of input set characteristics and variances on k-fold cross validation for a recurrent neural network model on waste disposal rate estimation. J Environ Manage 311:114869. https://doi.org/10.1016/j.jenvman.2022.114869
66. Bouktif S, Fiaz A, Ouni A, Serhani MA (2018) Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: comparison with machine learning approaches. Energies 11:1636. https://doi.org/10.3390/en11071636
67. Luo H, Paal SG (2023) A novel outlier-insensitive local support vector machine for robust data-driven forecasting in engineering. Eng Comput 39:3671–3689. https://doi.org/10.1007/s00366-022-01781-9
68. Acquaye AA, Duffy AP (2010) Input–output analysis of Irish construction sector greenhouse gas emissions. Build Environ 45:784–791. https://doi.org/10.1016/j.buildenv.2009.08.022
69. Zhang Y, Yan D, Hu S, Guo S (2019) Modelling of energy consumption and carbon emission from the building construction sector in China, a process-based LCA approach. Energy Policy 134:110949. https://doi.org/10.1016/j.enpol.2019.110949
70. Liu G, Chen R, Xu P, Fu Y, Mao C, Hong J (2020) Real-time carbon emission monitoring in prefabricated construction. Autom Constr 110:102945. https://doi.org/10.1016/j.autcon.2019.102945
71. Zhang G, Li Y, Li Q (2010) A miniaturized carbon dioxide gas sensor based on infrared absorption. Opt Lasers Eng 48:1206–1212. https://doi.org/10.1016/j.optlaseng.2010.06.012
72. Postolache OA, Pereira JMD, Girao PMBS (2009) Smart sensors network for air quality monitoring applications. IEEE Trans Instrum Meas 58:3253–3262. https://doi.org/10.1109/tim.2009.2022372
73. Spachos P, Hatzinakos D (2016) Real-time indoor carbon dioxide monitoring through cognitive wireless sensor networks. IEEE Sens J 16:506–514. https://doi.org/10.1109/jsen.2015.2479647
74. Spachos P, Hantzinakos D (2014) Scalable dynamic routing protocol for cognitive radio sensor networks. IEEE Sens J 14:2257–2266. https://doi.org/10.1109/jsen.2014.2309138
75. Nizetic S, Solic P, Lopez-de-Ipina Gonzalez-de-Artaza D, Patrono L (2020) Internet of things (IoT): Opportunities, issues and challenges towards a smart and sustainable future. J Clean Prod 274:122877. https://doi.org/10.1016/j.jclepro.2020.122877
76. Zhang H, Zhang J, Wang R, Peng Q, Shang X, Gao C (2020) Construction of smart carbon monitoring platform for small cities in China Based on Internet of Things. In: Wang X, Leung VCM, Li K, Zhang H, Xiping H, Liu Q (eds) 6GN for Future Wireless Networks: Third EAI International Conference, 6GN 2020, Tianjin, China, August 15-16, 2020, Proceedings. Springer International Publishing, Cham, pp 263–277. https://doi.org/10.1007/978-3-030-63941-9_20
77. Zhang H, Zhang J, Wang R, Huang Y, Zhang M, Shang X, Gao C (2021) Smart carbon monitoring platform under IoT-Cloud architecture for small cities in B5G. Wireless Netw 30:3837–3853. https://doi.org/10.1007/s11276-021-02756-2
78. Xu J, Zhang Q, Teng Y, Pan W (2023) Integrating IoT and BIM for tracking and visualising embodied carbon of prefabricated buildings. Build Environ 242:110492. https://doi.org/10.1016/j.buildenv.2023.110492
79. Mao C, Tao X, Yang H, Chen R, Liu G (2018) Real-time carbon emissions monitoring tool for prefabricated construction: an iot-based system framework. Int Conf Constr Real Estate Manage 2018:121–127. https://doi.org/10.1061/9780784481738.015
80. Ming FX, Habeeb RAA, Md Nasaruddin FHB, Gani AB (2019) Real-time carbon dioxide monitoring based on IoT & cloud technologies. In: Proceedings of the 2019 8th international conference on software and computer applications, pp 517–521. https://doi.org/10.1145/3316615.3316622
81. Géron A (2022) Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. Place, Published: " O'Reilly Media, Inc." https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632. Accessed 11 Feb 2024
82. Rolnick D, Donti PL, Kaack LH, Kochanski K, Lacoste A, Sankaran K, Ross AS, Milojevic-Dupont N, Jaques N, Waldman-Brown A, Luccioni AS, Maharaj T, Sherwin ED, Mukkavilli SK, Kording KP, Gomes CP, Ng AY, Hassabis D, Platt JC, Creutzig F, Chayes J, Bengio Y (2022) Tackling climate change with machine learning. ACM Comput Surv 55:1–96. https://doi.org/10.1145/3485128
