



Review article

AI-driven systems for advancing smart building infrastructure: An integrated review for energy management, occupant comfort, and cybernetics

Ijaz Ahmed ^{a,*,}, Rehana Khan ^{b,}, Muhammad Rehan ^{a,c,}, Mohammed Alqahtani ^{d,},
Muhammad Khalid ^{a,c,}

^a Interdisciplinary Research Center for Sustainable Energy Systems (IRC-SES), King Fahd University of Petroleum & Minerals (KFUPM), Dhahran, 31261, Saudi Arabia

^b University of Engineering and Technology (UET), Taxila, Punjab, 47050, Pakistan

^c Electrical Engineering Department, KFUPM, Dhahran, 31261, Saudi Arabia

^d Department of Industrial Engineering, King Khalid University, Abha, 62529, Saudi Arabia

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ABSTRACT

The development of smart building infrastructure requires integrated approaches that balance energy efficiency, occupant well-being, and resilient control mechanisms. This study reviews the advanced computational systems, supporting three interconnected fields: cybernetic coordination, energy management, and occupant comfort. Principles of cybernetics provide the overall framework, emphasizing feedback loops, system resilience, and adaptive management to ensure resilient building performance in the face of uncertain or external disturbances. Energy management data-driven optimization strategies, like real-time load forecasting, adaptive HVAC control, and integration with renewable energy sources, have shown measurable reductions in consumption. Research demonstrates the positive effects on occupant comfort of sensor-based monitoring and adaptive environmental controls that adjust to shifting air quality, temperature, and individual preferences. The key technological enablers highlighted in this review include interoperable communication networks, predictive modeling frameworks, and cross-domain integration strategies. It also highlights the ongoing issues such as the lack of equality in standards, inability of prototypes to operate on large scale building projects, and data security and privacy. In contrast to traditional surveys, this review implements a cybernetics-oriented integrative approach, which synthesizes AI-driven smart building functionality as a network of feedback systems and not autonomous parts of technology. This review brings in engineering, architecture, and systems science discoveries to bring out a holistic analysis of how intelligent control systems can contribute to safe, human-specialized and sustainable building settings. These results suggest that occupant behavior should be considered in system design, resiliency against cyber-physical attacks, and disciplinary gaps between application and research should be overcome in the future. Besides energy efficiency, the integrated approach also introduces smart buildings as versatile, socio-technical systems, which can help to attain the long-term sustainability objectives.

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* Corresponding author.

E-mail addresses: ijaz.ahmed.1@kfupm.edu.sa (I. Ahmed), rehanakhan1260@gmail.com (R. Khan), muhammad.rehan@kfupm.edu.sa (M. Rehan), m.alqahtani@kku.edu.sa (M. Alqahtani), mkhalid@kfupm.edu.sa (M. Khalid).

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1. Introduction

Smart buildings (SBs) are advanced constructions that utilize intelligent automation to provide inhabitants with secure, pleasant, and efficient environments while green buildings focus on sustainability and resource efficiency; intelligent buildings emphasize automated control systems with predefined logic; whereas SBs integrate Artificial intelligence (AI), IoT, and data analytics to enable real-time, adaptive, and user-centric decision-making. AI and IoTs are prominent advanced technologies utilized in building automation to enhance security and safety, facilitate remote management of appliances and systems, monitor people, boost efficiency, and improve thermal and visual comfort. Historically, residential and commercial edifices, such as offices, hospitals, schools, and healthcare facilities, were built to provide their occupants with essential utilities such as gas, electricity, and water along with comfort. Consequently, it is imperative to track, monitor, and supervise a building in real time, along with its inhabitants, systems, appliances, environment, and health. This illustrates the imperative of automation in both business and domestic settings (Lawal and Rafsanjani, 2022). SB infrastructure is progressively disrupting the established norms of the traditional construction sector, which has yet to completely adopt digitization, prompting a reassessment of the concept of “building”. Smart construction technology has swiftly emerged as an essential element of the building industry owing to the seamless integration of digitalization and architecture (Ferrari et al., 2023; Hu et al., 2026). In the twenty-first century, several industrialized and developing countries have prioritized sustainable architecture. The “Horizon Europe” work program, released by the European Commission in 2022, demonstrated the importance of research in digital transformation for achieving green transformation (Zamanidou et al., 2024; Wang et al., 2025b). Similarly, several countries have enacted various regulations to promote SB technology (Bakar et al., 2024). The British government initiated the Digital Built Britain project to promote digital construction; Germany has advanced Industry 4.0 in the construction sector, emphasizing SBs and automated construction, while also creating a technology innovation fund; and the National Institute of Standards and Technology (NIST) in the United States has published the “Digitalization Roadmap for the Construction Industry”, which facilitates research and the implementation of intelligent development (Haiyirete et al., 2024).

The continuous global population rise will affect the built environment by increasing the need for energy, water, and natural resources. These changes will burden biological systems and progressively degrade the environment by elevating energy demand. The construction industry is among the highest energy consumers, accounting for 40% of total power production, 12%–16% of available water, 32% of combined renewable and non-renewable resources, 25% of lumber, and 40% of raw materials. The construction industry contributes 35%–40% of CO₂

emissions and generates 30%–40% of total solid waste (Razmjoo et al., 2022). Moreover, unwanted and potentially harmful air emissions constitute almost one-third of all greenhouse gas emissions, significantly contributing to climate change and global warming. Consequently, a technique to impartially mitigate these detrimental consequences is to attain sustainability in construction (Hafez et al., 2023). Sustainable and green buildings can mitigate their adverse impacts on the economy, society, and environment. Ensuring building safety, mitigating pollutant release, reusing materials, reducing greenhouse gas emissions through the utilization of natural resources, and meeting indoor environmental quality (IEQ) criteria are other methods of attaining sustainability in buildings (Sleiman and Ouf, 2025). Digital tools like demand-response systems, smart meters, and automated controls help SBs communicate with the energy grid, enabling them to make real-time changes based on changing environmental conditions, what occupants need, and energy prices. Sustainable buildings are environmentally conscious constructions designed to achieve net-zero carbon status and commitment to reducing greenhouse gas emissions more efficiently than conventional constructions (Xenakis et al., 2025). To attain low-energy, ultra-low-energy, green, sustainable, and zero-energy buildings, it is essential to include energy efficiency as a core principle. Enhancing energy efficiency in both new and existing structures serves as an immediate solution to mitigate the industry’s adverse impacts on the environment, financial benefits, culture, and other domains (Wang and Lin, 2025; Sivasankari and Rathika, 2025).

Achieving sustainability in buildings necessitates a focus on high energy effectiveness, which can be accomplished through energy-efficiency comparison strategies, energy-saving policies, the inclusion of wind generation plant and voltage topologies (Su et al., 2026) in towering structures (Li et al., 2026), a comprehensive multifaceted strategy, energy simulation, photovoltaic facilities, advanced lighting solutions, high-performance building envelopes, resource-efficient materials, and innovative energy concepts. By utilizing life cycle assessment (LCA) (Alhassan et al., 2024), developing cost-benefit analyses, applying green price premiums, and implementing optimal design methodologies for multi-energy infrastructures in buildings such as photovoltaic power generation systems, solar water heating systems, and seasonal cold storage, minimizing total life cycle costs can effectively mitigate economic impacts through cost savings and reduced operational expenses (both hard and soft costs). The four elements of IEQ—acoustics, aesthetics, thermal comfort, and indoor air quality are crucial for ensuring comfort within a building (Minassian et al., 2025). A range of sensor technologies is employed in smart facilities to analyze user activity and enable building automation. These sensors facilitate the establishment of thermal and visual comfort, energy saving, and the monitoring and enhancement of Indoor Air Quality (IAQ) (Silva et al., 2024).

Buildings are components of intricate ecosystems in which their main functions take precedence over their energy use. For example, the precedence applies to commercial structures such as hospitals, retail

establishments and tourism infrastructure (Gao et al., 2024; Xing et al., 2025). The development of building intelligence is focused on plug-in devices and different building instrumentation devices, such as sensors, actuators, and controllers, that allow for energy-efficient building automation while maintaining building occupant comfort (Li, 2025). Indoor building ecology may respond slowly to control adjustments, which could cause moments of discomfort. Historically, the solution was to use constant setpoints to keep indoor conditions comparatively steady. Nevertheless, this method is energy inefficient. Additionally, the proliferation of renewable energy sources (RES) forces buildings to provide greater energy flexibility, for example, through demand response systems. As a result, there are continuous attempts to create strategies for better building energy management in both industry and research. Control planning can take system dynamics into account by using models and predicted model inputs. Systems with high inertia, such as those with significant thermal mass, find this trait particularly alluring (Zheng et al., 2025). The concept of smart and energy-efficient (SEE) buildings has emerged as a viable solution to address the challenges of power consumption and global warming by utilizing contemporary technologies, including big data analytics, machine learning (ML) algorithms, and smart sensors. The primary objectives of SEE designs are occupant satisfaction, health, energy efficiency, and building durability (e Habiba et al., 2024). A SB (educational, commercial, or residential) has hundreds of components that need to be taken into account, such as the HVAC system, plugged loads from IT devices and appliances, etc. The Building Energy Management Systems (BEMSs), considered a key component of SBs, are required to integrate energy efficiency with smart grid technology. BEMS integrates methods to increase a building's energy savings and efficiency. Key energy management duties that BEMS must carry out include automated demand response, energy supply information monitoring, energy use anomaly detection, energy cost supervision, and automatic control. BEMSs and their associated subsystems have been the subject of countless investigations (Aguilar et al., 2021). By using AI-powered solutions, energy use can be tracked, predicted, and decreased, which can result in significant cost savings and improved energy use (Alijoyo, 2024).

Model predictive control (MPC) is a technique applied to building automation to increase occupant comfort and energy efficiency. For the MPC algorithm to plan for maximum comfort and energy efficiency, it should ideally take into account the baseline state, weather forecast, and planned and present consumption of the controlled environment (Aruta et al., 2025). The literature suggests that an MPC application is required that (1) takes into account a variety of goals, (2) can utilize a variety of data resources, and (3) offers a method for successfully integrating with heterogeneous automation systems for buildings so that the method may be applied to various installations (Lu et al., 2025). (Khan et al., 2024) developed a predictive optimum control system based on OCF-IoTivity as shown in Fig. 1 to address the aforementioned problems to maximize thermal comfort and minimize energy expenses. The OCF protocol improved interoperability and standardization. The ML model was trained and inferred, and the actuators were optimally controlled in this suggested system. The designed framework used sensors and a smart meter to gather energy, temperature, and humidity data. The indoor environment greatly impacts building occupants' productivity, health, and well-being. Thermal comfort directly influences occupant productivity, making it one of the most significant elements. HVAC systems that are energy-conscious and comfort-driven have been shown to be effective in reaching this objective, saving anywhere from 4% to 32% on energy costs. Making the interior environment thermally comfortable is the main goal of HVAC systems (Boutahri and Tilioua, 2024).

Recent survey works on SBs presented narrow aspects of AI-driven SBs rather than offering a comprehensive overview (Table 1). For example, the work in Aghili et al. (2025), Billanes et al. (2025), Álvarez-López et al. (2026) is mainly related to the optimization of energy use via AI and distributed energy management, while (Alsaferi

et al., 2023; Duan et al., 2026) are related to the comfort of the occupants and occupant behavior modeling. Likewise, the works of Almusaed et al. (2023), Ullah et al. (2025b) explore the concepts of Industry 6.0, digital twins, and 6G technology as well as smart infrastructures, whereas (Al-haimi et al., 2025; Pourzolfaghar et al., 2026) focus on cybersecurity, modular systems, and secure digital environments. Further, Panchalingam and Chan (2021), Szmelter-Jarosz (2026) explore the concept of AI applications, energy policies, and governance from a broader conceptual perspective (Yan et al., 2026). The proposed review, however, offers an extensive review and synthesis of the concepts of AI, cybernetics, occupant behavior, adaptive control, digital twins, and real-time feedback mechanisms for intelligent SBs. Additionally, it examines the existing problems in implementation such as interoperability, scalability, explainability, and security and suggests future research directions for the development of resilient, energy-efficient, and human-centric SB ecosystems, making it a single reference framework and strategic roadmap that goes beyond the scope of the current surveys. Specifically, this work synthesizes AI applications through the lens of closed-loop control, adaptive system behavior, and cross-domain coordination, rather than isolated functional optimization. By explicitly linking energy management, occupant comfort, and communication infrastructures within a unified cyber-physical feedback structure, this review provides a systems-level perspective that is largely absent in existing literature. Furthermore, it highlights the role of real-time feedback, resilience, and dynamic adaptation as core principles governing next-generation SBs, thereby extending beyond conventional survey methodologies. It also investigates how real-time feedback might enhance the performance of buildings and provide assessment of communication standards for both centralized and distributed building systems with particular focus on cybernetics. This study highlights AI's transformative role in reshaping energy management and use in the construction industry. AI-driven energy management systems use algorithms, machine learning, and data analytics to monitor, analyze, and optimize energy use in SBs. For optimal performance, these systems combine sensors, data pre-processing, optimization methods, and control systems. Key functions include predictive analytics for energy forecasting, adaptive HVAC control, occupancy-based lighting management, and integration with renewable energy to enhance sustainability. AI also enables small businesses to join demand response programs that adjust energy use to grid conditions and prices, cutting costs and improving grid stability and resilience. However, these systems face challenges such as data privacy, interoperability, scalability, technological barriers, and the need for skilled operators. The paper underlines AI-driven power control systems as key tools for optimizing energy use, improving building efficiency, and achieving sustainability goals in SBs.

The paper will adopt a narrative review approach to offer an integrative and in-depth evaluation of SB systems. The relevant terms were searched in major databases, such as Scopus, Web of Science, and Google Scholar. The databases like Scopus and Web of Science were used to conduct the literature review of the studies published between 2023–2025. The keywords were SBs, AIs in buildings, energy management, occupant comfort, and cybernetics. Relevance, peer-reviewed, and attention to building systems driven by AI were used to select articles, and non-English, duplicated, and irrelevant studies were filtered out. Also, a search strategy, predefined inclusion and exclusion criteria and a PRISMA flow diagram (Fig. 2) are used to facilitate the selection and filtering of the relevant research.

