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Applications of artificial intelligence for energy efficiency throughout the building lifecycle: An overview

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ABSTRACT

The use of Artificial Intelligence (AI) technologies in buildings can assist in reducing energy consumption through enhanced control, automation, and reliability. This review aims to explore the use of AI to enhance energy efficiency throughout various stages of the building lifecycle, including building design, construction, operation and control, maintenance, and retrofit. The review encompasses multiple studies in the field published between 2018 and 2023. These studies were identified through keyword searches that best represent the topic, using various research databases. In addition to summarizing the technologies and approaches related to AI and energy efficiency, this review discusses future opportunities for the application of AI in energy efficiency within these lifecycle stages. The review highlights that AI-based solutions are currently employed in building design generation and optimization, decision-making, predictive and adaptive control, fault detection and diagnosis, as well as energy benchmarking. These applications effectively facilitate energy efficiency in buildings to meet today's energy needs. However, further research is needed to explore the use of AI in the construction phase to support the development of energy-efficient construction techniques and systems, in addition to scheduling and predictive decision-making.

1. Introduction

The Architecture, Engineering, and Construction (AEC) industry has witnessed multiple developments over the years due to technological advancements. The use of Computer-Aided Design (CAD) and Building Information Modeling (BIM) with software such as AutoCAD, Fusion 360, ArchiCAD, SketchUp, Revit, among others, has replaced drafting with pen and paper. This shift aims to create accurate digital models [14] and streamline workflows among AEC professionals, representing popular developments in the industry. The AEC industry is also increasingly moving towards more sustainable buildings, which require more complex systems and collaboration among various AEC professionals. The utilization of simulation software and optimization algorithms has been integrated into the AEC industry, especially concerning energy and carbon efficiency [20]. This integration seeks to enhance efforts in reducing the environmental impact of the industry. According to the 2020 Global Status Report for Buildings and Construction, the AEC industry is responsible for 35 % of energy consumption and 38 % of CO_2 emissions [117].

Energy efficiency, as defined by Islam & Hasanuzzaman [59], refers to "the portion of the total energy input to a machine or system that is consumed in useful work and not wasted as useless heat or otherwise." In simpler terms, energy efficiency means achieving the same results using less energy while maintaining the same level of service or quality. Several researchers have discussed energy efficiency in buildings and how to measure it. Fairey & Goldstein [35] defined energy efficiency in terms of energy performance, taking into account the engineered system, operation and maintenance practices, and occupant needs. They define energy efficiency as the performance of a building's engineered system, assuming the other dimensions remain constant. Various energy

Abbreviations: AEC, Architecture, Engineering and Construction; AI, Artificial Intelligence; ANN, Artificial Neural Network; BEMS, Building Energy Management Systems; BES, Building Energy Systems; BIM, Building Information Modelling; CAD, Computer-Aided Design; DSS, Decision Support System; DL, Deep Learning; DRL, Deep Reinforcement Learning; DT, Digital Twining; EA, Evolutionary Algorithms; FDD, Fault Detection and Diagnosis; GD, Generative Design; HVAC, Heating, Ventilation, and Air Conditioning; IEQ, Indoor Environmental Quality; IoT, Internet of Things; ML, Machine Learning; MPC, Model Predictive Control; TPD, Traditional Project Delivery.

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efficiency metrics and programs, such as Energy Use Index (EUI) and Energy Star, have been developed to improve the energy efficiency of buildings and their components. The utilization of computational methods for predicting and managing building energy use is an effective strategy that can improve building energy efficiency and mitigate the risks associated with increasing energy consumption rates [92,113].

The adoption of Artificial Intelligence (AI) can enhance construction sustainability and building energy efficiency, aligning with Sustainable Development Goals 9, 11, and 7. AI is a field of computer science that was established in the 1950 s, with its roots traced back to Alan Turing's 1950 article titled "Computing Machinery and Intelligence." The term "artificial intelligence" was coined in 1956 at the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI), organized by John McCarthy and Marvin Minsky [46]. Joiner [61] defines AI as "technology with problem-solving and reasoning abilities," while Kaplan & Haenlein [62] describe AI as "a system's ability to correctly interpret external data, learn from that data, and use those learnings to achieve specific goals and tasks through flexible adaptation." To perform these functions, AI relies on a combination of fast processors and software that incorporates various algorithms, computer codes, and simulation packages [81], as shown in Fig. 1.

AI encompasses a broad range of types, components, and subfields, as noted by Abioye et al. [1]. Some of the various AI subfields include Machine Learning (ML), natural language processing, computer vision, optimization, knowledge-based systems, robotics, and automated planning and scheduling. In the building industry, vision, robotics, and natural language processing are emerging AI subcategories, while Machine Learning (ML) and automated planning and scheduling are more developed. These technologies can effectively contribute to significant energy savings in buildings by assisting architects and engineers in designing and operating energy-efficient buildings [124]. This study aims to review the use of AI to enhance energy efficiency in buildings. The review examines several papers in the fields of Machine Learning (ML) and automated planning and scheduling to identify their contributions to energy efficiency in different stages of the building's predisposal lifecycle (Fig. 2).

Edge AI is a crucial concept in this context. It has been called by various names and defined differently in research, depending on the context and other factors. Edge AI, as defined by Alsalemi (2023), involves the distributed implementation of ML and/or DL algorithms on resource-constrained devices with specialized hardware optimized for computational performance and efficiency. Edge computing, as defined by Cao et al. [22], is a computing resource at the network's edge, closer to the data source, such as mobile devices or sensors, instead of relying on a centralized data center. Edge computing's origins date back to the 1990 s and have since been employed in various industries, including healthcare, retail, manufacturing, automation, agriculture, oil and gas, among others.

In buildings, edge AI is used in various lifecycle stages, with greater utilization in the operation and maintenance phase. It is applied in smart meters and occupancy sensors to analyze energy and occupancy data, as explored by Himeur et al. [8,50,105]. They developed a hybrid edge-cloud computing architecture ideal for tracking real-time energy consumption, anomaly detection, and minimizing wasted energy. Similarly, Alsalemi et al. [8,105] introduced an economical, high-performance internet of energy platform that collects, measures, and processes data on energy usage, temperature, illuminance, humidity, and occupancy within a space to improve occupants' consumption behavior. This platform was further expanded by Alsalemi et al. [9] to provide automation options for appliance management and visualization, allowing end-users to respond to anomaly detection warnings and recommendations to minimize energy wastage.

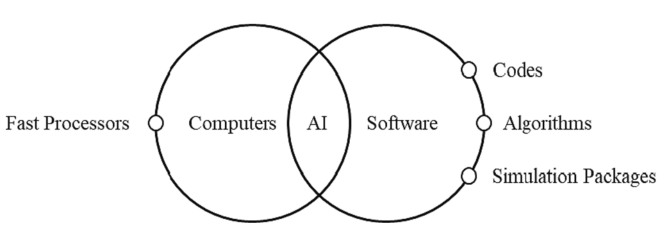

Fig. 1. Components of the AI platform [81].

