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Review

A Systematic Review of the Applications of AI in a Sustainable Building's Lifecycle

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Abstract: Buildings significantly contribute to global energy consumption and greenhouse gas emissions. This systematic literature review explores the potential of artificial intelegence (AI) to enhance sustainability throughout a building's lifecycle. The review identifies AI technologies applicable to sustainable building practices, examines their influence, and analyses implementation challenges. The findings reveal AI's capabilities in optimising energy efficiency, enabling predictive maintenance, and aiding in design simulation. Advanced machine learning algorithms facilitate data-driven analysis, while digital twins provide real-time insights for decision-making. The review also identifies barriers to AI adoption, including cost concerns, data security risks, and implementation challenges. While AI offers innovative solutions for energy optimisation and environmentally conscious practices, addressing technical and practical challenges is crucial for its successful integration in sustainable building practices.

Keywords: artificial intelligence; sustainability; building lifecycle; design optimization; digital twins; Internet of Things

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1. Introduction

In recent years, sustainable building practices have attracted critical focus within the construction industry, a focus driven by growing concerns about the environmental impacts of traditional design and construction methods. With buildings accounting for nearly 40% of global energy consumption and contributing up to 30% of annual greenhouse gas emissions [1], there is a pressing need to address these issues. Moreover, as the world's urban population is projected to double by 2050 [2], enhancing the sustainability of buildings and infrastructure has never been more urgent.

Amidst these challenges, there is a deep optimism surrounding the potential of emerging technologies, particularly artificial intelligence (AI) [3–6], to revolutionize how we approach sustainable building practices. By leveraging AI across various stages of the building's lifecycle, from design and construction to operation and maintenance, a unique opportunity exists to mitigate systemic inefficiencies and drive meaningful change [7]. One of the most pressing issues facing the building industry is the staggering amount of waste generated during construction. Globally, 11–15% of materials are wasted on construction sites [8], highlighting the need for more efficient processes and resource utilization. Furthermore, operational inefficiencies contribute significantly to carbon footprints. For example, lighting, heating, and cooling accounted for nearly 28% of commercial building energy use in the United States [9], and commercial and residential buildings in China contributed 41.10% to the total energy consumption [10]. Residential buildings alone accounted for over 80% of the total energy consumed in Nigeria [11].

Furthermore, as AI technologies advance, a growing focus is on leveraging decentralized and autonomous systems to optimize building operations and resource management. For example, AI-driven decentralized energy systems can optimize energy generation [12], storage [13], and distribution [14] within buildings and across smart grids, enhancing resilience and sustainability while reducing the dependence on centralized energy sources. While the potential of AI to improve building sustainability has been widely studied, only some studies have synthesized the current knowledge on implemented applications spanning the lifecycle of buildings: design, construction, and operations phases. Indeed, this is an unfolding critical body of knowledge and a highly potent field of study. Despite this great significance, a few systematic reviews exist concerning how AI can enhance the sustainability of buildings throughout the buildings' lifecycles and their design, construction, and operations stages. Furthermore, although AI technologies, like machine learning and computer vision, are gaining ground for enhancing building sustainability, most current applications focus on the operational stage, with less attention on the design and construction stages. This systematic literature review was, therefore, conducted to fill that gap. This review aims to gather existing research on AI technologies applied in sustainable building, focusing on the less-studied areas and identifying the remaining gaps needing investigation.

There is immense, untapped, and significant potential regarding leveraging AI for various building aspects, generative design, construction automation, predictive maintenance, and lifecycle optimization, practices that would reduce the environmental footprints of buildings. However, attention must also be given to the challenges inherent in the technology, including data availability, validation, and industrial adoption.

Therefore, the study aligned with the literature published on AI applications used at the different stages of the building's lifecycle. It presents how the applications have enhanced sustainability and identifies the challenges of applying them in the building industry. The study further identified potential solutions to these challenges to assess the application of AI in the building's lifecycle to enhance sustainable building delivery. To attain the aim, this review was guided by the following research questions:

- How is AI conceptualized and applied in the context of sustainable buildings, according to the current literature?
- What are the AI technologies applicable to sustainable buildings' lifecycles?
- How does AI application influence sustainable a building's lifecycle?
- What are the barriers to AI application in a sustainable building's lifecycle?
- What knowledge can be drawn from existing studies on AI application in the sustainable building's lifecycle?

The systematic literature review on using AI in sustainable building lifecycles was conducted to answer these questions. Among the research works reviewed were those related to AI, AI application in sustainable construction, AI technology tools, and challenges to AI application in sustainable buildings, which were analyzed comprehensively. The gaps were also identified and discussed. By answering these review questions, the study contributes to knowledge and impacts the improvement and understanding of AI integration with sustainable building practices. Thus, this paper makes a modest contribution to discussing AI technology tools and their applications to sustainable building. It guides designers and construction personnel on the appropriate deployment of AI technologies. Specifically, the review is significant in applying relevant AI technologies and tools before, during, and after construction to examine a sustainable building's lifecycle.

This review is structured as follows: Section 2 outlines the materials and methods used in conducting this review, detailing the search strategy and analysis process. Section 3 presents the findings and discussions, exploring the current applications of AI in sustainable building lifecycles, their influences, and the challenges faced in implementation. Section 4 summarizes the review's key findings, highlighting the most significant insights uncovered. It also discusses the implications of this study for the construction industry and sustainable building practices. Finally, Section 5 concludes the review and recommends future research directions. By providing this roadmap, we aim to guide readers through the structure of the paper and prepare them for the in-depth exploration of AI applications the in sustainable building lifecycles that follow. Each section builds upon the previous, culminating in a comprehensive understanding of the current state of AI integration in sustainable building practices and the potential for future developments in this field.

2. Materials and Methods

Essentially, this review categorized documented applications of AI in sustainable building lifecycles across the three primary stages: design, construction, and operations. Moreover, the review focused on the literature that reported demonstrated applications and implementations of AI technologies rather than just conceptual proposals. The systematic review of the published literature was conducted as the primary research design. It was conducted by adopting the methodological model proposed by Brocke [15], which stressed the importance of rigor in the documentation of the literature search process. The model is based on a five-phase framework for the literature search process, which is as follows: (1) definition of review scope, (2) conceptualization of topic, (3) literature search strategy, (4) literature analysis and synthesis, and (5) research agenda. Subsequently, these phases were explained with particular reference to applying AI appropriately in a sustainable building lifecycle.

2.1. Definition of Review Scope

To clearly define the scope of this systematic literature review, a reference was made to an established taxonomy presented by Cooper [16], who established six characteristics of the literature review: focus, goal, organization, perspective, audience, and coverage. Regarding Cooper's [16] taxonomy of the review scope discussed earlier, Table 1 summarizes the authors' choices in this review.

Table 1. Cooper's taxonomy applied to the smart city and digital city literature review. Adapted from [16].

Characteristic	Cooper's Options	Author's Choice
Focus	Type of papers involved (methodological, theoretical, practices, applications, outcomes)	Practices and applications
Goal	Integration, criticism, central issue	Central issue
Organization	Chronological, conceptual, methodological	methodological
Perspective	Neutral, espousal of a position	Neutral
Audience	Groups of people whom the review is addressed	Researchers, practitioners, policy-makers, and stakeholders
Coverage	Exhaustive, with selective citation, representative, central, pivotal	Selective citation

It should be noted that certain constraints limited the scope; only the literature from 2013 to 2023 was considered, focusing on modern deep learning advances. Furthermore, only English-language publications related to residential and commercial buildings were included. The defined scope and purpose allowed a focused synthesis of the emerging field of AI in sustainable building practices.

2.2. Conceptualization of the Review Topic

Brocke [15] suggested that a review must begin with a broad conception of what is known about the topic and potential areas where knowledge may be needed. Therefore, the conceptualization of this study topic evolved through a meticulous process of understanding and synthesizing existing knowledge. The study commenced with a broad exploration of AI and sustainable building practices. By delving into the extensive literature on these topics, foundational insights were gained into the potential intersections between the domains.

As the review progressed, attention was shifted towards identifying specific areas within the building lifecycle where AI could offer innovative solutions to sustainability challenges. This involved examining the prevailing environmental issues that the construction industry faces, such as energy inefficiency, material wastage, and carbon emissions. Concurrently, an appreciation for the increasing importance of sustainable practices in building design, construction, and operation emerged, driven by global imperatives, such as climate change mitigation and resource conservation.

Furthermore, the conceptualization process entailed recognizing the transformative capabilities of AI technologies in addressing these sustainability challenges. It analyzed the potential applications of AI across the various stages of a building lifecycle, from design optimization to operational efficiency enhancement.

2.3. Literature Search Strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach was used to gather data for this systematic review during the literature search phase. This methodology technique is widely used in systematic review studies because it clearly outlines the methods used to find, filter, include, and exclude the relevant literature, thus improving the accuracy and precision of the systematic review process. This study employs a step-by-step approach to obtain the relevant literature on the topic, employing targeted keywords to refine research papers in accordance with the inclusion and exclusion standards illustrated in Figure 1. The approach of applying the PRISMA technique in this investigation is described in the steps that follow.

First, the online databases of Science Direct and Google Scholar were selected to as the database sources among the available ones. The choice was based on the fact that they included a broad base of publications comprising journal articles, books, citations and patents, many of which focused on the subject of this study, especially the first two.