In addition, a bibliometric analysis was carried out to map the global research landscape on ML for SB energy management. A bibliometric analysis was also performed using VOSviewer to visualize the world energy management in ML for SB. Selected publications were retrieved from the data base and analyzed to form collaboration and keyword co-occurrence networks. The international partnership network in SB energy management ML research is illustrated in Fig. 3.

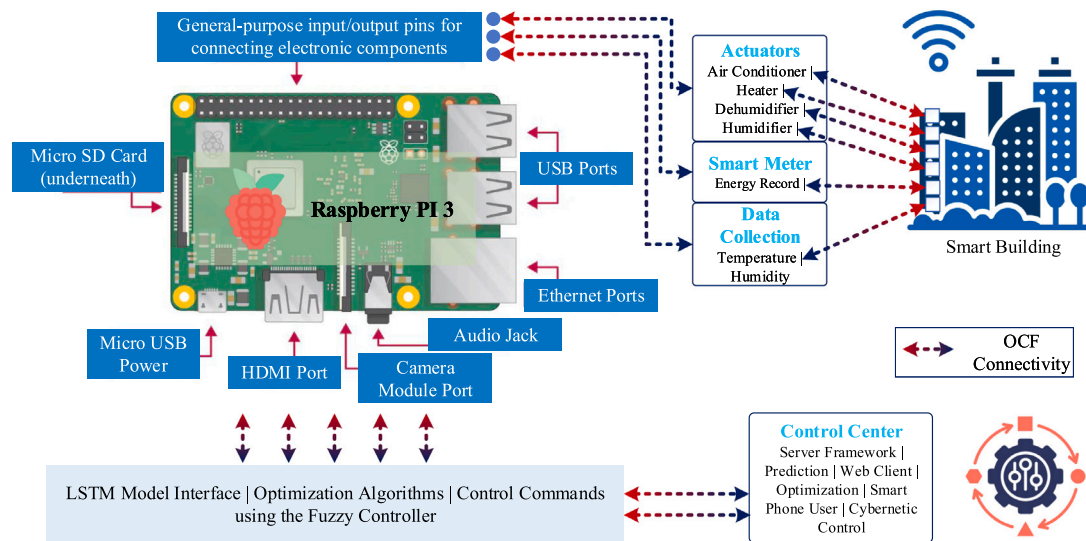


Fig. 1. Conceptual model of the mechanism for energy cost optimization.
Source: Adopted from Khan et al. (2024).

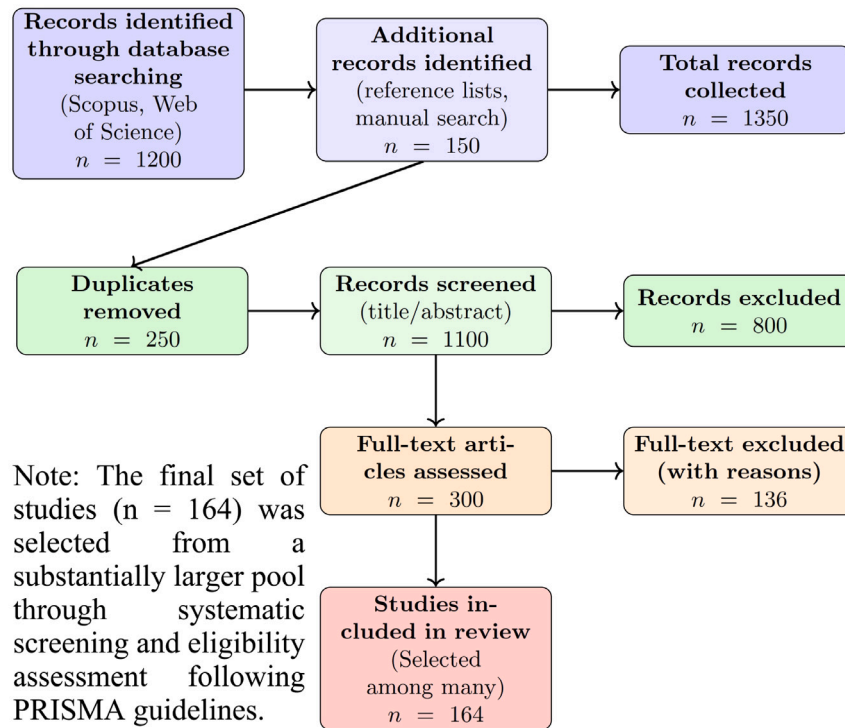


Fig. 2. PRISMA flow diagram for inclusion as well as exclusion criteria.

China is the largest contributor and cooperating center, followed by the UK, Canada, South Korea, Singapore, India and the Netherlands. The visualization reveals a significant degree of cooperation between the rich economies and less from many emerging economies. The network of co-occurrence of keywords is displayed in VOSviewer as shown in Fig. 4. The other most popular research themes are “Energy efficiency” and “ML”, followed by “AI”, “DL”, “RL”, “HVAC systems”, “Thermal comfort”, “Energy management”, “SBs”, “Building automation”, and “Green buildings”. Clustering demonstrates the research fields regarding intelligent energy optimization, occupant comfort, predictive control, RL, indoor environmental quality and sustainable building operation.

2. Smart buildings technologies and components

Sustainable development in the building industry has enabled the integration of natural resources through interdisciplinary knowledge and the implementation of appropriate management systems, thereby promoting socioeconomic development and environmental balance. The products of the built landscape are manufactured using the most efficient ways to optimize energy consumption, recycle raw materials, and achieve a carbon-neutral and ecological environment, exemplifying the application of technology in the construction industry (Ejidike and Mewomo, 2023). For SBs to meet building development goals like energy efficiency, lifetime, comfort, and satisfaction, flexibility

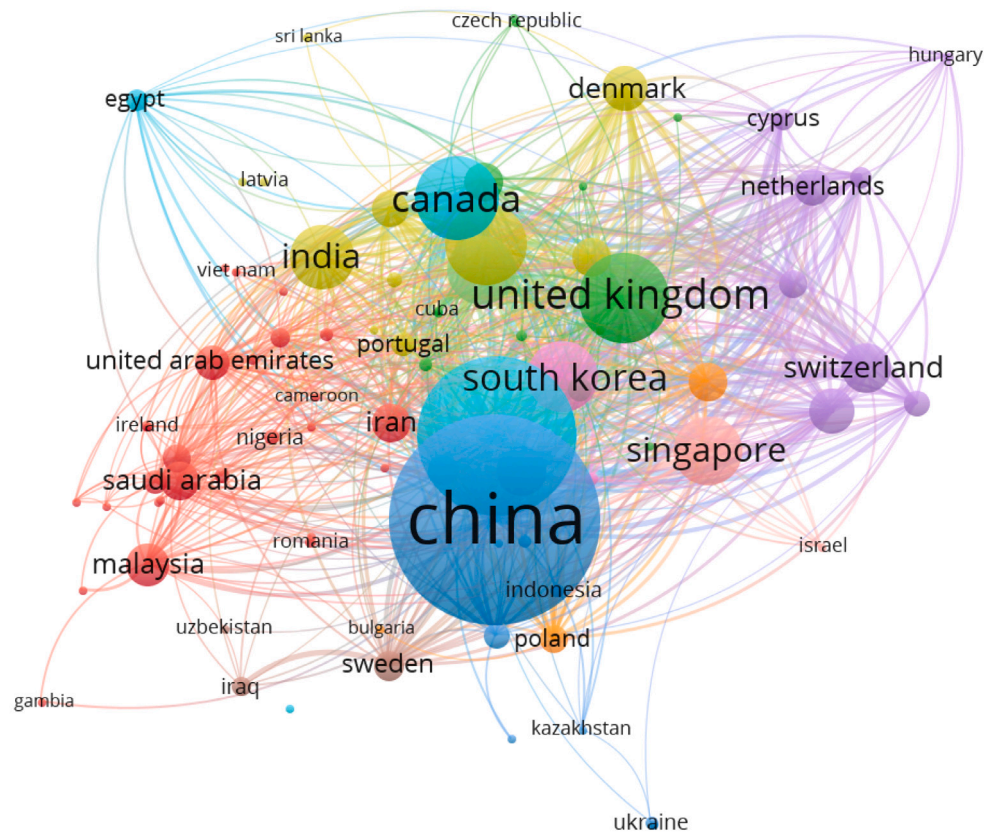


Fig. 3. Countries contributing to research on ML for SB energy management.

is more important than responsiveness. They combine construction, materials, control, commercial operations, and information into a single system. As these systems evolve, the SB might be able to adjust by collecting and evaluating additional data from several sources. As new infrastructure is developed and sophisticated data processing, artificial intelligence, and control systems are integrated, SBs are established (Arun et al., 2025b). Smart technologies are essential for enabling buildings to react to internal building requirements, such as human needs, and external variables, such as the climate and grid. SBs are almost zero-energy buildings that can adjust to shifting grid conditions and climate conditions while achieving primary energy reductions of 30% to 80%. It should employ a BEMS to forecast operational faults and communicate with users. While reducing grid interaction to 10% to 30% on an hourly basis over the year, it should allow load shifting in accordance with RES generation and electricity pricing by 30% to 70% yearly. Additionally, it should cover 20% to 70% of the load using RES each year and permit 30% to 70% RES self-consumption (Dakheel et al., 2024).

A key element of a SB is the smart lighting system, which uses sensors and IoT devices to automate lighting in response to occupancy and daylight levels (Z. Liu et al., 2025). These devices, often coupled with daylight sensors and occupancy sensors, guarantee that the lights are only on when absolutely needed, thus saving energy (Shankar et al., 2025). The other key element is the HVAC (heating, ventilation and air conditioning) system, which controls indoor conditions. Smart controls allow HVAC systems in SBs to monitor and regulate humidity, temperature and air quality according to specified criteria and real-time information. Machine learning can be used to optimize energy consumption while maintaining occupant comfort in HVAC systems. Smart meters can increase energy efficiency by directly communicating with the utility company using demand response and time-of-use pricing. In SBs, this granularity of data is crucial to energy savings.

Building automation systems (BAS) serve as a SB's control center. The BAS links the subsystems, such as lighting, HVAC, security and metering, on a single screen with real-time monitoring and control (Qiang et al., 2023). BAS systems coordinate the building systems to improve energy efficiency and enhance building performance through automation of the routine operations and providing valuable information (Morales-Gonzalez et al., 2024). The optical properties of solar radiation absorption by buildings can be modified by electrochromic (EC) smart windows based on the weather and user preferences. In recent years, dual-band electrochromic smart windows (DESWs) are becoming advanced due to the capability to control low-voltage visible (VIS) and near-infrared (NIR) light separately. There are four modes of operation for these devices: "warm", "cool", "dark", and "bright". In green cities, DESWs are a key component of low-carbon buildings because of these benefits (Qin et al., 2024). Traditional buildings mostly use stand-alone devices and manual processes to control basic features like security, HVAC, and lighting. The majority of tasks in traditional systems require human intervention because they do not function autonomously. If automation is available, it is not dynamically responsive and is limited. Traditional buildings require technical know-how and hands-on operation for maintenance and optimization. These systems typically require reactive maintenance, only discovering issues after failures have occurred (e Habiba et al., 2024).

Conventional building construction and maintenance are estimated to represent between thirty and forty percent of world power use and emissions of carbon dioxide in the built environment. In the built environment, sustainable construction methods have so far contributed to some degree of improvement. Both industrialized and developing nations have adopted several sustainable construction methods. SB technology (SBT), modular construction, information modeling, and green roofs and buildings are some examples of these sustainable practices (Ejidike and Mewomo, 2023). Computers and cell phones may

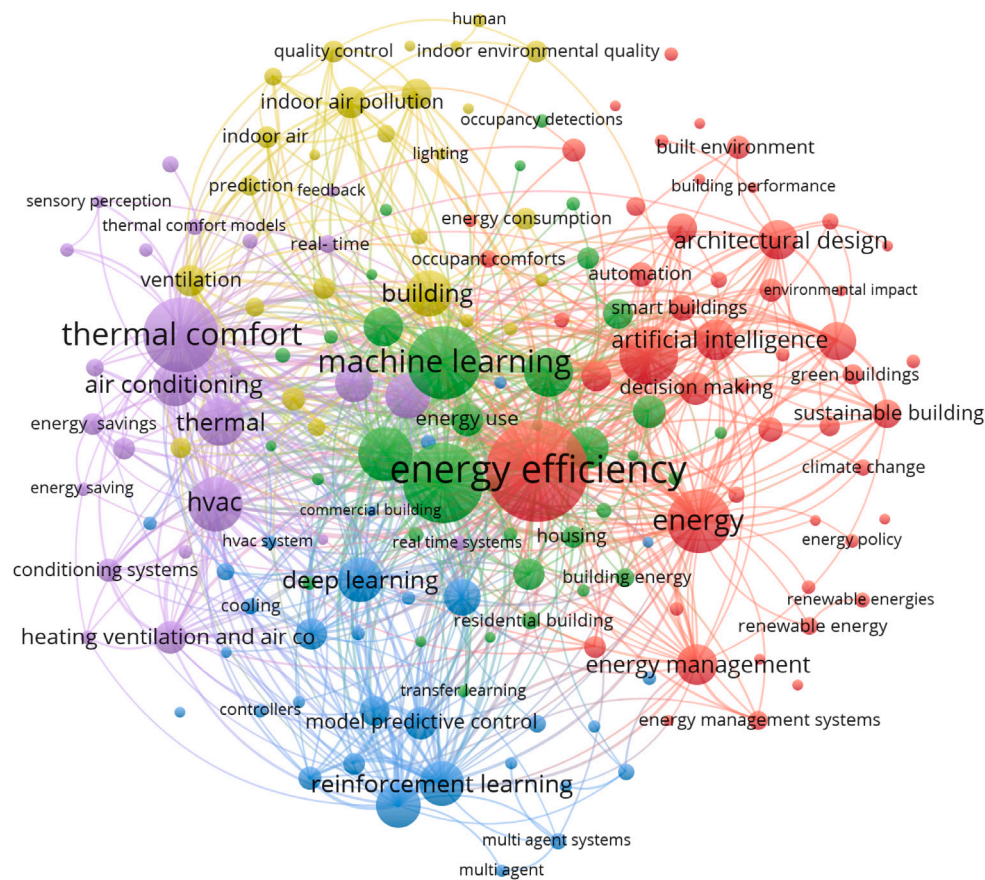


Fig. 4. Keyword co-occurrence network generated using VOSviewer.

significantly streamline tasks like basic maintenance, interior climate control, and security monitoring in “intelligent” buildings. Buildings that are intelligent establish connections between their different components. As the Internet of Things (IoTs) concept gains traction, smart grids are being incorporated into larger networks more and more (Aazami et al., 2025). The usage of artificially intelligent buildings in recently constructed buildings is a relatively recent concept. Furthermore, the greatest energy management offered by recently created technologies such as AI algorithms and other associated facilities has assisted in the creation of AI buildings (AIB) (Arun et al., 2025b). SB platforms use cutting-edge technology like AI, data analytics, and the IoT to establish a unified building management system (Khan et al., 2025). These platforms provide a single solution for tracking and improving building performance by enabling connected devices to exchange data, communicate, and automate tasks. Smart platforms gather information from several building systems, including security, water management, HVAC, and lighting, and use it to identify inefficiencies, forecast maintenance requirements, and automate processes (Baduge et al., 2022). Integration of various components with AI is shown in Fig. 5 (Baduge et al., 2022). Additionally, they facilitate the incorporation of renewable energy, assisting buildings in meeting sustainability standards and objectives.

