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Review Article

Application of Artificial Intelligence (AI) in the Lifecycle of Sustainable Buildings: An Exhaustive Literature Review

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Abstract. With architectural structures accounting for significant share of global energy consumption and greenhouse gas emissions, the integration of *Artificial Intelligence* (AI) is a promising avenue for enhancing sustainability throughout the building lifecycle. This paper aims to investigate current insights regarding AI's potential to improve energy efficiency and mitigate environmental impacts in building design, construction, and operational management. A comprehensive literature review and synthesis was conducted to identify relevant AI technologies that promote sustainable construction practices, assess their impacts, and examine challenges to effective real-world implementation. The review utilized rigorous search methodology with specific keywords related to AI applications in sustainable building design, construction, and operations. The findings reveal AI's capabilities in optimizing energy efficiency through advanced control systems, improving predictive maintenance, and facilitating beneficial design simulations. Machine learning algorithms enable data-driven analytics and forecasting, while digital twin technologies offer real-time insights for strategic decision-making. The review identifies impediments to AI adoption, such as cost concerns, data security vulnerabilities, and challenges in implementing advanced systems. AI has transformative potential for enhancing sustainability in the built environment, providing innovative strategies for energy optimization and eco-friendly practices. Addressing technical and practical challenges is crucial for effective integration of AI into sustainable building methodologies.

Keywords. Artificial Intelligence, Energy consumption, Carbon footprints, Sustainable construction, Green buildings

Mathematics Subject Classification (2020). 68T01, 68T05, 68T20, 68T27

1. Introduction

In contemporary discourse, sustainable building methodologies have garnered substantial attention within the construction sector, a scrutiny propelled by escalating apprehensions regarding the ecological ramifications of conventional design and construction practices. With edifices constituting approximately 40% of global energy consumption and contributing up to 30% of annual greenhouse gas emissions [48], there exists an urgent imperative to confront these challenges. Furthermore, as the global urban populace is anticipated to double by 2050 [104], the necessity to augment the sustainability of buildings and infrastructure has reached an unprecedented level of urgency.

In light of these obstacles, a profound sense of optimism prevails regarding the capabilities of emergent technologies, particularly *Artificial Intelligence* (AI) [19, 26, 39, 40], to transform the methodologies employed in sustainable building practices. By harnessing AI throughout diverse phases of the building lifecycle, encompassing design, construction, operation, and maintenance, a singular opportunity emerges to alleviate systemic inefficiencies and instigate significant transformation [51]. One of the most critical challenges confronting the building industry is the alarming volume of waste produced during construction activities. On a global scale, it is estimated that between 11% and 15% of materials are squandered on construction sites [5], underscoring the necessity for more efficient processes and optimized resource utilization. Additionally, operational inefficiencies substantially contribute to carbon footprints. For instance, lighting, heating, and cooling systems accounted for nearly 28% of energy consumption in commercial buildings within the United States [105], while commercial and residential structures in China were responsible for 41.10% of total energy consumption [4]. Specifically, residential buildings in Nigeria alone accounted for over 80% of the nation's total energy consumption [54].

Moreover, as AI technologies progressively advance, there is an increasing emphasis on utilizing decentralized and autonomous systems to enhance building operations and resource management. For instance, AI-driven decentralized energy systems possess the capacity to optimize energy generation [102], storage [71], and distribution [95] within buildings and across intelligent grids, thereby augmenting resilience and sustainability while diminishing reliance on centralized energy sources. Although the potential of AI to bolster building sustainability has been extensively investigated, there exists a paucity of studies synthesizing current insights on implemented applications across the lifecycle of buildings—including the design, construction, and operational phases. Indeed, this represents a burgeoning and critical body of knowledge, as well as an immensely promising domain for scholarly inquiry. In light of its importance, systematic reviews on AI's role in enhancing building sustainability throughout their lifecycle remain scarce, particularly concerning design, construction, and operational phases. Although AI technologies like machine learning and computer vision are acknowledged for their contributions to building sustainability, most current applications focus primarily on the operational phase, neglecting design and construction. Hence, this systematic literature review was initiated to fill this void. The review aims to compile existing research on AI technologies in sustainable building practices, emphasizing underexplored areas and identifying gaps warranting further study.

Significant unexploited potential exists for applying AI in various building aspects, such as generative design, construction automation, predictive maintenance, and lifecycle optimization, which could greatly reduce the environmental impact of buildings. Nonetheless, the challenges associated with this technology, including data availability, validation, and industrial adoption, must also be recognized. The investigation aligns with literature on AI applications throughout different phases of the building lifecycle, illustrating their contributions to sustainability while also acknowledging the challenges faced in their implementation. Moreover, the research identifies potential solutions to these challenges, aiming to assess AI's role in promoting sustainable building practices throughout the building lifecycle. To achieve this aim, the review is guided by the following research questions:

What is the understanding of AI in relation to sustainable building? Which AI technologies are relevant to the sustainable building lifecycle? How does AI application influence the sustainable building lifecycle? What obstacles hinder AI application in the sustainable building lifecycle? What insights can be gleaned from existing literature on AI applications within the sustainable building lifecycle? This systematic literature review concerning AI's application in the sustainable building lifecycle was conducted to answer these questions. The analyzed scholarly works encompassed AI, its role in sustainable construction, relevant technological tools, and challenges related to AI in sustainable buildings, leading to a comprehensive discussion of existing gaps. By addressing these review inquiries, the research enriches the knowledge base and has implications for improving the integration of AI with sustainable building practices. Consequently, this paper contributes modestly to the discourse surrounding AI technologies and their applications in sustainable building, serving as a reference for designers and construction professionals regarding the effective implementation of AI technologies. Specifically, the review is crucial for the application of relevant AI technologies and tools throughout the entire construction process, with the goal of achieving a sustainable building lifecycle.

2. Materials and Methods

Essentially, this review categorized the documented applications of AI in the sustainable building lifecycle across three primary stages: design, construction, and operations. Furthermore, the review concentrated on literature that reported actual applications and implementations of AI technologies, rather than solely theoretical proposals. A systematic review of published literature was executed as the foundational research design, adhering to the methodological framework proposed by Brocke [25], which emphasizes the necessity of rigor in documenting the literature search process. The model is predicated on a five-phase framework for the literature search process, which includes: (1) Definition of review scope, (2) Conceptualization of the topic, (3) Literature search strategy, (4) Literature analysis and synthesis, (5) Research agenda. Subsequently, these phases were elucidated with specific reference to the application of artificial intelligence (AI) in the sustainable building lifecycle.

3. Definition of Review Scope

To clearly delineate the scope of this systematic literature review, reference was made to an established taxonomy articulated by Cooper [31], who identified six characteristics of literature reviews, namely Focus, Goal, Organization, Perspective, Audience, and Coverage. With respect to Cooper's [31] taxonomy of the review scope previously discussed.

Table 1. Decisions made in this review by the author

S. No.	Characteristic	Cooper's options	Author's choice
1	Focus	Type of papers involved (methodological, theoretical, practices, applications, outcomes)	Practices and applications
2	Goal	Integration, criticism, central issue	Central issue
3	Organization	Chronological, conceptual, methodological	Methodological
4	Perspective	Neutral, espousal of a position	Neutral
5	Audience	Groups of people whom the review is addressed	Researchers, practitioners, policy-makers, and stakeholders
6	Coverage	Exhaustive, with selective citation representative, central, pivotal	Selective citation

It is noteworthy that certain limitations served to constrain the scope; only literature published between 2013 and 2023 was considered, with an emphasis on contemporary advancements in deep learning. Additionally, only English-language publications pertaining to residential and commercial buildings were incorporated. The defined scope and intent facilitated a concentrated synthesis of the emerging domain of AI in sustainable building practices.

