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A Machine Learning Framework for Reducing CO2 Emissions in UK Green Buildings: A Review

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Chronicle

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Abstract

It is very important for the building industry to reduce its negative effects on the environment because it is a major source of carbon emissions. The UK wants to reach net-zero carbon emissions by 2050, which means that buildings need to have fewer carbon footprints. This makes it more important than ever to come up with new ways to do this. This research looks at a machine learning (ML) system that can anticipate the carbon effects of different design and material choices. The goal is to reduce both embodied and operational CO_2 emissions in green buildings. The methodology uses real-world building data from the UK to show which materials and practices can help reduce total lifespan emissions most effectively. By forecasting how much energy buildings will use and improving how they work, the use of machine learning models makes buildings more energy efficient. This lowers energy demand and operational carbon footprints by a large amount. Furthermore, the article investigates how machine learning (ML) applications might influence the selection of sustainable building materials, assuring long-term environmental sustainability. Specifically, the implementation of smart energy systems and predictive maintenance is essential for the mitigation of CO_2 emissions resulting from the operation of existing buildings. This work contributes to the reduction of emissions by proposing data-driven methods to optimize building performance, thereby providing essential tools for architects, engineers, and policymakers. This paper provides a roadmap for the UK to achieve its net-zero emissions objective by 2050 by optimizing energy consumption, reducing CO_2 emissions, and supporting the transition to sustainable building practices, in accordance with global actions to address climate change.

Keywords: Machine Learning, CO2 Emissions, UK Green Buildings, Low-Carbon Construction, Sustainable Construction, Net-Zero Target

INTRODUCTION

Global warming, namely climate change poses significant challenges for humans and other living species. It is very important that these environmental problems are fixed through effective actions [1]. The growth of the global economy has been fueled by a number of industries including manufacturing, automotive and construction which have had a major influence on the built and natural surroundings [2-4]. The majority of greenhouse gases produced globally are mostly sourced from the built environment [5-7]. Greenhouse gases are being released as a result of increased global industrialization and growth, which might cause high temperatures and environmental damage [8–10]. Consequently, there is an imperative necessity to attain net-zero carbon emissions (NZCEs) inside companies and globally. NZCEs are anthropogenic greenhouse gases that may be reabsorbed by the atmosphere [11-13]. It would be beneficial to safeguard the ecological environment and mitigate the harm caused to the natural environment by achieving NZCEs. A worldwide objective is to acquire NZCEs by 2050 in order to accomplish industrialization and sustainable development [14]. Everyone including government policies, individuals and corporate entities must contribute to this endeavor. It may appear difficult but the highest priority is to maintain persistence, plan long-term objectives and strive for continuous improvement. For example, several nations have already made plans to reach NZCEs [15–19]. Italy's long-term plan for full decarbonization includes better government policies and more money going into technology, research and development [20]. A full evaluation model shows that Brazil and the United States reached NZCEs sooner than the worldwide average [16, 17].

The sustainable construction processes contribute to the preservation of the natural environment and the promotion of economic justice [21, 22]. On the other hand, they contribute to the reduction of environmental harm during the development of projects [23]. Sustainable construction is a modern way of building that hurts the natural balance between people and nature. It is known and useful all over the world, but some people still think of it as a difficult process or method because of cost issues, unprofitable building projects or the need for long-term resource management [16, 24]. There are three ways to make building projects more sustainable: conserving resources, being cost-effective, and designing buildings that humans can adapt [25]. These methods show that using the latest digital technology is necessary. But compared to other industries, the construction industry is reluctant to implement digital transformation [26]. The chart shows the distribution of global CO2 emissions by sector, highlighting the contributions of building operations, industry, transportation, and construction as shown in figure 1.

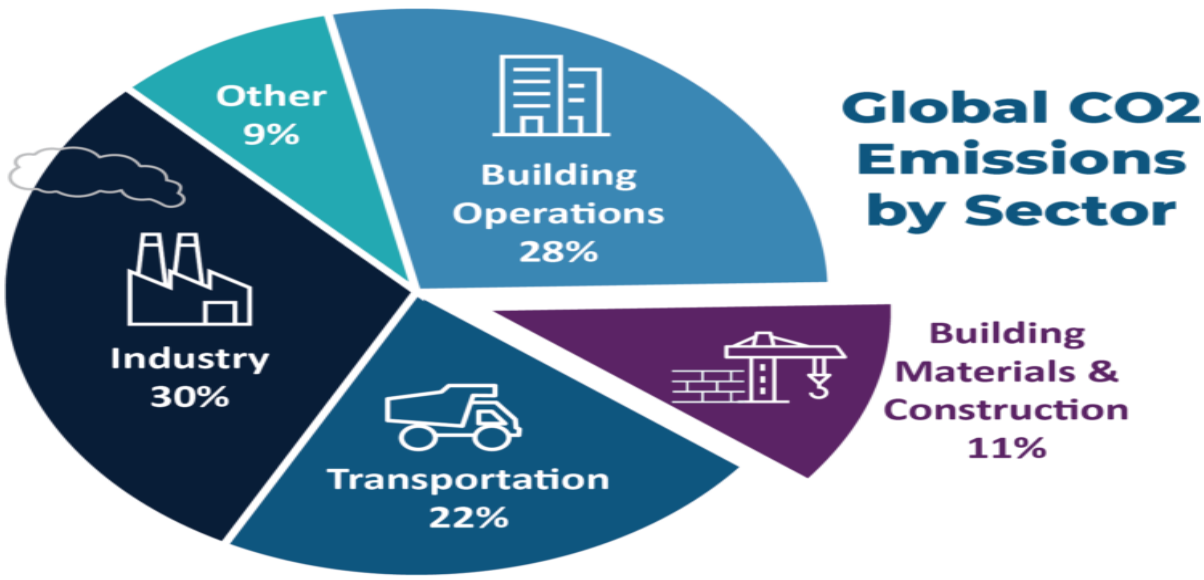

Figure 1.
The distribution of global CO2 emissions by sector

The term "Artificial intelligence (AI)" refers to the theory and development of computer systems. It can perform tasks that often require human intelligence like visual perception, translation, speech decision-making, recognition and language [27]. There are a number of AI tools that may be used in the Architecture, Engineering, and Construction (AEC) business. These include genetic programming, neural networks, fuzzy logic, heuristic search and computer software [28–30]. Previous research has looked into how AI may make real-world projects in the AEC field better [31–33].