Smart platforms can significantly save long-term costs by increasing operating efficiency and averting expensive malfunctions. The energy savings alone frequently justify investing in these systems. Advanced monitoring, access controls, and emergency response capabilities are all part of smart systems. A prompt reaction to building crises or security concerns is ensured via real-time monitoring. Large volumes of data are gathered and analyzed by smart platforms, which then produce actionable insights that assist building managers in allocating resources, performing maintenance, and making modifications. Applications of AI

for the building construction sector are broadly categorized into six sections. Design optimization, construction, project management, smart building systems, safety and security, and sustainability as illustrated in Fig. 6 (Cai et al., 2025).

SBs are the fundamental components of smart cities (Castanho et al., 2025) and are crucial to assessing how well they function. With better durability, cost savings, comfort, and overall satisfaction, SBs are a more advanced version of intelligent buildings (IBs); they improve on traditional buildings by using advanced control systems and automating linked parts. By enabling communication between an SB's systems and devices, the IoT makes it possible to utilize web-connected gear, remote controls, and networked sensors effectively. Without constant human interaction to perform automated tasks, an SB can learn to predict the building's future states by examining the environment and tenant behavior (Peiris et al., 2023). The construction of green or intelligent buildings has increased due to the many advantages they provide. Simultaneously, experts have identified several artificial intelligence techniques that are relevant for these structures, aiming to rationalize, optimize, and innovate their functioning. There is a great deal of promise for increasing structural stability and reducing adverse ecological effects on the ecosystem and society through the integration of AI techniques with green and SBs (Rodríguez-Gracia et al., 2023).

IoT, a platform for wired and wireless sensor networks that combines a wide variety of heterogeneous devices, is one of the main technologies raising the automation and intelligence levels of modern SBs. IoT provides services to intelligent scenarios in various contexts, effectively managing communication, software, and hardware resources to reduce expenses in a particular area. Consequently, it is feasible to expand the capabilities of SBs and make efficient computations using the real-time data about the environment they generate (Lavrinovica et al., 2024). Enhancing the system-level flexibility of buildings to

Table 1
Comparative analysis of the proposed review with recent studies.

Ref.	Year	AIM	AD	KC	EG	OC	AC	CYB	DT	RTF
Aghili et al. (2025)	2025	AI/ML	HVAC Optimization	AI-driven HVAC optimization for energy efficiency	✓	×	✓	×	×	✓
Panchalingam and Chan (2021)	2021	AI Systems Review	Security & Comfort	Review of AI applications for occupant safety and comfort	○	✓	×	×	×	×
Billanes et al. (2025)	2025	Heuristic Algorithms	Energy & Business Strategy	Market-oriented heuristic optimization	✓	×	×	×	×	×
Alsafery et al. (2023)	2023	Machine Learning	Occupant Comfort	ML techniques for improving occupant comfort	×	✓	○	×	×	✓
Almusaed et al. (2023)	2023	Big Data, IoT, Robotics	AEC/Smart Buildings	Industry 6.0 technologies for SBs	✓	○	○	×	○	○
Ullah et al. (2025b)	2025	AI, Digital Twins, 6G	Smart Infrastructure	AI-enabled digital twins with 6G communication	✓	×	✓	○	✓	✓
Al-haimi et al. (2025)	2025	Modular Systems, Cybersecurity	System Design & Security	Secure modular smart building architecture	×	×	○	○	×	✓
Qiu et al. (2025)	2025	IIoT, CPS	Industrial Smart Systems	IIoT and CPS for industrial automation	✓	×	✓	○	○	✓
Pourzolfaghar et al. (2026)	2025	AI-driven Threat Detection, IoT, Edge Computing	Smart Construction Cybersecurity	Reviews cybersecurity challenges and AI-enabled secure-by-design frameworks	×	×	○	×	○	✓
Duan et al. (2026)	2025	Data-driven & Stochastic Models	Building Energy Simulation	Systematic review of occupant behavior modeling and simulation tools	✓	✓	○	×	×	○
Szmelter-Jarosz (2026)	2025	Data-driven Energy Management	Smart Cities/Energy Management	Reviews energy-efficient policies, adaptive governance, and digital infrastructure	✓	○	○	×	○	○
Álvarez-López et al. (2026)	2025	ML, RL, Multi-Agent Systems, IoT-Edge-Cloud	Distributed Energy Management	Reviews explainable AI, federated learning, and distributed energy intelligence	✓	×	✓	○	×	✓
Proposed Review	–	AI, ML, Cybernetics	Integrated SBs	Comprehensive review integrating AI, energy management, occupant behavior, adaptive control, cybernetics, digital twins, and real-time feedback	✓	✓	✓	✓	✓	✓

Note: ✓ = Fully addressed; ○ = Partially addressed; × = Not addressed; AI Method = AIM; Application Domain = AD; Key Contribution = KC; Energy = EG; Real-Time Feedback = RTF; Digital Twin = DT; Cybernetics = CYB; Adaptive Control = AC; Occupant = OC.

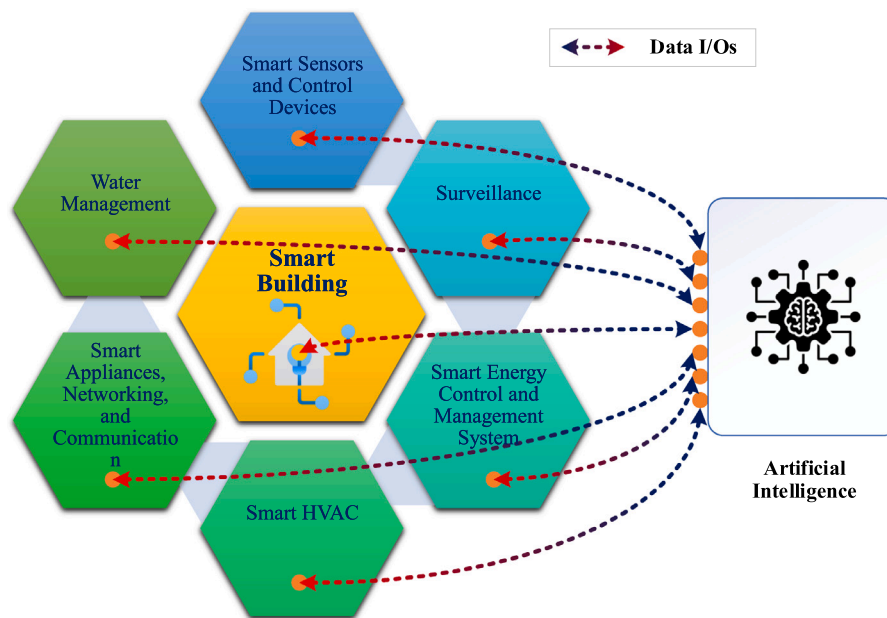


Fig. 5. SB Components with AI Integration.

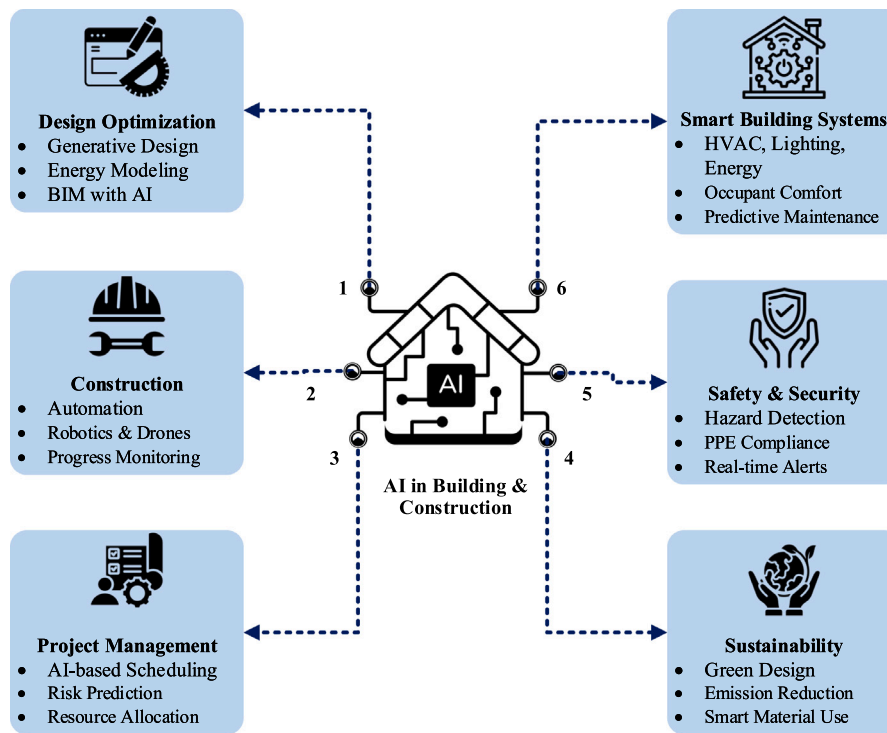


Fig. 6. AI application domains in the building and construction sector.

unforeseen changes and utilizing DTs for training environments could both be beneficial. Future aspirations for SBs include making sure residents are comfortable and easy to use. Relevant details must be extracted from the vast amounts of streaming data produced and captured by SB devices and appliances to provide quick response and better decision-making (Alanne and Sierla, 2022). Thermal cameras, pressure sensors, smart meters, current transformers (CTs), and leak detection sensors are components of SBs. Surveillance cameras (IP cameras), smart door/window sensors, glass break sensors, smoke and fire detectors, and carbon monoxide detectors are examples of sensors used in SBs. Smart thermostats, variable air volume (VAV) controllers, duct dampers and motorized louvers, dimmable LED lights with wireless control, motion-activated lighting, Energy-efficient refrigerators, ovens, coffee machines, automated vending machines, connected elevators for traffic flow optimization, Biometric readers (fingerprint, facial recognition), smart locks and turnstiles, license plate recognition cameras, space availability sensors, and EV charging stations with networked status reporting are also parts of SBs. Fuzzy logic allows for flexible and adaptable decision-making by taking into account linguistic factors and fuzzy rules, which facilitate the modeling and management of complex systems. The suggested system may successfully adjust to a number of variables affecting energy usage, such as customer preferences, meteorological conditions, occupancy patterns, and energy pricing, by utilizing fuzzy logic approaches (Alghassab, 2024). The system can compute and modify interior temperature in real time using a sensor data fusion technique and an electrical energy variable acquisition algorithm, and it can give precise measurement results (Li, 2025). Table 2 summarizes research work done in the field of AI-driven SBs.

3. AI and machine learning for intelligent smart building operations and energy optimization

Climate change's unexpected operational changes threaten building-integrated energy systems' resilience, flexibility, and efficiency. However, rapid ML and AI progress has enabled structures to learn. AI training with ML algorithms is a major trend (Amangeldy et al., 2025). Because their environment is complex, "reinforcement learning (RL)"

and "deep reinforcement learning (DRL)" have helped autonomous construction networks. Analyzing AI's function in constructing research suggests that learning aims fall into five categories: checking the system's state, forecasting changes, altering how it operates, processing data, and connecting with people.

Table 3 illustrates how AI training can improve BAS performance across many functions using the classification (Alanne and Sierla, 2022). AI picks parameters and control variables to adapt to the operating environment and independently activates control operations. The five kinds of RL applications for intelligent buildings are listed in Table 4 "Application". Table 4 describes each application category using the four core RL system components: training environment, state, action, and reward. Smart building surveillance systems with person identification features use AI algorithms to identify and track people, improving security. Automation of temperature and lighting systems to match occupancy and ambient conditions saves energy. Managing energy-saving projects in SBs highlights challenges such as identifying inefficiencies, optimizing energy use, and ensuring occupant comfort (Oulefki et al., 2025). AI's potential to be employed in several building life-cycle stages and inside construction industry 4.0 has boosted its utilization in the building sector. Previous reviews have focused on the use of AI in various life-cycle stages and energy efficiency (Yussuf and Asfour, 2024). Fig. 7 shows SB learning system applications.

ML approaches can be classified various ways. Many classify ML models by how much supervision they receive during training. Fig. 8 illustrates three ML model categories: SL, unsupervised learning, and RL (Baduge et al., 2022). A dataset with outcomes, labels, and predictors is SL. Supervised ML model training begins with the labeled dataset. The learnt ML model may make conclusions about unknown data. Unsupervised learning finds internal structures or hidden patterns in unlabeled datasets (Shi et al., 2025). RL trains ML models using rewards and penalties for desired and unwanted actions. Reinforcement learning agents observe and respond in ways that will reward or punish them. The objective is to find the best policy by maximizing rewards over time (Khan et al., 2025). Researchers have used RL to improve system flexibility, regulate indoor comfort, and optimize energy costs (Shen et al., 2025). ML systems can regulate lighting, heating, and

Table 2
Summary of Recent AI-based Approaches in literature for SB.