The development and exploration of various AI subfields have increased significantly in research, leading to numerous review papers that summarize these technologies in various fields (Table 1 and Table 2). Most review papers tend to focus on specific areas of application, such as energy modeling, simulation and prediction, and building management systems (BMS), among others. For example, Tien et al. [116,125] conducted a comprehensive review of Deep Learning (DL) and ML approaches used in buildings to address interconnected problems related to HVAC systems and enhance building performance. They focused on the relationship between energy forecasting, indoor air quality, occupancy comfort prediction, occupancy detection and recognition, and fault detection and diagnosis. These interrelated building problems call for the integration of multiple approaches, such as the integration of ML and smart building sensor devices (Petrosanu et al., 2019), cameras [25], learning algorithms, and actuators [42] in smart buildings to enhance comfort and energy efficiency. Chen et al. [25] also discussed ML techniques for building energy management based on ante-hoc and post-hoc approaches, emphasizing their success in predicting energy loads.

Aguilar et al. [3] focused on self-management of smart buildings, exploring different AI techniques for data analysis, control schemes, and decision-making. Yu et al. [132] discussed Decision Reliability in building energy management at different system scales, exploring the practicality. Merabet et al. [84] reviewed 20 AI tools for energy consumption and comfort control, including Artificial Neural Network (ANN) for identification and recognition, Fuzzy Logic for modeling occupants' decision-making, and smart meter installation for data collection, among others. Mehmood et al. [81] highlighted the growing importance of AI and big data in designing and operating energy-efficient buildings, suggesting research directions for fast data mining, user-friendly interfaces, and smart homes. The ability of buildings to learn is crucial for their adaptability, and learning can be achieved through AI training algorithms or shared learning between humans and a building, as discussed by Alanne & Sierla [5].

Another area explored in previous research papers is building energy modeling, simulation, and prediction. Building energy demand prediction models are categorized into four levels: data-driven, physics-based, large-scale building energy forecasting, and hybrid approaches (Ahmed et al., 2018). Westermann & Evins [126] discussed the use of statistical models as simulation models in conceptual design, sensitivity analysis, and sustainable building design optimization. The increasing research in building energy simulations has led to the development of various methods and approaches. Waibel (2019) developed a new metric to compare convergence times, stability, and robustness of black-box optimization algorithms. Seyedzadeh et al. [108] reviewed four main Machine Learning (ML) approaches for improving building energy performance. de Wilde [29] explored the conceptual differences between AI/ML, Digital Twins, cyber-physical systems, IoT, and data mining.

The rapid development of AI and its wide-ranging applications have highlighted the need for efficient data translation, which remains a limitation in AI research. Alsalemi et al. [10] present a visual approach to understanding energy data using a Gramian Angular Fields classifier, capable of classifying up to 7 million data points with 90 % accuracy. This study employs edge AI and GAF for data processing applications in IoT, smart health, and energy efficiency. There is also a significant gap between technological research development and its practical adoption. Himeur et al. [53] evaluated a behavioral change-based building energy efficiency solution using an AI classifier, edge-based micro-moment analysis, and an explainable recommender system. This low-cost

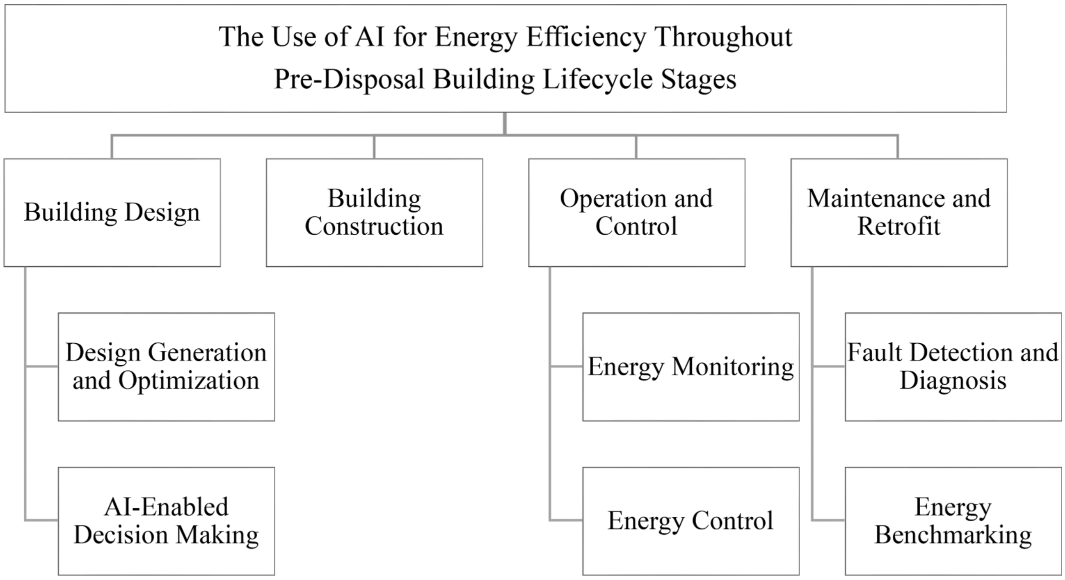

Fig. 2. The reviewed AI applications in the pre-disposal building lifecycle stages.

Table 1
Summary of the focus of previous review papers.

Source	Focus
Ahmad et al [4]	Exploration of first-rate data-driven approaches for building energy analysis in various building types.
Seyedzadeh et al [108]	A review of selected Machine Learning (ML) approaches, focusing on their applications, advantages, drawbacks, potential improvements, and future recommendations.
Mehmood et al [81]	AI and Building Data Analytics and their applications in energy-efficient commercial and residential buildings.
Petroșanu et al [97].	The integration of ML models with sensor devices in smart buildings to enhance sensing, energy efficiency, and optimal building management.
Waibel et al [121]	The performance of various black-box optimization algorithms in a large set of building energy simulation problems.
Westermann & Evins [126]	The use of statistical models as surrogates for detailed simulation models in sustainable building design research.
Ghahramani et al [42]	The importance of an integrated system of sensors, infrastructure, learning algorithms, and actuators in buildings for improved comfort and energy efficiency.
Hong et al [55]	A comprehensive summary of Machine Learning (ML) applications across different stages of the building life cycle.
Aguilar et al. [3]	A review and analysis of ML models for energy self-management in smart buildings.
Merabet et al [84]	AI approaches for Building Energy Management Systems (BEMS) that improve energy efficiency and thermal comfort.
Yu et al [132]	Decision Reliability in building energy management, highlighting its limitations and practicality.
Alanne & Sierla [5]	The learning ability of buildings from a system-level perspective, focusing on autonomous ML applications and Digital Twinning (DT) as training environments.
Baduge et al [15]	Integration of AI, ML, and DL in the building and construction industry 4.0, focusing on architectural design, material optimization, offsite manufacturing, smart operation, durability, life cycle analysis, and the circular economy.
Tien et al [116,125].	ML and DL methods for the built environment, focusing on holistic approaches.
Chen et al [25]	ML techniques for building energy management, focusing on ante-hoc and post-hoc approaches.
de Wilde [29]	The connection between building performance simulation and emerging digital areas like AI/ML, DT, cyber-physical systems, IoT, and data mining.

solution can save up to 28 %-68 % of energy, leading to a decision to commercialize the technology and bridging the existing gap between technological research development and practical implementation.