83. Yevu SK, Owusu EK, Chan APC, Sepasgozar SME, Kamat VR (2023) Digital twin-enabled prefabrication supply chain for smart construction and carbon emissions evaluation in building projects. J Build Eng 78:107598. https://doi.org/10.1016/j.jobe.2023.107598
84. Xikai M, Lixiong W, Jiwei L, Xiaoli Q, Tongyao W (2019) Comparison of regression models for estimation of carbon emissions during building's lifecycle using designing factors: a case study of residential buildings in Tianjin, China. Energy Build 204:109519. https://doi.org/10.1016/j.enbuild.2019.109519
85. Chen C, Guo J, Zhang L, Wu X, Yang Z (2024) Robust multiscale time series prediction for building carbon emissions with explainable deep learning. Energy Build 312:114159. https://doi.org/10.1016/j.enbuild.2024.114159
86. Yang L, Driscol J, Sarigai S, Wu Q, Chen H, Lippitt CD (2022) Google earth engine and artificial intelligence (AI): a comprehensive review. Remote Sens 14:3253. https://doi.org/10.3390/rs14143253
87. Gharibi G, Walunj V, Nekadi R, Marri R, Lee Y (2021) Automated end-to-end management of the modeling lifecycle in deep learning. Emp Softw Eng 26:1–33. https://doi.org/10.1007/s10664-020-09894-9
88. Maddireddy BR, Maddireddy BR (2022) Real-time data analytics with AI: improving security event monitoring and management. Unique Endeavor in Business & Social Sciences 1:47–62. https://unbss.com/index.php/unbss/article/view/42. Accessed 18 Feb 2024
89. Li X, Wen J (2014) Review of building energy modeling for control and operation. Renew Sustain Energy Rev 37:517–537. https://doi.org/10.1016/j.rser.2014.05.056
90. Afram A, Janabi-Sharifi F (2014) Theory and applications of HVAC control systems—a review of model predictive control

(MPC). Build Environ 72:343–355. https://doi.org/10.1016/j.buildenv.2013.11.016

91. Nguyen N-H, Tran Q-T, Leger J-M, Vuong T-P (2010) A real-time control using wireless sensor network for intelligent energy management system in buildings. In: 2010 IEEE workshop on environmental energy and structural monitoring systems pp 87–92. https://doi.org/10.1109/EESMS.2010.5634176
92. Linder L, Vionnet D, Bacher J-P, Hennebert J (2017) Big building data-a big data platform for smart buildings. Energy Procedia 122:589–594. https://doi.org/10.1016/j.egypro.2017.07.354
93. Zhang X, Manogaran G, Muthu B (2021) IoT enabled integrated system for green energy into smart cities. Sustain Energy Technol Assess 46:101208. https://doi.org/10.1016/j.seta.2021.101208
94. Yayla A, Świerczewska K, Kaya M, Karaca B, Arayici Y, Ayözen Y, Tokdemir O (2022) Artificial Intelligence (AI)-based occupant-centric heating ventilation and air conditioning (HVAC) control system for multi-zone commercial buildings. Sustainability 14:161707. https://doi.org/10.3390/su142316107
95. Kök İ, Ergun Y, Uğur N (2023) Explainable AI-powered edge computing solution for smart building energy management in green IoT. Low-Cost Digital Solutions for Industrial Automation (LoDiSA 2023), pp 150–157. https://doi.org/10.1049/icp.2023.1747
96. Himeur Y, Elnour M, Fadli F, Meskin N, Petri I, Rezgui Y, Bensaali F, Amira A (2023) AI-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives. Artifcial Intelligence Review 56:4929–5021. https://doi.org/10.1007/s10462-022-10286-2
97. Mocanu E, Nguyen PH, Gibescu M, Kling WL (2016) Deep learning for estimating building energy consumption. Sustain Energy Grids Netw 6:91–99. https://doi.org/10.1016/j.segan.2016.02.005
98. Farzaneh H, Malehmirchegini L, Bejan A, Afolabi T, Mulumba A, Daka PP (2021) Artificial intelligence evolution in smart buildings for energy efficiency. Appl Sci 11:20763. https://doi.org/10.3390/app11020763
99. Yuan J, Song X, Yang X, Yang C, Wang Y, Deng G, Wang Z, Gao J (2023) Indoor carbon dioxide capture technologies: a review. Environ Chem Lett 21:2559–2581. https://doi.org/10.1007/s10311-023-01620-3
100. Himeur Y, Ghanem K, Alsalemi A, Bensaali F, Amira A (2021) Artificial intelligence based anomaly detection of energy consumption in buildings: a review, current trends and new perspectives. Appl Energy 287:6601. https://doi.org/10.1016/j.apenergy.2021.116601
