Review

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Artificial Intelligence and Digital Twins for Bioclimatic Building Design: Innovations in Sustainability and Efficiency

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Abstract: The integration of Artificial Intelligence (AI) into bioclimatic building design is reshaping the Architecture, Engineering, and Construction (AEC) industry by addressing critical challenges in sustainability and efficiency. By aligning structures with local climates, bioclimatic design addresses global challenges such as energy consumption, urbanization, and climate change. Complementing these principles, AI technologies - including machine learning, digital twins, and generative algorithms - are revolutionizing the sector by optimizing processes across the entire building lifecycle, from design and construction to operation and maintenance. Amid the diverse array of AI-driven innovations, this research highlights Digital Twin (DT) technologies as a key to AI-driven transformation, enabling real-time monitoring, simulation, and optimization for sustainable design. Applications like façade optimization, energy flow analysis, and predictive maintenance showcase their role in adaptive architecture, while frameworks like Construction 4.0 and 5.0 promote human-centric, data-driven sustainability. By bridging AI with bioclimatic design, the findings contribute to a vision of a built environment that seamlessly aligns environmental sustainability with technological advancement and societal well-being, setting new standards for adaptive and resilient architecture. Despite the immense potential, AI and DTs face challenges like high computational demands, regulatory barriers, interoperability and skill gaps. Overcoming these challenges will be crucial for maximizing the impact on sustainable building, requiring ongoing research to ensure scalability, ethics, and accessibility.

Keywords: artificial intelligence; digital twin; bioclimatic building design; building performance; Internet of Things (IoT); energy efficiency

1. Introduction

In recent years, the construction industry has undergone a significant transformation, driven by advances in both sustainable design and digital technologies. Bioclimatic design, as a key aspect of sustainable building, optimizes natural resources such as solar radiation, wind, and thermal regulation to enhance climate-responsive structures, minimize energy consumption, and reduce environmental impact. The growing emphasis on sustainability is being reinforced by the adoption of the Sustainable Development Goals (SDGs), with the construction sector increasingly aligning its practices with green building standards, sustainable materials, lifecycle assessments, and collaborative research efforts. This shift towards sustainability is driving a more environmentally responsible and inclusive future, with stakeholders throughout the industry working together to meet global sustainability targets.

At the same time, the integration of Artificial Intelligence (AI), particularly through Machine Learning (ML) and Deep Learning (DL), has revolutionized decision-making in the construction

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sector. These technologies enable advanced decision support systems that assist construction professionals by providing intelligent capabilities to enhance project outcomes [1]. As industry faces the dual challenges of digitalization and sustainability, AI has emerged as a powerful tool that can address both. The strategic application of AI across the entire lifecycle of building projects - from design and construction to operation and maintenance - presents unique opportunities to reduce inefficiencies and drive significant improvements in performance [2].

AI plays a crucial role in optimizing building designs to improve energy efficiency and reduce environmental impact. Through comprehensive data analysis and scenario simulations, AI enables architects and engineers to make well-informed decisions that align with rigorous green building standards. Beyond enhancing sustainability, AI is also advancing construction materials and technologies, driving innovation and resilience in structural design. The use of AI algorithms and machine learning techniques has led to the development of novel materials that enhance the durability, safety, and efficiency of buildings. These innovations not only promote sustainable construction practices but also address the challenges posed by urbanization, climate change, and the evolving needs of infrastructure development [3].

Despite the growing interest in AI and ML applications in construction engineering, there is a notable research gap that requires attention. While some studies have explored specific aspects of AI and ML within the industry, a comprehensive review that synthesizes the various methodologies and examines their collective impact is still lacking [1].

This work aims to fill that gap by providing an in-depth analysis of the latest developments in AI and ML within Architecture, Engineering and Construction (AEC) industry, as well as identifying potential areas for future research and improvement. By exploring the intersection of AI and bioclimatic design, this work aims to provide insights into how cutting-edge technologies can address environmental challenges, improve building performance, and shape the future of sustainable architecture.

2. Main Principles and Strategies of Bioclimatic Building Design

Bioclimatic design integrates climate-responsive principles into architecture, optimizing solar radiation, temperature, wind, and humidity in order to reduce energy consumption. It aims to minimize dependence on artificial systems while ensuring environmental integration. Precise climate analysis is essential for effective design, with tools like bioclimatic diagrams aiding in visualizing climate-passive design relationships and informing material selection and energy-efficient solutions (Figure 1) [4].