Second, the most suitable keywords and search criteria were identified to extract representative subsets from the selected online databases. The databases were searched using the words "AI in the building life cycle" OR "AI in Sustainable building life cycle" with the search filters set to find the keywords, "only in the title of the paper", "abstract", and "keywords", excluding all citations and patents. With those parameters, the search results included 237,839 papers, out of which 4839 came from Science Direct and 233,000 came from Google Scholar. The databases were then queried to sort all the results by year of publication within the 2013–2023 range. The review chose this 10-year range to have a reasonably representative scientific literature set, excluding works in progress; hence, the range excluded 2024. Having filtered the search results using the year range, the results were reduced to 21,688 papers, of which 3488 came from Science Direct and 18,200 came from Google Scholar.

Third, consideration was given to whether to apply a "backward and forward search". However, the substantial volume of the literature already identified through the initial process, resulting in a diverse array of sources, journals, conference proceedings, book chapters, and industry reports, was resolved to be adequate. The pool of scientific literature provided a comprehensive foundation for exploring the application of AI in the sustainable building lifecycle. Therefore, an additional backward and forward search was deemed unnecessary, as the breadth and depth of the literature accessed were considered sufficient to support the research objectives and facilitate a thorough review of the research topic.

Fourth, evaluation in "all phases means limiting the amount of literature identified by keyword search to only those articles relevant to the topic at hand" [15]. The literature evaluation process was performed manually, and some criteria were applied to restrict the search. The manual method was used due to the absence of a literature review storage database (LRS-DB), usually used as a source input platform. The process removed duplicates, theses, PowerPoint presentations, white papers, book introductions, competition announcements, all works not in English and without full abstracts available, and all unpublished works which did not undergo peer review. The review also adopted three sets of criteria for inclusion and exclusion. Firstly, the articles were selected based on how relevant they were to the study themes, using a rating system; "1" meant "low significance", "2" meant "moderate significance", and "3" meant "high significance". This assessment scale had been utilized by earlier researchers [17–19]. Each article's applicability was evaluated according to its methodological rigor and conclusions. As a result, all publications that provided case studies and practical applications of AI adoption in sustainable building lifecycles received a "3" rating and were added to the review. Secondly, articles with a high number of citations were prioritized, and a select few were added to the review. All other articles that did not fall within the "2" and "3" ratings indicated their low significance to the review. The articles were restricted to the application of AI in the lifecycle of sustainable buildings, excluding roads, bridges, and other construction practices in the building industry. Most articles chosen for evaluation were published within the last five (5) years. Applying these criteria resulted in the exclusion of many studies, resulting in a total of 900 relevant to the present review. This search strategy is depicted in Figure 1.

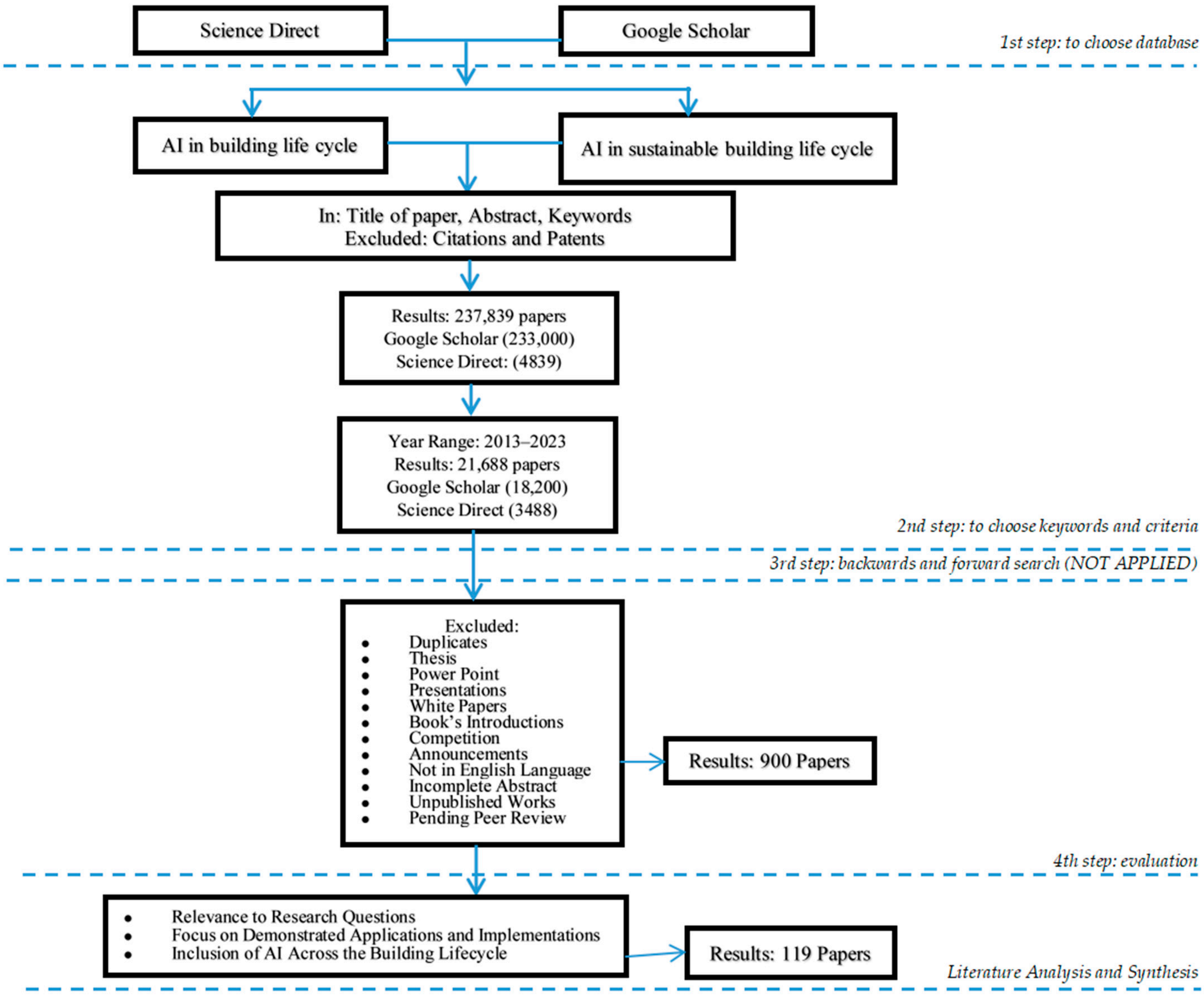

Figure 1. Description of the stages involved in retrieving the literature, filtering, defining inclusion and exclusion criteria, and classifying study records using the PRISMA approach.

2.4. Literature Analysis and Synthesis

After collecting sufficient scientific literature on the topic, the processes of analysis and synthesis were conducted [15]. To accomplish this goal, the 900 papers were systematically organized to align with the following three investigative foci.

2.4.1. Relevance to Research Questions

The first aspect of the investigation involved assessing the relevance of each paper to the research questions posed. It ensured that the literature reviewed directly addressed the inherent objectives of the research questions. Papers were, therefore, evaluated based on their alignment with the key themes and topics of interest related to the application of AI in sustainable building lifecycles. Any paper that did not directly contribute to answering the research questions was filtered out to maintain the focus and coherence of the review.

2.4.2. Practical Applications and Implementations

Another critical aspect of the investigation was to ascertain whether the literature primarily reported demonstrated applications and implementations of AI techniques or merely presented conceptual proposals. This criterion ensured that the review focused on practical, real-world examples of AI integration in sustainable building lifecycles rather than theoretical discussions or speculative ideas. Furthermore, the papers were evaluated based on their ability to provide empirical evidence, case studies, or documented implementations of AI technologies in actual building projects across the various phases of the building lifecycle.

2.4.3. Inclusion of AI across the Building Lifecycle

Lastly, the investigation sought to determine the extent to which the literature addressed the inclusion of AI technologies across the entire building lifecycle. It, therefore, involved analyzing the papers covering AI applications in all stages of the building lifecycle, namely design, construction, and operations, thereby providing a comprehensive understanding of how AI contributes to sustainability across the building lifecycle.

Overall, these three investigative foci ensured that the collected literature was systematically analyzed and synthesized to address the research objectives effectively. By prioritizing relevance, practical applications, and comprehensive coverage of a building lifecycle, the review offered valuable insight into the role of AI in advancing sustainability in the built environment. More filtering efforts were made to read the abstracts of the 900 articles and, in some cases, their methodologies and findings. From that filtering exercise, the articles relevant to the research questions were identified; only 119 articles met the criterion and, hence, were the ones used for this review.

2.5. Distribution of Identified Literature

From the searches conducted in the two online databases, Science Direct and Google Scholar, to identify relevant publications on AI applications in sustainable building practices, 24 (20%) of all identified resources were from Science Direct, while 95 (80%) were from Google Scholar (Figure 2). Figure 2 also revealed the types of literature identified from the online searches, showing that, for Science Direct, 9 (38%) were review articles, 14 (58%) were research papers, and 1 (4%) was a book chapter. For Google Scholar, 26 (27%) were review articles and 69 (73%) were research papers.