Building information modeling (BIM) may assist keep track of a building's complete life cycle in a single database. When combined with AI, it can also be used to figure out prices, find problems with products, and improve the quality of construction [34]. It talks about the most up- to-date studies on AI in the AEC field. They discovered that genetic algorithms, neural networks, fuzzy logic, sets, and machine learning were the most common AI methods used in the AEC field [35]. Similarly, Pan and Zhang [36] conducted an in-depth review of AI applications in management, engineering and construction.

They discovered that several AI techniques have had significant impact in changing the building business. AI has been able to speed up and automate the processes of learning, reasoning and sensing in construction engineering and management by using a lot of data. This has a lot of potential for handling different engineering tasks depending on their own specific needs. Also, unlike traditional computer methods and expert opinions, AI is very good at dealing with complicated and constantly changing situations with a lot of uncertainty and a lot of data. As a result, they are more likely to give accurate and convincing results for making tactical decisions. These studies have shown that different AI-related methods can eventually do three main things that are useful for the AEC industry: model and pattern optimization, detection and prediction.

These things help with automation, risk reduction, digitalization, improved efficiency and computer vision [35–37]. The environmental impact of construction activities is considerably reduced and the path toward attaining NZCEs is accelerated by the integration of AI in these processes. This research shows how AI-powered technology may make complicated tasks easier by giving more accurate and data- driven information that was not possible to get using old approaches [32,35]. So, using AI is a big step forward in managing carbon emissions. It might make the building industry more environmentally friendly and sustainable. Earlier review studies looked at NZCEs and how AI is applied in different fields [34,38–40]. Ahmed et al. [41] used decision-making and prediction algorithms to show how artificial neural networks (ANNs) may be used to promote sustainable building projects in a way that takes into account the environment, the economy, and social factors. Chen et al. [42] also did a thorough study of the literature to look for AI-based solutions for climate change.

They found that the building sector uses life cycle assessments a lot to look at environmental implications, with carbon emissions being the main thing they look at. In recent years, the construction industry has employed a variety of random forests and neural networks to quantify and estimate its carbon emissions as a result of the ongoing advancements in big data technology and computer technology [43]. The objective of green building is to reach net-zero carbon emissions, which is in line with global environmental goals. Manzoor et al. [34] did a review based on a case study to come up with ways to use BIM in eco-friendly construction projects.

The results showed that workshops, lectures and conferences are used to raise public awareness. The most important ways to make construction projects more sustainable were found to be better information about the costs and benefits of sustainable materials and stronger support for the sustainable development. Adunadepo and Sunday [44] also did a review to find new ways to make it easier to use AI to achieve the long- term growth of smart buildings. They suggest using integrated project delivery and creative green design to make these ideas work and to help artificial intelligence evolve in buildings in a way that is good for the environment. Even if prior review studies are useful, they don't show how AI may be used in sustainable building projects to cut down on carbon emissions. The identification of mainstream research topics on the application of AI, particularly machine learning to combat NZCEs in sustainable construction projects is imperative due to the challenges posed by global warming. Recently, machine learning has been used in a wide range of ways not just to save energy but also to solve problems in science and engineering. Recent research in the construction sector has shown how it may be used to estimate energy use and improve the performance of buildings. For example, studies such as "Machine learning as a surrogate to building performance simulation: Predicting energy consumption under different operational settings" underlines the capacity of ML models to reliably estimate energy demands allow improved resource management [45]. The research "Machine Learning Method Based on Symbiotic Organism Search Algorithm for Thermal Load Prediction in Buildings" also looks at more complex algorithms for predicting thermal loads to make sure that buildings utilize energy efficiently and are comfortable [46,47]. These examples show how ML may change the construction sector in many ways, making it an essential tool for tackling engineering problems today.

Also, none of the prior review studies used a mixed-method approach that included both a systematic literature review (a qualitative technique) and a science mapping methodology (a quantitative way) to look at how AI is used in NZCEs for constructing projects that are good for the environment. There has been a lot of study done on how artificial intelligence (AI) may be used in several fields, such as construction and environmental management. This study looks at how AI may help sustainable construction projects reach net-zero carbon emissions (NZCEs). This provides it a valuable resource for both academics and practitioners in this constantly changing field [39, 48].