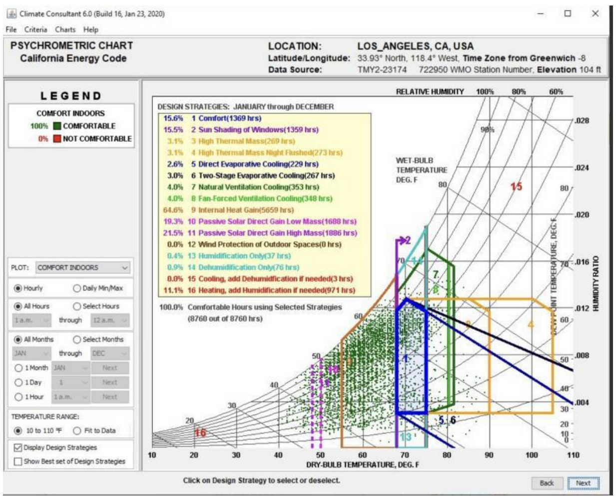

Figure 1. Example of psychrometric Building Bio-Climatic chart from Climate Consultant 6.0.

The core principles of bioclimatic building design, including thermal comfort, daylighting, and energy efficiency, align building design with local climate conditions, reduce energy consumption, enhance comfort, and promote environmental and economic sustainability, addressing global challenges like energy use and climate change [5].

In the past decade, the building sector has drawn significant attention due to its high energy consumption and carbon emissions, accounting for 35% of global energy use and 38% of CO_2 emissions in 2019 [6]. Bioclimatic design helps mitigate climate change by reducing reliance on non-renewable energy sources and minimizing emissions [7]. Incorporating locally available renewable resources further decreases dependence on large-scale energy supplies. Effective design strategies have achieved energy savings of up to 60%, highlighting their potential for sustainable development [8]. This approach should be applied not only to new buildings but also as a key component of renovation strategies, as outlined in the Revised Energy Performance of Buildings Directive (EPBD) approved in 03/2024 [9]. The directive introduces tools like the renovation passport, offering a roadmap for phased renovations, helping property owners and investors plan interventions [10].

The implementation of bioclimatic principles varies depending on the local climate, building type, and geographical location (Figure 2).

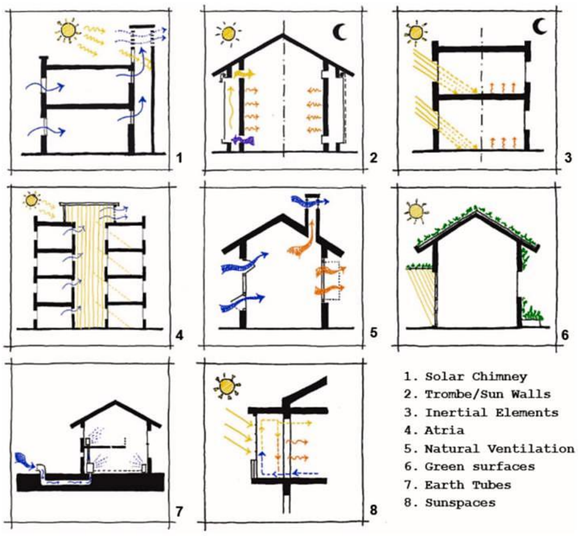

Figure 2. Graphic schemes of bioclimatic design strategies [10].

However, the main strategies are broadly applicable in different contexts, as follows.

- **Natural Ventilation**: Conventional passive cooling strategies, such as shading transparent surfaces and employing cross-ventilation and stack ventilation, facilitate natural cooling and enhance indoor air quality [4,11,12].
- **Passive Solar Heating**: Optimizing orientation, window placement, and building rotation maximizes winter solar gain, enhances ventilation, balances daylight, and leverages thermal mass for heat storage [7,8].
- **Shading and Solar Control**: In warm climates, passive shading devices - such as overhangs, louvers, and pergolas-along with vegetative solutions like green walls, are employed to reduce excessive solar exposure and mitigate overheating [13].
- **Thermal Insulation**: Effective insulation, reflective materials, and high-performance windows, significantly reduce heat transfer - lowering energy consumption by up to 60% and ensuring thermal stability [8].
- **Green Roofs and Walls:** Vegetation integrated into building designs provide insulation, reduce energy use, mitigate urban heat island effects, and improve biodiversity [7,14].
- **Rainwater Harvesting and Greywater Recycling**: Rainwater harvesting, greywater recycling, and water features reduce potable water use and contribute to passive cooling [11].
- **Integration of Smart and Renewable Technologies:** The adoption of on-site renewable energy generation (e.g.,

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- photovoltaic panels), local energy storage systems, and intelligent building automation enhances energy autonomy, operational efficiency, and environmental performance [15,16].