The application of AI in the building industry has gained significant traction for its current and potential use across the different stages of the building lifecycle [55] and in the context of construction industry 4.0 [15]. Previous reviews have typically focused on either using AI to achieve energy efficiency or its application in different lifecycle stages, As shown in Table 1 and Table 2. However, there is a lack of systematic overview showing the different AI tools, and analyzing them for every lifecycle stage. This review synthesizes the use of AI to achieve energy efficiency throughout the building's pre-disposal lifecycle, bridging these two areas. It particularly examines AI's role in enhancing energy efficiency in buildings through ML and automated planning and scheduling, focusing on various stages of the building's pre-disposal lifecycle. The literature also showed that most of these developments in AI are still in the testing stage, with limited studies that conduct post-occupancy evaluation after the implementation of these technologies in actual buildings [116,125]. This comprehensive overview is essential for stakeholders in the building industry to enhance their understanding of these emerging technologies which will in turn ease the translation of research developments into real life applications.

2. Methodology

This review explores the extent to which artificial intelligence is being investigated to improve energy efficiency in the pre-disposal phases of construction. This section elucidates the different stages involved in this research. The methodology adopted in this review includes three major steps as proposed by Levy and Ellis [72]: inputs (gathering and screening of relevant literature), processing (data analysis and synthesis); and outputs (writing the review), which are explained in the following sub-sections.

2.1. Keyword search

This step is carried out as the first step in understanding how much research has been conducted in the research area. The search was implemented using several relevant keywords that represent the topic on various search engines, including Scopus, Web of Science (WoS), and Google Scholar. A customized search was conducted on Scopus and WoS to narrow down the search to the most relevant options in various fields.

Table 2
Summary of the scope of previous review papers.

Source	AI Model						Energy Efficiency						Building Lifecycle			
	ML	BD	IoT	S	SM	A	ES&P	EO	EM	EC	FDD	EB	BD	BC	BO&C	BM&R
Ahmad et al (2018)																
Seyedzadeh et al (2018)																
Mehmood et al (2019)																
Petroşanu et al (2019).																
Waibel et al (2019)																
Westermann & Evins (2019).																
Ghahramani et al (2020).																
Hong et al (2020).																
Aguilar et al (2021)																
Merabet et al (2021)																
Yu et al (2021)																
Alanne & Sierla (2022)																
Baduge et al (2022)																
Tien et al (2022).																
Chen et al (2023)																
de Wilde (2023)																

The advanced search option was used for a preliminary search using the keywords "AI" OR "artificial intelligence" AND "energy efficiency" on the above-mentioned two search engines. The search results were streamlined using:

- Time frame, only sources published between 2018 and 2023 were included.
- Journal papers were prioritized over other types.
- Only papers written in English language were considered.

The search also included many review papers, which were analyzed to develop the context of this study by streamlining the lifecycle stages that have been considered in similar review papers over the years and to ensure novelty. This analysis led to conducting several other searches for the different lifecycle stages. The search was conducted using keywords in the title, which are: AI, energy efficiency, and building lifecycle (different search variations are shown in Table 3). This was carried out as an extra measure to ensure that all papers covered in this field are considered.

Table 3
Keywords used in the literature search.

Artificial Intelligence OR AI AND Energy Efficiency	AND Building Lifecycle AND Design AND Construction AND Operation OR Control AND Maintenance AND Retrofit

2.2. Identification of relevant publications

The first step revealed many articles that exist in this subject area, which were screened individually using their title, keywords, abstract, and full text. Snowballing based on references was also used [65]. The title and keywords of all papers were considered to ensure they cover the topics: energy efficiency in buildings, AI, and any of the selected lifecycle stages. This was a fast and efficient process that helped in excluding papers that were irrelevant to the research topic. The introduction and abstract of the papers were then analyzed to ensure relevance to the topic. At this point, papers with similar problem-solving approaches were excluded based on the depth of coverage and relevance to the topic. Also, papers referenced by others that are relevant to the research were included.

2.3. Data synthesis

This step involves the extraction, collation, summarization, aggregation, organization, and comparison of relevant information from the research papers selected from the previous step. This step forms the main body of the review paper. The information from this step was categorized into the different lifecycle stages, as shown in Fig. 2, making the review easy to comprehend and differentiating this paper from other review papers in the same field.

3. Applications of AI for energy efficiency in buildings

The energy required to sustain buildings has continued to drastically increase, leading to researchers exploring several alternate measures to ensure the efficient use of energy in buildings. AI can establish a relationship between energy use, comfort, health, and safety to achieve sub-optimal operating conditions, essentially turning buildings into living organisms [37]. Research in AI for energy efficiency has explored on-site energy generation, detection and reduction of operational failures, and energy savings monitoring, among others, which have proven to improve building energy performance and minimize costs simultaneously [16]. The efficiency of AI is highly dependent on the features of the building, meaning building components and features must be built to complement the AI platform required. This section highlights the different aspects that have been explored in research, where AI has been used in the different lifecycle stages over the last five years.

3.1. Building design phase

The process of designing can be seen as an evolutionary process, as every design solution leads to potentially new problems, in such a way that a continuous loop of revisions and alterations is required to reach the project goals [7]. The Traditional Project Delivery (TPD) requires stakeholders to come up with solutions based on their experience and creativity while considering the project objectives and restrictions. In this process, the computer is primarily used for drafting, documentation, and analysis [44]. In recent times, the function of the computer in the AEC industry keeps increasing to include more complex tasks, aided by AI, including energy modeling, design generation, decision-making, optimization, and energy prediction. ML has been the major focus in this regard and has been explored in several ways. In building design, the common ML algorithms used include regression algorithms (RA), Evolutionary Algorithms (EA), Neural Network Algorithms (NNA), and Reinforcement Learning (RL). Several studies have been conducted in this regard as summarized in Table 4 and explained in the following sections.

Table 4
Summary of the reviewed literature in the building design stage.

Source	Focus
A. Design Generation and Optimization	
Bianconi et al. [18]	Design generation using evolutionary principles
Kosovic et al. [68]	Solar radiation measurements using ML
Seyedzadeh et al. [107]	energy performance prediction using ML
Mui et al. [86]	annual cooling energy consumption prediction
Zhang et al. [134]	Building energy forecasting using active learning
Ji [60]	Architectural design optimization using Neural Networks
Konhäuser et al [66]	predictions of buildings' energy performance and benchmarking using ML
Piotrowska-Woroniak & Szul [98]	Estimation of energy demand for heating using rough set theory (RST)
Razmi et al. [100]	building performance optimization using PCA-ANN integrated NSGA-III framework
Sari et al. [103]	Prediction of energy efficiency, indoor environmental quality, water efficiency using ML
Szul [112]	Prediction of energy consumption for heating
Liang et al [74]	Predicting of cooling/heating loads using surrogate modelling
Mazzeo et al. [79]	predicting monthly green roof's internal and external surface temperatures and internal air temperatures using ANN
Verma et al. [120]	Prediction of energy efficiency and comfort using constrained nonlinear optimization and DL
Zhang et al. [135]	Prediction of energy usage and greenhouse gas emissions using DL
B. AI-Enabled Decision Making	
Casado-Mansilla et al. [23]	Energy consumption using IoT, edge-computing and smart metering
Karan & Asadi [63]	Design generation using Markov decision process (MDP) and mathematical framework for decision-making
Mohanta & Das [83]	Maintenance performance simulation

A. AI-Enabled Design Generation and Optimization

Design generation and optimization are two different processes but are mostly carried out consecutively. They both involve an iterative process that integrates human creativity, domain knowledge, and AI techniques to achieve designs that are both innovative and functional and fulfill the project objectives. A typical AI-driven design generation process involves three steps (Fig. 3):

- Data Preparation: This involves the process of collecting data in various forms (images, constraints, user preferences, and so on). The data is then pre-processed to be compatible with the chosen generation technique.
- Model Selection: In this process, a new model can be designed, or an existing model can be employed. In both cases, a single algorithm or a combination of several algorithms that best suit the problems are selected and trained. Algorithms for design generation include Generative Adversarial Network (GAN), Neural Style Transfer, and so on. The model learns the patterns, styles, and characteristics of the provided data in the training process.
- Generation Process: This phase is the final stage where results are acquired. The trained model is used to carry out the generation phase.
- After which the design options are evaluated, and several processes such as simulations are carried out to select the design option that best suits the project objectives.