4. Conceptualization of the Review Topic

Brocke *et al.* [25] posited that "a review must commence with a broad conception of what is known about the topic and potential areas where knowledge may be required". Thus, the conceptualization of the study topic developed through a rigorous process of understanding and synthesizing pre-existing knowledge. The investigation commenced with a comprehensive exploration of the domains of artificial intelligence (AI) and sustainable building practices. By engaging with the extensive literature surrounding these topics, foundational insights were acquired concerning the possible intersections between these fields. As the review advanced, the focus was redirected towards pinpointing segments within the construction life cycle where artificial intelligence (AI) could provide groundbreaking solutions to sustainability issues. This entailed a thorough investigation of the predominant environmental challenges encountered by the construction sector, including energy inefficiency, material waste, and carbon emissions. Simultaneously, recognition grew regarding the escalating significance of sustainable methodologies in building design, construction, and operational processes, propelled by global necessities such as climate change mitigation and resource preservation. Moreover, the process of conceptualization encompassed acknowledging the transformative potential of AI technologies in tackling these sustainability issues. It scrutinized the prospective applications of AI throughout the diverse phases of a building life cycle, ranging from design optimization to enhancements in operational efficiency.

5. Literature Search Strategy

In order to execute the literature search process, this study employed the following strategic measures:

Initially, to select the appropriate database sources from the available options, the online repositories of Science Direct and Google Scholar were employed. This selection was predicated on the inclusion of a comprehensive array of publications, comprising journal articles, books, citations, and patents, with a significant focus on the pertinent subject matter, particularly the first two categories.

Subsequently, the most pertinent keywords and search parameters were delineated to extract representative subsets from the chosen online databases. The databases were queried utilizing the terms "AI in the building life cycle" OR "AI in Sustainable building life cycle", with search filters configured to retrieve articles containing these terms exclusively in the title, abstract, and keywords, thereby excluding all citations and patents. By applying these parameters, the search yielded 237,839 publications, of which 4,839 originated from Science Direct and 233,000 from Google Scholar. The databases were then organized to categorize all findings by publication year within the 2013–2023 timeframe. This decade-long range was selected to ensure a reasonably representative corpus of literature, consciously omitting works in progress, thus excluding the year 2024. After filtering the search results according to the specified year range, the total was reduced to 21,688 publications, with 3,488 from Science Direct and 18,200 from Google Scholar.

Thirdly, consideration was given to the potential implementation of 'backward and forward search' methodologies. However, the considerable volume of literature already identified through the initial search process, resulting in a varied collection of sources including journals, conference proceedings, book chapters, and industry reports, was determined to be sufficient. This extensive pool of literature provided a robust foundation for investigating the application of AI in the sustainable building life cycle. Consequently, additional 'backward and forward search' was regarded as superfluous, as the breadth and depth of the literature already reviewed were deemed adequate to meet the research objectives and facilitate a comprehensive examination of the research topic. Fourthly, the evaluation process in "all phases means constraining the quantity of literature identified by keyword search to solely those articles pertinent to the topic at hand" [25]. The literature evaluation procedure was conducted manually, with specific criteria applied to refine the search.

The manual approach was necessitated by the absence of a Literature Review Storage Database (LRS-DB), typically employed as a source input platform. This process served to eliminate duplicates, theses, PowerPoint presentations, white papers, book introductions, competition announcements, all non-English language works without complete abstracts, and all unpublished works that had not undergone peer review. Additionally, the review adopted three distinct sets of criteria for inclusion and exclusion. Firstly, the articles were selected based on their relevance to the study themes, employing a rating system; "1" indicated 'low significance', "2" denoted 'moderate significance', and "3" represented 'high significance'. This evaluative scale had been utilized by prior researchers [17, 47, 55]. Each article's relevance was assessed based on its methodological rigor and conclusions. Consequently, all publications that presented case studies and practical applications of AI implementation in sustainable building life cycles received a "3" rating and were incorporated into the review. Secondly, articles exhibiting a high citation count were prioritized, with a select few included in the review. All other articles that did not achieve "2" or "3" ratings were indicated as having low significance to the review. The content of the selected articles was confined to the application of AI in the life cycle of sustainable buildings, explicitly excluding roads, bridges, and other construction practices within the building sector. The majority of articles chosen for evaluation were published within the last five (5) years. The application of these criteria resulted in the exclusion of numerous literature sources, culminating in a total of 900 publications relevant to the present review.

6. Literature Analysis and Synthesis

Subsequent to the accumulation of a substantial body of literature pertaining to the subject matter, the methodologies of analysis and synthesis were meticulously executed [25]. In pursuit of this objective, the 900 scholarly articles were systematically categorized to correspond with the subsequent three investigative focal points:

7. Relevance to Research Questions

The initial dimension of the investigation entailed evaluating the pertinence of each scholarly article to the research inquiries formulated. This procedure ensured that the literature subjected to review unequivocally addressed the fundamental aims of the research questions. Consequently, the articles were assessed based on their congruence with the principal themes and topics of interest concerning the application of artificial intelligence (AI) within the sustainable building lifecycle. Any article that did not contribute directly to the resolution of the research inquiries was excluded to preserve the focus and coherence of the review.

8. Practical Applications and Implementations

An additional pivotal aspect of the investigation was to ascertain whether the literature predominantly reported or demonstrated applications and implementations of AI methodologies or merely introduced theoretical proposals. This criterion guaranteed that the review concentrated on practical, real-world instances of AI integration in sustainable building lifecycle as opposed to abstract discussions or speculative notions. Furthermore, the articles were evaluated on their capacity to furnish empirical evidence, case studies, or documented implementations of AI technologies within actual building projects across the various stages of the building lifecycle.

9. Inclusion of AI Across the Building Lifecycle

Lastly, the inquiry aimed to ascertain the degree to which the literature encompassed the integration of AI technologies throughout the entire building lifecycle. This analysis involved scrutinizing the articles that addressed AI applications within all phases of the building lifecycle; design, construction, and operations, thus providing a holistic understanding of how AI contributes to sustainability throughout the building lifecycle.

Overall, these three investigative focal points ensured that the amassed literature was systematically analyzed and synthesized to effectively address the research objectives. By emphasizing relevance, practical applications, and comprehensive coverage of the building lifecycle, the review provided valuable insights into the role of AI in promoting sustainability within the built environment. Further filtering efforts were undertaken to examine the abstracts of the 900 articles and, in certain instances, their methodologies and findings. From this filtering procedure, the articles pertinent to the research inquiries were identified, resulting in the selection of only 119 articles that fulfilled the criteria, which were subsequently utilized for this review.

10. Distribution of Identified Literature

From the searches conducted in the two online databases, Science Direct and Google Scholar, to identify pertinent publications concerning AI applications in sustainable building practices, 24 (20%) of all identified resources originated from Science Direct, while 95 (80%) were sourced from Google Scholar (Figure 1). Figure 1 also illustrated the types of literature identified from the online searches, indicating that, for Science Direct, 9 (38%) were review articles, 14 (58%) were research papers, and 1 (4%) constituted a book chapter. In the context of Google Scholar, 26 (27%) were review articles, and 69 (73%) were research papers.