Authors	Reference	Input data	Control objective	Performance outcome
Xie et al.	Xie et al. (2025)	Sensor + fire data	Fire prediction	Real-time fire detection improvement
Arun et al.	Arun et al. (2025b)	Policy, system data	Decision support	Improved planning and policy efficiency
Hassan et al.	Hassan et al. (2025)	Climate + building data	Thermal comfort optimization	Improved comfort and energy efficiency
Haghighat et al.	Haghighat et al. (2025)	Energy system data	Energy optimization	Enhanced interpretability and efficiency
Han et al.	Han et al. (2025)	System architecture data	System modeling	Reduced complexity and improved modeling
Habib Sadri	Sadri (2025)	BMS + DT data	System integration	Improved security and data management
Behnam et al.	Mohseni-Gharyehsafa et al. (2025)	Energy consumption data	Energy optimization	Improved prediction accuracy
Teixeira et al.	Teixeira et al. (2025)	Solar + façade data	Energy-efficient glazing	Improved thermal and energy performance
Shapi et al.	Shapi et al. (2021)	Energy usage data	Energy prediction	Higher prediction accuracy using ML models
Bai et al.	Bai and Tan (2024)	HVAC + IAQ data	Multi-objective optimization	Improved comfort and energy efficiency
Boutahri et al.	Boutahri and Tilioua (2024)	Thermal + energy data	Energy prediction	Improved prediction performance
Tahmasbi et al.	Tahmasbi et al. (2025)	Façade + climate data	Energy efficiency	Enhanced façade performance
Gundogdu et al.	Gundogdu et al. (2024)	Lighting + occupancy data	Lighting control	Energy savings and improved visual comfort
Alghassab et al.	Alghassab (2024)	Energy demand data	Energy optimization	Reduced peak demand and improved efficiency
Hu et al.	Hu et al. (2025)	Load + clustering data	Load forecasting	Improved forecasting accuracy

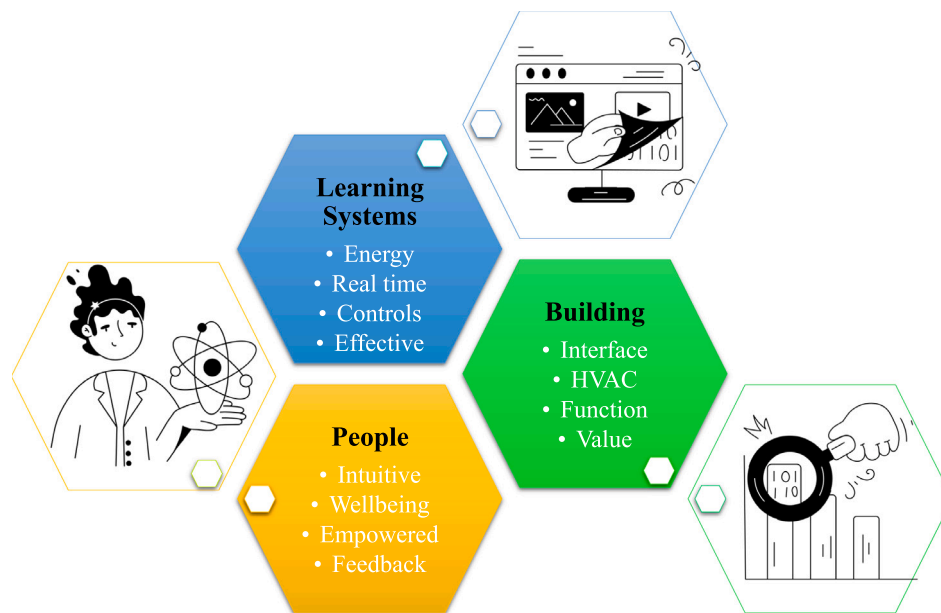


Fig. 7. Implications of ML and AI in SBs.

Table 3
Developments in BAS Resulting from AI Training.

Feature	AI training	Remark	Advantages
Observe	Anomaly Identification (Alsafery et al., 2023)	AI frameworks are designed to oversee detectors, recording devices, and building components in actual time, identifying anomalous trends.	Accelerated issue authentication, enhanced security, ongoing surveillance.
Predict	Estimation Analysis (Al Sayed et al., 2024)	AI forecasts projected demands, including energy consumption, HVAC efficiency, and spatial usage, by analyzing previous information.	Decreased operating expenses, anticipatory problem-solving, enhanced resource distribution.
Adjust	Optimization of Nonlinear Systems (Fernandez et al., 2025)	AI modifies building infrastructure (lighting, HVAC, etc.) in current time according to occupancy, meteorological conditions, or resource consumption habits.	Enhanced comfort, less power usage, enhanced operating economy.
User Cognitive Engagement	Intelligent Interfaces, Customization (Makanadar, 2024)	The use of AI facilitates more intelligent user screens, such as speaking commands, by responding to human needs for lighting, climate, and other factors.	Augmented user interface, individualized control, heightened efficiency.
Information Handling	Computerized Information Acquisition (Alijoyo, 2024)	The use of AI streamlines the aggregation and synthesis of varied sources of information, providing instantaneous observations and assessment.	Enhanced decision-making, improved productivity, and more precise prediction algorithms.

Table 4
Developments of ML in BAS.

Implication Domain	RL Approaches	Objectives	Advantages
HVAC	Meta-RL (Al Sayed et al., 2024)	Enhance the power performance of the HVAC plant while preserving comfort standards.	Decreased resource usage, enhanced comfort, and adaptive modulation according to occupancy.
Lighting Control	Fuzzy Inference (Vashishtha et al., 2024)	Modify lighting according on occupancy, temporal conditions, and the accessibility of daylight.	Resource conservation, increased lighting efficacy, elevated ease for users.
Power Scheduling	Neuro-fuzzy (Ahmed et al., 2023)	Regulate energy usage in accordance with demand by controlling electric vehicle loads.	Decreased energy expenditures, enhanced energy efficiency, improved load prediction.
Buildings safety mechanisms	Multi-agent (Sun et al., 2024)	Augment the facility's safety by proactively identifying and response to security problems.	Enhanced security, immediate danger response, upgraded surveillance systems.
Fault Recognition and Diagnostics	MPC (Andersen et al., 2024)	Identify anomalies or defects in facility systems and implement automatic repair measures.	Accelerated failure identification, enhanced system dependability, reduced downtime.

cooling in SBs using real-time sensor data to boost energy efficiency. Modern energy monitoring and regulation technologies limit human involvement, lowering costs and environmental effect (Nikpour et al., 2025).

AI can develop and create high-quality materials and composites that consider these characteristics. Additive manufacturing, or 3D printing, with ML algorithms is changing computer-based and intelligent production. AI approaches may be more beneficial with 4D printing, allowing items generated through 3D printing to adapt to environmental stimuli like temperature, light, and heat Islam et al. (2025). AI has enhanced risk management, project success predicting, and progress monitoring in construction (Khan et al., 2025). All these connected gadgets generate vast volumes of data, called Big Data (BD). The most popular BD category is IoT-Big Data. Small sensing devices with limited resources are wirelessly connected in wireless sensor networks (WSNs). Cloud computing allows WSN nodes to shift by continually collecting measurements from several sites (Arun et al., 2025a).

ML and DL need data to train models. The accuracy and adaptability of models depend on a good dataset. The majority of effort for ML/DL model deployment is spent on dataset preparation, including collection, cleaning, analyzing, visualizing, and feature engineering (Berkani et al., 2025). This section briefly discusses building and construction ML/DL data collection methodologies. Connection to a data acquisition system is required. IoT embeds smaller, cheaper, and more energy-efficient sensors into everything to perform intelligent analysis, assessment, and administration in a cloud-based system. These sensors are connected to the internet via data exchange and communication protocols. Spectroscopic imaging and camera sensors can record discrete wavelength energy reflected from objects. After measuring reflected wave energy, chemometrics approaches can identify the substance based on its chemical properties (Martinez et al., 2025). Several prediction approaches and algorithms are analyzed and compared to enable the system to automatically do several jobs utilizing IoT devices spread across the building and appropriate modules. RL and heuristic algorithms like PSO and GAs are used to forecast and dynamically change energy use. ML models like LSTM networks and SVMs are utilized in smart homes to anticipate energy usage patterns and control load scheduling (Li, 2025).

The two most popular supervised tasks are regression and classification in ML. Regression tasks predict a continuous value, while classification tasks predict a discrete class label. Neural networks, linear regression, logistic regression, SVMs, and k-Nearest Neighbors are a few of the popular supervised learning algorithms (Afaq and Akram,

2025). Occupancy estimates and energy usage forecasts are done using linear or logistic regression (Bakar et al., 2024). In electrical or HVAC systems, SVMs are utilized to detect anomalies. Decision trees and random forests are employed in predictive maintenance and FDD (Ahmad et al., 2014). KNN is used to model occupant behavior or classify environments. To find hidden patterns or underlying structures in data, unsupervised learning uses an unlabeled dataset. An ML technique called reinforcement learning uses rewards for good actions and penalties for undesirable ones to train the ML model. In response to real-time data (temperature, occupancy), Q-learning/deep Q-networks are used to optimize HVAC settings, illumination control, etc. MPC supplemented with RL is ideally suited for modifying building systems while taking future states and restrictions into consideration (Djenouri et al., 2019).

AI technologies, particularly DL, have advanced significantly recently in their ability to learn from data and create new ideas. This advancement sets AI technologies apart from traditional expert systems and biologically inspired algorithms. Using ML algorithms to gain insight from data and create new content, generative AI design has been named one of the top ten technological trends (Assareh et al., 2025). DL, a branch of ML, utilizes multiple layers of computational components, including neural networks. MLP (Multi-Layer Perceptron), CNN (Convolutional Neural Network), GAN (Generative Adversarial Network), RNN (Recurrent Neural Network), LSTM, and RBFN (Radial Basis Function Network) are the most commonly used algorithms in deep learning. Often referred to as Multi-Layer Perceptrons (MLPs), feedforward neural networks (FNNs) are a popular DL approach that only allows input to flow forward without any feedback. The CNN is a special kind of artificial neural network (ANN) (Zhang and Ph.D., 2025) that can handle data with a grid-like structure. The majority of CNNs uses are in computer vision and image classification (Mehraban et al., 2025). Fig. 9 displays the various domains of AI (Baduge et al., 2022). Another well-liked deep generative technique is Variational Autoencoder (VAE). The VAE is a type of autoencoder that regularizes the distribution of encodings during training. An encoder, a decoder neural network, and a latent space make up an autoencoder. In order to attempt to recreate the original features, the decoder reverses the process by which the encoder converts old features to fresh feature representations in the latent space. The data is used to train an autoencoder, and an iterative optimization procedure is used to find the optimal encoding-decoding method (Dissem et al., 2024). ANNs and CNNs, as well as RNNs, train their algorithms using a dataset.

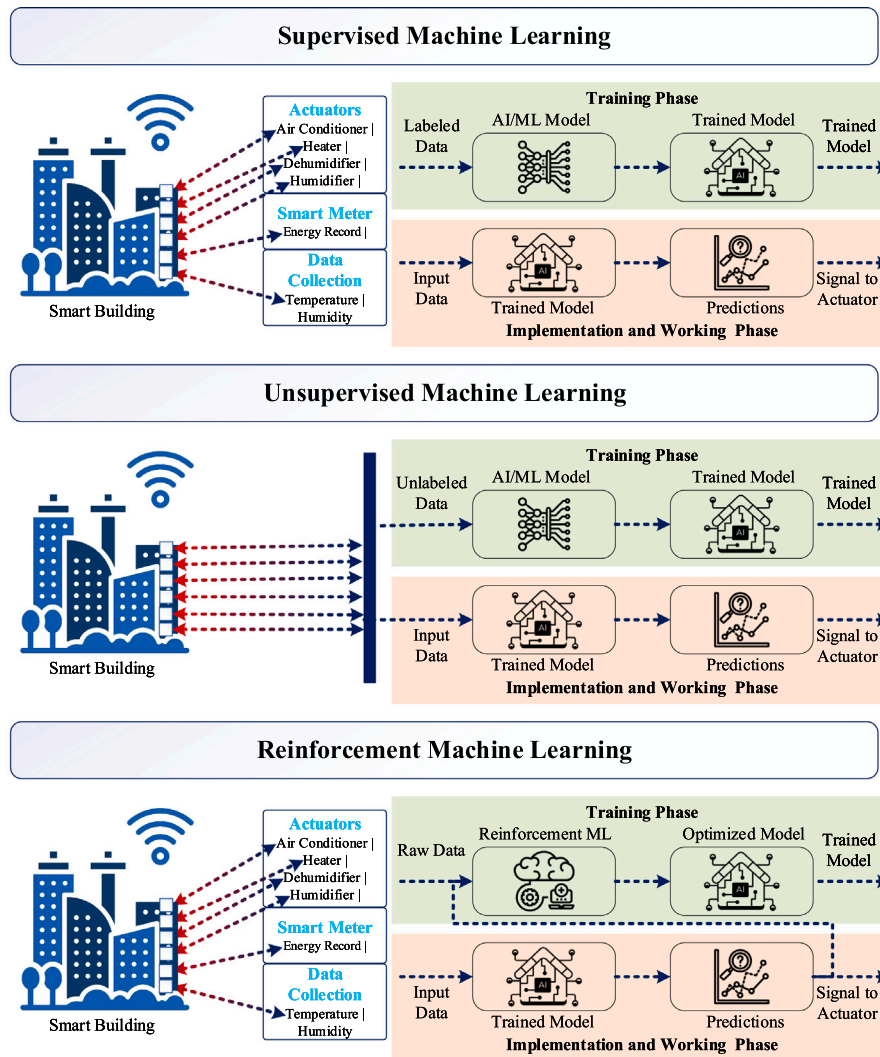


Fig. 8. Classification of learning techniques in SBs context.

RNNs, as opposed to ANNs and CNNs, use previous inputs to affect the network's current input and output. Additionally, there are other variations of RNN that have been applied in construction, including GRUs, bidirectional RNNs, and LSTMs. Automated generative layout of architectural components, including facades, interior design plans, floor plans, and building masses, has been transformed by GANs (Wan et al., 2025). Different AI models vary in effectiveness depending on the SB application. LSTM/RNN excel in time-series forecasting, SVM/KNN in classification and anomaly detection, while reinforcement learning is suited for real-time control like HVAC optimization.

The principles of cybernetics can offer a guiding framework to comprehend AI-based SB systems. The concept of feedback is achieved by sensor-based data loops that constantly update system states in AI models like RL and model predictive control. The adaptability is obtained through ML algorithms that dynamically modify the control strategies according to changing environmental conditions and the behavior of occupants. Predictive analytics and fault-tolerant control mechanisms help create resilience to allow systems to stay stable in the face of uncertainty and disturbances. SB systems formalize cybernetic concepts by employing concrete AI control architectures as mentioned in Table 5. The feedback mechanisms are applied through continuous sensor data streams as parts of ML and reinforcement learning models, which allow real-time updates in states. Learning-based controllers, including RL and adaptive MPC, enable adaptation of system behavior in response to changes in the environment and occupants. Predictive

analytics and fault-tolerant control strategies contribute to resilience to ensure the stable functioning in the case of uncertainties. This system level diagram illustrates that cybernetics can become practical on the framework of AI-driven SBs out of a theoretical notion.