Design generation by AI is facilitated by various Machine Learning (ML) algorithms, including Evolutionary Algorithms (EA). Researchers have identified in research, where different types of EAs, among which Genetic Algorithms dominate in terms of energy, form, and building envelope optimization [34]. Generative Design (GD) in the Architecture, Engineering, and Construction (AEC) industry refers to an iterative process that employs algorithms to generate various outputs to meet specific project objectives [30]. GD now serves as a means to enhance efficiency by merging the designer's creativity with the capabilities of

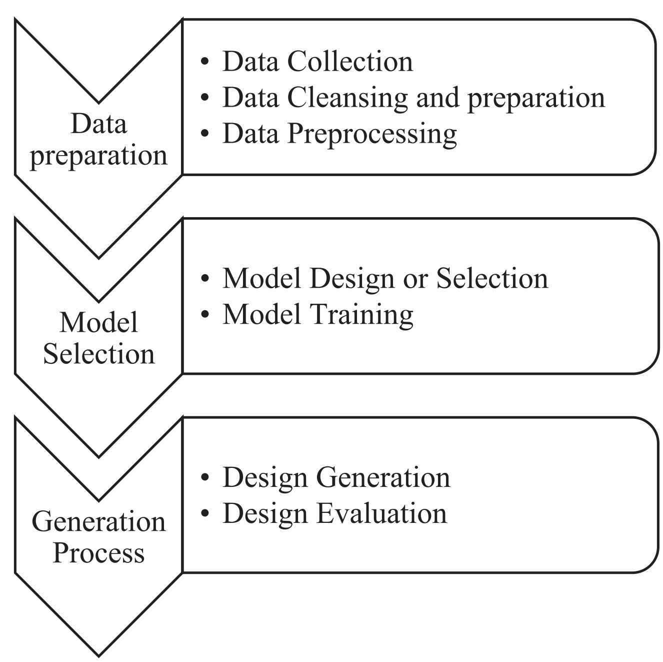

Fig. 3. Design generation process.

technology. This concept has been explored in several research works, such as Razmi et al. [100], where GD was employed to generate and modify two design configurations of a dormitory for further optimization. Zhang et al. [134] also investigated GD for generating design schemes based on predicted performance flow patterns. Their algorithm extracted spatial form features, automatically generated and simulated new schemes, and ultimately identified the optimal scheme with the lowest heating and cooling loads. In a similar vein, Bianconi et al. [18] utilized GD to create a web-based design catalog for timber structures featuring 18 energy-efficient designs. This process streamlines the time allocated for alterations and enables designers to focus more on critical design aspects.

AI has also been harnessed in the design of green buildings using various algorithms, such as Artificial Neural Networks (ANN), for energy forecasting. Energy prediction or forecasting is the process of predicting future energy needs to achieve demand and supply equilibrium [109]. Numerous research works have been conducted to ascertain the most effective ML methods for energy forecasting. For example, Kosovic et al. [68] conducted a study to determine which ML method efficiently estimates solar radiation using the Internet of Things (IoT) in smart buildings. They concluded that, for short-term estimation, Random Forest outperforms neural networks, while for long-term estimation, a hybrid model outperforms all other models, making it the most compatible choice for IoT applications. Similarly, Konhäuser et al. [66] explored twelve ML learning models and found that ensemble models perform better than stand-alone models in predicting building energy performance. Mui et al. [86] investigated the efficiency of integrating AI and EnergyPlus. The simulation model they developed was used to analyze the impacts of construction materials and indoor-to-outdoor temperature variations on cooling energy consumption. The results contributed to establishing general criteria for building components, creating a standard for achieving energy efficiency in buildings.

The choice of ML techniques for prediction varies, primarily depending on the criteria or features considered, their effectiveness in providing predictions close to the real measured results, and the impact of unpredictable factors. Seyedzadeh et al. [107] developed an ML-based model for energy performance prediction, applicable to non-domestic buildings, providing rapid energy performance estimates for multi-objective optimization of energy retrofit planning. Sari et al. [103] developed a predictive model using ML techniques, considering four criteria for the design of green buildings: indoor environmental quality, energy efficiency, site planning, and water efficiency. They noted that one potential limitation in this context is the availability of data to feed into the algorithm. Mazzeo et al. [79] also encountered a similar limitation in their study on the potential effects of green roofs in mitigating urban heat islands and improving building thermal performance. The use of thermal method characteristics-based models for estimating energy consumption was evaluated in single-family residential buildings by Szul [112] and in public buildings by Piotrowska-Woroniak & Szul [98]. In both studies, the quality of the predictive model was assessed using the ASHRAE calibration standards, demonstrating its efficiency in estimating energy consumption.

Zhang et al. [135] employed a deep learning model to predict energy usage and greenhouse gas emissions in residential buildings, identifying influential variables and evaluating their importance. Elnour et al. [32] reviewed the literature on building operation management and optimization for sports facilities in hot climatic zones, suggesting that operation-oriented optimization offers more practical solutions and encourages active participation in energy markets to address challenges. Himeur et al. [54] surveyed AI-big data analytics in Building Management Systems (BAMSs), focusing on tasks like load forecasting, water management, and occupancy detection. Liang et al. [74] introduced a surrogate modeling method for predicting all-year hourly cooling/heating loads in high resolution for retail, hotel, and office buildings, using 16,384 surrogate models and K-nearest-neighbors (KNN) as data-driven algorithms. The Manhattan distance emerged as the optimal metric for predicting building thermal loads, with the highest LEHR median values.

After the design generation phase, a manual process follows, where each design option generated is individually simulated and evaluated. If necessary, design elements are adjusted at different stages of generation to meet the design objectives. To streamline this process, generation algorithms are often equipped with optimization algorithms to readily identify optimal design solutions. Building energy optimization gained momentum in the 1990 s and was firmly established in the 2000 s. This technique generates optimal building designs based on the results of energy simulations and user-defined design objectives [110]. A typical design optimization process comprises three steps: problem formulation of optimization, problem-solving, and interpretation and evaluation of optimization results [133]. Fig. 4 illustrates a detailed process of design optimization. The four-dimensional building design has highlighted the utilization of technology that leverages data to save time. A study conducted by Wortmann et al. (2022) found that design optimization is primarily employed in the concept design phases and mainly focuses on optimizing geometry and environmental aspects. The goal of energy optimization in achieving energy efficiency has been explored and confirmed by multiple studies, including Ji [60], Verma et al. [120], and Zhang et al. [135]. Razmi et al. [100] utilized an integrated Artificial Neural Network (ANN) to optimize various aspects of a dormitory building, resulting in a 42.24 % increase in heating and lighting energy efficiency.