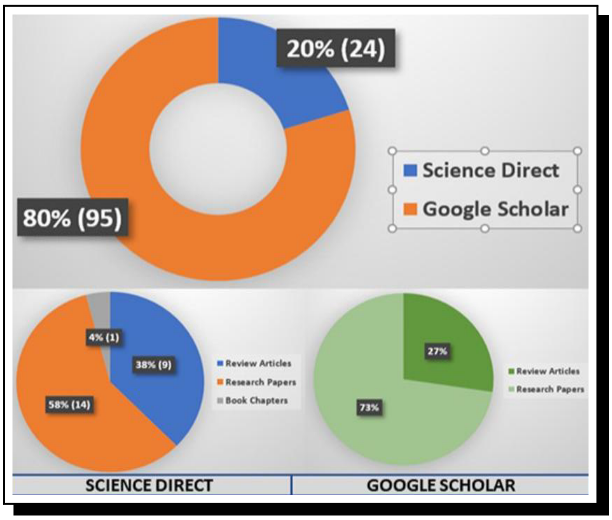

Figure 1. Distribution of identified literature

11. Findings and Discussions Artificial Intelligence in Sustainable Building

Artificial intelligence (AI) encompasses tasks that can be automated utilizing autonomous mechanical and electronic devices equipped with intelligent control systems [87]. According to McLean *et al*. [63], there exist three conceptualizations of AI: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI is employed in language translation and meteorological forecasting, AGI is envisioned to independently resolve complex issues, incorporating cognitive models and personality traits, while ASI, a prospective concept, possesses the potential to exceed human capabilities across various domains, as posited by Bughin *et al*. [27]. According to Debrah *et al*. [33], the application of Artificial Intelligence (AI) in sustainable buildings pertains to the adoption and integration of AI technologies specifically aimed at optimizing energy efficiency, mitigating environmental impact, and enhancing the overall sustainability of built structures. AI presents substantial potential in augmenting collaboration and communication among stakeholders throughout the building lifecycle [66]. By enabling data sharing and facilitating real-time collaboration, AI platforms can optimize project management processes [108], enhance decision-making [97], and promote innovation in sustainable building practices [115]. For instance, AI-enabled digital twins facilitate virtual simulations and predictive modelling [92], thereby allowing stakeholders to foresee performance outcomes and refine building designs for both sustainability and resilience [85].

The amalgamation of artificial intelligence with traditional methodologies such as modelling, simulation, and analytics possesses the capacity to transform the diverse phases of building design, construction, and operations [22]. During the building design phase, advancements in artificial intelligence provide unparalleled capabilities to enhance sustainability objectives within various architectural and engineering frameworks [15, 33]. Artificial intelligence-driven generative design, for instance, can swiftly analyse multiple design alternatives, taking into account various parameters to minimize embodied carbon and improve overall sustainability [15]. Through iterative design generation and evaluation, AI-driven methodologies can ascertain optimal solutions that substantially reduce environmental impacts in comparison to conventional approaches. Moreover, AI simulation tools are instrumental in evaluating building performance at the early stages of design [34]. By simulating variables such as energy consumption and indoor environmental quality, these tools empower designers to make well-informed decisions that prioritize sustainability while not sacrificing functionality or comfort [70]. For example, AI algorithms can scrutinize various design alternatives and select the most sustainable option based on specific criteria [17]. This anticipatory strategy guarantees that sustainability measures are seamlessly incorporated from the beginning, thereby diminishing the necessity for expensive retrofits in subsequent phases [2, 17, 70].

At the construction phase, AI technologies provide functionalities that enhance efficiency, particularly in waste reduction. Through the deployment of computer vision and AI-driven analytics, construction sites can be monitored in real-time to detect inefficiencies and mitigate risks [28]. For example, AI-enabled tracking of materials and equipment has demonstrated a reduction in waste by over 40% [99], resulting in substantial cost savings [49] and environmental advantages [6]. Furthermore, AI-powered analysis of project data can identify potential safety hazards, facilitating proactive risk management and enhancing construction site safety [120]. Additionally, AI-powered robotics can execute tasks such as welding, drilling, and cutting with remarkable precision and efficiency, thus minimizing errors and decreasing material waste. Furthermore, the integration of AI can be employed to forecast material performance [35], durability [37], and embodied carbon emissions [41], thereby enabling more informed decisions regarding material selection and construction methodologies.

At the operational stage, once buildings are functional, AI continues to be instrumental in maximizing efficiency and performance. Smart building systems utilize machine learning algorithms to optimize the management of various building systems, such as lighting, HVAC, and security, based on real-time data and occupancy patterns [121]. By dynamically adjusting system parameters in response to fluctuating conditions, AI-enabled automation can significantly curtail energy consumption and operational expenditures while ensuring occupant comfort and productivity [113]. Research has indicated that AI-driven building automation could yield energy savings of 20-30% in commercial buildings [65], while in residential settings, energy savings of 8.48% and cost reductions of 7.52% have been observed [58]. According to de Wilde [109], in the realm of maintenance and repairs, which are integral to the building operation stage, AI facilitates the prediction and diagnosis of maintenance and repair requirements, thereby minimizing downtime and enhancing building performance. A typical illustration involves AI-powered predictive maintenance systems that can analyze data from building sensors to anticipate equipment failures, enabling proactive maintenance and reducing equipment downtimes. Additionally, renewable energy integration occurs at this stage, wherein AI can assist in blending energy sources such as solar and wind into building systems, thus optimizing energy production and consumption. For instance, AI-powered energy management systems can assess real-time data from renewable energy sources and building loads, adjusting energy production and consumption correspondingly to maximize efficiency and minimize energy costs [58,116]. Furthermore, continuous commissioning and fault detection, enabled by artificial intelligence-driven analytics, facilitate anticipatory maintenance and troubleshooting [109]. Through the analysis of data derived from building systems and equipment, artificial intelligence algorithms are capable of identifying anomalies and potential complications prior to their escalation, thereby minimizing operational downtime and extending the longevity of building assets. This predictive maintenance methodology not only enhances operational efficiency but also contributes to overarching sustainability objectives by mitigating resource consumption and minimizing waste. To provide a coherent framework for comprehending the implementation of artificial intelligence technologies across various dimensions of construction projects, particularly concerning the stages of the building lifecycle, it is imperative to establish a robust theoretical foundation for the discourse.

12. Theoretical Underpinning for AI Integrated Sustainable Buildings Lifecycle

In addressing the existing knowledge gap regarding the implementation of artificial intelligence technologies, several theoretical constructs can be embraced as foundational underpinnings. The primary theoretical framework informing this study is the Technology Acceptance Model (TAM), conceptualized by F. D. Davis in 1985 and initially articulated in his 1989 publication [32], which has been extensively employed to elucidate and forecast the adoption and utilization of emerging technologies, including artificial intelligence. The model fundamentally posits that perceived usefulness and perceived ease of use are critical determinants influencing an individual's intention to engage with a specific technology. In the context of the building lifecycle, perceived usefulness refers to the notion that stakeholders, including construction professionals and facility managers, may regard artificial intelligence technologies as beneficial if they believe such technologies can enhance their operational performance, productivity, or decision-making capabilities [68, 69]. For instance, AI-driven predictive maintenance systems may be regarded as advantageous by facility managers, as they assist in anticipating equipment failures and optimizing maintenance schedules, thereby yielding cost reductions and enhancing building operations. Similarly, AI-enhanced design optimization tools may be viewed favorably by architects and engineers, as they can facilitate the creation of more efficient building designs and lower construction expenses.