SB AI-controlled systems vary in maturity. Most solutions are still in simulation, but pilot implementation in controlled labs and small-scale, full-scale deployment in real buildings have been shown (see Table 6). This classification helps us assess AI-based HVAC and lighting system readiness and scalability. These systems should communicate with central or decentral AI controllers to optimize energy use, human comfort, and system operation. Occupancy can affect HVAC and lighting control, and renewable energy can dynamically control load scheduling. With feedback control systems and adaptive control techniques, this system-wide approach emphasizes system-level coordination for integrated and efficient building operation.

3.1. Predictive models for energy consumption

Predictive energy consumption models anticipate how much energy a system will consume over a given time period (Ahmed et al., 2023). DBNs, RNNs, ANNs, and CNNs are only a few examples of NN approaches used to forecast energy consumption and reduce the demand/supply gap. Predictive modeling approaches that forecast HVAC usage can assist these active control systems. This enables adaptive system modifications that depend on environmental data, resulting

Table 5
Summary of AI/ML Algorithms Used in Smart Building Applications.

Algorithm	Type	Application domain	Key function
ANN	ML/DL	Energy, HVAC	Nonlinear modeling and energy prediction
CNN	DL	Surveillance, Fault Detection	Image-based monitoring and anomaly detection
RNN/LSTM	DL	Energy, Occupancy	Time-series prediction and dynamic modeling
SVM	ML	Fault Detection	Pattern recognition and classification
KNN	ML	Occupant Behavior	Similarity-based classification
Decision Tree/RF	ML	Maintenance	Fault detection and decision analysis
RL/DRL	RL	HVAC, Energy Control	Adaptive control via reward-based learning
Fuzzy Logic	Hybrid	HVAC, Comfort	Rule-based decision-making under uncertainty
MPC	Hybrid Control	Energy Systems	Predictive optimization using system models
GA/PSO	Optimization	Energy Scheduling	Load and energy optimization

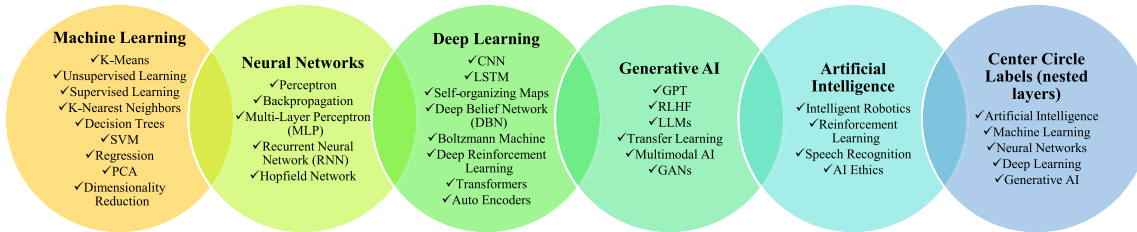


Fig. 9. Classification of AI domain in SBs applications.

Table 6
Deployment Maturity of AI-based HVAC and Lighting Systems.

Study	Domain	AI method	Deployment level
X. Gao et al. (2026)	HVAC	RL/MPC	Simulation
Erbay and Icier (2009)	HVAC	Fuzzy/ML	Pilot-scale
Zhu et al. (2021)	HVAC	Hybrid AI Control	Full-scale
Kong et al. (2025)	Lighting	ANN/Optimization	Simulation
Seth et al. (2025)	Lighting	Sensor-based Control	Pilot-scale
Huang et al. (2025)	Lighting	Smart Control Systems	Full-scale

in increased energy efficiency as well as overall performance (Rätz et al., 2019). Alternative approaches, such as using neuro-fuzzy, neural, and Bayesian networks, can produce better results than linear modeling techniques. NNs can be used to control energy usage with outstanding precision and ease of implementation. NN models offer viable alternatives to sequential regression models for understanding energy consumption trends and projecting energy use. The NNs-based utilization model accurately predicted cooling consumption without overfitting, utilizing relatively simple parameters such as (i) cooling area, (ii) operational temperature, (iii) operating average temperature, (iv) outdoor humidity, and (v) building age. This demonstrated the NNs's ability to characterize cooling demand without the use of complex input parameters, relying on data from local meteorological stations, integrated inside sensors, and building designs (Vergés et al., 2024). A hybrid approach that combines Agent-Based Modeling (ABM), System Dynamics (SD), BIM, and ML techniques forecasts energy usage in various indoor layout configurations such as rectangle, square, and compound shapes. This hybrid model (ABM-SD-BIM) emphasizes creating a complete and exact dataset. In general, hybrid approaches are usefulness, particularly in compound-shaped configurations, in accurately estimating energy usage in diverse indoor layouts (Uddin et al., 2025).

The Deep Energy Predictor Model (DEPM) is used to increase the reliability and performance of power usage projections. This unique hybrid model merges the classification characteristics of XGBoost with the DL abilities of DNN. The model employs sophisticated feature mining techniques, such as Cascaded ResNet, to identify intricate patterns

within the data. The DEPM, implemented in Python, achieves precision of 0.97, 98% accuracy, recall of 0.99, and F1-score of 0.98, marking a new standard for energy forecasting models. The findings showed that DEPM has the potential to considerably improve the dependability of electricity consumption projections, making it a useful instrument for energy planning and management (Ragupathi et al., 2024). Another MPC technique combined an encoder-decoder LSTM model along with an online learning optimizer to forecast future energy usage, IAQ, temperature, and relative humidity (Ellis and Chinde, 2020). The multi-variable regression model precisely predicted annual cooling requirements, achieving a R^2 of 0.98, a MAPE of 1.59%, and a CVRMSE of 1.47%. Adjusting the indoor temperature set-point offered yearly utility savings of up to 70 kWh/m², leading to a possible decrease in carbon emissions of 31.5 kg CO₂/m²/year, predicated on a regional power pollution rate of 0.45 kg CO₂/kWh (Sha et al., 2025). A novel soft computing-based bi-Objective Evolutionary Mating approach was developed to tackle the fundamental challenges of optimizing the comfort index and energy usage in SB systems. MOEMA provides a strong foundation for managing the delicate balance between comfort index and energy usage of a smart building's, outperforming NSGA-II by 0.03% and consuming 10.65% less energy (Nordin et al., 2025). Linear Regression, ARIMA (Auto Regressive Integrated Moving Average), SARIMA, SVM, Gradient Boosting Machines (XGBoost, LightGBM), ANN, back-propagation neural network (BPNN), RNN, CNN, LSTM, Decision Trees (DT), GA and RF are some other predictive models used for energy consumption prediction.

3.2. Adaptive HVAC control systems

Adaptive HVAC control systems comprise intelligent systems that modify heating, cooling, and ventilation functions in real time depending on variables such as occupancy, weather, and user preferences. These technologies are designed to improve efficiency in energy use and comfort and reduce operating costs. The construction of a multi-indicator adaptive HVAC control system entails physical environment-triggered adjustments to ventilation system parameters of the digital environment operation, as well as digital environmental control response to the physical environment. Zhang et al. (2023). A novel method is employed to minimize interference and perturbations that affect the operational precision and efficiency of complex HVAC systems, integrating RL with active interference rejection approach. A

primary controller employs a twin delayed deep predictable policy gradient for the regulation of zone supply airflows, while an auxiliary controller utilizes active disturbance rejection control to manage the fresh air ratio, addressing perturbation issue. The EnergyPlus-Python co-simulation platform, utilizing real-world data, demonstrates that the AD-RL technique enhances indoor comfort and IAQ. Additionally, it has the potential to reduce daily HVAC power usage by as much as 22.37% and 13.53%, respectively (Cui et al., 2025). The power consumption of HVAC systems is influenced by various factors, making it difficult to determine the extent of their Demand Response (DR) capacity. A valid DR capacity evaluation approach is built around gray-box models (Ambroziak and Borkowski, 2025). This approach uses a stochastic approach to predict HVAC utilization benchmark phases and an adaptive analogous thermal variable model to calculate realistic DR capacity periods. The intervals can depict the nonlinear relationship between numerous uncertainties and DR capabilities. To estimate the baseline intervals, a probabilistic model is suggested that combines a temporal convolutional network with ensemble quantile regression. In addition, an adaptive analogous thermal component model is used to estimate the DR capability at various regulatory levels and confidence levels (Jiang et al., 2025). The Weather-Adaptive Fuzzy Control (WAFC) technique enables the HVAC system to successfully adjust to changing environmental circumstances by adaptively aligning indoor conditions with exterior temperatures and humidity levels. The Fuzzy Logic Controller (FLC) analyzes a control variable to establish optimal setpoints while balancing energy consumption and occupant comfort. The WAFC is compared to a standard fixed setpoint strategy, and the results show that the WAFC greatly reduces heating and humidifying demands, especially in high air change per hour situations. Weather-adaptive setpoint control considerably improves the ecological viability of HVAC processes, making it a feasible solution for improving energy efficiency for urban settings (Safdari et al., 2025). ADNM optimizes the simulation framework calibration coefficients to reduce the error between anticipated and measured results in a short computing time. ADNM produces an initial simplex using the Sobol sequence and prior optimal solutions to reduce objective function robustly under changing operating conditions. This novel method, tested with real HVAC data, reduces temperature inaccuracies by 60%–70% compared to the standard NM algorithm and 10%–60% compared to Bayesian optimization (BO), while consuming the same computation time. The GA technique had less errors but took three to six times longer to calculate, highlighting the ADNM approach's better accuracy and effectiveness (Lee et al., 2025). The model-free adaptive control (MFAC) approach is intended for multi-zone climate control and includes controller design, parameter estimates, and a reset mechanism to ensure system performance. Model validation demonstrates that the MFAC hybrid model's zone climate prediction agrees better with real measured data. The step response results indicate that the hybrid model-based MFAC can enhance multi-zone climate control by reaching the desired conditions more quickly without any consistent errors. In comparison to prior studies, the dual model-based MFAC demonstrates enhanced capability to align with real-world scenarios in economical multi-zone climate management. Adaptive-predictive control methods (APCS) appear highly successful for regulating heating and cooling in residential and commercial buildings, as they may autonomously alter and enhance performance in response to unforeseen changes or malfunctions. APCS employs online optimization via a dynamic system model to determine an optimal pattern of variables as inputs to reduce the prediction error for future values of an objective function (Jiang et al., 2023).

3.3. Lighting control and optimization

Lighting is a significant consumer of power in architecture, accounting for around one-third of total power consumption in commercial structures and much more in office structures. Numerous ways have

been created to increase potential by implementing control systems to regulate the light control and optimization. It has been observed that an increase in natural light directly reduces energy consumption for lighting. However, if there is a proper balance of insulation with solar gains, it may lead to increased thermal demand, which could negatively impact cooling needs (Chiesa et al., 2020). Installing new lighting control systems that use sensor data (like occupancy and light sensors), advanced structures (such as wireless and network systems), and smart control methods (like artificial intelligence and optimization) can greatly lower energy use (Shankar et al., 2025). The lighting controls can be divided into three types: controller-based, optimization-based, and hybrid. An effectively designed illumination system can optimize energy conservation while ensuring optimum visual comfort for building residents. Light technologies also contribute to energy efficiency in workplaces, with LED being a significant energy-efficient light that has superior photometric efficiency and greater controllability than other lamps (Z. Liu et al., 2025).

There are two types of sensing-based illumination system control strategies: occupancy-based and illuminance-based (Wagiman et al., 2020). Passive infrared (PIR) sensors are used in occupancy-based control for occupant identification due to their simplicity and cost. WiFi occupancy detection has also used RFID tags and mobile devices (MDs) in addition to PIR sensors. Switch-on/off (OOF) and dimming control systems exist. Control schemes focus on on-off control and continuous control. The EN12464-1-based ODM scheme dims artificial lighting based on passenger status. Additional illumination controllers include PI, PID, ANN, FL, adaptive, Q-Learning, and model-based control (Wagiman et al., 2020). Implementing building lighting control systems has shown greater potential for energy savings than retrofitting lighting with more energy-efficient options like LED, T8, and T5 lamps. A building lighting control framework can be developed by installing switches, dimmers, and scene settings in addition to time organizing, group control, occupancy adaptation, daylight harvesting, personal control, demand response, and a combination of occupancy and daylight adaptation. Additionally, modern smart control tactics include wireless distributed lighting control systems and power-over-ethernet (POE) centralized lighting control systems (Roisin et al., 2008; Shen, 2019). Illuminance control is a realization of a sensing-based control strategy, such as a steady illuminance control strategy (CICS), which may control the illuminance level while taking into account the lighting system's age. When the illuminance level is too high, the system reduces the lumen output of the lights. If the illuminance is too low, the system will boost the lighting's lumen output. Daylighting is one of the key parts of building design and lighting control strategy, according to EN12464-1 (Baharudin et al., 2021). A control system is designed for regulating the lighting control system's dimming levels. This system compares the light performance to other approaches, with results demonstrating superiority in terms of the total number of sensors and the optimum sensor position. Additionally, it provides substantial savings in energy of up to 30.8% and suitable visual comfort in accordance with the European standard EN12464-1 (Feyzi and Mojallali, 2024).