B. AI-Enabled Decision Making

Decision-making in building design is facilitated by Decision Support Systems (DSS), interactive computer-based systems that use data and models to address unstructured problems. DSS provides architects, engineers, and decision -makers with knowledge, models, and tools for data processing to make informed decisions in various situations [85]. Automated decision-making in building design aids in selecting the right materials, technology, or construction methods for building systems to achieve energy efficiency [83]. For instance, Markov Decision Process (MDP) is an AI decision-making technique that has been used in designing windows. It was concluded that AI offers scalability and self-learning capabilities, providing advantages over human intelligence. However, AI for decision-making faces challenges related to data collection and interpretation [63], which can impact results. Another challenge lies in selecting the right AI technique for decision-making, which can be addressed by understanding the learning methods of various AI domains. AI-integrated DSS also supports human-centric design, a concept that considers the needs and behaviors of occupants in the design process. An aspect of human-centric design, -based energy management, was enhanced using DSS in a study by Casado-Mansilla et al. [23]. They developed a device combining lightweight edge computing and smart metering equipment to reduce energy consumption.

3.2. Building construction phase

Traditional building construction methods consume substantial resources, including energy. Just as in the design phase, professionals in the AEC industry should reconsider construction processes to enhance their efficiency. However, the construction phase has received less attention concerning the energy efficiency of its processes compared to other lifecycle phases. This creates a significant gap in the building energy efficiency movement within the AEC industry. The focus is mainly on other phases, such as design, operation and control, maintenance, and retrofit phases, which indirectly inform construction.

AI applications in the construction stage include reimagining the construction techniques for existing building systems [111]. AI is also employed in process scheduling and predictive decision-making [2], facilitated by Digital Twining (DT). Decision-making in construction

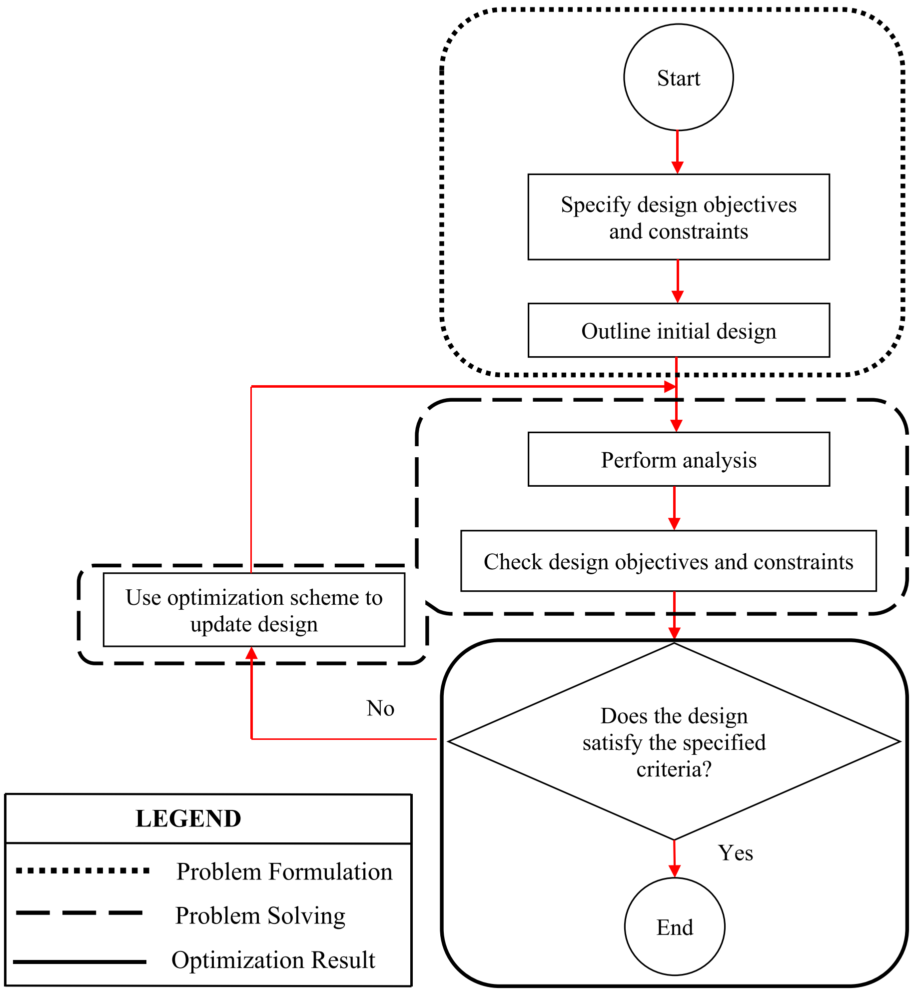

Fig. 4. A typical process of design optimization (.
adapted from [56]

processes has evolved with the introduction of DT, enabling real-time assessment of complex "what-if" scenarios. There are four types of digital twinning: descriptive, informative, predictive, comprehensive, and autonomous twinning (Autodesk, 2023). In a study by Agostinelli et al. [2], they explored a methodology that integrates DT with AI to refine the database and integrate the national power grid with urban energy cells. DT also facilitates the cyber-physical integration of offsite building manufacturing, streamlining the development of smart buildings based on established standards [15].

Material selection and optimization, as well as offsite manufacturing automation, are areas in the construction phase where AI can be applied. AI utilizes criteria such as strength, durability, energy efficiency, thermal comfort, and aesthetics to design and combine materials with exceptional performance [15]. These materials are designed with a combination of favorable characteristics tailored to their intended functions. For instance, in a study by Yan et al. [129], ML and particle swarm optimization were used to analyze the composition of a solar pond, resulting in the addition of coal cinders to the pond's bottom instead of its regular floor finish, optimizing heating and cooling in a building using renewable energy without releasing pollutants into the environment. Materials can be designed to suit building prefabrication, which entails the assembly and disassembly of buildings, effectively spreading the embodied energy of building materials over generations. The use of AI in building prefabrication is enabled through automation, and 3D printed buildings are among the innovative applications being explored worldwide.

3.3. Building operation and control phase

Building energy can be categorized into embodied energy, representing 10–20 % of the building's total energy, and operational energy, accounting for 80–90 % of the building's total energy consumption, depending on the timeframe. Operational energy pertains to the energy required to operate a building and its various systems, including Heating, Ventilation, and Air Conditioning (HVAC) systems, lighting systems, and water systems [58]. This lifecycle phase consumes significantly more energy compared to other phases, primarily due to buildings' long lifespans. This energy covers the operation of the building until it is demolished or disposed of. AI has been explored in research for energy management, encompassing energy monitoring and control. Several computerized systems monitor and control building services related to energy, such as HVAC systems and lighting systems. Building Energy Management Systems (BEMS) are Internet of Things (IoT) enabled systems, and the evolution of IoTs is expanding, offering new possibilities that leverage the power of AI and ML [115]. Numerous studies have been conducted in this area, as summarized in Table 5 and elaborated on in the following sections.

A. AI-Enabled Energy Monitoring

Energy monitoring is crucial in buildings, as they require complex systems to function sustainably. Ensuring energy efficiency in buildings is critical, as the complexity and variability of these systems demand

Table 5
Summary of the reviewed literature in the building operation and control stage.