With respect to perceived ease of use, users' perceptions regarding the user-friendliness and simplicity of artificial intelligence technologies can significantly influence their intention to adopt these technologies throughout the building lifecycle. For example, AI-enabled building information modeling (BIM) tools may be perceived as intuitive and straightforward to navigate. Consequently, construction professionals may exhibit a greater propensity to integrate these tools for the coordination of design, planning, and construction activities. Conversely, should AI-based energy management systems be perceived as intricate and challenging to configure, facility managers may demonstrate a reluctance to employ them for enhancing building energy performance. The Technology Acceptance Model has undergone continual examination and refinement, with two principal advancements being TAM 2 [110] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [91]. Within the realm of construction, TAM aids in elucidating the determinants that influence the acceptance and integration of artificial intelligence technologies, tools, and systems by construction professionals, including factors such as perceived benefits and ease of use.

Another relevant theoretical framework is that of Innovation Diffusion, conceptualized by Rogers *et al*. [91], which fundamentally investigates the gradual dissemination of new ideas, practices, or technologies within a population, rather than instantaneous adoption. This theory emphasizes the process by which an innovation, such as artificial intelligence, is communicated through specific channels over time among members of a social system, while also identifying variables that affect the rate of adoption. Furthermore, it considers the relative advantages attributed to perceived benefits, compatibility with pre-existing processes, complexity, trialability, and observability. In the construction context, this theory encompasses a broad array of considerations that aid scholarly inquiry in comprehending the diverse factors influencing the awareness and adoption of artificial intelligence technologies across the various stages of a building's lifecycle. Examining the dissemination of artificial intelligence (AI) technologies throughout the lifecycle of buildings, through the framework of the innovation diffusion theory, one can observe an instance in the implementation of AI-enhanced building information modeling (BIM) tools as well. This phenomenon may initiate with pioneering construction enterprises and progressively extend to the wider industry as the advantages of the technology become increasingly evident. The integration of AI-augmented energy management systems within edifices may exhibit a comparable diffusion trajectory, wherein early adopters among facility managers pioneer the initiative, subsequently influencing broader engagement by additional building proprietors and administrators. The innovation diffusion theory further delineates several pivotal factors that affect the effective propagation of innovations, including the intrinsic characteristics of the innovation, the communication modalities employed, the societal framework within which the innovation is introduced, and the duration required for the innovation to attain acceptance.

13. AI Technologies Applicable to Sustainable Building Lifecycle

According to Regona *et al*. [87], products within the building sector are swiftly assimilating into a networked ecosystem comprising hardware and software, thereby forming tailored "constellations" predicated on validated use cases. Prominent constellations, as illustrated in the building industry technology cartography, encompass supply chain optimization, robotics, digital twin technology, modularization, AI, and analytics. Certain technologies, such as digital twins, 3D printing, and AI supplemented by analytics, are projected to yield transformative impacts. In the immediate future, the construction sector is positioned to reap the benefits of foundational technologies including blockchain, AI, the Internet of Things (IoT), big data analytics, and information communication technology (ICT). Table 2 presents a comprehensive overview of predominant AI technologies currently in global deployment, systematically categorized according to their application methodologies and specific objectives within distinct domains, all contributing synergistically to the attainment of a more sustainable building lifecycle. Digital twins, a crucial element of this technological evolution, facilitate seamless integration with various projects while providing real-time activity documentation for predictive decision-making [60]. These digital replicas empower project and facility managers to construct virtual construction sites and sustainable functional building models that are accessible remotely via network technologies [74]. Additionally, they establish the foundation for intelligent 3D models that enhance the efficiency of planning, design, and infrastructure management [89].

Table 2. Major AI technologies and their applications in sustainable building lifecycle [7, 52, 87]

S. No.	AI Technology/Subset	Application
1	Machine learning (ML) - 1	Big data and data analysis
2	Machine learning (ML) - 2	Robotics and automation
3	Pattern recognition	Data and system integration
4	Automation	Mobility and wearable
5	Digital twin (DT)	Real-time monitoring and management
6	Internet of things (IoT)	Automated control of building systems and services

The incorporation of artificial intelligence (AI) technologies, encompassing image recognition capabilities, serves not only to detect hazardous practices but also to facilitate continuous training of personnel, thereby indicating a significant transition towards a more technologically-driven, efficient, and safer future within the construction sector [90]. These technologies are perceived as applicable throughout the entirety of the building lifecycle, thereby being supported by relevant theoretical frameworks.

14. Application

The amalgamation of big data and data analytics markedly improves the sustainability of the building lifecycle by yielding comprehensive insights into patterns of energy consumption, which allows for real-time modifications aimed at enhancing energy efficiency. Predictive maintenance fosters proactive scheduling, thereby averting equipment malfunctions and prolonging operational lifespan, whilst lifecycle cost analysis supports informed decision-making regarding both economic and environmental repercussions. The utilization of robotics and automation is essential in achieving sustainable construction, as it diminishes time expenditures, augments precision, and reduces errors. The integration of data and systems facilitates uninterrupted communication, thereby optimizing energy efficiency and minimizing waste.

Mobility and wearable technologies optimize construction management, elevate occupant well-being, and aid in energy monitoring endeavors. Real-time monitoring and management across multiple dimensions enhance the optimization of energy utilization, water conservation, waste management, and fortify building security. The automated regulation of building systems is directed towards operational efficiency, resource conservation, and performance enhancement, contributing positively to grid stability and the reduction of carbon emissions.

15. AI Applications Deployed in Stages of a Building Lifecycle

Artificial Intelligence (AI) has been instrumental in reshaping building methodologies, emerging as a well-established and influential entity within the construction industry. Numerous scholars have reached a consensus regarding the advantageous subsets of AI applicable to the building sector, encompassing design, construction, maintenance, and decommissioning. These subsets are meticulously categorized based on their applications and distinct functions at various phases of the building lifecycle. As previously noted, the extensive application of AI across diverse building practices is anticipated to significantly transform the conventional building lifecycle into a more sustainable and efficient framework. Several studies within the reviewed literature have addressed the three stages of a building lifecycle. Notable among these are Tchana *et al*. [101], and Regona *et al*. [87, 88], who underscored AI's influence on performance across the three stages, particularly in facilitating early detection of deficiencies and achieving cost efficiencies. Collaboration, which permeates all three stages, has been identified as a critical advantage, streamlining communication between clients and designers through AI-enhanced digital twins, the Internet of Things (IoT), and machine learning [103], thereby promoting transparency [85] and efficiency [92].

16. AI in Construction Stage of Sustainable Building Lifecycle

Artificial Intelligence (AI) is fundamentally transforming traditional construction methodologies, heralding a new epoch for the building sector. AI encompasses the development of intelligent devices and programs that emulate cognitive processes to effectively tackle complex challenges [20]. Despite substantial global investments exceeding USD 26 billion in engineering and construction technologies, including AI, the fundamental construction processes have remained predominantly static over the past four decades. Various impediments, such as insufficient business models, a deficit of critical skills, and pervasive knowledge gaps within the industry, have obstructed the widespread assimilation of AI in building development and lifecycle processes [43, 68, 118].