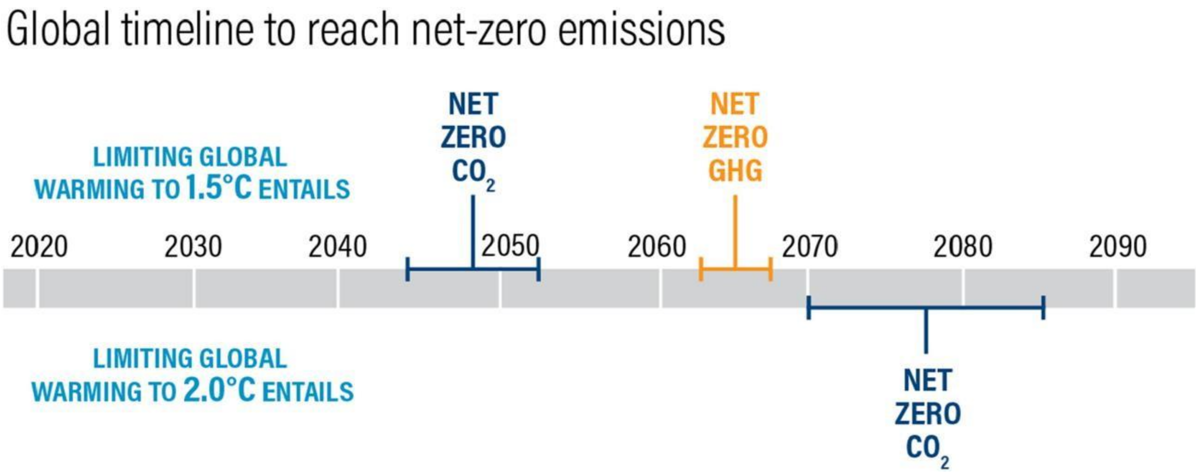

Figure 2.
Global timeline showing the projected milestones to achieve net-zero emissions, with key targets for CO_2 and GHG reduction. [135]

As global concerns about climate change escalate the reducing carbon emissions has become a key priority across various sectors [49]. The building sector is responsible for a significant share of carbon dioxide (CO2) emissions that plays a crucial role in the fight against climate change. In the United Kingdom, buildings contribute to nearly 40% of the nation's energy use and 33% of CO2 emissions. [50]. The push for sustainable architecture and the promotion of "green buildings" has gained momentum as part of efforts to reduce the environmental impact of the built environment [51]. Green buildings are designed to minimize energy consumption, reduce CO2 emissions and use renewable resources throughout their lifecycle from construction to operation [52, 53]. The innovative technologies like Machine Learning (ML) have become essential tools in optimizing energy usage, improving building performance and enhancing sustainability.

Machine learning is a subset of artificial intelligence and has shown great promise in revolutionizing energy management in buildings [54]. Machine learning algorithms can forecast energy demand, optimize building systems and recommend design changes to save energy usage by examining complicated patterns in huge datasets [55]. In the context of green buildings, ML has the potential to improve energy management systems, optimize heating, ventilation and air conditioning (HVAC) systems. It assists in building design simulations that contribute to a reduction in CO2 emissions [56]. ML models are also being applied in smart building systems where they monitor energy usage in real-time, make predictive adjustments and offer valuable insights to improve energy efficiency [57].

In the UK, various building management systems (BEMS) equipped with machine learning algorithms are already being employed to optimize energy consumption, predict peak demand and adjust building systems accordingly [58]. These systems utilize data collected from a variety of IoT sensors deployed in buildings which track parameters like temperature, humidity, occupancy and energy use. Machine learning helps in analyzing this data to identify trends and adjust building systems in real-time ensuring that energy is used efficiently and CO2 emissions are minimized [59]. For instance, ML-powered systems can adjust HVAC settings based on occupancy levels and weather forecasts, significantly reducing unnecessary energy consumption. Predictive maintenance is another area where ML can help by forecasting potential equipment failures and minimizing downtime for further improving energy efficiency [60]. This **figure 2** shows the projected atmospheric CO2 concentrations (in ppm) from 2000 to 2100 under various scenarios. The black line represents the central estimate, while the red lines indicate different possible trajectories, highlighting a significant increase in CO2 levels by the end of the century, depending on future emissions. The circled point near 2020 marks the current atmospheric CO2 level.

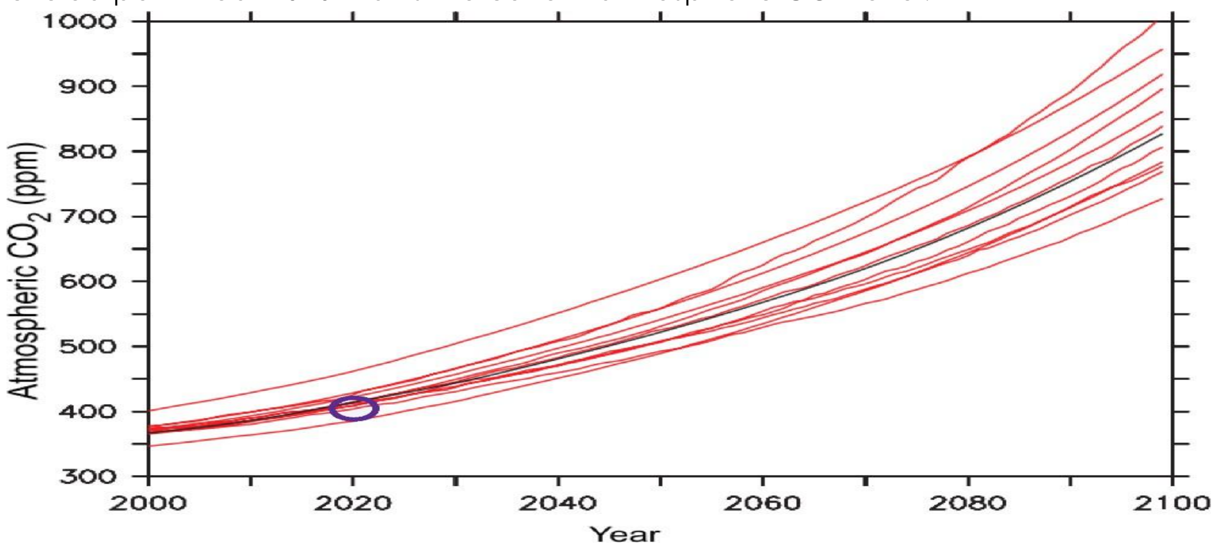

Figure 3.
CO2 Emission Forecasts by IPCC Model [134]

The integration of machine learning with energy storage systems and renewable energy sources further enhances the ability of green buildings to reduce their carbon footprints [61]. ML models can predict the availability of renewable energy, such as solar or wind, and adjust building operations accordingly, ensuring that buildings rely on renewable energy whenever possible [62]. Furthermore, the adoption of energy-efficient building designs, optimized through machine learning, can help in achieving long-term sustainability goals. The reducing energy consumption and dependence on non-renewable energy sources may be achieved by construction projects through energy optimization throughout the design process. [63].