Source	Focus
A. AI-Enabled Energy Monitoring	
Rahman et al. [99]	Building energy modelling and prediction using ML and DL
Touzani et al [114]	Energy consumption predictions and saving estimations using ML (gradient boosting machine)
Chou & Truong [26]	Energy load monitoring and analyses using cloud forecasting system to monitor energy use by home appliances
Marinakis [76]	Decision-making on energy management using visualization tools, ML, DL, big data
Kwon et al. [69]	Comfort temperature derivation, device-free sleep prediction, and occupancy-probability-based outing prediction in BEMS
Ntafalias et al. [91]	Efficiency, grid flexibility, and occupant well-being using ML and IoT
Thangamani et al. [115]	Energy and comfort management using IoT
Wei et al. [116,125]	Heat gains detection and prediction using DL for energy efficiency in office buildings
Zhu et al [136]	Energy efficiency and IEQ using ANN
Giglio et al. [43]	Renewable energy generation and storage using DL to develop BEMS
Ngo et al. [90]	Building energy consumption prediction using web-based optimized AI
Selvaraj et al. [106]	Energy prediction and analysis, renewable energy production, and recycling evaluation using ML
B. AI-Enabled Energy Control	
Blum et al. [19]	Predictive control of HVAC systems
Fan et al. [36]	Development of cooling load prediction model
Park et al. [95]	Occupant-centered lighting control using reinforcement learning
Sardianos et al [101]	Energy consumption reduction using edge AI
Wang et al. [123]	Thermal envelope simulation using DL
Nam et al [89]	Prediction of airflow rate, energy consumption and CO_2 emissions using DL and AI-iterative dynamic programming
Sardianos [102]	Improving energy efficiency by recommending energy-saving actions to the users
Coraci et al. [27]	Enhancement of indoor temperature control using Soft Actor-Critic Agent
Luo et al. [75]	Shading control of blinds to improve visual comfort and energy savings using ML
Mustaqeem et al. [88]	Energy demand and consumption management using DL
Sayed et al [8,105]	Energy saving recommender system using edge AI
Elnour et al [33]	Predictive control systems for thermal comfort and air quality using Neural Networks
He et al. [47] and Lee et al. [70]	Prediction of thermal energy storage using ANN
Varlamis et al [118]	Smart sensor data to recommend personalized action for household energy reduction
Yayla et al. [130]	Improvement of energy efficiency and indoor temperature comfort using ANN
Xiang et al. [128]	Energy consumption monitoring using universal infrared communication system and Long Short-Term Memory (LSTM)
Khan et al. [64]	Electricity efficiency improvement using smart home energy management system

comprehensive operation and control schemes to achieve optimal comfort. BEMS are primarily explored in larger buildings, such as commercial buildings, given the complexity of these structures. Data from BEMS have led to the development of advanced methods to increase the automation and efficiency of these systems. BEMS have been equipped with functions such as energy consumption prediction and savings estimation, as demonstrated by Touzani et al. [114]. Hernandes et al. [48] developed a BEMS for optimal comfort and renewable energy utilization in a renovated school in Turkey. Rahman et al. [99] conducted a study to explore power disaggregation, breaking down data from buildings into device-level data. They proposed a new algorithm for disaggregating power consumption in HVAC systems.

Zhu et al. [136] developed a system that monitors the interior environment using wireless communication technology, allowing real-time regulation and intelligent management of ventilation, potentially saving up to 60 % of energy. Ngo et al. [90] designed an AI-based BEMS that monitors, compares, and predicts energy consumption using AI, metaheuristic optimization algorithms, and web applications. The system consists of a data layer, AI-based analytics layer, and a web-based layer. The prediction results closely matched the actual energy consumption in the buildings. Wei et al. [116,125] conducted research on equipment energy usage and the behavior of occupants in an office space. They noted limitations in their studies related to insufficient data and suggested the use of a system of connected 360-degree cameras to support demand-driven energy distribution. BEMS are also essential for energy distribution, as studied by Selvaraj et al. [106], who explored the use of monitoring systems for optimal energy distribution and suggested that smart grids can enhance real-time demand response. DSS can be integrated with BEMS to enable fault detection, as investigated by Chou & Truong [26] and Marinakis [76]. This integration creates a synergized system that can self-manage and optimize energy consumption, ultimately reducing energy usage. DSS-integrated BEMS have been shown to achieve around a 15 % reduction in energy consumption for individual building systems [69,91] and a 55 % reduction in total energy bills [43].

B. AI-Enabled Energy Control

Conventional building control systems are often lacking in energy efficiency as they can address only one aspect of energy efficiency at a time. These systems are pre-determined and overlook the influence of predictive information, such as weather conditions. This makes them insufficient for specific building occupancy types and climatic conditions, leading to suboptimal performance (Hong et al., 2020a). Control can take place on both an appliance scale building system scale, covering renewable energy systems, HVAC, lighting, and more. However, controlling on a smaller scale can be challenging due to variations in occupant behavior, introducing uncertainty into AI-enabled appliance control. A study by Nam et al. [89] aimed to develop an energy-efficient ventilation optimization system for underground subway stations. This innovative system integrates deep learning and AI-iterative dynamic programming.

Frassanito et al. [38] conducted a study where the control features of an HVAC system were automated, resulting in a substantial 33 % energy savings. AI can help address these issues by employing Machine Learning (ML) algorithms to predict, interpret, and analyze data from sensors, meters, and other sources. This data relates to occupant behavior, enabling intelligent decisions about building operations and energy consumption. Xiang et al. [128] introduced a plug-and-play device, AI-EMM, which uses universal infrared communication, smart user identification, and Long Short-Term Memory (LSTM) models to enhance energy consumption efficiency. Khan et al. [64] proposed an algorithm for real-time scheduling of home appliances, leading to a remarkable 48 % reduction in electricity costs. In the literature, two aspects of building control have been identified: adaptive and predictive control.

Model Predictive Control (MPC), also known as receding horizon control or moving horizon control, refers to control systems that use distinctive models [41]. The implementation of MPC in buildings has the potential to enhance occupant comfort, reduce costs, and facilitate grid integration [19]. AI strategies have been explored to improve the efficiency of MPC in various research works. For instance, Blum et al. [19] explored the challenges and possible mistakes in training automated MPC systems. Fan et al. [36] investigated the application of AI-enabled MPC for predicting cooling loads in HVAC systems in office buildings, providing data useful for other aspects of building energy efficiency. AI-enabled MPC has also been employed to enhance building energy efficiency by predicting space occupancy. Studies by Yi [131] and Yayla et al. [130] integrated MPC with sensors to detect room occupancy through changes in light, humidity, and CO_2 levels.

Wong & Li [127] identified criteria for ranking HVAC control according to their order of importance: total energy consumption, system stability and reliability, the cost of operating and maintaining the control systems, and the system's efficiency in controlling indoor humidity and temperature. The potential for energy saving is also listed as a criterion by Yayla et al. [130]. Elnour et al. [33] developed a neural network-based model predictive control system for HVAC systems, outperforming other Machine Learning (ML) models and achieving up to a 46 % reduction in energy usage, along with improved thermal comfort and air quality. This approach will be integrated into a computational urban sustainability platform for application in mega sports events. The use of AI for predicting electricity demand in a more efficient and reliable way has proven to be significant for energy efficiency but has received less focus compared to other areas [88]. Nonetheless, researchers in the past few years have made significant progress in this aspect. Although AI-based MPC has been proven to facilitate realistic real-time optimal control and reduce total operational costs by 9.1–14.6 % [70], there is still a need for further developments in their self-improvement and transfer learning [47].