17. AI in the Operation Stage of Sustainable Building Lifecycle

Concerning the operational phase of a building lifecycle, numerous researchers have accentuated the significance of AI-related applications. These encompass machine learning, digital twins, and the Internet of Things (IoT), which are characterized as vital elements that augment operations within sustainable building life cycles. Examples of such researchers include de Wilde *et al*. [109], Petri *et al*. [77], Boje *et al*. [23, 24], Baduge *et al*. [18], Adu-Amankwa *et al*. [3], Lucchi [59], Su *et al*. [98], Alanne and Sierla [7], Kineber *et al*. [52], and Arowoiya *et al*. [12]. Although the direct implementation of AI may be somewhat constrained, these technologies serve as crucial linkages that facilitate the effective enhancement of operations. In alignment with this perspective, various scholars, including Wang *et al*. [106], and Chen *et al*. [30] have emphasized the importance of digital twin systems that integrate deep learning with machine learning. Such systems have significantly improved collective building energy management, optimized the load of renewable energy sources, and effectively managed building systems.

Furthermore, de Wilde [109] classified applications of Artificial Intelligence (AI) into the domain of intelligent or smart buildings, emphasizing their ability to respond to human and organizational requirements through the incorporation of the Internet of Things (IoT), which facilitates a network of interconnected devices that allows for wireless data acquisition and sensing. Moreover, digital twins function as contemporaneous counterparts, providing opportunities for enhanced interventions, financial efficiencies, improved operational performance, and societal advantages. He further elaborated that, within the context of the sustainable building lifecycle, various technologies assume interrelated roles. Building Performance Simulation (BPS) models forecast the physical performance of buildings, whereas Machine Learning (ML) models contribute data-driven intelligence aimed at optimizing energy consumption and forecasting maintenance requirements. Digital Twins serve as real-time counterparts, delivering dynamic representations of structures, while Building Information Models (BIM) furnish comprehensive digital representations.

de Wilde [109] also asserted that Artificial Intelligence (AI) acts as a pivotal element, synthesizing insights from BPS models, the learning capabilities afforded by ML models, the real-time representations provided by Digital Twins, and the extensive data from BIM, ultimately enhancing overall intelligence and operational efficiency. Conceptual intersections include the enhancement of BPS precision by ML, as well as the interconnected nature of real-time insights (Digital Twins) and comprehensive data representation (BIM). Each technological category contributes unique features, such as the data-driven intelligence characteristic of ML and the emphasis on real-time monitoring intrinsic to Digital Twins. The literature emphasizes the mutually beneficial relationship among digital twins, IoT, and machine learning in conjunction with AI, illustrating their transformative effects on rendering buildings more intelligent, responsive, and efficient. The intricate interrelationships are depicted in Figure 2.

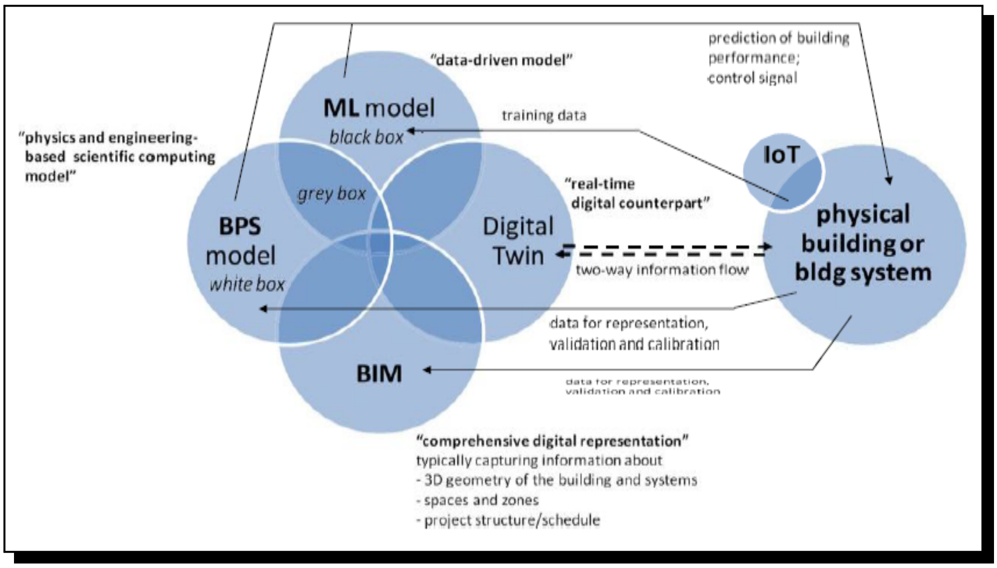

Figure 2. AI-integrated relationships among various technologies in a building lifecycle [109]

Machine learning algorithms, categorized as a subset of artificial intelligence, are pivotal in enhancing energy efficiency within architectural structures [14, 82]. These algorithms perpetually scrutinize real-time data sourced from sensors integrated into building systems to discern patterns regarding energy consumption and environmental variables. By meticulously processing this data, machine learning algorithms possess the capability to dynamically modify settings for HVAC systems, illumination, and various building apparatus to minimize energy consumption whilst ensuring occupant comfort is preserved. For instance, in scenarios characterized by reduced occupancy or favorable climatic conditions, machine learning algorithms may autonomously recalibrate thermostat settings or attenuate lighting to conserve energy without undermining comfort. This adaptive methodology towards energy management facilitates more efficient building operations, culminating in substantial energy conservation and diminished environmental repercussions over time.

Predictive analytics, which is another branch of artificial intelligence, transforms maintenance protocols by forecasting equipment failures prior to their occurrence [88, 101]. Through the examination of historical performance data and the identification of patterns that signify impending failures, predictive analytics algorithms can prognosticate the likelihood of equipment malfunctions. This anticipatory strategy empowers maintenance teams to orchestrate repairs or replacements during scheduled downtimes, thereby minimizing disruptions to building operations and circumventing costly emergency repairs. For example, predictive maintenance algorithms may discern early indicators of equipment deterioration in HVAC systems by analysing deviations from standard operational parameters, such as heightened vibration or temperature variations. By addressing these concerns proactively, predictive maintenance prolongs the operational lifespan of essential building systems and augments overall operational efficiency.

Data analytics tools, fuelled by artificial intelligence methodologies, afford comprehensive insights into the economic and environmental ramifications of building materials throughout their entire lifecycle [109]. These tools scrutinize data pertaining to material acquisition, manufacturing methodologies, transportation, installation, maintenance, and disposal to quantify the total cost of ownership and the environmental footprint linked with various building materials. By integrating both financial and environmental considerations, decision-makers are equipped to assess the long-term sustainability and cost-effectiveness of diverse material alternatives. For instance, data analytics algorithms may evaluate the lifecycle costs and environmental consequences of employing renewable materials in contrast to conventional alternatives, thereby assisting stakeholders in making informed decisions that align with sustainability objectives and fiscal constraints.