Artificial Intelligence Evolution, Techniques and Application in AEC

Artificial Intelligence (AI) is a subdiscipline of computer science focused on the development of systems that are capable of simulating human cognitive processes, such as perception, reasoning, problem-solving, natural language understanding, decision-making and learning from experience. The fundamental principles of AI center on the capacity of machines to replicate or enhance human cognitive functions, encompassing autonomy, learning, reasoning, problem-solving, and adaptation.

The origins of AI date back to the mid-20th century, marked by the Turing Test and the Dartmouth Conference, where the field was formally established [17,18]. Early research focused on symbolic reasoning and rule-based systems but was limited by computational constraints. In the late 20th century, the focus shifted toward machine learning and neural networks, laying the groundwork for deep learning. In the 21st century, growing computational power and the availability of big data have enabled major breakthroughs in pattern recognition, natural language processing, and computer vision. Recent advancements in reinforcement learning and generative models, such as Generative Adversarial Networks (GANs), have further expanded AI's capabilities. Its integration with big data, cloud computing, and the Internet of Things (IoT) has expanded its application areas. Moreover, AI-specific hardware like Graphic Processing Units (GPU) and Tensor Processing Units (TPU) has accelerated AI training and inference [18].

Contemporary research emphasizes explainable AI (XAI) for model transparency, ethical considerations, and applications in healthcare, robotics, and autonomous systems, shaping the future of intelligent technologies [19].

This growing focus on responsible and transparent AI aligns with broader trends in the field, as highlighted by the AI Index Report 2024. The report shows a rapid rise in open-source AI research, with projects on GitHub growing from 845 in 2011 to 1.8 million in 2023 - a 59.3% increase in 2023 alone - demonstrating both the accelerating pace of innovation and the importance of collaborative development [20].

In parallel with technological progress, ethical considerations and governance frameworks are becoming central to AI deployment. The EU has taken a leading role by introducing regulations for "trustworthy AI," combining legal, ethical, and technical standards [21,22]. These guidelines define seven key requirements: human oversight, safety, privacy, transparency, fairness, societal well-being, and accountability (Figure 3). This risk-based regulatory model is central to the EU AI Act, ensuring responsible AI development and use [23].

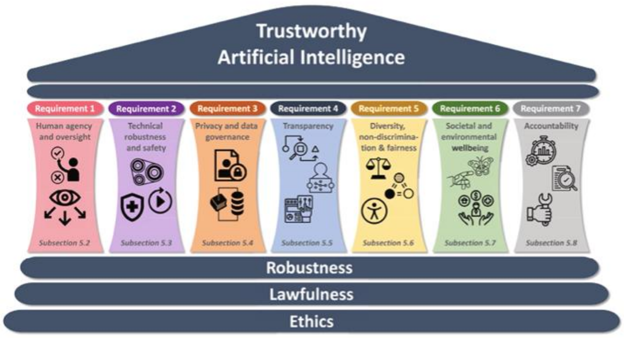

Figure 3. Pillars and requirements of trustworthy AI [21].

3.1. Artificial Intelligence techniques

AI can be based on several different techniques, depending on the application and the problem being solved. Some of the most commonly used techniques in AI are based on the Machine Learning and Deep Learning. Figure 4. visually illustrate relationship and the distinction between Machine Learning and Deep learning in terms of feature extraction and learning.

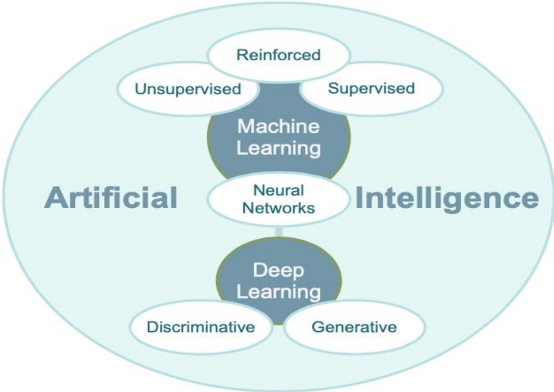

Figure 4. AI Taxonomy.