Energy control also includes Adaptive Control, which is a method of controlling that adapts to the varying or uncertain parameters of the controlled system [21]. This control type relies on parameter estimation, which is the system's ability to determine values related to its operation [13]. AI-based adaptive control is crucial in building systems as it enables real-time intelligent adjustments by analyzing large amounts of data to optimize system performance and energy efficiency. The most commonly used Machine Learning (ML) approach for adaptive control is Reinforcement Learning (RL). RL has the capability to adapt to different environments by learning a control policy through direct interaction with the environment [11]. Several control systems have been explored in research using the RL approach. Park, Dougherty, Fritz, and Nagy [95] investigated the use of RL for lighting control in their system called LightLearn. This control system adapts its parameters to individual occupant behaviors and indoor environmental conditions, successfully achieving a balanced relationship between occupants' comfort and energy consumption.

Control has become two-way, involving the control of building systems and the control of occupants. The use of recommender systems has allowed for a practical way of influencing occupants' behavior by identifying habits that do not support energy efficiency and suggesting preferable actions to the occupants. Himeur et al. [51] provided a comprehensive reference for energy-efficiency recommendation systems, highlighting the role of IoT and AI technologies in promoting energy efficiency in buildings. Sayed et al. [8,105] proposed integrating an energy efficiency framework into the Home-Assistant platform, allowing users to visualize consumption patterns and receive understandable energy-saving recommendations via mobile notifications. This was the first attempt to develop an energy-saving recommender system on edge devices, ensuring privacy preservation. Varlamis et al. [118] introduced an online recommender system for energy-saving applications in smart homes and offices, utilizing sensor data and user habits to provide personalized recommendations. The EM3 platform evaluates sensor data, user habits, and feedback to identify optimal micro-moments for recommended actions, with an efficiency range of 93 % to 97 %. Varlamis et al. [119] propose a project aiming to improve energy efficiency in smart homes and offices by combining data collection, information abstraction, timed recommendations, and automations. The solution handles thousands of sensor events daily, providing analytics and recommendations for habit change. Sardianos et al. [101] presented an energy consumption reduction system using sensors, smart meters, and actuators in an office environment. The system targets specific user habits and uses a messaging API to recommend energy-saving actions. Implemented on the Home Assistant open-source platform, the system reduces energy consumption and encourages sustainable habits through user actions. Sardianos et al. [102] explored REHAB-C, a goal-based, context-aware recommendation system designed to help users improve their energy habits and prioritize recommendations based on their goals.

AI-based energy-efficient adaptive control does not necessarily result in lower energy consumption compared to conventional systems. AI systems often aim to optimize occupant comfort and might, in some cases, use more energy in pursuit of the best possible comfort for occupants, thus exceeding the energy consumption of conventional systems. This is demonstrated in research by Coraci, Brandi, Piscitelli, and Capozzoli [27], where a water-based heating system for an office building integrated trained Deep Reinforcement Learning (DRL) agents. The best DRL agent significantly improved occupant comfort but also led to an 11 % increase in heating energy consumption. Luo, Sun, and Yu (2021) proposed a novel Model-Based Control (MBC) strategy to control window blinds in an open office to optimize daylighting quality, ultimately reducing lighting energy consumption. They achieved this by optimizing vertical eye illuminance, resulting in a 77 % decrease in lighting load on selected summer days and a 64 % reduction on certain winter days.

3.4. Maintenance and retrofit phase

Building energy retrofitting is globally important due to the untapped potential for energy efficiency [67]. AI-based decision-making in this phase is critical [28] as it plays a crucial role in reducing energy consumption. Achieving energy efficiency during and after retrofitting requires the assessment of current building performance, identification of energy conservation methods, and post-retrofit assessment, all of which depend on access to building information and operational data (Hong et al., 2020b). To achieve energy efficiency, building systems need to be synchronized and automated to ensure real-time data capture, monitoring, and storage, which can be achieved using AI. Sarmas et al. [104] explored an ML-based framework for predicting energy savings in energy-efficient retrofit projects, utilizing an ensemble approach to moderate the effects of uncertainty. The application of AI in retrofit projects can be further discussed under two areas: Fault Detection and Diagnosis (FDD) and Energy Benchmarking. Several studies in this field are summarized in Table 6 and explained in the following sections.

A. AI-Enabled Fault Detection and Diagnosis (FDD)

FDD is a specialized application of anomaly detection, involving the identification of deviations from expected data behavior. Several research efforts have explored anomaly detection and fault detection, investigating their possibilities and limitations. Himeur et al. [8,52,105] introduced a taxonomy for algorithm classification in AI-based energy consumption, addressing domain-specific issues such as inaccurate power consumption definitions, annotated datasets, unified metrics, reproducibility platforms, and privacy preservation. Lei et al. [71] introduced a dynamic anomaly detection algorithm for building energy consumption data, combining unsupervised clustering and supervised algorithms to detect outliers and support building management strategies. Copiaco et al. [24] presented the first research on deep anomaly detection in building energy management using two-dimensional (2D) image representations as features of a supervised deep transfer learning (DTL) approach.

Himeur et al. [49] introduced a new method for detecting energy consumption anomalies using micro-moment features from daily user actions, utilizing a deep neural network architecture for efficient detection and classification. Pan et al. [93] introduced a deep learning-based method for real-time anomaly detection in buildings, using high-dimensional data to predict users' electricity consumption. The system aims to identify abnormal usage by users, depending on availability, privacy constraints, and data stream computing power. Gulati & Arjunan [45] released an annotated version of the ASHRAE Great Energy Predictor III data set, containing 1,413 time series and

Table 6
Summary of the reviewed literature in the building maintenance and retrofit stage.

Source	Focus
A. AI-Enabled Fault Detection and Diagnosis (FDD)	
Li et al. [73]	FDD using tree-based fault diagnosis method
McArthur et al. [80]	Maintenance issue classification using ML and BIM visualization
Gallagher et al. [39]	Energy performance deviation detection using ML and cloud computing
Hu et al. [57]	Energy performance monitoring through fault detection using ML
Márquez et al. [77]	Improvement of asset performance and energy efficiency using ANN
Márquez et al. [78]	Energy efficiency and fault detection using ANN
Himeur et al (2020)	Anomalous energy consumption detection using micro-moments and deep neural networks
Pan et al (2020)	Real-time energy anomaly detection using DL method
Parzinger et al. [96]	FDD in building's HVAC systems using predictive modelling data
Agostinelli et al. [2]	Building energy management using DT
Albayati et al. [6]	FDD tools for HVAC systems
Bezyan & Zmeureanu [17]	Faults detection in HVAC systems using ML and Rule-Based techniques
Merino-Cordoba et al. [82]	Smart hot water system using sensors and artificial intelligence to improve identify faults
Gulati & Arjunan [45]	Energy anomaly detection in buildings using large-scale annotated dataset.
Copiaco et al [24]	Deep anomaly detection using energy time-series images
B. AI-Enabled Energy Benchmarking	
Kontogiorgos et al. [67]	Assessment of energy saving in buildings using mixed-integer programming model
Papadopoulos & Kontokosta [94]	Grading of buildings' energy performance using clustering algorithm
Arjunan et al. [12]	Building energy benchmarking using explanatory methods
Mulero-Palencia et al. [87]	Analysis of BIM data and proposing energy conservation measures for deep renovation projects
Galli et al. [40]	Energy performance benchmarking of buildings using data-driven benchmarking process
Eiraudo et al. [31]	Energy benchmarking based on buildings' electric profiles using ML (decomposition and clustering algorithms)

benchmarked eight state-of-the-art anomaly detection methods.