101. Bouabdallaoui Y, Lafhaj Z, Yim P, Ducoulombier L, Bennadji B (2021) Predictive maintenance in building facilities: a machine learning-based approach. Sensors 21:1044. https://doi.org/10.3390/s21041044
102. Çınar ZM, Abdussalam Nuhu A, Zeeshan Q, Korhan O, Asmael M, Safaei B (2020) Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. Sustainability 12:8211. https://doi.org/10.3390/su12198211
103. Hou L, Chen H (2024) The prediction of medium- and long-term trends in urban carbon emissions based on an ARIMA-BPNN combination model. Energies 17:1856. https://doi.org/10.3390/en17081856
104. Hsu A, Wang X, Tan J, Toh W, Goyal N (2022) Predicting European cities' climate mitigation performance using machine learning. Nature Commun 13:7487. https://doi.org/10.1038/s41467-022-35108-5
105. Gao H, Wang X, Wu K, Zheng Y, Wang Q, Shi W, He M (2023) A review of building carbon emission accounting and prediction models. Buildings 13:1617. https://doi.org/10.3390/buildings13071617
106. Jin Y, Sharifi A, Li Z, Chen S, Zeng S, Zhao S (2024) Carbon emission prediction models: a review. Sci Total Environ 927:172319. https://doi.org/10.1016/j.scitotenv.2024.172319
107. Nassef AM, Olabi AG, Rezk H, Abdelkareem MA (2023) Application of artificial intelligence to predict CO_2 emissions: critical step towards sustainable environment. Sustainability 15:7648. https://doi.org/10.3390/su15097648
108 Acheampong AO, Boateng EB (2019) Modelling carbon emission intensity: application of artificial neural network. J Clean Prod 225:833–856. https://doi.org/10.1016/j.jclepro.2019.03.352
109. Meng Y, Noman H (2022) Predicting CO_2 emission footprint using AI through machine learning. Atmosphere 13:1871. https://doi.org/10.3390/atmos13111871
110. Hien NLH, Kor A-L (2022) Analysis and prediction model of fuel consumption and carbon dioxide emissions of light-duty vehicles. Appl Sci 12:803. https://doi.org/10.3390/app12020803
111. Luo H, Li Y, Gao X, Meng X, Yang X, Yan J (2023) Carbon emission prediction model of prefecture-level administrative region: a land-use-based case study of Xi'an city. China Appl Energy 348:121488. https://doi.org/10.1016/j.apenergy.2023.121488
112. Sun W, Huang C (2022) Predictions of carbon emission intensity based on factor analysis and an improved extreme learning machine from the perspective of carbon emission efficiency. J Clean Prod 338:130414. https://doi.org/10.1016/j.jclepro.2022.130414
113. Zhang Q, Wang Y, Qin D, Zhao K, Xie W, Li S, Wei L, Ai X (2022b) Carbon emissions forecasting based on stacking ensemble learning. In: 2022 IEEE 5th international electrical and energy conference (CIEEC), pp 2725–2730. https://doi.org/10.1109/CIEEC54735.2022.9845939
114. Fang Y, Lu X, Li H (2021) A random forest-based model for the prediction of construction-stage carbon emissions at the early design stage. J Clean Prod 328:129657. https://doi.org/10.1016/j.jclepro.2021.129657
115. Ahmad MW, Mourshed M, Rezgui Y (2017) Trees vs neurons: comparison between random forest and ANN for high-resolution prediction of building energy consumption. Energy Build 147:77–89. https://doi.org/10.1016/j.enbuild.2017.04.038
116. Zhao Y, Liu R, Liu Z, Liu L, Wang J, Liu W (2023) A review of macroscopic carbon emission prediction model based on machine learning. Sustainability 15:6876. https://doi.org/10.3390/su15086876
117. Li L, Dai S, Cao Z, Hong J, Jiang S, Yang K (2020) Using improved gradient-boosted decision tree algorithm based on Kalman filter (GBDT-KF) in time series prediction. J Supercomput 76:6887–6900. https://doi.org/10.1007/s11227-019-03130-y
118. Cui X, Shaojun E, Niu D, Chen B, Feng J (2021) Forecasting of carbon emission in china based on gradient boosting decision tree optimized by modified whale optimization algorithm. Sustainability 13(21):12302. https://doi.org/10.3390/su132112302
119. Wang L, Xue X, Zhao Z, Wang Y, Zeng Z (2020) Finding the de-carbonization potentials in the transport sector: application of scenario analysis with a hybrid prediction model. Environ Sci Pollut Res 27:21762–21776. https://doi.org/10.1007/s11356-020-08627-1