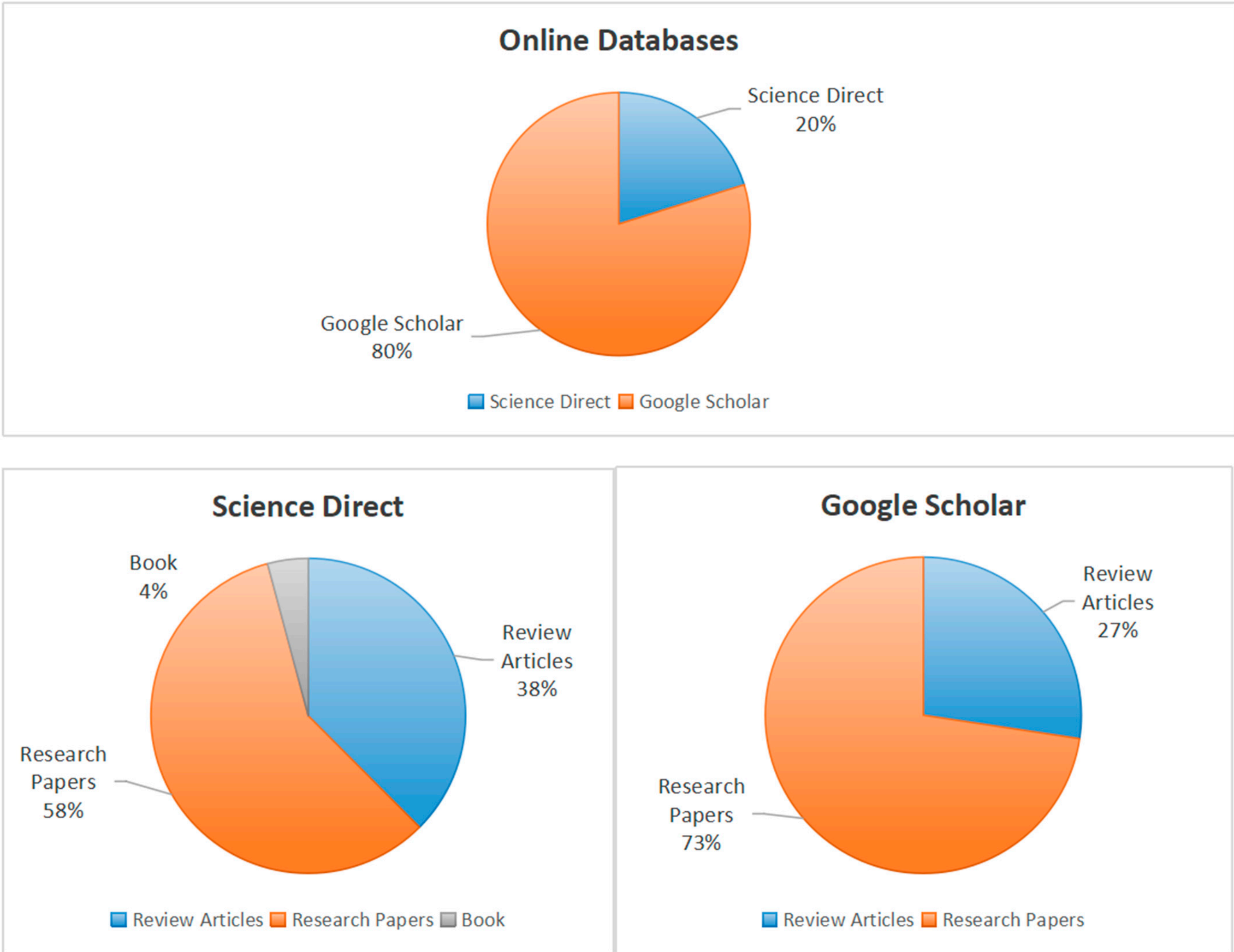

Figure 2. Distribution of the identified literature.

3. Findings and Discussions

3.1. AI in Sustainable Buildings

AI encompasses tasks that can be automated using self-governing mechanical and electronic devices with intelligent control [20]. According to McLean [21], there are three conceptualizations of AI, namely artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI). ANI is utilized in language translation and weather forecasting, AGI is envisioned to solve complex problems independently, incorporating mental models and personality features, while ASI, a futuristic concept, could potentially surpass human abilities in various fields, as Bughin [22] claimed.

According to Debrah [23], AI in sustainable buildings refers to adopting and integrating AI technologies to optimize energy efficiency, reduce environmental impact, and enhance the overall sustainability of buildings. AI holds much promise in improving collaboration and communication among stakeholders throughout the building's lifecycle [24]. By facilitating data sharing and real-time collaboration, AI platforms can streamline project management processes [25], improve decision-making [26], and foster innovation in sustainable building practices [27]. For example, AI-powered digital twins enable virtual simulations and predictive modelling [28], allowing stakeholders to anticipate performance outcomes and optimize building designs for sustainability and resilience [29].

Integrating AI with conventional techniques, such as modelling, simulation, and analytics, can potentially revolutionize the various stages of building design, construction, and operations [30]. At the building design stage, advancements in AI offer unprecedented capabilities to optimize sustainability goals within various architectural and engineering parameters [23,31]. AI-driven generative design, for instance, can rapidly analyze multiple design options, considering different parameters, to minimize embodied carbon and enhance overall sustainability [31]. By iteratively generating and evaluating designs, AI-driven processes can identify optimal solutions that significantly reduce environmental impact compared to conventional methods. Furthermore, AI simulation tools are crucial in assessing building performance early in the design process [32]. By simulating relevant factors, such as energy consumption and indoor environmental quality, these tools enable designers to make informed decisions that prioritize sustainability without compromising functionality or comfort [33]. For instance, AI algorithms can analyze various design options and select the most sustainable one based on specific criteria [18]. This proactive approach ensures that sustainability measures are integrated seamlessly from the outset, minimizing the need for costly retrofits in later stages [18,33,34].

At the construction stage, AI technologies offer capabilities that enhance efficiency, especially in reducing waste. Through computer vision and AI-driven analytics, construction sites can be monitored in real-time to identify inefficiencies and mitigate risks [35]. For example, AI-enabled tracking of materials and equipment has been shown to reduce waste by over 40% [36], leading to significant cost savings [37] and environmental benefits [38]. AI-powered project data analysis can also identify potential safety hazards, allowing for proactive risk management and improved construction site safety [39]. Yet again, AI-powered robots can perform tasks, such as welding, drilling, and cutting, with high precision and efficiency, minimizing errors and reducing material waste. Furthermore, AI integration can be utilized to predict material performance [40], durability [41], and embodied carbon emissions [42], enabling more informed material selection and construction methods.

At the operation stage, once buildings are operational, AI continues to play a crucial role in maximizing efficiency and performance. Intelligent building systems leverage "machine learning algorithms" to optimize the control of various building systems, such as lighting, HVAC, and security, based on real-time data and occupancy patterns [43]. By dynamically adjusting system settings in response to changing conditions, AI-enabled automation can significantly reduce energy consumption and operational costs while maintaining occupants' comfort and productivity [44]. Studies have suggested that AI-driven building automation could lead to energy savings of 20–30% in commercial buildings [45], while in residential buildings, there is a savings of 8.48% in energy and 7.52% in cost [46]. According to De Wilde [47], in the aspect of maintenance and repairs, considered part of the building's operation stage, AI helps to predict and diagnose maintenance and repair needs, thereby reducing downtime and improving building performance. A typical example is where AI-powered predictive maintenance systems can analyze data from building sensors and predict when equipment will likely fail, allowing for proactive maintenance and reducing equipment downtime. At this stage, there is renewable energy integration, where AI can help integrate energy sources, like solar and wind, into building systems, thereby optimizing energy production and consumption. For instance, AI-powered energy management systems can analyze real-time data from renewable energy sources and building loads, adjusting energy production and consumption accordingly to maximize efficiency and reduce energy costs [46,48].

Moreover, ongoing commissioning and fault detection, facilitated by AI-powered analytics, enable proactive maintenance and troubleshooting [47]. By analyzing data from building systems and equipment, AI algorithms can detect anomalies and potential issues before they escalate, minimizing downtime and prolonging the lifespan of building assets. This predictive maintenance approach enhances operational efficiency and contributes to overall sustainability by reducing resource consumption and waste. It is essential to establish a theoretical underpinning for the discussion to provide a structured approach to understanding the application of AI technologies in various aspects of construction projects, focusing on the building's lifecycle stages.

3.2. Theoretical Underpinning for an AI-Integrated Sustainable Building's Lifecycle

In addressing the knowledge gap regarding the application of AI technologies, several theories can be subscribed to as theoretical underpinnings. The first theory underpinning this study is the technology acceptance model (TAM), developed by Fred Davis in 1985 and first proposed in his 1989 paper [49], widely utilized for understanding and predicting the application and use of new technologies, such as AI. The model postulates that perceived usefulness and ease of use are key determinants of a person's intention to use a particular technology. Perceived usefulness in the context of the lifecycle of buildings points to how stakeholders, such as construction professionals and facility managers, may perceive AI technologies as useful if they believe that such technologies can enhance their performance, productivity, or decision-making abilities [50,51]. For example, facility managers may perceive AI-powered predictive maintenance systems as useful since they can assist in anticipating equipment failures and optimizing maintenance schedules, leading to cost savings and improved building operations. Similarly, architects and engineers may perceive AI-driven design optimization tools as valuable because they can generate more efficient building designs and reduce construction costs.

Regarding perceived ease of use, users' beliefs in the friendliness and effortlessness of AI technologies can impact their intention to use them in the building lifecycle. For example, AI-powered building information modelling (BIM) tools may be perceived to be intuitive and easy to navigate. As a result, construction professionals may be more inclined to adopt them for coordinating design, planning, and construction activities. Conversely, AI-based energy management systems, for example, are perceived as complex and challenging to configure. In that case, facility managers may be less likely to utilize them to optimize building energy performance.

The TAM has been continuously studied and expanded, with two significant upgrades being the TAM 2 [52,53] and the unified theory of acceptance and use of technology (UTAUT) [54]. In the context of construction, TAM helps to understand the factors that influence construction professionals' acceptance and adoption of AI technologies, tools, and systems, such as perceived benefits and ease of use.