Building maintenance is optimized when FDD is integrated with AI as it reduces breakdowns and malfunctions of energy systems [2]. This has been confirmed by studies conducted by Li et al. [73], Gallagher et al. [39], Parzinger et al. [96], and Bezyan & Zmeureanu [17]. Identifying faults in building systems, such as HVAC and lighting, could optimize maintenance scheduling, minimize downtime, and improve energy efficiency. Non-automated FDD processes are often challenging and do not lead to energy and cost optimization [6]. However, AI-enabled FDD integrated into energy management systems allows for widespread operation, as faults can be predefined by users [57], and priorities can be assigned based on location and problem types [80].

Márquez et al. [77] proposed a method that combines ANN and data mining tools to monitor asset performance. The method was further developed by Márquez et al. [78] to create a tool that can adapt prediction models to existing operating conditions, allowing for easy training and testing. It was able to predict asset degradation and risks related to building operation, eliminating preventive maintenance activities and reducing operational costs in the long run. Another study by Merino-Cordoba et al. [82] developed an energy-efficient heating system for conventional water tanks. The smart hot water system automates pressurization and solenoid valves, using sensors and artificial intelligence to improve energy efficiency and identify faults.

B. AI-Enabled Energy Benchmarking

Building energy retrofitting requires accurate benchmarking of energy efficiency [122], which can be achieved through AI integration. Energy benchmarking is the process of measuring a building's energy performance in comparison to similar buildings to identify inefficiencies [12]. Building Energy Management Systems (BEMS) are essential for energy benchmarking as they collect and store the data required. Papadopoulos & Kontokosta [94] argued that automated energy benchmarking or AI-powered benchmarking should be based on principles such as robustness, reliability, recreation, scalability, and generalization. Mulero-Palencia et al. [87] conducted a study on building pathologies using existing building databases. The data acquired was used to design an ML-based algorithm for diagnosing critical areas in buildings for renovation and proposing alternatives based on energy conservation measures. Galli et al. [40] proposed a methodology for automated energy benchmarking and tested it on a collection of energy performance certificates of over a hundred thousand flats in Italy. Another study conducted by Eiraudo et al. [31] explored an automated method for grouping using clustering algorithms to simplify data gathering for the Architecture, Engineering, and Construction (AEC) industry.

4. Current challenges and future works

Data is a crucial aspect of AI as it directly affects the efficiency or inefficiency of the results. Data processing in AI involves several steps, including data collection, data processing, data transformation, data input, data processing, data output, and data storage. At every step involved, data is exposed to several risks. The first risk data is susceptible to is data inaccuracy. This could be due to several reasons, such as the unpredictable nature of the data to be collected, the tools and techniques involved in the collection process, and human error. There is also the issue of data privacy and security. In today's world, data is a vital investment for companies and individuals, opening them up to cyber threats, especially in building systems due to the vast amount of data they generate.

A major challenge that remains a gap in AI is the translation of AI development in research to real-life implementation. These AI developments are carried out by experts in their respective fields, mostly excluding the input of professionals in the building industry. The major concepts of these technologies are not fully understood by these professionals and the building occupants, who are the intended end users. Research on creating user-friendly systems with friendly user interfaces has been conducted, but more work is needed to further bridge this gap. Additionally, cost and scalability remain continuous challenges in the implementation of research-developed techniques in real life. The energy efficiency requirements for buildings and their systems vary and change continuously depending on the problem and the existing technology available, and the continuous and exponential development of these systems results in previously developed systems becoming obsolete. Government and regulatory bodies should ensure the compliance of these systems with energy efficiency and AI regulations, ensuring an organized and monitored transition of AI technology from research to real-life implementation.

The aim of this review paper is to summarize, further extensive research should be carried out to analyze specific AI applications, using a range of keywords to focus on specific subfield of AI, and for a more detailed analyses, as well as their implementation in the real world. Also, the use of edge AI should be further studied to explore its usefulness for energy efficiency in the different building lifecycle stages. Future research should also explore:

- Data security, as it a continuous and endless cycle. The more AI advances, the more advanced the issues regarding security.
- Refining data validation methods at very step of data processing in AI development.

- The seamless integration of several building systems and AI techniques to achieve energy efficiency.
- The integration of AI studies into school curriculum for degrees relating to the building profession.

5. Conclusion

This study highlighted the various applications of AI for energy efficiency in the different building lifecycle stages, categorized into design, construction, operation and control, and maintenance and retrofit. The different lifecycle stages are covered by different sub-fields of AI, with ML and automated planning and scheduling being the most researched areas in the past few years. AI-based solutions are being used for building design generation and optimization, decision-making, predictive and adaptive control, fault detection and diagnosis, and energy benchmarking. The review concluded that in building design, ML algorithms are the most used and have so far facilitated design generation, energy modeling, decision-making, energy prediction, and optimization. In this context, DSS supports human-centric design, achieving an increase in human comfort levels in buildings and reducing energy loads. The review also found that the use of AI in the construction phase is mostly explored indirectly through the effects of the other lifecycle stages. Energy efficiency of the construction processes was not commonly researched in the last five years. However, DT is widely adopted in the construction phase to aid the development of new construction techniques and systems for building components and process scheduling or predictive decision-making.

In building operation and control, an efficient building BEMS must combine several sub-fields of AI for optimal results. DSS-integrated BEMS creates a fully synergized system that can manage itself as well as the building and its occupants' needs, leading to a reduction in energy consumption and total energy bills. In the maintenance and retrofit stage, AI-enabled FDD improves maintenance scheduling, minimizes downtime, and improves energy efficiency. Studies have shown that automated energy benchmarking can help identify inefficient behavior and optimize design choices for energy retrofitting. Some limitations of research relating to AI were also discussed, including the collection and accuracy of data. The quality of output from every algorithm is largely dependent on the data input and the programming process, which are done by humans and are prone to several human errors and biases. There is also a lack of clarity in the processes involved in the use of AI due to the lack of dialogue. The adoption of AI should be regulated because of the increasing lack of ethics and unemployment.

In conclusion, AI displays significant potential to significantly improve energy efficiency throughout the different building lifecycle stages. This study provides resources for researchers, AEC practitioners, and policymakers in this regard. Although, the comprehension of this review is limited by the keyword, namely AI, it still provides resources for researchers, AEC practitioners, and policymakers in this regard. Despite the intensive research work conducted in this field, several challenges remain. This includes the need to develop AI applications that have user-friendly interfaces such that professionals in the building industry with little to no knowledge of AI can easily use these technologies effectively. In this context, the seamless integration of energy systems and AI techniques to achieve energy efficiency in buildings is needed. The possibilities of AI should also be emphasized in the schools of architecture and engineering, to understand the extent to which it can reshape the industry. In addition, filtering and analyzing data based on the various sub-fields of AI will enhance the accuracy of the results, and thereby, expand the repository of AI-based application in the construction industry. Future research should focus on addressing the following issues: challenges of implementation and training of building professionals, the potential of AI in increasing the energy efficiency of construction processes, cost-effective AI-enabled systems for energy efficiency, and data accuracy and security and how it can affect the AEC industry.

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Data availability

Data will be made available on request.

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