However, the widespread adoption of machine learning in green buildings is not without challenges. The primary hurdle lies in the availability and quality of data, as ML models rely on accurate and comprehensive datasets for effective predictions and optimizations [64]. Moreover, integrating ML solutions into existing buildings or infrastructure can be complex and costly especially for older buildings that require retrofitting. Additionally, privacy and security concerns arise with the increased use of IoT sensors and data-driven systems which must be addressed to ensure the integrity of the data collected and the safety of building occupants [65].

Looking ahead, the potential for machine learning to transform the building sector is vast. As advancements in AI, IoT, and building technologies continue ML will play an increasingly important role in optimizing energy use, reducing CO2 emissions and helping buildings move closer to achieving carbon neutrality [66]. The integration of autonomous building systems, AI- driven design optimizations and circular economy principles will further enhance the role of ML in the construction and operation of green buildings. The building sector may significantly advance toward a more sustainable future by utilizing machine intelligence. [67].

Table 1.
Summary of selected studies on artificial intelligence (AI) and machine learning (ML) applications in carbon emission reduction, sustainable construction, and energy management.

Study	Title	Year	Key Focus	References
1	Achieving China's carbon neutrality: Predicting driving factors of CO2 emission by artificial neural network	2022	CO2 emission prediction using artificial neural networks for carbon neutrality in China	[41]
2	Artificial intelligence-based solutions for climate change: A review	2023	Review of AI applications for climate change mitigation, including carbon emissions reduction	[21]
3	Artificial neural networks for sustainable development of the construction industry	2022	Application of ANN for promoting sustainable development in the construction industry	[48]
4	Machine learning for sustainable energy management in buildings	2023	Using machine learning in energy management for sustainable building Systems	[54]
5	Artificial intelligence in net-zero carbon emissions for sustainable building projects: A systematic literature and science mapping review	2024	Review of AI in achieving net-zero carbon emissions for sustainable building projects	[108]
6	Machine learning applications for building energy consumption	2022	Machine learning in predicting energy	[70]

	prediction and CO_2 reduction		consumption and CO_2 reduction in buildings	
7	AI-powered energy efficiency solutions in buildings	2022	AI-based energy efficiency solutions in building Systems	[72]
8	Data-driven decision support for sustainable material selection in buildings	2025	Data-driven decision-making for sustainable Materials selection in building projects	[73]
9	Smart building energy management systems using machine learning techniques	2022	ML-based smart building systems for energy management and efficiency	[94]
10	Machine learning in smart buildings: A review of methods, challenges, and future trends	2025	Review of ML techniques in smart buildings, including challenges and future trends	[97]

Based on the literature review, several gaps in current studies on machine learning (ML) applications for reducing CO_2 emissions in buildings have been identified, highlighting areas that need further exploration. One significant gap is the focus on new buildings, while there is limited research on retrofitting existing buildings with ML systems. More attention should be given to integrating ML into older buildings that were not originally designed for energy efficiency, especially considering the challenges of upgrading infrastructure and retrofitting. Another key issue is the lack of high-quality, comprehensive datasets, particularly for older buildings that may lack the necessary energy performance data. Improving data collection methods and addressing privacy and security concerns related to IoT sensors and smart building systems should be prioritized.

Additionally, ML models often struggle with generalization across different building types and regions, and more research is needed to develop models that can adapt to diverse building characteristics and environmental conditions. The integration of renewable energy sources and smart grid technologies with ML is another underexplored area, and future research should investigate how these technologies can work together to optimize energy use and reduce CO_2 emissions. Furthermore, predictive maintenance using ML for building systems such as HVAC, lighting, and energy management is still in the early stages and requires more development to help ensure efficient operation and minimize energy waste.

There is also a gap in the practical implementation of AI-powered material selection during the building design phase. Research should focus on integrating AI with Building Information Modeling (BIM) to assist architects in selecting sustainable materials based on carbon footprint and lifecycle assessments. The cost and complexity of implementing ML systems, particularly for smaller buildings or projects with limited resources, remain a barrier to wider adoption. Therefore, research into more cost-effective and accessible ML solutions for these buildings is needed. Finally, while real-time energy optimization using ML is an important area, further refinement of these algorithms is required to ensure they can be applied effectively across various building types and operational conditions. There is also a need for a comprehensive framework that integrates different AI techniques, including ML and neural networks, to optimize both operational and embodied carbon emissions throughout the building lifecycle. Research should also focus on the long-term impact of ML models, ensuring they remain effective in reducing CO2 emissions as technologies evolve and building use changes over time. Addressing these gaps will contribute to the development of more sustainable, energy-efficient, and low-carbon buildings.

Machine Learning Techniques for Carbon Emissions Reduction in Building Design

Machine learning techniques are becoming increasingly integral in reducing carbon emissions in building design, offering innovative solutions to optimize energy performance and enhance sustainability [68]. One of the key applications of machine learning in this context is energy performance prediction where algorithms such as decision trees, support vector machines and neural networks can be employed to forecast energy consumption in buildings at different stages of the design process [69]. By utilizing historical data from similar buildings, these models can

predict energy needs and offer suggestions for design adjustments, helping to minimize energy consumption and consequently carbon emissions. For instance, energy simulations can be improved by machine learning models that offering more accurate predictions than traditional methods. This predictive capability allows architects and engineers to make informed decisions during the design phase, selecting materials and features that will lead to more energy-efficient buildings [70].