Another applicable theory, innovation diffusion, developed by Everett Rogers [54], examines how new ideas, practices, or technologies spread within a population gradually rather than all at once. It focuses on how innovations, such as AI, are communicated through specific channels over time among members of a social system, and also identifies factors that influence the adoption rate. It further includes their relative advantages based on perceived benefits, compatibility with existing processes, complexity, ability to be tried, and ability to be observed. In the context of construction, the theory covers a broad scope of thought, assisting research in understanding the various factors that influence the awareness and adoption of AI technologies in the different construction stages within the lifecycle of a building.

Looking further into the diffusion of AI technologies in the lifecycle of buildings through the lens of the innovation diffusion theory, an example can be seen in the adoption of AI-powered building information modelling (BIM) tools. That may start with innovative construction firms and gradually spread to the broader industry as the benefits of the technology become more apparent. Adopting AI-driven energy management systems in buildings may follow a similar diffusion pattern, with early-adopting facility managers leading the way and then influencing the broader adoption by other building owners and managers. The innovation diffusion theory further identifies several key factors that influence the successful spread of innovations, such as the characteristics of the innovation itself, the communication channels used, the social system in which the innovation is introduced, and the time it takes for the innovation to be adopted.

3.3. AI Technologies Applicable to a Sustainable Building Lifecycle

According to Regona [20], building industry products rapidly integrate into a networked hardware and software ecosystem, forming customized "constellations" based on validated use cases. As depicted in the building industry technology map, notable constellations include supply chain optimization, robotics, digital twin technology, modularization, AI, and analytics. Some technologies, like digital twins, 3D printing, and AI plus analytics, are anticipated to have revolutionary effects. Figure 3 visually represents the AI technologies and their applications across different stages of the building lifecycle.

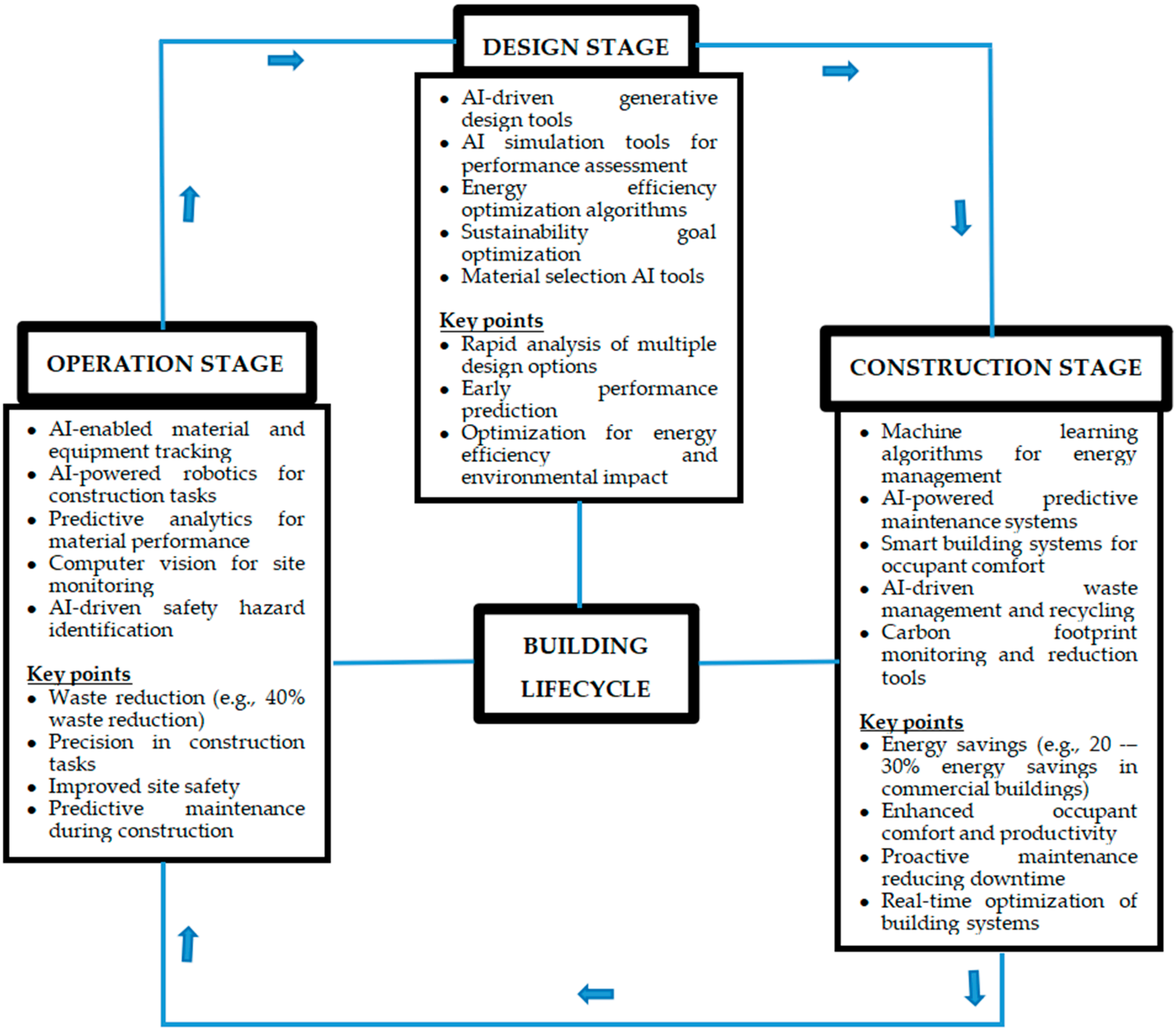

Figure 3. Building lifecycle artificial intelligence (AI) application diagram.

In the short term, the building sector can benefit from fundamental technologies, such as blockchain, AI, the Internet of Things (IoT), big data analytics, and information communication technology (ICT). Table 2 outlines major AI technologies currently deployed globally, systematically organized based on their application methods and specific purposes within distinct areas, all contributing cohesively to realizing a more sustainable building lifecycle. Digital twins, a pivotal component of this technological revolution, enable seamless integration with various projects and offer real-time activity capture for predictive decision-making [55]. These digital replicas empower project and facility managers to create virtual construction sites and sustainable, functional building models accessible remotely via network technologies [56]. They further lay the groundwork for intelligent 3D models that enhance efficiency in planning, design, and infrastructure management [57].

Table 2. Major AI technologies and their applications in a sustainable building lifecycle. Adapted from [20,58,59].

AI Technology/Subset	Application
Machine learning (ML)—1	Big data and data analysis
Machine learning (ML)—2	Robotics and automation
Pattern recognition	Data and system integration
Automation	Mobility and wearable
Digital twins (DTs)	Real-time monitoring and management
Internet of Things (IoT)	Automated control of building systems and services

Integrating AI technologies, including image recognition, identifies unsafe practices and contributes to ongoing worker training, marking a paradigm shift towards a more technology-driven, efficient, and safer future in the building industry [60]. These technologies are seen to be applied across the building lifecycle, which appropriate theoretical propositions have underpinned.

Application

Integrating big data and data analytics significantly enhances a building's lifecycle sustainability by providing detailed insights into energy consumption patterns, enabling real-time adjustments for energy efficiency. Predictive maintenance ensures proactive scheduling, preventing equipment failures and extending the lifespan, while lifecycle cost analysis aids decision-making on economic and environmental impacts. Robotics and automation are pivotal in sustainable construction, reducing time, enhancing precision, and minimizing errors. Data and system integration enable seamless communication, optimizing energy efficiency and waste reduction. Mobility and wearable technologies streamline construction management, enhance occupant well-being, and contribute to energy monitoring. Real-time monitoring and management across multiple dimensions optimize energy usage, water conservation, and waste management and improve building security. Automated control of building systems focuses on operational efficiency, resource conservation, and performance enhancement, contributing to grid stability and carbon emission reduction. Table 3 provides information on the purpose of these systems and their applications for a sustainable building's lifecycle. They have been matched with the pertinent literature to provide specific data sources regarding the identified major AI applications.

Table 3. Major AI technologies/applications for a sustainable building's lifecycle, citing their sources in literature.

AI Technology/Subset	Application	Purpose	Sources
Machine learning (ML)	Big data and data analysis	Big data and data analytics play a pivotal role in the building industry, fostering sustainability by optimizing energy efficiency, enabling predictive maintenance, supporting lifecycle cost analysis, enhancing occupant comfort, facilitating waste reduction, tracking carbon footprints, and aiding in simulation and design optimization throughout the building lifecycle.	[20,22,23,34,47,52,58,59,61–67]
Machine learning (ML)	Robotics and automation	Robotics and automation in the building industry contribute to sustainability by streamlining construction processes, optimizing energy management, enhancing building efficiency, improving maintenance and inspections, fostering smart building systems, facilitating demolition with material recovery, and promoting waste management and recycling.	[20,23,34,58,59,62–72]

Table 3. *Cont.*

AI Technology/Subset	Application	Purpose	Sources
Pattern recognition	Data and system integration	Data and system integration in the building industry facilitates sustainability by optimizing energy efficiency, enabling smart building automation, supporting predictive maintenance, reducing waste, conducting lifecycle assessments, enhancing occupant well-being, fostering collaboration, and ensuring regulatory compliance throughout the building's lifecycle.	[20,23,34,58,59,63,64, 67,69,71–73]
Automation	Mobility and wearable technologies	Mobility and wearable technologies enable enhanced site safety, emergency response, construction productivity, asset tracking, and data-driven facility management through capabilities, like motion detection, spatiotemporal monitoring, real-time alerts, and remote system controls.	[20,34,47,59,62–64,66,69,71,72,74–79]
Digital twins (DTs)	Real-time monitoring and management	Real-time monitoring and management play a pivotal role in building lifecycle sustainability by optimizing energy efficiency, ensuring occupant comfort, enabling predictive maintenance, conserving water, improving waste management, monitoring occupancy, managing indoor air quality, enhancing security and safety, optimizing space utilization, and reducing the building's carbon footprint through informed and proactive decision-making.	[20,23,34,47,58,59,62, 67,79–81]
Internet of Things (IoT)	Automated control of building systems and services	Automated control of building systems and services is instrumental in promoting building lifecycle sustainability by optimizing energy efficiency, implementing demand response strategies, adapting to occupancy patterns, facilitating predictive maintenance, conserving water, maximizing natural light utilization, integrating building management, reducing carbon emissions, incorporating adaptive learning systems, and enhancing user comfort and productivity through informed and automated decision-making processes.	[47,59,62,64,65,69,70, 73,74,76,79–85]

3.4. Technological Roadmap for AI in a Sustainable Building's Lifecycle

Integrating AI technologies into sustainable building practices is an evolving process that requires a structured approach. This technological roadmap outlines the key stages and milestones for implementing AI across the building lifecycle, from design to operation and maintenance.