Smart building systems exploit artificial intelligence-driven technologies to augment occupant comfort and productivity through customized environmental regulation [75]. These systems amalgamate sensors, actuators, and feedback mechanisms to observe occupant preferences and modify indoor conditions correspondingly. For example, intelligent thermostats outfitted with machine learning algorithms can assimilate occupants' temperature preferences over time and autonomously adjust settings to sustain optimal comfort levels. In a similar vein, lighting systems equipped with occupancy sensors and daylight harvesting functionalities can dynamically regulate lighting intensities to minimize energy consumption while ensuring adequate illumination for occupants. By personalizing environmental conditions to suit individual preferences and activities, smart building systems foster more comfortable and productive indoor environments.

Data analytics tools facilitate the monitoring and examination of waste generation, recycling rates, and material utilization throughout the lifecycle of a building [23, 75]. These tools leverage artificial intelligence techniques to pinpoint inefficiencies and opportunities for enhancement in waste management methodologies. For example, data analytics algorithms may scrutinize historical waste data to identify trends and patterns, such as peak periods for waste generation or recurrent sources of waste. Armed with such insights, stakeholders can formulate targeted strategies to diminish waste generation, elevate recycling rates, and optimize material utilization. By reducing waste and maximizing resource efficiency, buildings can lower their environmental footprint and contribute to a more sustainable constructed environment.

Table 3. Positive Influences of Integrating AI with Sustainable Building Lifecycle

S. No.	Benefits
1	Energy Efficiency Optimization
2	Predictive Maintenance Life
3	Cycle cost analysis
4	Occupant Comfort and Productivity
5	Waste Reduction and Recycling
6	Carbon footprint reduction

Big data analytics, in conjunction with artificial intelligence algorithms, assume a vital role in assessing and monitoring a building's carbon footprint [18,33]. These analytical tools evaluate data concerning energy consumption, transportation emissions, and material usage to quantify the greenhouse gas emissions associated with building operations. For instance, AI-powered algorithms may analyse energy consumption data derived from smart meters and building management systems to ascertain carbon emissions resulting from electricity usage. By offering insights into the primary sources of carbon emissions and their environmental repercussions, big data analytics enable stakeholders to devise targeted strategies aimed at mitigating the carbon footprint. Such strategies may encompass implementing energy efficiency initiatives, adopting renewable energy sources, optimizing transportation logistics, and promoting sustainable procurement practices. By alleviating carbon emissions, buildings can significantly contribute to global efforts to combat climate change and foster a more sustainable future.

Computational methodologies and sophisticated algorithms significantly enhance the processes of simulating and optimizing architectural designs prior to the commencement of construction activities [3,18]. Such instruments empower architects and engineers to investigate diverse design alternatives, forecast performance outcomes, and refine design parameters to fulfil specific objectives, including energy efficiency, occupant comfort, and sustainability. For instance, simulation software augmented by artificial intelligence algorithms can accurately model the thermal performance of building envelopes across varying climatic conditions, thereby enabling designers to assess the efficacy of insulation materials and glazing configurations. Through iterative refinement of designs informed by simulation data, designers can optimize building performance and mitigating environmental impacts even prior to the initiation of construction.

18. Influence of AI Application in Sustainable Building Lifecycle

Notwithstanding substantial advancements in artificial intelligence technologies, the construction sector has exhibited a comparatively sluggish pace in embracing these innovations [22, 88]. This delay can be ascribed to multiple factors, including the intricate nature of construction projects, the entrenched characteristics of the industry, and a deficiency in awareness or comprehension of the prospective advantages offered by AI. In contrast to other industries that have more readily adopted AI, such as finance or healthcare, the construction sector has exhibited caution in the integration of new technologies, primarily due to apprehensions regarding disruption, risk aversion, and a dependence on established methodologies. Consequently, the literature review elucidated critical issues that have contributed to the gradual assimilation of AI within the sustainable building lifecycle, which can be characterized as the challenges confronting this technology (Table 4).

While AI is posited to yield significant long-term advantages, including enhanced productivity, cost reductions, and improved decision-making capabilities, the initial financial outlay for implementing AI solutions can be prohibitive for numerous construction enterprises [64, 73, 114]. These expenditures generally encompass investments in hardware, software, training, and necessary upgrades to infrastructure. Furthermore, there may exist concealed expenses related to customization, integration with pre-existing systems, and continuous maintenance and support. To surmount this barrier, construction firms are compelled to meticulously assess the prospective return on investment (ROI) associated with AI initiatives and formulate strategic plans to manage upfront expenditures while optimizing long-term gains [1, 11, 83, 107].

With the escalating digitization of construction processes and the widespread adoption of Internet of Things devices, ensuring the security and privacy of sensitive data has emerged as a critical concern [88, 101]. Construction endeavours necessitate the collection and storage of vast quantities of data, encompassing proprietary designs, financial records, and personal information pertaining to workers and clients. Any compromise of this data could result in severe repercussions, including financial losses, reputational damage, and legal liabilities. Consequently, construction firms have been required, and must continue, to implement robust cybersecurity measures, such as encryption, access controls, and regular security audits, to protect sensitive information and ensure compliance with data protection regulations [74, 81]. The lack of standardized frameworks and protocols for artificial intelligence applications in the construction sector obstructs interoperability, collaboration, and scalability [16,56]. Unlike other industries where comprehensive standards have been established, such as HL7 in healthcare [21, 93] or ISO 9000 in manufacturing [46, 100], the construction industry remains devoid of standardized frameworks for data exchange, interoperability, and quality assurance. This absence of standardization complicates effective communication between disparate AI systems and existing building technologies, resulting in delayed implementations, inefficiencies, and compatibility challenges [62]. Therefore, there exists an urgent necessity for the creation of industry-wide standards and protocols to enhance interoperability and facilitate the seamless incorporation of AI technologies into construction workflows.

The deficiency of proficient individuals possessing specialized knowledge in artificial intelligence, data science, and associated domains presents a considerable obstacle to the extensive implementation of AI within the construction sector [29, 67]. The design and execution of AI solutions necessitate particularized expertise and technical capabilities, encompassing programming, machine learning, and data analysis. Nonetheless, there exists a pronounced disparity between the requirement for AI talent and the availability of qualified professionals [8, 44]. Mitigating this skills shortfall demands coordinated initiatives from industry participants, educational institutions, and governmental organizations to formulate training programs, certification courses, and workforce development strategies tailored to the

Table 4. Challenges in the application of AI in Sustainable Building Lifecycle

S. No.	Challenges
1	Initial Implementation Costs
2	Data Security and Privacy Concerns
3	Lack of Standardization
4	Skills Gap
5	Interoperability Issues
6	Ethical Considerations

construction industry's requirements [36, 50]. By committing resources to talent cultivation and upskilling endeavours, construction enterprises can cultivate a workforce adept at leveraging the comprehensive capabilities of AI technologies, thereby fostering innovation within the sector [36]. Facilitating seamless communication and integration among diverse AI systems as well as existing building infrastructures presents significant technical challenges [88]. Construction undertakings encompass numerous stakeholders, each employing distinct software platforms, tools, and technologies. The integration of these heterogeneous systems and the assurance of interoperability can be intricate and protracted, resulting in delays, cost overruns, and disruptions to project timelines [84, 86]. To address interoperability challenges, construction firms must embrace open-source platforms, standardized interfaces, and middleware solutions that promote effective data interchange and communication across various systems. Furthermore, collaborative methodologies such as Building Information Modelling (BIM) and Integrated Project Delivery (IPD) can aid in optimizing workflows and enhancing coordination among project stakeholders, culminating in more efficient project execution and improved outcomes [9, 84, 86].