The machine learning algorithms can adapt HVAC systems in real-time to guarantee optimal energy consumption while preserving comfort by evaluating massive information on temperature, humidity and occupancy levels [71]. This not only improves energy efficiency but also reduces the building's operational carbon footprint. For example, ML-powered systems can dynamically adjust HVAC settings based on predictive weather models or occupancy patterns, thereby reducing energy wastage [72]. Furthermore, machine learning aids in the selection of building materials by evaluating the environmental impacts of various options. Machine learning models help architects choose sustainable materials that contribute to reducing the overall carbon footprint of the building by considering factors like embodied carbon, lifespan and energy performance [73].

The use of machine learning in building design is not limited to energy optimization but also extends to broader sustainability goals. For instance, machine learning can support the integration of renewable energy sources such as solar and wind power into building systems [74]. Building operations may be modified to rely more on renewable energy sources by using machine learning models that estimate their availability. This reduces reliance on non-renewable energy. This seamless integration of renewable energy into building systems is crucial for achieving long-term sustainability. Moreover, machine learning can be used in conjunction with building performance monitoring systems to track energy usage throughout the building's lifecycle, allowing for continuous optimization of energy consumption and the identification of opportunities for further emissions reduction [75]. Incorporating various machine learning techniques into the design phase of buildings significantly enhances their ability to meet sustainability targets ensuring that both operational and embodied carbon emissions are minimized. The ability of machine learning to predict energy needs, optimize system performance and guide material selection makes it an indispensable tool in the drive toward reducing carbon emissions in the construction industry [76].

Real-Time Energy Optimization Using Machine Learning

Machine learning is changing the way buildings use energy by optimizing it in real time. If we combine machine learning with Internet of Things (IoT) sensors and smart building technologies, buildings can always keep an eye on and improve how they consume energy based on what's happening at the moment [77]. These IoT sensors keep an eye on things like temperature, humidity, occupancy, and energy use. Machine learning algorithms look for trends in this data, guess how much energy will be needed and automatically make sure that different building systems such heating, ventilation and air conditioning (HVAC), lighting and power systems utilize the least amount of energy possible. For instance, a machine learning model may change the HVAC system's settings based on the number of people in a room, the weather outside, and past energy use data. This makes sure that energy is only used when it is needed [78].

Machine learning systems can continuously modify energy use by utilizing real-time data which lowers waste and boosts productivity. A key advantage is that these systems can forecast energy consumption surges particularly during peak hours and modify building systems accordingly to reduce energy waste [79]. This predictive ability helps in fine-tuning energy settings allowing buildings to use energy only when it is needed and to avoid unnecessary consumption during periods of low demand. Additionally, by predicting future energy requirements, machine learning models can ensure that the building remains within energy efficiency targets, preventing overuse and reducing carbon emissions [80].

Real-time optimization is very beneficial in HVAC systems. Machine learning algorithms can forecast temperature and humidity fluctuations within a building and proactively regulate heating or cooling systems results in optimizing energy efficiency. This optimization is particularly essential in extensive structures with fluctuating occupancy patterns where regulating energy use might otherwise be intricate [81]. Furthermore, these systems can automatically detect malfunctions or inefficiencies in equipment and triggering predictive maintenance before issues lead to higher energy consumption or equipment failure. This further reduce unnecessary emissions and improving the building's overall energy performance [82].

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 [136].

The use of machine learning for real-time energy optimization not only reduces carbon emissions but also lowers operational costs for building owners. Automating energy management enables buildings to markedly decrease energy waste resulting in considerable cost savings.

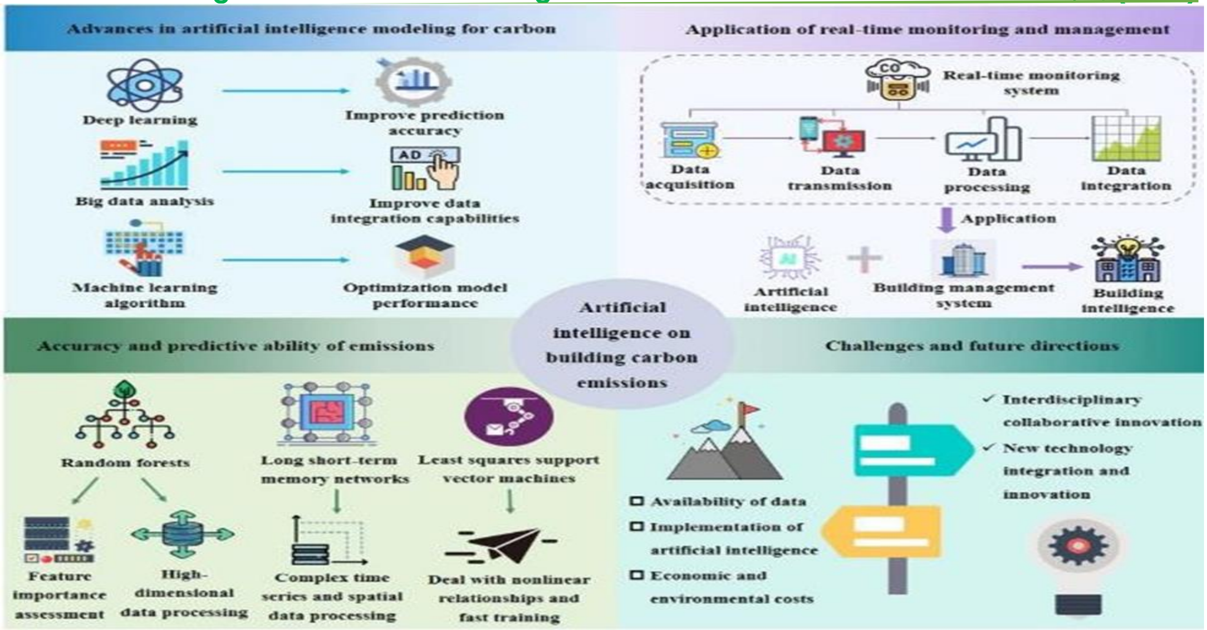

Figure 4.
Artificial Intelligence on Building Carbon Emissions

Moreover, real-time modifications allow structures to respond to varying external circumstances, such as temperature fluctuations or occupancy changes which conventional building systems may inadequately manage [82]. This real-time adaptability ensures that buildings operate efficiently and sustainably contributing to the long-term goal of reducing overall carbon footprints in urban environments [83].