3.4. Integration of RESs in smart buildings

Renewable energy (RE) is being promoted as the main pathway for future sources of energy owing to its long-term viability and carbon neutrality potential (Ahmad et al., 2025). One important trend in the development of BES is the large-scale integration of RE sources, including solar thermal, photovoltaic, and wind power (Ahmed et al., 2025a). These technologies lower the cost of energy supplies while also replacing fossil fuels. RE outputs, however, are erratic and intermittent by nature (Ahmed et al., 2025b). The utilization of renewable energy in structures has become essential in the contemporary construction industry to attain environmentally friendly growth (Shu et al., 2026). To mitigate the sporadic nature of renewable energy supplies, energy storage systems are being integrated into buildings to facilitate a reliable

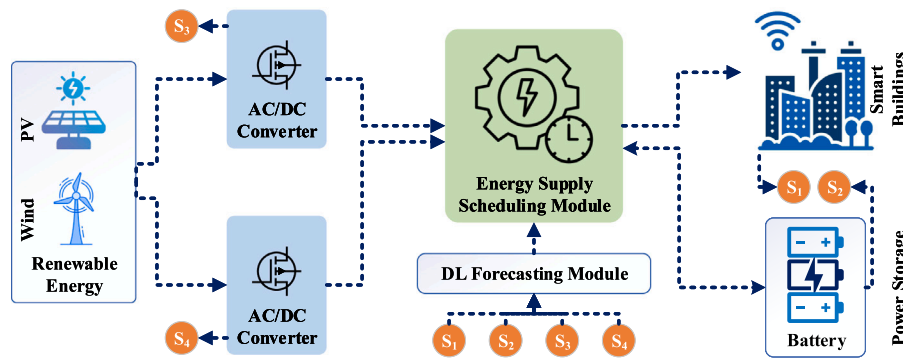


Fig. 10. Architecture of RE integration in SBs.

and efficient renewable energy provision (Luo et al., 2025). Reducing emissions in the construction sector requires a larger proportion of RE for BES, which is essential to supporting global efforts towards carbon neutrality.

Hybrid energy storage (HES) systems provide better financial viability and regulatory potential than single ESUs, which makes them more appropriate for increasingly complicated BES. Energy flow transitions and interactions become more complex when HES is added, which presents significant difficulties for BES development, layout, and optimization management. A hybrid system that combines FNN with the Falcon Optimization Algorithm (FOA) assures efficient data navigation, resulting in increased energy usage and network lifetime. This system also has a strong key management mechanism that uses the Advanced Diffie–Hellman (IDH) algorithm (Vignesh and Jeyanthi, 2025). A bi-level stochastic method is given for the integration of storage systems with high adoption in isolated 100% green microgrids. In the initial level, each SB utilizes its operational scheduling system to communicate its intended supply of power to the microgrid; in the subsequent level, the microgrid operator formulates its operational strategy model, considering all SB requests. The results indicate that storage solutions enhance the daily profit of small businesses by 95%. The data also demonstrate that DR as well as building-to-grid capability boost SBs' daily profits by 43.8% and 164%, respectively (Wang et al., 2025a). Fig. 10 depicts the generic architecture of RE integration in SBs.

Combining AI-controlled systems with energy storage systems pose a number of operational challenges. These are the uncertainty in renewable energy production, which makes it hard to make decisions in real-time, and the coordinated control strategies between the storage units and building loads. Moreover, AI controllers may suffer due to the latency of data and communication, and heterogeneous devices may not be seamlessly integrated due to interoperability problems. Stability of systems, scalability and robust functioning under changing operating conditions are critical issues of practical need in deployment.

4. Enhancing occupant comfort through AI

4.1. Occupant behavior modeling and prediction

With rapid scientific advances towards net-zero energy targets, occupant behavior is a major driver of building sustainability. Stochastic models, statistical analysis, data mining and agent-based models are used to model occupant behavior in public buildings. RL is now being accepted as a way of modeling occupant behavior. The application of RL in occupant behavior modeling lays the groundwork for improving the indoor environment as well as energy efficiency in public building operations (Piselli and Pisello, 2019). An agent-based modeling (ABM) approach dynamically predicts interactions in shared office spaces between occupants, HVAC systems, illumination, and IoT-based control techniques. This approach explicitly incorporates behavioral elements

into energy models, such as occupant choices and social interactions (Wang et al., 2026), in order to more accurately capture the complexities of human-building interactions. IoT-based control techniques can reduce total energy use by incorporating the occupants standard and energy-conservative behaviors. Adopting options aligned with occupant preferences can enhance energy consumption while maintaining satisfaction and ease of use. The framework consists of three major steps. Modeling occupancy operations, such as resident mobility and presence (Yu and Xu, 2024). The input system integrates the likelihood of occupant resource consumption behavior in region, better reflecting real-time and intricate linkages between energy, occupants in buildings. The prediction system has a better balance of time and precision (Zhang et al., 2024). To analyze typical behavior patterns and forecast occupant behaviors, data-mining models including logistic regression, K-means clustering, DTs, and XGBoost were widely used. However, significant limitations of data-mining-based models remain, such as their static nature and inability to simulate the adaptive and unpredictable aspects of occupant trends, as well as their inadequate applicability and dependency on databases.

Probabilistic models and Markov chain modeling are frequently utilized in the development of unpredictable occupancy scenarios. For generating accurate occupant behavioral trends, it is essential to ascertain the probability range of characteristics when employing predictive models. Stochastic models for simulating interactions of occupants with the built environment can account for extreme variability and combinations of human behavior, as well as their effects on building devices (Gao et al., 2025). AC, windows, and fans are integrated using a FMCDM model for occupancy behavior modeling. Fuzzy VIKOR and survival analysis predict many devices' usage priority and time. AC, window, and fan ventilation techniques provide more accurate and objective occupant behavior and energy consumption predictions than single-device OB models (Luo et al., 2023). Blind control models (BC-OBMs) in building performance simulations showed a 73.8% preference for closed blinds. The BMLR and RF models demonstrated substantial correlations between blind usage and contextual variables, achieving preciseness of 0.847 and 0.734, respectively. This enables architects to make precise early-stage designing assessments without BPS instruments (Chen et al., 2025). The high-resolution shading occupant behavior (HRSOB) model, which takes into account how many people are in a space, how easy it is to use shading, and uses data analysis methods, sorts different ways people use shading and can be added to building controls that focus on the occupants. Markov chain models for occupancy considerably increase their reliability in predicting stochastic shading behavior. Information-driven methodologies, such as feature selection and soft participating in elections facilitate analysis, train, and apply shading behavior data, as well as rigorously evaluate and validate the HRSOB model. The HRSOB framework outperformed the usual shading occupant behavior (SOB) model by 10.92% (Verma et al., 2025).

The occupant behavior model is essential for the measurement and attainment of indoor comfort through quantitative indices. Traditional

Table 7
Relationship between occupant behavioral modeling approaches to measurable comfort indices.

Occupant behavioral techniques	AI technique	Comfort index	Energy management application	Findings
Occupancy prediction (Sarker et al., 2025)	Machine learning, Deep Learning, LSTM	PMV, PPD	Predictive HVAC scheduling and lighting control	Lowers energy waste and preserves thermal comfort.
Occupancy pattern forecasting (Maheepala et al., 2025)	LSTM, GRU, Time-series learning	PMV, Adaptive comfort	Predictive energy demand and ventilation control	Promotes HVAC functioning by predicting occupancy changes and reducing energy usage.
Occupant activity recognition (Abderrahim et al., 2025)	CNN, Computer Vision, Sensor fusion	Adaptive comfort	Dynamic HVAC and ventilation adjustment	Adapts indoor environments to occupant behaviors to improve efficiency.
Occupant preference learning (Almadhor et al., 2025)	Reinforcement Learning, Preference learning	Personalized comfort metrics	Personalized HVAC temperature and airflow control	Thermal tolerances and energy efficiency are balanced.
Occupant feedback integration (Onweh et al., 2025)	Supervised learning, Online learning	Personalized comfort indices	Continuous HVAC optimization	Enhances user contentment by utilizing adaptive learning to account for thermal demands.
Human-in-the-loop control (Karjou et al., 2025)	Reinforcement Learning	PMV, Personalized comfort	Multi-objective HVAC optimization	Concurrently optimizes occupant comfort and reduces energy utilization.
Behavior-aware demand response (Lin et al., 2026)	Machine learning, Optimization algorithms	Adaptive comfort	Demand response and load shifting	Maintains occupant comfort while reducing peak electricity demand.
Digital Twin-based behavioral modeling (Walczyk and Ozadowicz, 2026)	Digital Twins, AI, IoT	PMV, Adaptive comfort, Personalized comfort	Real-time building operation and predictive maintenance	Provides continuous optimization of building energy performance and occupant comfort using virtual building replicas.
Multi-zone occupant modeling (Frahm, 2025)	Deep Learning, Multi-agent systems	PMV, Zone-specific comfort metrics	Zone-level HVAC optimization	Accounts for diverse occupant preferences across different building spaces, improving comfort and reducing energy use.
Context-aware behavioral modeling (Alotaibi, 2025)	Edge AI, IoT analytics	Adaptive comfort, Personalized comfort	Real-time environmental control	Supports autonomous decision-making based on occupancy, weather conditions, and indoor environmental parameters with low communication latency.
Wearable-assisted comfort prediction (Mendes et al., 2026)	Deep Learning, Sensor analytics	Personalized thermal comfort metrics	Personalized environmental control	Utilizes physiological and wearable sensor data to provide individualized thermal comfort while avoiding unnecessary HVAC operation.
Multi-objective behavioral optimization (Zhang and Kong, 2025)	Evolutionary algorithms, Reinforcement Learning	PMV, Adaptive comfort, Personalized comfort	Integrated energy-comfort optimization	Optimizes energy efficiency, occupant comfort, and operational cost simultaneously under dynamic building conditions.

indices, such as the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD), are used to calculate the static thermal comfort index. Adaptive comfort indices are used to measure the dynamic adaptation of occupants to their environment. AI-based occupant behavior models, such as RL and ML, can be used to predict occupant preferences and the potential to control environmental factors in real-time. Additionally, sensor data and user feedback can be employed to forecast personal comfort, as opposed to static indices and dynamic human-centered control systems. Table 7 systematically links the behavioral modeling approaches to measurable comfort indices reported in literature. It also shows that predictive ability should not be the only consideration when evaluating occupant behavioral modeling; its ability to maintain a quantifiable state of interior comfort while minimizing energy consumption should also be measured. Traditional assessment of thermal comfort has been based on the ISO 7730 indices, such as PMV and PPD. ASHRAE Standard 55 and EN 16798 recommended adaptive comfort models are more representative of naturally ventilated structures because they account for occupants' acclimatization to outside climate conditions (Ma and Liu, 2025). Personalized comfort models have recently emerged that have been incorporated into artificial intelligence and are based on the input of individual comfort requirements, as well as on wearable devices and IoT sensors. Combined with behavioral prediction, comfort measures enable AI-based energy management systems to optimize HVAC use through multi-objective decision-making, improving the energy efficiency of HVAC systems while increasing occupant comfort.

4.2. Personalized comfort settings and adaptive systems

Personalized comfort solutions, as opposed to traditional whole-space heating and cooling, can target individual needs while also reducing building energy use (Chen et al., 2024). Comprehending human thermal perception is essential to building comfortable and cost-effective spaces. Thermal Comfort Prediction Model with LSTM (TCPM-LSTM) networks, a dynamic deep learning framework, is combined with RL to model and forecast individualized thermal comfort in various scenarios. Using RL with a trained LSTM (TCPM-LSTM) instead of RL without an LSTM enhances the average reward by approximately 13.6%. This framework exhibits more steady learning behavior, with less reward fluctuation across the episodes, making it an effective tool for individualized comfort management (Li et al., 2025). The individuals' thermal comfort improved dramatically when they employed the six-air-nozzle, indicating that the air jets have a favorable cooling impact. Air drafts in the individuals' upper legs, as well as warmth in their chest and face, were the most important factors in their comfort sensations (Abdulraheem et al., 2025).

A non-skin interface portable gadget is integrated with an incorporated thermal comfort prognosis algorithm to enhance the accuracy of thermal comfort forecasting in buildings. The model improves device convenience by estimating skin temperature as well as moisture and then using these as input variables in the thermal comfort prediction algorithm by application of beluga whale optimization (IBWO) algorithm.

This method increases the reliability of thermal comfort estimates while decreasing computational resource requirements. In real-world office setting tests, the individuals' average thermal comfort forecast accuracy approached 98% (Schmeling et al., 2025). The performance of a hybrid personalized system (HPS), which combines main and personalized ventilation, is adjusted to ensure occupant-centric air quality, energy efficiency and thermal comfort in built environments (G. Liu et al., 2025). To enhance the precision of individualized climate forecasting, a hybrid thermal comfort framework is developed by integrating a mathematical framework with ML methodologies, so uniting the generalization ability of the mathematical model with the self-learning potential of ML. This model considerably simplifies the measurement by monitoring simply wrist skin temperature, indoor air temperature, and related periodic fluctuations, enhancing forecasting reliability by an average of 21.11% and up to 44.45% compared to the PMV system. The hybrid model beats the independent ML model by as much as 24.45%. The model displays strong performance and the potential for practical use in construction contexts (Fernandez et al., 2025).

The economical thermal comfort management mechanism efficiently collects and synthesizes temperature comfort information gathered by intelligent sensing hubs and digital surveys, enabling the development of customized thermal comfort characteristics. This technology can be employed for extensive thermal comfort assessments, for creating customized thermal comfort designs, and for administering individualized comfort technologies (Yang et al., 2025). PICO (Personalization-Integrated Co-Optimization) is a novel occupant-centric control system that aims to reduce power expenses (by scenario-based pricing) includes a punitive clause based on the occupants' stochastic personalized comfort frameworks. This system can adapt to various conditions, increasing operational efficiency. We demonstrated that PICO boosts peak time productivity by up to 18.37% across multiple realizations by combining energy financial reserves and user satisfaction indicators into an energy productivity measure (which quantifies the comfort improvement per unit of power used) (Geck et al., 2024; Warthmann et al., 2025). Co-zyBench is a unique benchmarking tool that uses Digital Twin (DT) technique to evaluate tailored thermal comfort provisioning systems. It uses a simulation-based DT over the building itself and its HVAC system, second DT to simulate the fluctuating actions of its occupants, and collaboration middleware to ensure that the DTs work together seamlessly. It comprises procedures for generating DTs using data like architectural models of buildings, sensor measurements, along with occupant temperature sensation data. It also contains reference DTs for standard buildings, HVAC systems, and different occupant thermal profiles (Meimand and Jazizadeh, 2024).

4.3. Real-time feedback and environmental adjustments

Real-time Feedback is information that is delivered immediately or almost immediately in reaction to an action, circumstance, or input. It enables speedy decision-making or correction. Meanwhile, environmental adjustments are modifications made to an environment, either automatically or manually, in response to feedback or changes in conditions. The merging of DTs and NNSs, utilizing the potential of ZigBee-enabled wireless sensor networks, is an innovative solution to real-time temperature regulation for smart homes. Integrating these devices offers a robust and efficient approach for live temperature regulation in smart residences, resulting in notable improvements in both convenience and resource efficiency (Ma et al., 2025). Table 8 presents the comparative analysis of NN and hybrid approaches, contrasting important features in the context of DTs.