120. Zhu B, Ye S, Jiang M, Wang P, Wu Z, Xie R, Chevallier J, Wei Y-M (2019) Achieving the carbon intensity target of China: a least squares support vector machine with mixture kernel function approach. Appl Energy 233–234:196–207. https://doi.org/10.1016/j.apenergy.2018.10.048
121. Fenton SK, Munteanu A, De Rycke K, De Laet L (2024) Embodied greenhouse gas emissions of buildings—machine learning approach for early stage prediction. Build Environ 257:111523. https://doi.org/10.1016/j.buildenv.2024.111523
122. Wen L, Cao Y (2020) A hybrid intelligent predicting model for exploring household CO_2 emissions mitigation strategies derived from butterfly optimization algorithm. Sci Total Environ 727:138572. https://doi.org/10.1016/j.scitotenv.2020.138572

123. Hu Y, Lv K (2020) Hybrid prediction model for the interindustry carbon emissions transfer network based on the grey model and general vector machine. IEEE Access 8:20616–20627. https://doi.org/10.1109/ACCESS.2020.2968585
124. Wang Z, Zhao Z, Wang C (2021) Random forest analysis of factors affecting urban carbon emissions in cities within the Yangtze River Economic Belt. PLoS ONE 16:e0252337. https://doi.org/10.1371/journal.pone.0252337
125. Ding X, Feng C, Yu P, Li K, Chen X (2023) Gradient boosting decision tree in the prediction of NOx emission of waste incineration. Energy 264:126174. https://doi.org/10.1016/j.energy.2022.126174
126. Sun W, Liu M (2016) Prediction and analysis of the three major industries and residential consumption CO_2 emissions based on least squares support vector machine in China. J Clean Prod 122:144–153. https://doi.org/10.1016/j.jclepro.2016.02.053
127. Rahman M, Rashid F, Roy SK, Habib MA (2024) Application of extreme learning machine (ELM) forecasting model on CO_2 emission dataset of a natural gas-fired power plant in Dhaka. Bangl Data Brief 54:110491. https://doi.org/10.1016/j.dib.2024.110491
128. Niu H, Zhang Z, Xiao Y, Luo M, Chen Y (2022) A study of carbon emission efficiency in Chinese provinces based on a three-stage SBM-undesirable model and an LSTM model. Int J Environ Res Public Health 19:5395. https://doi.org/10.3390/ijerph19095395
129. Han Z, Cui B, Xu L, Wang J, Guo Z (2023) Coupling LSTM and CNN neural networks for accurate carbon emission prediction in 30 Chinese provinces. Sustainability 15:13934. https://doi.org/10.3390/su151813934
130. Khajavi H, Rastgoo A (2023) Predicting the carbon dioxide emission caused by road transport using a Random Forest (RF) model combined by meta-heuristic algorithms. Sustain Cities Soc 93:104503. https://doi.org/10.1016/j.scs.2023.104503
131. Wang X, Yan C, Liu W, Liu X (2022) Research on carbon emissions prediction model of thermal power plant based on SSA-LSTM algorithm with boiler feed water influencing factors. Sustainability 14:15988. https://doi.org/10.3390/su142315988
132. Chen Y, Jin S (2023) Artificial intelligence and carbon emissions in manufacturing firms: the moderating role of green innovation. Processes 11:2705. https://doi.org/10.3390/pr11092705
133. Liu T, Zhou B (2024) The impact of artificial intelligence on the green and low-carbon transformation of Chinese enterprises. Manag Decis Econ 45:2727–2738. https://doi.org/10.1002/mde.4164
134. Gao B, Kong X, Liu G, Xiang T, Gao Y, Luo S, Wang Y (2024) Monitoring high-carbon industry enterprise emission in carbon market: a multi-trusted approach using externally available big data. J Clean Prod 466:142729. https://doi.org/10.1016/j.jclepro.2024.142729
135. Moraliyage H, Dahanayake S, De Silva D, Mills N, Rathnayaka P, Nguyen S, Alahakoon D, Jennings A (2022) A robust artificial intelligence approach with explainability for measurement and verification of energy efficient infrastructure for net zero carbon emissions. Sensors 22:9503. https://doi.org/10.3390/s22239503
136. Amadi KW, Alsaba MT, El Achkar JH, Elgaddafi RM (2024) AI-driven green optimization in well construction: carbon emission management through technical limit performance benchmarking. GOTECH Day 1 Tue, May 07, 2024. https://doi.org/10.2118/219214-ms