3.1.1. Machine Learning (ML)

This is the backbone of most AI applications. ML involves training algorithms to recognize patterns in data and make predictions based on that data, without being explicitly programmed for specific tasks. ML techniques allow computers to recognize patterns, make predictions, and perform decision-making tasks based on historical data. There are three primary types of machine learning:

- Supervised Learning: The model is trained using labeled data (input-output pairs), where the desired output is known. The model learns to map inputs to correct outputs. This branch of ML includes methods like Linear Regression, Bayesian network, K-nearest neighbours (kNN), Decision Tree etc.
- Unsupervised Learning: The model is trained using unlabeled data, meaning the system must identify patterns or groupings on its own. The algorithm must find structure or patterns in the input data without guidance. The main goal of unsupervised learning is to explore the data and extract useful insights. This includes Fuzzy C Means, Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) and K-Means.
- Reinforcement Learning: The system learns by interacting with its environment and receiving feedback in the form of rewards or penalties, optimizing its behavior over time: Q-Learning, Markov decision process [24].

3.1.2. Deep Learning (DL)

Being a subset of machine learning, deep learning uses multi-layered neural networks to model complex patterns in data. These networks are inspired by the human brain's structure and are capable of handling vast amounts of data and performing complex tasks like image recognition, speech processing, and natural language understanding. Deep learning has achieved remarkable success in fields such as autonomous driving, medical image analysis, and Natural Language Processing (NLP) due to its ability to automatically learn features from raw data without needing explicit programming or feature engineering.

Artificial Neural Networks (ANNs) composed of layers of neurons that work together to process input data and produce output predictions. Each neuron in a layer is connected to several neurons in the previous and next layers, creating a network of computational units [25].

- Discriminative (Supervised) models: focus on learning the boundary between different classes in a dataset, rather than modeling data distribution. These supervised deep models typically estimate class probabilities from observable data, enabling accurate classification. In simple terms, discriminative models learn to distinguish between different categories or labels by focusing on the differences in the corresponding data. Common models include Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNNs), Recurrent Neural Networks

(RNN), and their variations. The most powerful class of this type is CNNs, which are extensively used across a range of tasks, such as object detection, speech recognition, computer vision, image classification, and bioinformatics by learning hierarchical features from raw data.

- Generative (Unsupervised) models: The primary objective of generative models (GMs) is to produce data resembling real-world distributions. Despite ongoing research challenges, recent advancements have expanded their applications, particularly in computer vision research. GMs utilize training data from an unknown data-generating distribution to create new samples that match the original distribution. Key models include Auto-Encoder, Generative Adversarial Network (GAN), Restricted Boltzmann Machine (RBM), and Deep Belief Network (DBN) [26].

Artificial Intelligence is a rapidly evolving field that allows machines to perform tasks that were traditionally thought to require human intelligence. By leveraging techniques like machine learning, deep learning, natural language processing, and computer vision, AI systems can analyze vast amounts of data, learn from it, and make decisions or predictions autonomously.

Today, AI systems are transforming industries ranging from healthcare to finance, manufacturing, and even architecture, playing a pivotal role in driving Industry 5.0 and Society 5.0- concepts that emphasize the integration of human intelligence, AI, and other emerging technologies for a sustainable future [27]. Its impact spans multiple sectors,including Architecture, Engenieering and Construction (AEC) and Natural Hazards Engineering (NHE) [28,29].

AI in Bioclimatic Building Design

The application of AI in the AEC sector has evolved significantly over the past few decades from early automated design tools like Computer-Aided Design (CAD) to advanced generative algorithms and sustainable design solutions. In 1976, Cedric Price developed the concept of the "Generator" - a vision of AI-driven architecture, followed by Soddu's artificial DNA model for medieval cities in 1987 [25,30]. By the 2000s, AI integrated data-driven decision-making to enhance energy efficiency, resource management and waste reduction. Innovations like genetic algorithms for ecological design and optimization tools such as GENE-ARCH and OPTIMUS have advanced sustainable architecture [30]. Today, AI, alongside big data and cloud computing, is crucial for smart cities and green building solutions, optimizing environmental performance in real time.