In the short term (1–3 years), the focus should be on laying the groundwork for AI integration. This involves building a robust data infrastructure, including deploying IoT sensors and establishing data collection protocols. Simultaneously, efforts should be directed towards developing and implementing basic AI applications, such as energy consumption prediction models and simple automation systems for building controls [59,63,64,73].

The medium-term horizon (3–5 years) should see more advanced AI applications coming into play. This includes the widespread adoption of digital twins for building design and operation, AI-driven generative design tools for optimizing sustainability parameters, and more sophisticated predictive maintenance systems. During this phase, there should also be a concerted effort to address interoperability issues and develop industry-wide standards for AI implementation in construction [58,62–64,68,73,74,82].

Long-term goals (5–10 years) involve the full integration of AI across the entire building lifecycle. This includes developing fully autonomous building management systems, AI-powered circular economy solutions for construction waste management, and advanced simulations that can accurately predict a building's environmental impact over its lifespan. Additionally, this phase should see the emergence of AI systems capable of self-learning and adapting to changing environmental conditions and user needs without human intervention [66,69,72,75,76,79–81,84,85].

Throughout this roadmap, parallel efforts must be made in workforce development, addressing ethical considerations and ensuring regulatory compliance. Regularly assessing and updating the roadmap will be crucial in order to account for technological advancements and changing industry needs. Following this roadmap, the construction industry can systematically integrate AI technologies to enhance sustainability across the building lifecycle, from initial design concepts to long-term operation and eventual decommissioning.

3.5. AI Applications Deployed in Stages of a Building's Lifecycle

AI has been shaping building methods, becoming a well-established and influential force in the building sector. Several authors have reached a consensus on the beneficial subsets of AI in the building industry, including design and construction, maintenance, and even decommissioning. These subsets are intricately categorized based on their applications and specific roles at different stages of the building lifecycle. As previously highlighted, the widespread use of AI across various building practices is expected to significantly transform the traditional building's lifecycle into a more sustainable and efficient paradigm.

Several studies within the reviewed literature covered the three stages of a building's lifecycle. Among them were Tchana [20], Regona [62] and Regona [64], who emphasized AI's impact on performance throughout the three stages in the aspects of facilitating early detection of deficiencies and cost savings. Collaboration, also cutting across the three stages, was identified as a significant advantage, streamlining communication between customers and designers through AI-driven digital twins, the IoT, and machine learning [86], thereby fostering transparency [29] and efficiency [28].

3.5.1. AI in the Construction Stage of a Sustainable Building's Lifecycle

AI is revolutionizing traditional construction methods, ushering in a new era for the building industry. AI involves creating intelligent devices and programs that effectively mimic cognitive processes to address complex problems [87]. Despite significant global investments exceeding USD 26 billion in engineering and construction technology, including AI, over the past five years (2014–2019), the basic construction procedures have remained unchanged for the last four decades. Various obstacles, such as inadequate business models, a lack of essential skills, and industry-wide knowledge gaps, have hindered the widespread adoption of AI in building development and lifecycle processes [88–90]. AI has demonstrated potential across various stages of construction, including planning, design, and the actual construction phase. In the planning and design stages, AI enhances the accuracy of cost estimates, establishes precise milestones, and reduces on-site risks through constructive alternative analysis. For instance, construction firms can leverage vast amounts of internal and external unstructured data to gain insights from previous projects. This allows businesses to generate more accurate estimates, reduce budget and timeline deviations by an estimated 10–20%, and cut engineering hours by 10–30% [64,88].

During the construction phase, AI-driven technologies significantly boost productivity, streamline work processes, and minimize the likelihood of on-site accidents. AI's capability to provide real-time insights is instrumental for project managers in ensuring efficient resource utilization, anticipating potential risks, and enhancing overall safety. The application of AI can lead to substantial cost savings, potentially reducing total construction costs by 10–15% through data analytics and related technologies [64]. The sentiment towards AI in construction varies across regions and industries. In Australia, for example, the government's commitment through an "AI Action Plan" to invest AUD 125 million in AI research and development has positively influenced public perception of technological innovation and advancement in nation building. The AI Roadmap outlines strategies for utilizing AI to improve the built environment, aiming to capture social, economic, and environmental benefits [64]. Despite these advancements, there are still significant challenges to overcome. Key obstacles include the high costs and time required to collect accurate data for training AI algorithms, project risk concerns, data security issues, and a general lack of capabilities within the industry to effectively integrate AI technologies [64,89].

Moreover, AI's integration into construction remains in the initial stages, with larger construction companies beginning to reap the benefits. This gradual adoption highlights the ongoing debate regarding AI's impact on the construction workforce and the potential for job displacement. Nonetheless, the benefits of AI, such as preventing cost overruns, improving site safety, and efficient project management, are becoming increasingly evident [64,90].

While AI offers promising solutions for enhancing construction processes, its full potential is yet to be realized due to various implementation challenges. Addressing these obstacles through focused research, investment, and skill development is crucial for the widespread adoption of AI in the construction industry. The shift towards AI-enabled construction is not just about adopting new technologies but also about transforming traditional business models and practices to meet the demands of a rapidly evolving industry.

3.5.2. AI in the Operation Stage of a Sustainable Building's Lifecycle

Regarding the operation stage in a building's lifecycle specifically, many researchers have emphasized the importance of AI-related uses. These include machine learning, digital twins, and the Internet of Things (IoT), and they are described as critical components that enhance operations within sustainable building lifecycles. Examples of those researchers were, De Wilde [47], Petri [73], Yvan [62], Boje [82], Baduge [65], Adu-Amankwa [83], Lucchi [66], Su [71], Alanne [58], Kineber [59], Boje [67], and Arowoiya [85]. While the direct application of AI may be limited, these technologies serve as crucial connections that enable effective operations enhancement. In line with this, various authors, including Wang [91], Chen [92], You [48], and Yu [93], and with relation to AI, highlighted the significance of digital twin systems integrating deep learning with machine learning. These systems improved collective building energy management, optimized renewable energy source load, and managed building systems efficiently.

Furthermore, Pieter [47] categorized AI applications into intelligent or smart buildings, highlighting responsiveness to human and organizational needs through the integration of the IoT, which creates a network of connected devices, enabling wireless data collection and sensing. Additionally, digital twins serve as real-time counterparts, enabling better interventions, financial savings, improved performance, and societal benefits. He went further to show that, within the realm of sustainable building lifecycle, various technologies play interconnected roles. Building performance simulation (BPS) models predict physical building performance, while machine learning (ML) models introduce data-driven intelligence for optimizing energy usage and predicting maintenance needs. Digital twins act as real-time counterparts, offering dynamic representations of buildings, and building information models (BIMs) provide comprehensive digital representations.

Pieter [47] still showed that AI served as a central force, integrating insights from BPS models, learning capabilities from ML models, real-time representation from digital twins and comprehensive data from BIM, ultimately enhancing overall intelligence and efficiency. Conceptual overlaps include ML improving BPS precision, the interconnectedness of real-time insights (digital twins), and comprehensive data representation (BIM). Each technology contributes distinctive features, such as ML's data-driven intelligence and digital twins' focus on real-time monitoring. The literature underscored the symbiotic relationship of digital twins, the IoT, and machine learning with AI, showcasing their transformative impact on making buildings more intelligent, responsive, and efficient. The complex inter-relationships are depicted in Figure 4.