Data-Driven Decision Making for Sustainable Materials Selection

Data-driven decision-making plays a crucial role in the selection of sustainable materials for building projects. It helps in providing architects and engineers with valuable insights to reduce the environmental impact of construction. Machine learning models that powered by large datasets. It can analyze the lifecycle impacts of various building materials including their embodied carbon, energy consumption during manufacturing and overall environmental footprint [84]. Machine learning algorithms can analyze data on the environmental implications of materials, including emissions from manufacture, shipping and disposal to discover the most sustainable solutions that reduce both operating and embodied carbon emissions in buildings [85].

Machine learning can assess a variety of materials using data-driven methods based on important performance metrics including carbon emissions, cost-effectiveness, energy efficiency and durability [86]. These models can also incorporate data on local climate conditions, material availability and supply chain sustainability to provide tailored recommendations for specific building projects. For example, machine learning algorithms can compare different insulation materials and their associated environmental impacts, consider factors such as heat retention, resource usage and long-term sustainability and suggest the most effective options for reducing energy demand and lowering emissions in the finished building [87].

The integration of machine learning with Building Information Modeling (BIM) systems enables real-time analysis of material choices during the design process. BIM systems when combined with machine learning. It allows architects to visualize how material selections will affect energy consumption and carbon emissions over the building's lifecycle [88]. This integration streamlines the decision-making process provide instant feedback on how each material choice impacts sustainability goals. For instance, if a designer chooses a particular material for structural components, the machine learning model can instantly calculate its environmental impact, offering an alternative if the emissions are too high or if a more sustainable material is available at a comparable cost [89].

In addition to environmental benefits, data-driven decision-making in material selection helps reduce construction waste and improve resource efficiency. Machine learning models can forecast the amount of material needed based on building design and project specifications, reducing over- ordering and minimizing waste. They can also suggest material recycling or reusing options based on the specific characteristics of the construction site. This ability to optimize material use in real- time not only supports sustainability but also leads to cost savings by reducing unnecessary expenditure on raw materials and disposal costs [90, 91].

Table 2.
Thematic Table about Machine Learning Frameworks for Reducing CO_2 Emissions in UK Green Buildings.

No.	Study Title	Primary Outcome	Theme	Reference
1	Predicting whole-life carbon emissions for buildings using ML algorithms	RF and GB models provided accurate WLCE predictions and screening potential	Whole-life carbon prediction	[137]
2	Predicting WLCE in Cornwall residential properties	Compared 10 ML algorithms; identified best models and key features	UK case study; WLCE	[138]
3	Building Energy Usage Predictions using EPC data	Predicted energy efficiency ratings; highlighted drivers like property type & fuel	EPC dataset; interpretability	[139]
4	XAI-driven EPC diagnostic framework	Explainable ML improved robustness of EPC-based energy models	Explainable AI; diagnostics	[140]
5	ONS: Predicting EPC ratings	Demonstrated EPC predictions using admin data for UK policy	Public-sector EPC prediction	[141]
6	Data-driven AI model with SAP & EPC	Combined EPC + SAP to build retrofit decision support	Retrofit decision support	[142]
7	City-scale residential energy prediction with GNN	Graph neural networks improved forecasting accuracy with EPC data	Graph ML; city-scale	[143]
8	Multi-source DL fusion with EPC & admin data	Linking administrative + EPC data enhanced energy efficiency estimation	Data fusion; DL	[144]
9	ML approaches for CO_2 predictions to 2050	Sectoral ML forecasts consistent with net-zero pathways	Long-term forecasting	[145]
10	AI in net-zero buildings: a review	Synthesised AI across design, operation, and net-zero strategies	Review; AI toolkit	[146]
11	Designing RL algorithms for HVAC	DQN controller improved comfort and energy efficiency	RL for HVAC	[147]
12	Efficient RL-based HVAC control	Domain knowledge reduced training time; maintained savings	Sample-efficient RL	[148]

13	RL for HVAC in intelligent buildings	Summarised RL studies showing consistent energy savings	Review; RL-HVAC	[149]
14	Occupancy detection using sensors & ML	Classifiers inferred occupancy for demand-driven control	Occupancy inference	[150]
15	Vision-based DL for occupant activity	Deep learning detected activities, enabling fine-grained HVAC/lighting control	Computer vision	[151]

Challenges in the Application of ML for CO2 Emissions Reduction

Machine learning (ML) has the potential to significantly reduce CO2 emissions in the design and operation of buildings. However, its pervasive implementation is impeded by a number of problems. A primary difficulty is the accessibility and quality of data [92]. However, in the context of building energy management such data can often be sparse, inconsistent or difficult to obtain. For example, many buildings especially older ones may lack the necessary energy performance data or sensor infrastructure to generate the kind of real-time data that machine learning models require. Inaccurate or incomplete data can lead to unreliable predictions that affect the effectiveness of the energy optimization and emissions reduction efforts [93].

Another significant challenge is the integration of ML solutions into existing building systems. The integrating ML models into these buildings often requires substantial upgrades to infrastructure including the installation of new sensors, smart meters and building energy management systems (BEMS) [94]. The cost and complexity of such upgrades can be a barrier for building owners, especially in the case of smaller or budget-constrained projects. Additionally, the process of retrofitting older buildings to support advanced ML technologies can be time- consuming and expensive, making it a less attractive option for some [95].