The deployment of an end-to-end data healing pipeline contributes to more precise energy usage, higher occupant comfort, and improved building operations. All of these enhancements support the broader aims for sustainability as well as energy efficiency for SBs (Teng et al., 2025). Unstructured text, encompassing tenants' qualitative opinion

regarding indoor environmental quality, may provide us with significant insights into the fundamental causes of comfort as well as dissatisfaction within buildings. Feedback can be obtained by open-ended questions in surveys, interviews, or crowdsourced data. The Bidirectional Encoder Representations from Transformers (BERT) design automates the identification as well as classification of unstructured Indoor Environmental Quality (IEQ) feedback, refining it using human annotated IEQ text input. The IEQ-BERT methodology can be employed independently or with building automation systems to identify actions and trends in occupant input, emphasize areas for improvement, and assist in the development of customized IEQ strategies (Stefanopoulou et al., 2025).

5. Cybernetics and AI integration for smart buildings

5.1. An overview of cybernetics

SBs are often built on the basis of automation and control along with communication systems and their architectures (Carli et al., 2017). The study of combined communication systems with control strategies has emerged as an interesting area called cybernetics (Wang et al., 2009; Ciftcioglu and Bittermann, 2025). This field employs various computation techniques to implement control systems. These control strategies apply computations for design and for implementation to ensure decision making tasks. The role of AI and ML is challenging in both the design and implementation of these strategies. As control strategies are implemented over a network environment, the consideration of communication strategies and architectures is an integral part of SBs. Consequently, this section covers central and distributed automation strategies in the mentioned buildings. Then, we address the communication mechanisms for use in SBs. Another challenging issue in cybernetics is cyber-security (Ding et al., 2020; Ren et al., 2022), which arises on combining the control and network environments. In addition to the traditional issues related to cybersecurity, AI-based SB systems present new sophisticated threats related to learning-based architectures. Adversarial AI attacks have the potential to alter sensor readings or model behavior, resulting in wrong control measures in sensitive systems like HVAC and safety monitoring. Although federated learning allows decentralizing the training of models and enhancing their privacy, it poses several issues such as model consistency, communication overhead, and susceptibility to distributed attacks. Moreover, data governance such as data ownership, access, and regulatory compliance are paramount because of the ongoing gathering of occupant and operational data. To overcome these issues, it is necessary to have strong security models, learning methods that do not compromise privacy, and uniform data management strategies to guarantee reliable implementation of AI in cyber-physical SB systems. In cyber-security, we can apply two strategies: First, we can construct secure software, which does not allow tempering. Second, we can attain resilient strategies which can be robust or adaptive to tackle the cyber-attacks in the event of software tempering.

5.2. Centralized and distributed AI control systems

The distinction between distributed and centralized AI control networks depends on the way AI decision-making and data processing are organized within a system. A single central unit or node handles every decision-making as well as data processing for centralized autonomous control systems. Deciding and processing are shared among numerous independent nodes for distributed AI control systems, which frequently operate both locally and collectively. The heightened functional advantages of a distributed AI network may encompass integrated AGI, an internationally accessible commons facilities worldwide stakeholder engagement, and democratic governance (Sadick and Chinazzo, 2025; Zheng et al., 2026). Compared with centralized ordered control, decentralized distributing control techniques can (i) react to disruptions

Table 8
Comparative analysis of NN and hybrid approaches in the context of DTs.

Feature	NNs technique	Hybrid techniques	Performance outcome
Aim	Forecast patterns using historical data	Integrates modeling with real-time prediction	Hybrid improves accuracy and control efficiency
Architecture	Pattern-based DL models	NN + DT integration	Hybrid enables real-time system representation
Information Usage	Relies on historical data	Uses real-time + historical data	Hybrid improves adaptability
Framework Intricacy	Less complex	More complex	Hybrid provides richer system modeling
Calibration	Requires large datasets	Uses real-time updates	Hybrid improves calibration accuracy
Precision	High but static	Higher with real-time updates	Hybrid achieves better accuracy
Flexibility	Limited adaptability	Real-time adaptation	Hybrid supports dynamic control
Temporal Efficiency	Affected by variability	Real-time response	Hybrid improves responsiveness
Energy Performance	Dependent on prediction quality	Optimized via real-time control	Hybrid improves energy efficiency
DTs Implication	Used for prediction	Integrated with real-time DTs	Hybrid enhances DT performance
Scalability	Limited in real-time systems	Highly scalable	Hybrid supports large-scale deployment

faster, boosting the efficiency of the system using limited resources; (ii) ensure the stability of the system, particularly when a fault develops and certain distributed energy resources are cut off from the main network; and (iii) promote greater adoption of DERs within the system, having lower computational complexity along with scarce communication networks. Distributed AI (DAI) is being stimulated by technology advancements in communications, hardware, and networking, as well as the type of data provided by linked, distributed, and heterogeneous things. DAI is projected to provide a productive environment for creative, sophisticated, resilient, and scalable AI technologies that support the goal of smart societies (Montes and Goertzel, 2019; Hou, 2026). Examining the efficiency of Centralized Federated Learning (CFL) as well as Decentralized Federated Learning (DFL) for distributed forecasting of load reveals that DFL is more resistant to adversarial attacks and manufactured noise than CFL. Adversarial model poisoning assaults specifically harm the intended client using DFL, whereas CFL is more extensively affected. Artificial noise showed a less apparent influence on CFL than DFL. Decentralized Random Layer Aggregation (DRLA) could be used to strengthen DFL, providing more insights into enhancing FL techniques in the energy sector (Janbi et al., 2023). A comparison of centralized and distributed systems is given in Table 9.

5.3. Communication protocols in SBs management

The IoT serves as an evolving communication framework that facilitates an intelligent and dynamic environment by seamlessly connecting a vast array of devices for data transfer and transmission via the internet. Machine-to-machine (M2M) connectivity, radio frequency identification (RFID), and computing with context awareness constitute the innovations that comprise the IoT. Various wireless communication protocols generally used in IoT applications in SBs are LoRaWAN, WiMAX, ZigBee, NB-IoT, SigFox, RFID, BLE, Ethernet, and WiFi (Manzoor et al., 2024; He, 2025). Table 10 shows a comparison of different communication protocols applied in SBs. 5G-enabled IoT platforms and programs, encompassing enhanced mobile broadband (eMBB), ultra-reliable low-latency characteristics communication (URLLC), and massive machine-type communication (mMTC), are presently functional and demonstrate the capability to deliver future IoT services characterized by high speed, low latency, and improved energy efficiency. To support the full potential and attributes of future IoT, 6G networks with their associated technologies are predicted to provide higher quality of service (QoS) due to their superior characteristics over previous generations of networks. Because of the limits of current IoT-based

systems, advanced 6G technologies such as integrated sensing and communication (ISAC), ML, visible light communication (VLC), reconfigurable intelligent surfaces (RIS), and blockchain (BC) are preferable. These technologies integrate 6G abilities with smart building requirements such as human-device communication and energy efficiency with robust security (Avşar and Mowla, 2022).

With advances in next-generation communication technologies, huge-scale IoT device installations in SBs encounter issues such as restricted bandwidth, prolonged latency, and network traffic. A two-layer network architecture utilizing non-orthogonal multiple access (NOMA) is implemented to enhance the effectiveness, productivity, and security of IoT communications, establishing a robust foundation for prospective smart city deployments (Ullah et al., 2025a). Ethernet is a standardized LAN methodology that utilizes wired cables to connect gadgets for transmitting information, with speeds contingent upon the wire's type, making it optimal for short-distance data transfer. Wi-Fi is a wireless LAN that employs radio waves to offer network access for data transmission between computing devices. Wi-Fi has several advantages, including increased bandwidth, data rates, and transmission range. WiMAX is a microwave radio technology that connects computing devices with the internet. WiMAX has a longer transmitting range compared to Wi-Fi and thereby lowers interference.

ZigBee, an economical Wireless Personal Area Network (WPAN), is a sophisticated interface for communication designed for situations necessitating low signal transmission rates and minimal energy usage. ZigBee is presently the predominant mesh networking technology employed in infrastructure control and management. ZigBee offers several advantages, including affordability, reduced duty period, precise data transmission, simplicity attributed to its analog circuitry, ease of installation, and minimal power use (Guo et al., 2010). LoRaWAN is a novel communication protocol that is an open standard and intended for larger networks. In LoRaWAN, data is exchanged between devices and a central network server via gateways that are linked to the network server (Obiri and Van Laerhoven, 2024). RFID is a form of communication technology that identifies and tracks objects via radio waves. RFID comprises a tag affixed to an object for status monitoring, a reader to extract data from the tags and produce the corresponding indication, and an information system for data storage (Al-Doori et al., 2024). BLE is a low-power IoT communication standard designed primarily for battery-powered devices. The advantages of this technology include its low cost, availability on cellphones, and simplicity in deployment. BLE is predominantly utilized for locating functionalities in smart domestic and industrial structures, in addition to healthcare solutions. Xenakis et al. (2025).

Table 9

Feature of centralized and distributed AI control systems.

Domains	Centralized AI control system	Distributed AI control system
Advantages	- Ensures consistency with company objectives and principles. Corporations may centralize their AI strategy to optimize technology use and encourage the integration of new solutions. - Eliminates work redundancy and reduces expenses. A centralized AI decision-making hub may significantly enhance customer experience and decrease attrition. - Facilitates the exchange of ideas, data, and expertise among departments. The transition to an AI-centric enterprise involved strategic restructuring, cloud migration, and the integration of solutions into a unified shared service platform.	- Can address intricate circumstances by delegating tasks among several agents. Organizations may employ diverse AI agent systems to enhance product configuration, streamline workflows, and improve customer satisfaction. - In the event of a node's failure, other nodes might assume its tasks. - Realizes the whole capabilities of interconnected devices. - Enables rapid prototyping and enhanced alignment with business needs.
Disadvantages	- When the primary system malfunctions, it can disrupt the overall AI operation. - The system may have difficulties managing vast quantities of data and complex computations. - Centralized systems may exhibit the biases of the developer team. - Consolidating data renders the system vulnerable to privacy violations.	- It can be difficult to manage interactions between nodes. - Maintaining synchronization between dispersed systems can be difficult. - Overburdens infrastructures and causes latency concerns. - Distributed systems are prone to security breaches.
Adaptation	- Establishing an AI Center of Excellence may optimize operations, minimize redundancy, and concentrate on initiatives that provide substantial economic outcomes. - Integrate AI technology into their platform. - Building Firms engage in AI to enhance their operations rather than to acquire knowledge about it. Develop use cases that emphasize business roles and stakeholders.	- Employing edge AI technology for real-time adaptation and autonomous operation. - A synthesis of centralized foundations with decentralized creativity, utilizing public protocols for all stakeholders to govern the AI archetypes. - Incorporating digital transformation and AI into your routine operations and digital endeavors.
Governance	- Implementing rules and accountability frameworks to govern artificial intelligence ethics, data privacy, and security. - Establishing clear laws and criteria to guarantee ethical and responsible utilization.	- The advancement of decentralized AI systems to distribute power and foster creativity. - Involves establishing explicit regulations and criteria to guarantee ethical and responsible utilization.

Table 10

Communication Protocols used in SBs (Alkhaldi et al., 2024; Qays et al., 2023).

Protocol	Advantages	Limitations	Applications
LoRaWAN	- Enhance gateway capacity - Reduce interference - Support multiple data rates	- Inappropriate for real-time control systems - Restricted communication rates	Monitoring of power distribution (WAN NAN)
ZigBee	- Reduced prices - Lower power consumption	- Lower data rates - Narrow range - Interference-prone	- Building automation - Energy management (HAN)
WirelessHART	- Robustness; - Consistency	Absence of security guidelines	- Energy generation - Smart meters (HAN WAN)
Bluetooth	- Regressive compatibility - Minim power utilization	- Reduced data rate - Absence of security guidelines	Home automation (HAN)
NB-IoT	- Reduced cost, - Minimal complexity	- Reduced data rate; - Higher Latency	- Home automation - Advanced metering infrastructure (HAN and NAN)
BACnet	- Improved data exchange capabilities, - Enhanced network security	- Narrow bandwidth, - Complicated configuration	HVAC and Lighting control
KNX	- Interoperability, - Scalability	- Expensive hardware, - Complex setup	- Communication system - HVAC and Lighting control
Modbus	- Reliability - Simple, - Reliability	- Minimal security, - Limited bandwidth	- Home automation - Smart energy meters, - HVAC systems
Z-Wave	- Cost-effectiveness - Low interference	- No built-in security - Proprietary,	HVAC systems
Wi-Fi	- reliability - Mesh networking - Improved security - Enhance security	- low-latency - Network congestion - Not scalable for IoT - Susceptibility to hacking	- Home automation - smart appliances - High-bandwidth devices - Security & Surveillance

5.4. Cybersecurity considerations in SBs AI systems

Cybersecurity consists of measures designed to prevent malicious individuals from gaining unauthorized access to computers, networks, and data. AI, BD analytics, and the IoT are among the several components of SBs. However, SBs are vulnerable to cyber dangers comprising

the theft of information, and hacking operations. Information security concern, IoT networks, scarce resources, and essential infrastructure are among the particular difficulties and dangers that smart cities face. To ensure cybersecurity, stakeholders can take proactive efforts such as forming frameworks and collaborations, exchanging threat intelligence, and implementing incident response plans (Qays et al., 2023). From a

technological standpoint, there is a need for advanced security features that can function efficiently within the restricted resources of IoT gadgets while offering enough defense against various cyber-attacks (Hossain and Hasan, 2025). In response to escalating cyber risks, combining AI technology with cybersecurity is a good step forward, especially for SBs.