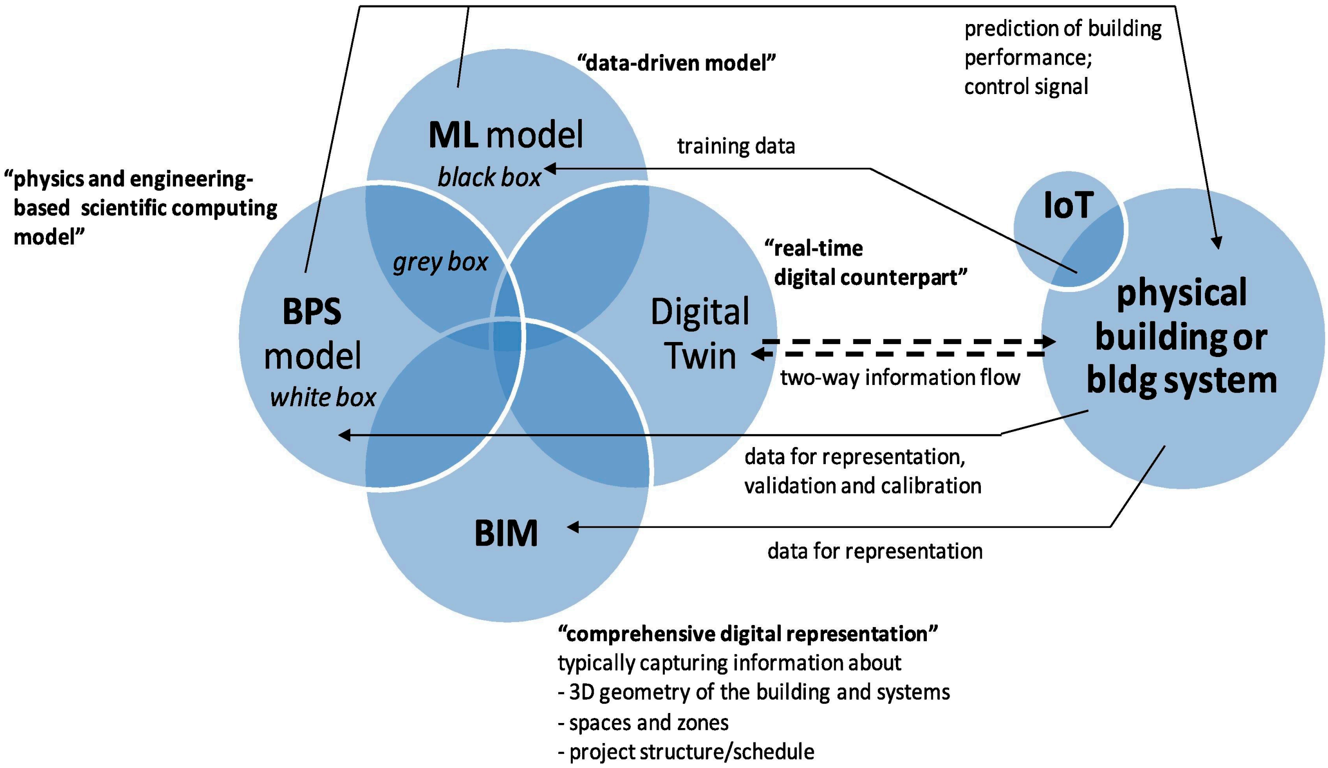

Figure 4. AI-integrated relationships among various technologies in a building's lifecycle. Reprinted from Energy and Buildings, with permission from Elsevier [47].

3.6. Influence of AI Applications in a Sustainable Building Lifecycle

Building industry practitioners should consider the positive influences and potential challenges associated with AI applications in projects. Professionals must establish clear short-term and long-term objectives to avoid inefficiencies and maintain momentum in adopting AI-related technologies. Effective prioritization of research, development, and investment in AI technologies is essential, focusing efforts when the positive influences outweigh the challenges. Additionally, a proactive approach involves identifying potential risks affecting AI implementation, facilitating strategic planning, and ensuring a smooth business transition. The positive influences have been derived from common discussion principles in the reviewed literature. However, it is pertinent to start this discussion by identifying key AI technologies deployed in the three stages of a building's lifecycle.

Integrating emerging technologies, particularly adaptive manufacturing, presents significant opportunities in construction, offering cost reductions and heightened efficiency [20,32,64]. Adaptive manufacturing, involving flexible machines for customizable part production, can revolutionize building methods and reshape job roles by integrating planning, design, and construction tasks. Recognizing the advantages of AI is crucial for practical integration into construction projects [94]. Results from the review revealed that the impact of AI spans various facets of a building lifecycle, including energy efficiency optimization, predictive maintenance, lifecycle cost analysis, occupant comfort and productivity, waste reduction and recycling, carbon footprint reduction, and simulation and design optimization. By leveraging AI technologies, the construction industry can achieve significant advancements in sustainability, enhancing the overall performance and environmental impact of buildings.

Machine learning algorithms, a subset of AI, are instrumental in optimizing energy efficiency within buildings [63,74]. These algorithms continuously analyze real-time data from sensors embedded in building systems to understand patterns in energy consumption and environmental conditions. By processing this data, machine learning algorithms can dynamically adjust settings for HVAC systems, lighting, and other building equipment to minimize energy usage while maintaining occupant comfort. For example, during periods of low occupancy or favorable weather conditions, machine learning algorithms may automatically adjust thermostat settings or dim lighting to conserve energy without compromising comfort. This adaptive approach to energy management helps buildings operate more efficiently, resulting in significant energy savings and reduced environmental impact over time.

Predictive analytics, another subset of AI, revolutionizes maintenance practices by predicting equipment failures before they occur [62,64]. By analyzing historical performance data and detecting patterns indicative of impending failures, predictive analytics algorithms can forecast when equipment is likely to malfunction. This proactive approach enables maintenance teams to schedule repairs or replacements during planned downtime, minimizing disruptions to building operations and avoiding costly emergency repairs. For example, predictive maintenance algorithms may identify early signs of equipment degradation in HVAC systems based on deviations from normal operating parameters, such as increased vibration or temperature fluctuations. By addressing these issues preemptively, predictive maintenance extends the lifespan of critical building systems and enhances operational efficiency.

Data analytics tools powered by AI techniques provide comprehensive insights into building materials' economic and environmental impacts throughout their lifecycle [47]. These tools analyze data related to material sourcing, manufacturing processes, transportation, installation, maintenance, and disposal to quantify the total cost of ownership and environmental footprint associated with different building materials. By considering financial and ecological factors, decision-makers can evaluate the long-term sustainability and cost-effectiveness of various material options. For instance, data analytics algorithms may assess the lifecycle costs and environmental implications of using renewable materials versus traditional alternatives, helping stakeholders make informed choices that align with sustainability goals and budget constraints.

Smart building systems leverage AI-driven technologies to enhance occupant comfort and productivity through personalized environmental control [69]. These systems integrate sensors, actuators, and feedback mechanisms to monitor occupant preferences and adjust indoor conditions accordingly. For example, smart thermostats with machine learning algorithms can learn occupants' temperature preferences over time and change settings to maintain optimal comfort levels. Similarly, lighting systems with occupancy sensors and daylight harvesting capabilities can dynamically adjust lighting levels to minimize energy usage while ensuring adequate illumination for occupants. Smart building systems create more comfortable and productive indoor environments by tailoring environmental conditions to individual preferences and activities.

Data analytics tools enable the tracking and analysis of waste generation, recycling rates, and material usage throughout the building's lifecycle [67,69]. These tools leverage AI techniques to identify inefficiencies and opportunities for improvements in waste management practices. For example, data analytics algorithms may analyze historical waste data to identify trends and patterns, such as peak waste generation periods or recurring sources of waste. With this information, stakeholders can develop targeted strategies to reduce waste generation, increase recycling rates, and optimize material usage. By minimizing waste and maximizing resource efficiency, buildings can reduce their environmental footprint and contribute to a more sustainable built environment.

Big data analytics and AI algorithms play a crucial role in evaluating and monitoring a building's carbon footprint [23,65]. These analytics tools analyze energy consumption, transportation emissions, and material usage data to quantify the greenhouse gas emissions associated with building operations. For example, AI-powered algorithms may analyze energy consumption data from smart meters and building management systems to calculate carbon emissions from electricity usage. By providing insights into the primary sources of carbon emissions and their environmental impact, big data analytics enable stakeholders to develop targeted strategies for reducing carbon footprint. These strategies may include implementing energy efficiency measures, adopting renewable energy sources, optimizing transportation logistics, and promoting sustainable procurement practices. By mitigating carbon emissions, buildings can contribute to global efforts to combat climate change and create a more sustainable future.

Computational techniques and advanced algorithms facilitate the simulation and optimization of building designs before construction begins [65,83]. These tools enable architects and engineers to explore various design alternatives, predict performance outcomes, and optimize design parameters to achieve specific objectives, such as energy efficiency, comfort, and sustainability. For example, simulation software powered by AI algorithms can simulate the thermal performance of building envelopes under different climatic conditions, allowing designers to evaluate the effectiveness of insulation materials and glazing configurations. By iteratively refining designs based on simulation results, designers can optimize building performance and minimize environmental impact even before breaking ground.

3.7. Challenges of AI Application in a Sustainable Building's Lifecycle

Despite significant advancements in AI technologies, the construction industry needs to catch up in adopting these innovations [30,64]. This lag can be attributed to several factors, including the complexity of construction projects, the traditional nature of the industry, and the need for more awareness and understanding of AI's potential benefits. Compared to other sectors that have embraced AI more readily, such as finance or healthcare, the construction industry has been cautious in adopting new technologies due to concerns about disruption, risk aversion, and reliance on established practices. The literature review highlighted key challenges that have led to the slow integration or adoption of AI in the sustainable building lifecycle. These challenges include initial implementation costs, data security and privacy concerns, lack of standardization, a skills gap, interoperability issues, ethical considerations, and regulatory compliance. Addressing these challenges is essential for the construction industry to fully leverage the benefits of AI technologies and enhance sustainability in building practices.

While AI holds much promise of significant long-term benefits, such as improved productivity, cost savings, and enhanced decision-making, the initial costs of implementing AI solutions can be prohibitive for many construction firms [95–97]. These costs typically include investments in hardware, software, training, and infrastructure upgrades. Additionally, there may be hidden costs associated with customization, integration with existing systems, and ongoing maintenance and support. To overcome this barrier, construction firms must carefully evaluate AI initiatives' potential return on investment (ROI) and develop strategic plans to manage upfront costs while maximizing long-term benefits [98–101].