Model generalization is another challenge when applying ML to a diverse range of buildings. Each building has unique features, from its architectural design and materials to its location and operational patterns. ML models that are trained on data from one building type may not perform as well when applied to a different building with distinct characteristics. This lack of generalization can limit the effectiveness of ML models across various building types and regions making it difficult to develop universal solutions for energy optimization and emissions reduction [96].

The use of machine learning in smart buildings is also heavily influenced by privacy and security considerations. The proliferation of IoT devices and the accumulation of extensive data pose considerable concerns to data privacy and cybersecurity. Environmental conditions, energy use trends and occupancy statistics are examples of sensitive data that might be compromised or accessed by unauthorized parties [97]. The effective use of ML technologies depends on safeguarding the privacy of building residents and ensuring the security of the data gathered. In the absence of stringent security measures, property owners may be reluctant to adopt machine learning technologies, so constraining their capacity to reduce carbon emissions [98].

The complexity of machine learning models themselves can be a barrier to their adoption. The ML models offer powerful capabilities for energy optimization, they can be difficult to understand and implement particularly for stakeholders who may not have a strong technical background. The “black box” nature of some ML algorithms. The decision-making process is not fully transparent and can make it challenging for building managers and owners to trust the recommendations made by these systems. Furthermore, the high computational power required for training and running Advancements. ML models can be a limitation, especially for smaller buildings or projects with limited resources [99]. Despite these challenges, continued advancements in data collection technologies, ML algorithms and smart building infrastructure are expected to address many of these obstacles. This make machine learning a more accessible and effective tool for reducing CO2 emissions in the built environment.

Machine Learning in Retrofitting Existing Buildings

The term “Retrofitting” involves upgrading or replacing outdated building systems and components. It is a critical strategy for achieving sustainability goals in the existing building stock particularly given the fact that many buildings in urban environments were not originally designed with energy efficiency in mind [100]. ML models can enhance the retrofitting process by providing predictive insights into the potential impacts of various upgrades such as insulation, HVAC system improvements or lighting optimizations. Machine learning algorithms can forecast how various retrofitting interventions would impact the building's energy consumption and carbon footprint by analyzing previous building performance data. This helps select the most efficient and economical approaches [101].

One of the main applications of ML in retrofitting is energy consumption prediction. Machine learning (ML) algorithms may detect trends in energy use and recommend areas for improvement by evaluating data from the building management systems (BMS) and the Internet of Things (IoT) sensors. For example, ML can predict the potential energy savings from installing more efficient insulation or replacing an outdated HVAC system with a more energy-efficient model [102]. ML assists building managers and owners in making well-informed decisions on which retrofitting initiatives will yield the highest return on investment in terms of energy savings and emissions reductions by modeling the effect of these upgrades on overall energy efficiency [103].

Another area where ML is particularly valuable in retrofitting is in predictive maintenance. Many existing buildings have older mechanical systems that require frequent repairs, leading to inefficient operation and increased energy consumption. ML models can also be used to monitor these systems in real time, identifying early signs of inefficiency or failure before they result in costly repairs or energy waste [104]. Also, the machine learning algorithms can analyze the performance of an HVAC system, detect when it is operating outside optimal parameters and predict when maintenance is required to ensure continued efficiency. This proactive approach helps to minimize downtime, reduce the need for extensive repairs and maintain a building's energy efficiency over time [105].

Machine learning can assist in the optimization of energy management during retrofitting projects by the integrating renewable energy sources, such as solar panels or wind turbines with existing building systems. [106]. The integration is crucial in reducing the operational carbon footprint of retrofitted buildings, making them more sustainable and less reliant on grid power [107]. Machine earning in retrofitting presents certain challenges such as the need for high-quality accurate data and the complexity of integrating ML systems into older building infrastructure. However, as technology continues to evolve and more data becomes available ML is expected to become an increasingly effective tool in improving the energy efficiency of existing buildings and contributing to the achievement of net-zero carbon emissions goals [108].

Future Trends and the Role of AI in Achieving Net-Zero Carbon Emissions

The future of achieving net-zero carbon emissions (NZCEs) in the building sector is closely tied to the continued development and integration of artificial intelligence (AI) technologies. As the global push for sustainability intensifies AI is expected to play an even more significant role in transforming the construction and building management industries [109]. One of the key trends is the development of autonomous building systems that utilize AI and machine learning (ML) to optimize energy use in real-time. These systems will be capable of independently adjusting building operations, such as heating, cooling, lighting and ventilation based on continuously collected data from IoT sensors and external environmental factors [110]. With AI-powered automation, buildings will be able to minimize energy consumption and reduce carbon emissions without human intervention, adapting dynamically to changing conditions such as occupancy levels and weather patterns [111].

The most emerging trend is the integration of AI-driven design optimizations in the early stages of building planning. By leveraging vast datasets and AI algorithms, architects and engineers can simulate and evaluate multiple design alternatives for energy efficiency, carbon emissions and overall sustainability [112]. AI models can quickly assess the environmental impact of various design choices, such as material selection, building orientation and energy systems enabling better decision-making and ensuring that buildings are optimized for low-carbon performance from the outset. This predictive design approach will be particularly valuable in meeting stringent energy performance and sustainability targets especially for new construction projects and large-scale urban development's [113].

AI in the circular economy is expected to become a key player in reducing construction-related emissions. AI models can support the reuse and recycling of materials identifying opportunities to repurpose building components and reduce the need for new resources [114]. Through advanced data analytics, AI can track the lifecycle of materials, assess their potential for reuse and optimize the deconstruction process to minimize waste. AI will help reduce both embodied and operational carbon emissions, making buildings more sustainable throughout their lifecycle by promoting the circular economy within the building sector [62, 115].