Anomaly detection is a vital AI application in cybersecurity that identifies odd patterns or behaviors that depart from the norm. AI/ML model can be employed in modern intrusion detection systems (IDSs) to detect anomaly-based attacks, but the difficulty of balancing both positive and negative results for effective threat detection remains (Ali et al., 2025a). AI algorithms may investigate large datasets from various sources, including sensor data, network logs, and user activity patterns, to identify potential vulnerabilities and assess the likelihood and impact of various cyberattacks (Xue et al., 2024). Fraud in the financial sector is a significant cybersecurity threat, inflicting financial harm and damaging the image of market entities, resulting in illegal data access and breaches, ultimately leading to financial risk. In order to avoid fraud detection, various ML algorithms are utilized, including a fraud identification model that utilizes a modified SVM classifier on multi-dimensional data. For instance, a fraud detection model has been employed via CNN in the work (Zeng et al., 2024). The false data injection attack (FDIA) is a prominent type of cyber-attack in which attackers introduce harmful data into controlling and measuring signals transmitted across the cyber sections (Gupta et al., 2025). A comparison of AI-based security approaches and their applications are summarized in Table 11.

Besides traditional cybersecurity issues, AI-based SB systems also pose new vulnerabilities that are unique to learning-based models. Training data may be compromised by model poisoning attacks resulting in wrong control decisions in building systems. Sensors can be spoofed and used to confuse AI models, which can cause disturbances in HVAC, lighting, or safety systems. Moreover, the occupant or operational information is exposed to threats of data leakage due to the continuous data collection and model training processes. Mechanisms to achieve secure training, anomaly detection, and privacy-preserving AI methods are needed to address these challenges to provide safe and reliable cyber-physical SB system operation.

6. Challenges and limitations

AI can improve security and identify intrusions, but it is also a prime target for hacker exploitation, cybercrimes, and privacy invasion. There is a risk of jeopardizing the safety of construction workers, potentially leading to fatalities or accidents. A security defense viewpoint and the requirement to create algorithms that can withstand sophisticated attacks are the driving forces behind the use of adversarial ML. More study must be done in this field, particularly on emerging technologies like computer vision and robotics that are being used in building research (Todorean et al., 2025). Cybersecurity risk management procedures should be implemented in conjunction with the smart city concept. A good communication network monitoring system created by such an application can lead to the early detection of threats, frauds, crimes, fires, and accidents. The integration of blockchain alongside other encryption techniques with AI can aid in the definition of asymmetrical behavior, the identification of threats, and the swift control of them in order to ensure data security inside SB systems (Abioye et al., 2021).

The gathering and handling of sensitive data such as occupancy trends, the environment, and personal preferences raise serious security concerns for residents. Implementing effective data anonymization technologies and obtaining informed consent from users are critical elements in data management that adheres to data protection regulations such as the General Data Protection Regulation (GDPR), California Consumer Privacy Act (CCPA), and Lei Geral de Proteção de Dados (LGPD), alongside other local legislation. To protect data integrity

and user confidence, strong security measures such as encryption, safe communication protocols, and regular security audits are required (Sharif and Pokharel, 2022). Building personnel should be taught so that they can handle AI-enabled technologies and spot any anomalies. Transparency, accountability, and bias are all key ethical concerns to keep in mind during the course of deployment. Promoting ethical AI methods will contribute to public trust. It is essential that they work with tech allies and specialists to take advantage of the latest breakthroughs and assure success during the deployment process (Hossain and Hasan, 2025). Software infection is synonymous with illicit software, which is designed to illegally collect users' personal data as well as digital wealth. The growing, concerning threat of malware is grouped into categories, complexities, and destructive powers that are stacked. Cybercrime and digital currencies processors have become increasingly prevalent threats (Ali et al., 2025a).

Facility executives and service workers may lack AI or data science skills, resulting in mishandling of AI systems or insufficient use of features; therefore, training, employing cross-functional teams, or adopting managed AI services can help to tackle this issue (Almulhim, 2025). The lack of common protocols as well as communication models prevents seamless integration of different building systems and components. Using intelligent components, tools, and specialized technical workers in SBs raises startup and construction expenses, which is particularly difficult for underdeveloped countries. Increased expenses encompass the start-up expense, capital expenditures, the cost of employing green power for sustainability-enhancing methods that depend on advanced technologies like the IoTs, as well as supplementary costs, including consultancy fees. Designing and project management practices and equipment come at a higher cost (Affonso et al., 2024).

Interoperability is the capacity of different IoT devices and systems to collaborate, regardless of producer, technology, or protocols. Standardization in the IoT refers to the adaptability and networking functionalities of IoT devices, including their interaction with control systems. It encompasses various levels, including device integration, information format synchronization, and seamless interconnectivity of services and applications across systems. The major concern in standardization in the IoT is numerous, including technical issues relating to the diversity of equipment and networks, as well as the necessity for universal protocols and standards to enable smooth communication. A typical instance is electricity trading applications, where buildings exchange energy to boost renewable energy generation (Hernández et al., 2024). IoT devices use a wide range of communication protocols, including Bluetooth, Wi-Fi, Zigbee, and LoRaWAN. The absence of homogeneity in these protocols complicates interoperability. Exchanging data across devices from various manufacturers increases the potential of unwanted access to sensitive information, raising major privacy concerns. Efficient power management is vital to interoperable IoT devices, particularly those that rely on batteries. Heavy power consumption because of frequent communication can reduce gadget effectiveness. The lack of defined protocols and frameworks among different manufacturers results in a fragmented ecosystem with compatibility difficulties (Dave and Mittapally, 2024). IoT systems should be scalable as the array of devices attached increases.

To summarize this section, a common security standard is necessary to ensure that all devices, regardless of vendor, follow the same security rules. In addition, as devices become increasingly networked, the attack space for possible threats grows. To balance security and interoperability, it is important to consider both the physical and digital levels of IoT connection. Scaling up entails not just technical overhead, but also large capital and operating costs, which can cause projects to be delayed or implemented partially. IoT interoperability can be improved by emerging technologies like edge computing and AI. Edge computing allows for local data processing, minimizing reliance on cloud platforms and improving real-time communication among IoT devices. AI can adapt and translate protocols and data types, enabling smooth device interaction in diverse situations.

Table 11
A Comparison of AI-based Security Approaches and their Applications (Ali et al., 2025a).

Technique	Key features	Strengths	Limitations	Applications	Communication networks applications
AD	Senses anomalies from standard trends	Detects unidentified hazards	High false positive rate	- Monitoring network traffic and - Detecting fraudulent activity	- Detecting anomalous behavior within the smart city infrastructure, - Finding corrupted IoT devices
Behavior Analysis	Monitoring users and entity behaviors	Context-based detection of threats	- Privacy concerns, - Extensive data requirement	- Detecting insider threats - User authenticity	- Analyzing device and citizen behavior for abnormalities - Enhance public safety.
ML	- Predictive analysis - Recognition of patterns.	Higher detection accuracy	Larger training datasets requirement	- Detecting Malware - Intrusion detection systems (IDS)	- Predictive maintenance of urban infrastructure - Traffic control systems.
DL	Neural networks for recognizing complex patterns	- Higher accuracy, - Large datasets handling	Computationally complex	- Advanced persistent threat (APT) detection, - Image recognition	- Real-time video surveillance, - Advanced traffic control systems
FL	Inclusive ML without sharing data	Safeguarding privacy	Communication latency.	- IoT device AD, - Distributed learning	Collaborative learning amongst smart city equipment while maintaining data privacy
RL	Learning the best solutions via error and trial	- Flexibility - Continual learning	Substantial training data requirement	- Autonomous networks - Active threat responses	- Optimize urban transportation - Adaptive energy control technologies.
TL	Utilizing data from one field to another	- Minimize training time - Enhances performance with minimal data.	Barriers regarding Domain Adaptation	- Cross-domain detection of threats - Model upgrading.	- Using pre-trained algorithms for new smart city projects - Improving security systems.
GANs	Generating synthetic data used for training	- Improve model robustness, - Detecting adversarial attacks	- Hard to train - Potential for producing harmful data	- Data enrichment - Adversarial training	- Developing synthetic data in smart city models - Enhancing the security model's robustness
GNNs	Analyzing structured data and links	- detecting complex network patterns, - Scalability	- Complex implementation requirement - Significant computing resources	- Network security - fraud detection	- Analyze smart grid systems - Detect irregularities in urban utilities.

7. Technological outlook

Smart robots, Cloud Virtual Reality (VR), Augmented Reality (AR), AI of Things (AIoT), DTs, 4D printing, and BC has been recognized as an especially potential AI-powered technology poised to control the future development market (Heidari et al., 2024). These technologies are now being extensively explored, and immediate usages in the construction industry are expected in the near future. Robotics is extensively employed in production and recycling industries. However, AI integrated robots may gain popularity in the construction sector for application such as module production of modular buildings, additive manufacturing (AM), brick and block placing, fusion welding, and tie placement. Digital twins generate an electronic model of an entity that can evolve over time as additional data becomes available over the building's existence. AI technology can be integrated with digital twins to improve the reliability of digital twin systems and perpetually refine such modeling by using the enormous amount of information collected during the construction phase and throughout the building's existence. 4D printing takes additive manufacturing technology to a new level by incorporating time-dependent variation of the printed model influenced by various factors like heat, pressure, electricity, and magnetism. Analogous to 3D printing, AI might be incorporated with 4D printing to generate schemes, simulate and predict the movements of robotic arms, and oversee the quality of manufactured components. A distributed ledger made up of linked data blocks is referred to as a BC. BC technology can be used in the construction industry to expedite

payment processing, improve supply networks, and perform predictive asset maintenance.

As new technologies develop, like 5G networks, edge computing, as well as augmented reality, upgrades will be required to incorporate them into IoT-based home automation systems. This integration improves connectivity, reduces latency, and opens up new functionality and experiences for smart homes. Another future direction may involve connecting Zero Energy Buildings (ZEBs) to local smart grids via Urban DTs (UDTs), improving energy delivery and utilization while focusing on real-time data evaluation and response abilities. Forming relationships between educational institutions and technology corporations could accelerate innovation in AI and AIoT applications in UDTs and ZEBs (Bibri et al., 2025). UAVs employing deep learning are deployed for diverse purposes, encompassing real-time data acquisition and critical analysis of visual information through edge computing. Panoptic reconnaissance images obtained from UAVs possess significant potential for promoting robotics-inspired intelligent methodologies in crisis management, terrain mapping, precision agriculture, and vegetation detection through autonomous real-time environmental monitoring. Edge AI is a game changer for 6G technology, allowing for smooth combination of detecting, estimating, connectivity, and adaptiveness by integrating the ability to train and deduce design at the network edge (Afaq and Akram, 2025).

Integrating IoT technology to Virtual Power Plants (VPPs) not solely improves power delivery robustness, maximizes green energy usage, and promotes clean energy objectives in sustainable societies (Z. Gao et al., 2026), but it also provides a flexible and reproducible paradigm.

IoT-powered VPPs dramatically improve energy management by dynamically controlling power generation, storage, as well as grid interactions. Implementing IoT-enabled VPPs necessitates a strong technological infrastructure, including dependable communications networks, cloud computing resources, and updated grids, as well as supporting legislative frameworks that encourage demand-side flexibility and permit peer-to-peer energy trading. Integration of IoT and personalized storage systems, along with localized demand response mechanisms, may improve electricity performance, reduce grid reliance, and promote global climate change mitigation, leading the path for more reliable and ecological safe cities (Sawilam et al., 2025; Yu et al., 2022).

Self-optimizing buildings or autonomous buildings are an important advance in the pursuit of high-performance, energy-efficient, and climate-responsive architecture. Integration of AI in facade systems provides real-time optimization, predetermined control, as well as self-directed operation depending on different atmospheric conditions, sun exposure, and use patterns. Integration of AI to networked sensors and IoT devices enables ongoing data gathering and self-governing decision-making, which significantly increase the energy efficiency and ecological performance. Further research in areas of cost savings and uniformity of components and easy-to-use integration protocols is necessary to expand acceptance to more building types and locations. Bridging disciplinary gaps is also in urgent need. Invention and deployment will need collaboration in different fields, which will be supported by interdisciplinary learning and new job descriptions. State-of-the-art AI systems have the capacity to handle visual, audio, and textual data, which can transform surveillance, emergency response, and safety detection. These models may be enhanced with contextual awareness to make research in autonomous buildings more advanced and dynamic urban environments (Jiang et al., 2026).

8. Conclusion

This review highlights the following key outcomes:

- AI-driven energy management systems have emerged as an effective solution for SBs, enabling intelligent monitoring, analysis, prediction, and optimization of energy consumption through advanced algorithms, ML, deep learning, and data analytics.
- AI-based energy management systems integrate sensors, data processing modules, optimization algorithms, and control systems to support predictive energy demand forecasting, adaptive HVAC control, occupancy-based lighting management, renewable energy integration, and demand response applications, thereby improving energy efficiency, reducing operating costs, and enhancing grid reliability.
- AI is transforming conventional buildings into intelligent and connected infrastructures by integrating with smart grids, urban infrastructure, virtual power plants, and energy communities, enabling resilient, distributed, and adaptive urban energy systems.
- AI and automation are accelerating the transition towards net-zero energy buildings through improved renewable energy utilization, energy storage management, and carbon emission reduction while supporting sustainable urban development.
- Despite these advantages, several challenges remain, including cybersecurity and data privacy concerns, interoperability issues, high implementation costs, legacy building integration, and the need for skilled personnel to operate and maintain AI-enabled systems.
- The adoption of open standards, modular system architectures, strategic retrofitting, digital twins, robust cybersecurity frameworks, and supportive policies can facilitate the wider deployment of AI-driven energy management systems in both existing and new buildings.

AI-driven SB systems have immense potential, but large-scale application presents practical obstacles. Retrofitting existing buildings is hindered by the high cost of sensors, communication equipment, and computational resources. Scalability is another challenge since many AI models are built and tested in controlled settings and may not work in all buildings and operational scenarios. Interoperability issues, integration with older systems, and experienced staff hamper deployment. These difficulties require cost-effective, standardized, and scalable AI architectures that perform predictably in the real world. Future SBs should prioritize occupant comfort, well-being, privacy, responsible AI implementation, and intuitive human-machine interaction alongside technological advancement, allowing buildings to evolve as self-optimizing, grid-interactive systems that actively contribute to the broader smart city ecosystem.

CRedit authorship contribution statement

Ijaz Ahmed: Writing – review & editing, Writing – original draft. **Rehana Khan:** Writing – original draft, Conceptualization. **Muhammad Rehan:** Writing – review & editing, Supervision. **Mohammed Alqahtani:** Writing – review & editing, Resources, Funding acquisition. **Muhammad Khalid:** Writing – review & editing, Supervision.

Declaration of generative AI in scientific writing

During the preparation of this work, the authors used Grammarly solely to improve the language, grammar, and readability of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

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

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