With the increasing digitization of construction processes and the proliferation of IoT devices, ensuring the security and privacy of sensitive data has become a paramount concern [62,64]. Construction projects involve collecting and storing vast amounts of data, including proprietary designs, financial information, and the personal data of workers and clients. Any breach of this data could have severe consequences, including economic losses, damage to reputation, and legal liabilities. Therefore, construction firms have had to, and must still implement, robust cybersecurity measures, such as encryption, access controls, and regular security audits, to safeguard sensitive information and ensure compliance with data protection regulations [102,103].

The presence of standardized frameworks and protocols for AI in the construction industry helps interoperability, collaboration, and scalability [104,105]. Unlike other sectors, where industry-wide standards have been established, such as Health Level Seven (HL7) in healthcare [106,107] or ISO 9000, a set of international standards on quality management and quality assurance in manufacturing [108,109], the construction industry lacks standardized frameworks for data exchange, interoperability, and quality assurance. This lack of standardization makes it challenging for different AI systems to communicate effectively with each other and with existing building systems, leading to slow implementations, inefficiencies, and compatibility issues [110]. Therefore, there is a pressing need to develop industry-wide standards and protocols to promote interoperability and facilitate the seamless integration of AI technologies into construction workflows.

The need for more skilled professionals with expertise in AI, data science, and related fields poses a significant challenge to the widespread adoption of AI in the construction industry [111,112]. Building and deploying AI solutions require specialized knowledge and technical skills, including programming, machine learning, and data analysis. However, there is a significant gap between the demand for AI talent and the supply of qualified professionals [113,114]. Addressing this skills gap requires concerted efforts from industry stakeholders, educational institutions, and government agencies to develop training programs, certification courses, and workforce development initiatives tailored to the needs of the construction sector [115,116]. By investing in talent development and upskilling initiatives, construction firms can build a workforce capable of harnessing the full potential of AI technologies and driving innovation in the industry [116].

Ensuring seamless communication and integration among AI systems and existing building systems poses technical challenges [64]. Construction projects involve multiple stakeholders using different software platforms, tools, and technologies. Integrating these disparate systems and ensuring interoperability can be complex and time-consuming, leading to delays, cost overruns, and project disruptions [117,118]. To overcome interoperability issues, construction firms must adopt open-source platforms, standardized interfaces, and middleware solutions that facilitate data exchange and communication among different systems. Additionally, collaborative approaches, such as building information modeling (BIM) and integrated project delivery (IPD), can help streamline workflows and improve coordination among project stakeholders, leading to more efficient project delivery and better outcomes [117–119].

As AI technologies become more prevalent in the construction industry, ethical considerations related to algorithmic bias, transparency, and accountability must be addressed [64,102]. AI algorithms can perpetuate or exacerbate existing biases and inequalities if not carefully designed and monitored [120]. For example, biased algorithms used in hiring or resource allocation decisions could lead to discrimination or unfair treatment. Therefore, construction firms must prioritize ethical considerations when developing, deploying, and using AI technologies. This includes implementing fairness and transparency measures, conducting regular audits and reviews of AI systems, and ensuring compliance with ethical guidelines and regulations [120,121].

Adopting evolving regulations and legal requirements related to AI implementation is crucial for construction firms [121]. As AI technologies become more prevalent in construction projects, regulators increasingly scrutinize their use and impact on safety, privacy, and other regulatory concerns [122]. Construction firms must stay informed about relevant regulations, engage with regulatory bodies, and integrate compliance measures into their AI initiatives to mitigate legal risks and ensure regulatory compliance [116,120]. This may involve conducting privacy impact assessments, obtaining necessary approvals or permits, and adhering to industry-specific regulations governing data protection, safety, and environmental impact [120–123].

The success of AI applications in construction depends on the quality and reliability of data used for training and inference [58,66]. Construction projects generate vast amounts of data from various sources, including sensors, IoT devices, and historical records [124]. However, this data may need to be completed, accurate, or updated, leading to biased or erroneous AI predictions and decisions [125]. Therefore, construction firms must implement robust data quality assurance measures, including data validation, cleansing, and normalization, to ensure the accuracy, completeness, and reliability of data used for AI applications [124,125]. This may involve deploying data management platforms, establishing data governance frameworks, and conducting regular data quality audits to proactively identify and address data quality issues.

4. Discussion of Key Findings

The systematic literature review highlights the transformative potential of AI in promoting sustainability across the three stages of a building's lifecycle: design, construction, and operation. Several key findings emerged from the review.

In the building design stage, AI-driven generative design offers unprecedented capabilities to optimize sustainability goals by rapidly analyzing multiple design options and considering key factors, like embodied carbon and environmental impact [23,31]. Furthermore, AI simulation tools are crucial in assessing building performance early in the design process, enabling designers to make informed decisions that prioritize sustainability without compromising on functionality or comfort [32,33].

During construction, AI technologies present opportunities to enhance efficiency, particularly in waste reduction. AI-enabled tracking of materials and equipment has been shown to reduce waste by over 40%, leading to significant cost savings and environmental benefits [36–38]. AI-powered robots can perform certain tasks, like welding, drilling, and cutting, with high precision and efficiency, minimizing errors and material waste [20]. Additionally, AI integration can predict material performance, durability, and embodied carbon emissions, enabling more informed material selection and construction methods [40–42].

Machine learning algorithms optimize energy efficiency in the building operation stage by dynamically adjusting HVAC, lighting, and building systems based on real-time data and occupancy patterns. This leads to 20–30% potential energy savings in commercial buildings [43–46]. AI-powered predictive maintenance systems analyze data from building sensors to predict equipment failures, allowing for proactive maintenance and reduced downtime [47]. AI-powered energy management systems can optimize energy production and consumption by integrating renewable energy sources, like solar and wind, into building systems [46,48].

Beyond the specific lifecycle stages, the review identified several benefits of AI integration in promoting sustainability across the building lifecycle. Machine learning algorithms continuously analyse real-time data from sensors to understand patterns in energy consumption and environmental conditions, enabling dynamic adjustments to building systems for minimising energy usage [63,74]. Predictive analytics algorithms forecast equipment failures by analysing historical performance data, extending the lifespan of critical building systems [62,64].

AI-powered data analytics tools provide insights into building materials' economic and environmental impacts throughout their lifecycle, enabling informed decision-making on material selection [47]. Intelligent building systems leverage AI-driven technologies to enhance occupant comfort and productivity through personalized environmental control [69]. Data analytics tools enable tracking and analysis of waste generation, recycling rates, and material usage, identifying opportunities for improvements in waste management practices [67,69]. Big data analytics and AI algorithms quantify a building's greenhouse gas emissions associated with energy consumption, transportation, and material usage, facilitating targeted strategies for carbon footprint reduction [23,65].

Moreover, computational techniques and AI algorithms facilitate the simulation and optimization of building designs before construction, enabling architects and engineers to explore various alternatives, predict performance outcomes, and optimize design parameters for energy efficiency, comfort, and sustainability [65,83].

Despite these significant benefits, the literature review highlighted several challenges in applying AI in a sustainable building lifecycle. These challenges include initial implementation costs [95–97], data security and privacy concerns [62,64,102,103], lack of standardization [104,105,110], a skills gap [111–116], interoperability issues [64,117–119], ethical considerations [64,102,120,121], and regulatory compliance [116,120–123]. The construction industry's relatively slow adoption of AI can be attributed to several factors, such as the complexity of construction projects, the traditional nature of the industry, and a need for more awareness or understanding of AI's potential benefits [30,64].

Additionally, the success of AI applications in construction depends on the quality and reliability of data used for training and inference [58,66,124,125]. Construction firms must implement robust data quality assurance measures to ensure the accuracy, completeness, and reliability of data used for AI applications.

The literature review underscores the transformative potential of AI in revolutionizing sustainable practices across the building's lifecycle while recognizing and addressing the challenges in its adoption. Integrating AI technologies, such as digital twins, robotics, and data analytics, presents opportunities for optimizing energy efficiency, reducing waste, and minimizing environmental impact throughout building design, construction, and operation stages.

This systematic literature review offers a comprehensive analysis of AI applications across the building lifecycle, revealing complex interrelations between various technologies and their impacts on sustainability. In the design phase, Regona [20] and Tchana [62] emphasize AI's role in early deficiency detection and cost savings, viewing AI as a proactive tool for risk mitigation. This perspective is complemented by De Wilde [47], who sees AI, particularly the integration of building performance simulation with machine learning, as a means to optimize energy usage. De Wilde's approach suggests a more holistic view of AI, where it serves as a bridge between predictive modeling and real-time optimization. Alanne [58] and Kineber [59] further expand this concept by focusing on digital twin systems, positioning AI as a central force in managing building energy, thus highlighting the shift towards more dynamic and responsive building management systems.

The construction phase reveals a different set of AI applications and perspectives. Regona [64] quantify AI's impact, suggesting a 10–15% reduction in total construction costs through enhanced productivity and streamlined processes. This view presents AI as a direct contributor to economic efficiency. In contrast, Adu-Amankwa [83] and Lucchi [66] focus on AI's role in computational design optimization, emphasizing its potential to enhance sustainability from the earliest stages of building conception. This difference in focus—between economic efficiency and sustainable design—highlights the multifaceted nature of AI's impact on construction.

The operational phase showcases yet another dimension of AI application. Chen [92] and You [48] demonstrate how integrated AI systems can optimize both building energy management and renewable energy utilization. Their work suggests a future where AI not only manages building systems but also interacts with broader energy infrastructure. Boje [82] and Baduge [65] expand on this, discussing real-time monitoring and management through the IoT and digital twins. Their perspective positions AI as a key enabler of the "smart building" concept, where continuous adaptation and optimization become possible.