As artificial intelligence technologies gain traction in the construction industry, it becomes imperative to tackle ethical considerations pertaining to algorithmic bias, transparency, and accountability [81, 88]. AI algorithms possess the capacity to reinforce or exacerbate pre-existing biases and inequalities if not meticulously designed and monitored [57]. For instance, biased algorithms utilized in recruitment or resource distribution processes could result in discrimination or inequitable treatment. Consequently, construction firms must accord priority to ethical considerations throughout the development, deployment, and utilization of AI technologies. This encompasses the establishment of measures to ensure fairness and transparency, the conduct of regular audits and evaluations of AI systems, and the assurance of adherence to ethical guidelines and regulatory stipulations [13, 57]. Compliance with the evolving landscape of regulations and legal obligations concerning the implementation of AI is of paramount importance for construction firms [13]. As AI technologies become increasingly integrated into construction activities, regulatory authorities are scrutinizing their application and ramifications concerning safety, privacy, and other regulatory issues [38]. Construction organizations must remain cognizant of pertinent regulations, engage with regulatory entities, and incorporate compliance strategies into their AI initiatives to mitigate legal liabilities and guarantee adherence to regulatory standards [36, 57]. This may necessitate conducting privacy impact assessments, acquiring requisite approvals or permits, and conforming to industry-specific regulations governing data protection, safety, and environmental considerations [13, 38, 57, 94].

The efficacy of AI applications within the construction realm is contingent upon the quality and dependability of the data employed for training and inference [7,59]. Construction endeavors produce substantial volumes of data from a myriad of sources, including sensors, IoT devices, and historical records [10]. However, this data may be deficient, inaccurate, or outdated, resulting in biased or erroneous AI forecasts and determinations [76]. Consequently, construction firms must institute comprehensive data quality assurance protocols, which encompass data validation, cleansing, and normalization, to ensure the precision, completeness, and reliability of data utilized for AI applications [10, 76]. This may involve the deployment of data management systems, the establishment of data governance frameworks, and the execution of regular data quality audits to proactively identify and rectify data quality challenges.

19. Key Findings

The comprehensive literature review underscores the revolutionary capacity of artificial intelligence (AI) in advancing sustainability throughout the three pivotal phases of a building's lifecycle: design, construction, and operation. Numerous salient findings emerged from the analysis. In the design phase of building construction, AI-driven generative design presents unparalleled capabilities to enhance sustainability objectives by swiftly evaluating numerous design alternatives while accounting for parameters such as embodied carbon and ecological impact [15,33]. Furthermore, AI simulation instruments are instrumental in evaluating building performance at the nascent stages of the design process, thus empowering designers to make judicious decisions that emphasize sustainability without compromising on functionality or occupant comfort [34, 70].

In the construction phase, AI technologies unveil prospects for augmenting efficiency, particularly in mitigating waste. AI-enabled monitoring of materials and equipment has demonstrated a reduction in waste by more than 40%, resulting in considerable cost savings and environmental advantages [6, 49, 99]. AI-powered robotic systems can execute tasks such as welding, drilling, and cutting with exceptional precision and efficiency, thereby minimizing errors and material wastage [87]. In addition, the integration of AI can facilitate predictions regarding material performance, longevity, and embodied carbon emissions, thus enabling more informed selections of materials and construction methodologies [35, 37, 41]. During the operational phase of buildings, machine learning algorithms enhance energy efficiency by dynamically modulating HVAC, lighting, and other building systems based on real-time data and occupancy trends, potentially leading to energy savings of 20-30% in commercial structures [58, 65, 113, 121]. AI-driven predictive maintenance frameworks analyze data sourced from building sensors to foresee equipment malfunctions, thereby allowing for proactive maintenance interventions and diminished downtime [109]. Additionally, AI-enhanced energy management systems can optimize energy generation and consumption by incorporating renewable energy sources such as solar and wind into building systems [58, 116].

Beyond the distinct lifecycle stages, the review delineated several overarching advantages of AI integration in fostering sustainability throughout the building lifecycle. Machine learning algorithms perpetually analyze real-time sensor data to discern patterns in energy use and environmental conditions, thereby enabling dynamic adjustments to building systems aimed at minimizing energy consumption [14, 82]. Predictive analytics algorithms anticipate equipment failures by examining historical performance data, consequently prolonging the operational lifespan of essential building systems [88, 101].

AI-driven data analytics tools furnish insights into the economic and environmental ramifications of building materials across their lifecycle, thus facilitating informed decision-making regarding material selection [109]. Intelligent building systems utilize AI-driven technologies to enhance occupant comfort and productivity through tailored environmental controls [75]. Data analytics tools facilitate the monitoring and evaluation of waste generation, recycling metrics, and material utilization, thereby identifying opportunities for enhancements in waste management practices [23, 75]. Moreover, big data analytics, in conjunction with AI algorithms, quantifies a building's greenhouse gas emissions stemming from energy consumption, transportation, and material usage, thereby enabling targeted strategies for the reduction of carbon footprints [18, 33]. Furthermore, computational methodologies and AI algorithms enable the simulation and optimization of building designs prior to construction, allowing architects and engineers to investigate various alternatives, forecast performance outcomes, and fine-tune design parameters for energy efficiency, comfort, and sustainability [3, 18].

Notwithstanding these considerable advantages, the literature review elucidated several obstacles in the implementation of AI within the sustainable building lifecycle. Such challenges encompass initial implementation expenses [64, 73, 114], concerns regarding data security and privacy [74,81,88,101], a lack of standardization [16,56,62], skill deficiencies [8,29,36,44,50,67], interoperability challenges [9, 84, 86, 88], ethical implications [13, 57, 81, 88], and regulatory compliance issues [13, 36, 38, 57, 94]. The construction sector's relatively sluggish adoption of AI can be attributed to various factors, including the intricacies associated with construction projects, the industry's conventional orientation, and a deficiency in awareness or comprehension of AI's potential advantages [22, 88]. Moreover, the efficacy of AI applications in the construction domain is contingent upon the quality and dependability of the data utilized for training and inference [7, 10, 59, 76]. Construction enterprises must establish robust data quality assurance protocols to ensure the accuracy, completeness, and reliability of data employed for AI applications. The literature review accentuates the transformative potential of AI in revolutionizing sustainable practices across the building lifecycle, while concurrently recognizing and addressing the challenges pertinent to its adoption.

20. Research Contributions

This systematic review investigated the amalgamation of artificial intelligence (AI) with sustainable building lifecycle practices, with the objective of synthesizing the extant literature on this pertinent subject. The review yielded several notable contributions to the comprehension of AI applications within the building industry and their prospective ramifications for sustainability. A principal contribution of this review lies in the aggregation of existing knowledge regarding the utilization of AI throughout the lifecycle of buildings, underscoring its capacity to augment sustainability [3, 6, 14, 15, 18, 23, 33–35, 37, 41, 49, 58, 65, 70, 75, 82, 87, 99, 101, 109, 113, 116, 121]. By compiling and scrutinizing findings from a multitude of studies, the review offers a holistic perspective on how AI applications can optimize various factors, including energy efficiency, predictive maintenance, lifecycle cost analysis, occupant comfort and productivity, waste reduction and recycling, carbon footprint minimization, as well as simulation and design optimization during the design, construction, and operational phases of buildings.