4.1. AI, Sustainable Building Design, and Construction 4.0 and 5.0

The construction industry is undergoing a major transformation driven by digitalization and AI. Construction 4.0 signifies a profound shift within the industry, characterized by the fusion of digital technologies and data-driven solutions, including the widespread adoption of Internet of Things (IoT) devices, Artificial Intelligence, robotics, 3D printing, and Building Information Modeling (BIM), which collectively work to optimize processes, reduce costs, and improve building performance. While Construction 4.0 focuses on digital integration and automation, Construction (Industry) 5.0 advances by prioritizing sustainability, environmental stewardship, principles of a circular economy and human needs and wellbeing (Figure 5) [27,31].

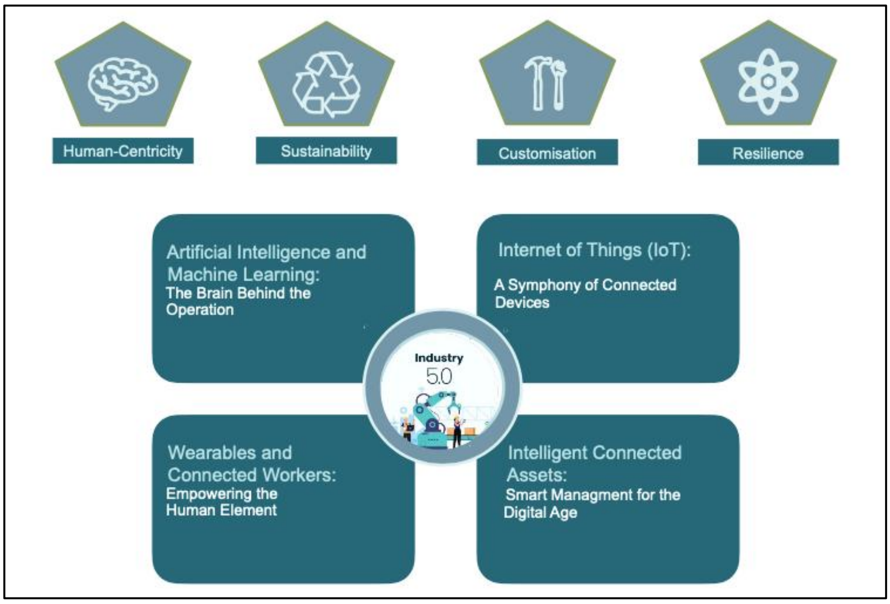

Figure 5. Focus and main priorities of the concept of Construction (Industry) 5.0.

AI enhances bioclimatic design by automating analysis, predicting performance, and optimizing energy efficiency. Its potential extends to generative design, automation, predictive maintenance, and lifecycle optimization, addressing inefficiencies and reducing environmental impact. The industry faces challenges like excessive material waste (11-15%) and high energy consumption, with buildings accounting for 28% of U.S. commercial energy use and 41.1% in China. AI-driven solutions offer a path toward more sustainable, resource-efficient construction [2].

4.2. Recent AI Techniques and Combination Technologies in AEC

The integration of AI in the AEC industry, particularly in sustainable and bioclimatic design, is advancing rapidly. AI enhances sustainability by optimizing energy efficiency, reducing environmental impact, and improving building performance. Its integration with conventional modeling, simulation, and analytics significantly enhances all phases of building design, construction, and operation (Table 1) [2].

Table 1. AI-driven technologies in AEC sector.

Building design	**Construction**	**Operation**
Big Data	Intelligent Decision Support Systems (DSS)	Building Performance Monitoring (BPM)
Generative design	Radio-Frequency Identification (RFID)	Predictive Analytics
Surrogate Modelling	Computer Vision Systems	Structural Health Monitoring (SHM)
Augmented Reality Virtual Reality	Iot Devices Construction Robots	Smart Building Systems

4.2.1. Building Design

At the building design stage, advancements in artificial intelligence provide exceptional opportunities to optimize sustainability objectives across a range of architectural and engineering parameters. Early-stage AI integration enhances decision-making, accelerates design processes, and improves energy efficiency to meet regulatory and cost-saving demands. Techniques such as Knowledge-Based Engineering (KBE), fuzzy logic, neural networks, and genetic algorithms are widely applied in AEC design [32]. Late 20th-century research explored design and morphogenesis,

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inspiring complex and unconventional forms. Contemporary studies, however, prioritize refining and optimizing existing designs, particularly through the optimization of their shapes [30].

Big Data is transforming architecture by providing architects with vast amounts of information, such as climate patterns, energy use, user behavior, and material performance. This enables data-driven design decisions, balancing aesthetics, functionality, and sustainability. For example, data-driven simulations optimize natural light, reducing reliance on artificial lighting, while its use in parametric design allows architects to generate numerous design variations through algorithms. Analyzing material, cost, and environmental impact data refines designs, minimizes waste, and promotes sustainability [27].