AI models will be used in the prediction for the availability of renewable energy sources such as solar and wind and optimize the use of these resources in building systems [116]. The overall carbon footprint of buildings will be reduced by reducing their reliance on non-renewable sources by dynamically revising energy consumption in accordance with the availability of renewable energy. Furthermore, AI will enable smarter integration of energy storage systems, helping to balance energy loads and store excess renewable energy for use during peak demand periods or when renewable resources are scarce [117].

The integration of disparate building systems and energy management platforms will be more seamless as data interoperability and standardization improve as AI continues to evolve. The ability to share and analyze data across various platforms will unlock new opportunities for optimizing building performance, reducing emissions and improving sustainability [118]. This increased connectivity will be critical in achieving large-scale reductions in carbon emissions particularly in urban areas with vast numbers of buildings [119]. The promising future of AI in achieving NZCEs challenges remain like the need for widespread data availability, cybersecurity measures and overcoming the complexities of integrating AI with existing infrastructure [120]. However, as technology advances and more data is generated, AI's potential to revolutionize the building sector and drive carbon-neutral initiatives will continue to grow. In the coming years, AI is expected to be a central tool in achieving global sustainability goals helping buildings become more energy-efficient, resilient and sustainable. This ultimately contribute to a world with significantly reduced carbon emissions [121].

Policy Implications and Regulatory Support for AI in Building Sustainability

The successful integration of artificial intelligence (AI) in achieving sustainability goals within the building sector is not only reliant on technological advancements but also on strong policy frameworks and regulatory support. The governments play a critical role in creating an environment that encourages the adoption of AI-driven solutions for energy optimization and CO2 emissions reduction in buildings [122]. In many countries including the UK, the push for net-zero carbon emissions by 2050 has resulted in policy initiatives that focus on improving energy efficiency and promoting sustainable building practices. This aims to reduce carbon emissions while supporting economic growth, and the Smart Systems and Heat program which promotes innovation in energy management [123].

To support AI adoption, governments need to introduce incentives and financial support for organizations and developers implementing AI-based technologies in their buildings. For instance, providing grants or tax rebates for energy-efficient retrofitting and the integration of smart building systems could encourage wider adoption of AI solutions [124]. Additionally, public-private partnerships (PPP) can accelerate the development of AI technologies by pooling resources and expertise from both sectors. In the UK, initiatives such as the Energy Innovation Program offer funding for innovations that drive energy efficiency and lower carbon emissions in buildings creating a favorable environment for the growth of AI solutions in this space [125]. Regulatory standards are essential for ensuring that AI technologies are applied responsibly and effectively. The development of building regulations that mandate the use of energy management systems

Powered by AI and machine learning could push building owners and developers to adopt these technologies as part of their compliance with sustainability targets [126]. In many jurisdictions, green building certifications such as BREEAM (Building Research Establishment Environmental Assessment Method) and LEED (Leadership in Energy and Environmental Design) reward the adoption of energy-efficient technologies and renewable energy systems including those powered by AI. As these standards evolve, they may increasingly incorporate AI-driven solutions as a criterion for certification, ensuring that the buildings meet the highest environmental standards [127].

Data privacy and security regulations also play an important role in facilitating AI adoption in smart buildings. The heightened use of IoT sensors and the accumulation of extensive data on building performance, tenant behavior and energy consumption need the safeguarding of this data's privacy and security [128]. The collection and use of personal data are already regulated by regulatory frameworks, such as the General Data Protection Regulation (GDPR) in Europe. However, there is a necessity for specific regulations that pertain to the data produced by smart buildings. Policies should provide precise rules for data security, storage and sharing in order to reduce risks and promote confidence in AI-powered systems 129]. The creation of AI-specific standards and certifications for the building sector could help streamline the implementation and monitoring of various technologies. The establishment of guidelines for machine learning algorithms used in energy optimization and emissions reduction will help ensure consistency, transparency and fairness in their application [130]. These standards would provide the building industry with a clear roadmap for AI implementation and help mitigate concerns around the "black box" nature of some AI algorithms [131]. AI continues to play an increasingly important role in building sustainability with the help of international collaboration.

The Paris Agreement aim to tackle climate change and could provide a platform for aligning policies and regulations across countries [132]. The collaboration between governments, industry leaders and researchers can help to standardize AI applications for energy efficiency and sustainability. This ensures the adoption of these technologies contributes to meeting global sustainability targets [133]. The Policy and regulatory support are crucial for unlocking the potential of AI in sustainable building practices. The governments can establish a favorable environment for AI-driven innovations that will assist in the attainment of net-zero carbon emissions and the promotion of sustainability in the built environment by fostering collaboration, providing financial incentives and establishing clear guidelines.

CONCLUSION

Machine learning provides a powerful toolkit for achieving energy efficiency and sustainability in the building sector, offering transformative solutions through predictive modeling, real-time energy optimization, and data-driven material selection. These technologies enable buildings to operate more efficiently, reducing both operational and embodied carbon emissions. The ML Models require comprehensive, high-quality datasets to generate accurate predictions and optimizations as data quality and availability are fundamental issues. Furthermore, the ability of ML models to generalize across various building types and conditions is still a work in progress, and the initial cost of implementing AI-driven solutions can be prohibitive for some projects, especially retrofitting older buildings with existing infrastructure. Looking ahead, the future of green buildings will undoubtedly be shaped by continued advancements in machine learning, artificial intelligence (AI), and sustainable design practices. ML models will improve as the building industry develops and more data becomes accessible and providing even more chances for energy management and carbon reduction. Machine learning has the potential to be a vital instrument in the global effort to achieve net-zero carbon emissions if it is given the right legislative backing, policy incentives and attention to resolving existing issues. Machine learning has the ability to greatly aid in the creation of a more sustainable and energy-efficient built environment through ongoing innovation and cooperation.

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