The review further delineated and classified diverse forms of AI applications within the building sector, elucidating their particular uses and contributions [3,7,10,12,14,18,23,24,42,45, 52,53,59,67,72,75,77,78,80,82,87,88,96,98,101,111,112,119]. This classification encompassed technologies such as machine learning, robotics and automation, pattern recognition, digital twins, and the Internet of Things (IoT), each serving distinct roles and applications aimed at fostering sustainability throughout the building lifecycle. Moreover, the review identified the potential benefits and obstacles associated with the integration of AI in establishing a sustainable building lifecycle [3, 7–10, 10, 13, 14, 16, 23, 29, 33, 34, 36, 44, 50, 56, 57, 59, 62, 64, 67, 73–76, 79, 81, 82, 84, 86–88, 94, 101, 109, 114]. While accentuating the advantages, such as the optimization of energy efficiency, predictive maintenance, and waste reduction, the review concurrently addressed challenges, including initial implementation expenditures, data security and privacy issues, lack of standardization, skills deficits, interoperability challenges, ethical implications, and regulatory compliance. By systematically organizing data into clusters derived from an extensive review of 119 pieces of literature, the study established a robust foundation for analyzing AI technologies and their applications within the building sector. This data analysis and clustering methodology facilitated a methodical examination of AI applications across key stages of a building lifecycle, notably the design, construction, and operational phases.

Importantly, the review acknowledged that the application of AI within the construction industry constitutes a relatively nascent and emergent concept [22, 88], thereby contributing to an enhanced understanding of this evolving topic. This acknowledgment highlights the importance of the review in establishing a foundation for future research in the progressive field of AI within the building sector. The insights derived from this review provide a basis for subsequent research initiatives aimed at further investigating the barriers to AI adoption and the opportunities it presents for the building sector. Future inquiries may build upon the findings and recommendations articulated in this review, thereby furthering the integration of AI technologies in the promotion of sustainable building practices. In conclusion, this systematic literature review enriches the existing corpus of knowledge by synthesizing and consolidating current research at the intersection of AI and sustainable building lifecycle practices, delineating specific AI applications, identifying benefits and challenges, and establishing a framework for future investigations in this rapidly evolving domain.

21. Implication of the Study

This systematic review presents numerous significant implications for the construction sector and its ongoing pursuit of sustainable building methodologies. By synthesizing the extant knowledge regarding the amalgamation of artificial intelligence (AI) with the building lifecycle, the study elucidates the transformative capabilities of AI technologies in the realization of sustainability objectives throughout the design, construction, and operational phases of edifices. A noteworthy implication is the discernment of particular AI applications that can catalyse sustainability enhancements within the building industry. From AI-enabled generative design and simulation tools at the design phase to predictive maintenance frameworks and energy management optimization during operational phases, this review furnishes a comprehensive comprehension of the diverse AI solutions that can be harnessed by stakeholders in the industry. This knowledge can inform strategic decision-making frameworks and steer investments toward the most promising AI technologies to bolster sustainability. Furthermore, the delineation of potential benefits and obstacles associated with AI integration holds critical ramifications for the industry's readiness and preparedness. By acknowledging advantages such as energy efficiency optimization, waste minimization, and carbon footprint reduction, the review accentuates the necessity of adopting AI as a pivotal enabler of sustainable building methodologies. Simultaneously, by emphasizing challenges such as implementation expenditures, data security apprehensions, and skill deficits, the study underscores the imperative for proactive measures to surmount these impediments and facilitate the successful assimilation of AI.

The review's recognition of AI applications as a relatively novel and emergent concept within the construction sector also bears implications for industry stakeholders. It underscores the significance of remaining abreast of the latest advancements, cultivating a culture of innovation, and investing in workforce development to cultivate the requisite skills and expertise essential for the effective utilization of AI. Moreover, the study's contribution to the corpus of knowledge and its provision of a robust foundation for prospective research bear implications for the academic and research communities. By identifying gaps and domains for further investigation, the review has the potential to stimulate and direct future inquiries, ultimately propelling the advancement of more sophisticated AI solutions and sustainable building practices. In summary, this systematic review encompasses far-reaching implications for the construction industry, policymakers, researchers, and other stakeholders engaged in the pursuit of sustainable building practices. It accentuates the transformative potential of AI, underscores the necessity for preparedness and strategic planning, and paves the path for ongoing research and innovation in this rapidly evolving discipline.

22. Conclusion and Recommendations

Notwithstanding the acknowledged limitations, further research and development initiatives are imperative to surmount these obstacles and unlock the comprehensive potential of AI in transforming sustainable building practices. Future research endeavours should concentrate on investigating practical technological advancements within the constraints delineated in this review. Emphasis should be placed on devising cost-effective solutions that address the high initial implementation expenditures, which can pose significant barriers for numerous construction enterprises. Additionally, research initiatives should explore innovative methodologies to alleviate data security and privacy concerns, as such issues may dissuade stakeholders from fully embracing AI solutions. Robust frameworks and protocols to safeguard sensitive information are crucial to fostering trust and facilitating the broader adoption of AI technologies within the construction sector.

Furthermore, this review has illuminated the urgent necessity to confront the skills gap that is currently prevalent within the industry. Future research should examine targeted initiatives and strategies to upskill the workforce and cultivate a culture of innovation that embraces AI technologies. Collaborative efforts among industry stakeholders, educational institutions, and governmental agencies could prove invaluable in formulating specialized training programs, certification courses, and workforce development initiatives tailored to the unique requirements of the construction sector. To augment the practicality and relevance of future research endeavours, a combination of interviews and surveys could yield a more comprehensive understanding of AI technologies and their applications within the building sector. Qualitative insights from industry professionals and stakeholders could provide valuable perspectives on elements such as cost considerations, implementation challenges, and strategies for promoting the adoption of AI in sustainable building practices.

While this review has delineated several challenges, including interoperability issues, ethical considerations, and regulatory compliance, further research is warranted to explore their implications more deeply and to develop comprehensive solutions. Interoperability challenges, for instance, necessitate the establishment of standardized frameworks and protocols to ensure seamless communication and integration among various AI systems and existing building infrastructures. Ethical considerations surrounding algorithmic bias, transparency, and accountability must be diligently addressed to maintain public trust and ensure the responsible deployment of AI technologies. Additionally, ongoing research is required to remain informed about evolving regulations and legal obligations pertinent to AI implementation, thereby enabling the industry to proactively adapt and ensure compliance. Additionally, this review has emphasized the paramount significance of data quality and dependability in securing the effectiveness of artificial intelligence applications within the construction sector. Subsequent investigations should prioritize the formulation of comprehensive data quality assurance protocols, encompassing data validation, purification, and normalization methodologies, to guarantee the precision and completeness of data utilized for training and inference within AI frameworks. This review has highlighted the transformative capacity of artificial intelligence in redefining sustainability practices throughout the building lifecycle. By delineating critical challenges, establishing research priorities, and underscoring practical ramifications, this review establishes a foundation for substantial advancement toward a more resilient and environmentally attuned built environment. Through ongoing research, collaboration among stakeholders, and an unwavering dedication to innovation, the construction industry can leverage the capabilities of artificial intelligence to promote sustainable building practices, enhance resource efficiency, and alleviate environmental repercussions, ultimately contributing to a more sustainable future.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

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