When examining the benefits and challenges of AI integration, a complex picture emerges. The integration of AI in sustainable building lifecycles presents a complex landscape of benefits and challenges, as revealed by various researchers in the field. On the benefits side, there is a consensus among Regona [20], Tchana [62], and Boje et al. [67] regarding AI's potential for enhancing energy efficiency, enabling predictive maintenance, and reducing waste. However, their focuses differ, providing a multi-faceted view of AI's impact. Tchana [62] takes a holistic approach, examining AI's benefits across the entire building lifecycle. This comprehensive perspective allows for an understanding of how AI can create synergies between different stages of a building's life. In contrast, Regona [20] narrows the focus to the construction industry specifically, highlighting how AI can transform traditional building practices. Boje et al. [67] concentrate on the operational phase, demonstrating how AI can significantly improve day-to-day building performance and management.

The challenges associated with AI integration reveal an even more diverse set of perspectives. The issue of implementation costs, for instance, is approached from various angles. McNamara and Sepasgozar [95] consider the broader economic implications, providing insight into how AI adoption might impact the construction sector at large. Olanrewaju [96] narrows the focus to small and medium enterprises (SMEs), highlighting the unique struggles these smaller players face in adopting AI technologies. This perspective is crucial, as SMEs form a significant portion of the construction industry. Yevu [97] adds another layer by examining the cost–benefit analysis of AI implementation in developing countries, where resources may be more constrained and the balance between investment and return is even more critical. Data security, another significant challenge, is examined through different lenses by Rafsanjani and Nabizadeh [102] and Omrany [103]. Rafsanjani and Nabizadeh [102] approach the issue from a regulatory standpoint, emphasizing the need for robust frameworks to protect sensitive data. This perspective is crucial as it highlights the role of governance in ensuring responsible AI use. Omrany [103], on the other hand, focuses on technical solutions, suggesting that the answer to data security concerns lies in technological advancements.

The lack of standardization, as discussed by Abioye [34], Lewis [104], and Auth [105], presents both a challenge and an opportunity. While it hinders seamless integration of AI systems, it also opens up possibilities for industry-wide collaboration to establish common standards. This dual nature of the standardization issue underscores the complexity of AI integration in the construction sector. Abioye [34] and Chen [112] frame the skills gap not just as a hurdle but as a call for educational reform in the construction industry. This perspective shifts the conversation from a simple lack of skills to a more profound need for systemic change in how construction professionals are trained and educated. Interoperability issues, as raised by Rane [117,118], are positioned within the broader context of digital transformation in construction. This framing helps to understand that AI integration is part of a larger shift in the industry, not an isolated technological challenge.

Finally, the ethical considerations and regulatory compliance discussed by Liang [120], Arroyo [121], and Emaminejad and Akhavian [122] highlight the societal implications of AI adoption. These authors emphasize that successful AI integration requires not just technical solutions but also careful consideration of fairness, transparency, and accountability. This multifaceted analysis reveals that AI in sustainable building lifecycles is a complex interplay of technological, economic, social, and environmental factors. The diverse perspectives underscore the need for an interdisciplinary approach to fully leverage AI's potential while addressing its challenges in sustainable construction. As the field continues to evolve, it is clear that successful AI integration will require collaboration across various domains, from technical experts to policymakers, to ensure that the benefits of AI are realized while potential risks are mitigated.

The review's methodology, which involves analyzing and clustering data from 119 pieces of scientific literature, provides quantitative backing to its findings. This data-driven approach enhances the reliability of the findings and provides a replicable framework for future studies. Moreover, by contextualizing AI in construction as an emerging field, the review contributes to the academic understanding of this evolving domain and sets the stage for future research directions. An essential aspect of this review is its demonstration of how AI intersects with various facets of building sustainability, including energy efficiency, waste management, occupant comfort, and carbon footprint reduction. This interdisciplinary perspective contributes to a more comprehensive understanding of sustainability in the built environment.

The review also lays out a clear path for future research, identifying key areas needing further investigation, such as addressing the skills gap and developing standardized frameworks. It guides future academic endeavors in this field by highlighting these research gaps. Additionally, it provides actionable insights for the construction industry, highlighting the transformative potential of AI and the challenges in its implementation. Policy considerations are another crucial contribution of this review. By touching on regulatory and ethical considerations, it provides valuable input for policymakers, highlighting the need for standards and regulations to govern AI use in construction. The ethical considerations raised can inform policy development in this emerging field. The review maintains a strong focus on sustainability, demonstrating how AI can contribute to more environmentally friendly building practices. It shows how AI can reduce energy consumption, minimize waste, and optimize resource use across the building lifecycle, aligning with global efforts to combat climate change and reduce the environmental impact of the built environment.

This systematic literature review substantially contributes to the knowledge of AI in a sustainable building's lifecycle by providing this comprehensive, critical, and forward-looking analysis. It synthesizes current research and provides a robust foundation for future investigations and practical applications in this rapidly evolving field, serving as a valuable resource for researchers, industry professionals, and policymakers alike.

5. Conclusions and Recommendations

This systematic review has shed light on the transformative potential of artificial intelligence (AI) in advancing sustainable building practices across the entire lifecycle of buildings. By consolidating current knowledge on AI integration in the construction industry, the study provides valuable insights for stakeholders and paves the way for future research and innovation. The review identifies machine learning, robotics, digital twins, and the Internet of Things (IoT) as particularly promising technologies, offering significant benefits across design, construction, and operation stages of buildings.

In the design phase, AI-driven generative design and simulation tools demonstrate the capability to optimize sustainability goals from the outset, potentially reducing the need for costly retrofits later. During construction, AI-enabled tracking can reduce material waste by up to 40% [36–38], while AI-powered robots increase precision and efficiency, minimizing errors and further reducing waste. In the operational stage, machine learning algorithms show potential for achieving 20–30% energy savings in commercial buildings through optimized system control [43–46]. These findings have significant implications for construction firms and facility managers, highlighting the potential for substantial improvements in sustainability and efficiency at each stage of the building lifecycle.

The review underscores AI's potential to enhance building sustainability through energy efficiency optimization, predictive maintenance, improved waste management and recycling, and reduced carbon footprint. However, it also brings to light significant challenges, such as high initial costs, data security concerns, lack of standardization, and skills gaps. This dual perspective emphasizes the need for proactive measures to overcome these hurdles and facilitate successful AI adoption.

For policymakers, the findings highlight the need for supportive regulatory frameworks that encourage AI adoption while addressing concerns related to data privacy, security, and ethical considerations. This may involve developing guidelines for responsible AI use in construction, incentivizing sustainable building practices enabled by AI, and supporting initiatives for upskilling the workforce. The lack of standardization identified in the review also suggests a need for policymakers to work with industry stakeholders in developing standardized protocols for AI implementation in construction. Facility managers can benefit from the insights provided in this review by understanding the potential of AI-driven solutions for optimizing building operations, enhancing energy efficiency, and improving occupant comfort. The potential for significant energy savings and enhanced maintenance through predictive analytics can guide decisions on implementing smart building technologies and AI-powered management systems. For construction firms, the review emphasizes the importance of fostering a culture of innovation and investing in skills development to leverage AI technologies effectively. The successful integration of AI in sustainable building practices necessitates a holistic approach that leverages expertise from various disciplines. This interdisciplinary collaboration is crucial for bridging the gap between technological capabilities and practical implementation in the building sector. Key collaborators in this approach include AI and data science experts, architects, engineers, sustainability professionals, construction managers, facility managers, and building information modeling (BIM) specialists. This collaborative approach enables a comprehensive understanding of building lifecycle challenges and opportunities, fostering innovative AI solutions that are both technically sound and practically implementable.

Despite the acknowledged limitations, further research and development efforts are crucial to overcome these obstacles and unlock the full potential of AI in revolutionizing sustainable building practices. Future research should focus on developing cost-effective AI solutions tailored to the construction industry, addressing data security and privacy concerns, and creating industry-wide standards and protocols. Studies could explore scalable AI technologies that offer a favorable return on investment for construction firms of various sizes, develop robust cybersecurity frameworks specifically designed for AI applications in the construction industry, and create standardized frameworks for data exchange and interoperability standards for AI systems in construction. Addressing the skills gap is another crucial area for future research. Studies could explore innovative approaches to workforce development, such as integrating AI and sustainable building practices into construction education curricula, developing specialized certification programs, or creating AI-powered training tools that can provide on-the-job learning experiences. Research into effective knowledge transfer methods from AI experts to construction professionals could also prove valuable in bridging this skills gap.

Ethical considerations in AI applications for sustainable buildings represent another vital research direction. Future studies should explore frameworks for ensuring fairness, transparency, and accountability in AI-driven decision-making processes throughout the building lifecycle. This could include research into methods for detecting and mitigating bias in AI algorithms used in design or resource allocation, developing explainable AI systems for construction applications, and creating ethical guidelines for AI use in sustainable building practices. Lastly, future research should address the challenge of data quality and reliability in AI applications for sustainable buildings. Studies could focus on developing advanced data validation and cleansing techniques specific to construction data, creating AI models that can effectively handle incomplete or noisy data common in construction environments, and exploring novel data collection methods that ensure high-quality inputs for AI systems.

In conclusion, this systematic review underscores the significant potential of AI in revolutionizing sustainable building practices. By addressing the identified challenges through focused research and development efforts, the construction industry can move towards a more sustainable and technologically advanced future. The successful integration of AI in sustainable building practices will require ongoing collaboration between industry stakeholders, policymakers, and researchers to overcome obstacles and unlock the full potential of these technologies. As the field continues to evolve, it is crucial for all parties involved to remain adaptable, innovative, and committed to the goal of creating more sustainable, efficient, and intelligent buildings for the future.

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