137. Giest S (2017) Big data analytics for mitigating carbon emissions in smart cities: opportunities and challenges. Eur Plan Stud 25:941–957. https://doi.org/10.1080/09654313.2017.1294149
138. Zhou K, Fu C, Yang S (2016) Big data driven smart energy management: from big data to big insights. Renew Sustain Energy Rev 56:215–225. https://doi.org/10.1016/j.rser.2015.11.050
139. Mayer-Schönberger V, Cukier K (2013) Big data: a revolution that will transform how we live, work, and think. Place, Published: Houghton Mifflin Harcourt. https://books.google.co.uk/books/about/Big_Data.html?id=uy4lh-WEhhIC&redir_esc=y. Accessed 20 Feb 2024
140. Cowls J, Tsamados A, Taddeo M, Floridi L (2023) The AI gambit: leveraging artificial intelligence to combat climate change—opportunities, challenges, and recommendations. AI & Soc 38:283–307. https://doi.org/10.1007/s00146-021-01294-x
141. Nishant R, Kennedy M, Corbett J (2020) Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int J Inf Manage 53:102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104
142. Dobbe R, Sondermeijer O, Fridovich-Keil D, Arnold D, Callaway D, Tomlin C (2020) Toward distributed energy services: decentralizing optimal power flow with machine learning. IEEE Trans Smart Grid 11:1296–1306. https://doi.org/10.1109/TSG.2019.2935711
143. Aftab M, Chen C, Chau C-K, Rahwan T (2017) Automatic HVAC control with real-time occupancy recognition and simulation-guided model predictive control in low-cost embedded system. Energy Build 154:141–156. https://doi.org/10.1016/j.enbuild.2017.07.077
144. Maheshwari A, Jain M, Tiwari V, Ingle M, Chourey A (2023) Is quantum computing a cybersecurity threat? Quant Comput Cybersecur 2023:353–368. https://doi.org/10.1002/9781394167401.ch21
145. Liu Z, Sun Y, Xing C, Liu J, He Y, Zhou Y, Zhang G (2022) Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: challenges and future perspectives. Energy AI 10:100195. https://doi.org/10.1016/j.egyai.2022.100195
146. Strubell E, Ganesh A, McCallum A (2020) Energy and policy considerations for modern deep learning research. Proc AAAI Conf Artif Intell 34:13693–13696. https://doi.org/10.1609/aaai.v34i09.7123
147. Liu J, Liu L, Qian Y, Song S (2022) The effect of artificial intelligence on carbon intensity: evidence from China's industrial sector. Socioecon Plann Sci 83:101002. https://doi.org/10.1016/j.seps.2020.101002
148. Delanoë P, Tchuente D, Colin G (2023) Method and evaluations of the effective gain of artificial intelligence models for reducing CO_2 emissions. J Environ Manage 331:117261. https://doi.org/10.1016/j.jenvman.2023.117261
149. Liu Y, Zhang X, Shen Y (2024) Technology-driven carbon reduction: analyzing the impact of digital technology on China's carbon emission and its mechanism. Technol Forecast Soc Chang 200:123124. https://doi.org/10.1016/j.techfore.2023.123124
150. Woo J, Asutosh AT, Li J, Ryor WD, Kibert CJ, Shojaei A (2020) Blockchain: a theoretical framework for better application of carbon credit acquisition to the building sector. Constr Res Congress 2020:885–894. https://doi.org/10.1061/9780784482858.095
151. Ashwani S, Tripathy AJ, Karna S, Jahanve PR, Rajagopal SM (2024) Quantum computing for climate change: a comprehensive review of current applications, challenges, and future directions. Paper presented at the 2024 15th international conference on computing communication and networking technologies (ICCCNT), pp. 1–7. https://doi.org/10.1109/ICCCNT61001.2024.10724347
152. Filipova M, Gospodinov G, Gotsev L, Kovatcheva E, Jekov B (2024) Quantum computing applications for addressing global warming and pollution: a comprehensive analysis. Environ Technol Res 1:154–160. https://doi.org/10.17770/etr2024vol1.8001
153. Konya A, Nematzadeh P (2024) Recent applications of AI to environmental disciplines: a review. Sci Total Environ 906:167705. https://doi.org/10.1016/j.scitotenv.2023.167705

154. Zhao P, Gao Y, Wu M, Sun X (2024) How artificial intelligence affects carbon intensity: heterogeneous and mediating analyses. Environ Dev Sustain. https://doi.org/10.1007/s10668-024-05085-4