Meanwhile, Generative Design - AI-driven generative design algorithms, or Generative Adversarial Network (GAN) - have become integral in the design process, allowing architects and engineers to explore vast numbers of design alternatives based on specific goals (e.g., energy efficiency, structural integrity, material optimization). GANs are applied to optimize building forms, orientations, and window placements to maximize passive heating in winter or minimize solar heat gain in summer, considering local weather patterns. Using the Generator-Discriminator principle, AI autonomously generates options, which are then evaluated and refined [25].

Recent studies highlight the effectiveness of surrogate modeling in optimizing low-energy building design. Surrogate models (SMs) mimic high-fidelity physics-based models by statistically correlating input (design variables) and output (performance targets) data from a sample within the design space. This research underscores the potential advantages of machine learning methods, including ANNs, in handling computationally demanding tasks like building design optimization. Surrogate-assisted building performance optimization models are used to optimize energy performance by improving systems such as HVAC, lighting, and insulation, reducing overall energy consumption. Additionally, surrogate models optimize building shape and layout, enhancing natural lighting, ventilation, and thermal comfort while reducing energy waste, using eco-friendly materials, and improving energy efficiency throughout the building's lifecycle [33].

In addition, Augmented Reality (AR) and Virtual Reality (VR) technologies enhance collaboration, enabling stakeholders to virtually walk-through buildings before they are constructed, adding design modifications and approvals more efficient and accurate [27].

4.2.2. Construction

The construction industry plays a crucial role in global economic development, with an estimated annual value surpassing $10 trillion. However, it often faces challenges such as high costs, project delays, and safety concerns with average cost overruns of 80% leading to significant financial consequences [1]. AI integration with traditional construction techniques, can optimize workflows, streamline processes, and ensure higher-quality construction outcomes.

Intelligent Decision Support Systems (DSS) utilize a vast amount of historical data, real-time information, and predictive analytics to provide accurate insights and recommendations. By automating repetitive tasks, optimizing resource allocation, and identifying potential risks, DSS help decision-makers improve project outcomes, boost productivity, and reduce costs [1].

AI algorithms optimize resource utilization, including materials, labor, and equipment, by processing real-time data from Radio-Frequency Identification (RFID) tags and sensors attached to shipments, ensuring timely delivery, reducing losses, and lowering inventory costs [27]. These systems are capable of dynamically adjusting construction schedules and resource allocations in response to variables such as weather conditions, material availability, or workforce productivity, thereby enhancing operational efficiency and minimizing resource waste. Furthermore, AI-powered computer vision systems conduct real-time inspections of construction materials and components, detecting defects and ensuring compliance with quality standards [3].

Construction sites are inherently complex and hazardous environments. Integration of IoT devices such as wearables, drones, and sensors facilitate real-time monitoring of both worker activities and site conditions. Wereable devices track workers’ movements and vital signs, providing

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safety alerts in the event of accidents, while drones conduct aerial surveys and assess progress, improving project management and decision-making [27]. These systems can trigger alerts or automatically shut down operations in hazardous situations, enhancing safety on the site [3].

Another revolutionary application of AI is the deployment of construction robots, which are capable of performing tasks such as bricklaying, concrete pouring, and 3D printing, improving speed, precision, and reducing reliance on manual labor [27].

4.2.3. Operation

AI integration with IoT and Big Data during the operational phase of bioclimatic design enhances building efficiency and sustainability by continuously monitoring and optimizing performance based on real-time data.

Building Performance Monitoring (BPM) algorithms analyze real-time data from sensors integrated into building systems to detect patterns in energy use and environmental conditions. By processing this data, machine learning algorithms can automatically adjust settings for HVAC systems, lighting, and other equipment, enhancing efficiency while maintaining occupant comfort [2].

Predictive analytics, another subset of AI, revolutionizes maintenance practices by forecasting equipment failures based on variables such as temperature, vibration, and usage patterns, enabling proactive maintenance, minimising downtime and reducing costly repairs [3]. Structural Health Monitoring (SHM) utilizes IoT sensors to assess the integrity of buildings, bridges, and infrastructure by tracking vibrations, deformation, and stress. Real-time data analysis enables early detection of damage, ensuring timely maintenance, preventing severe failures and ensuring both occupant safety and structural longevity. Additionally, IoT-driven systems optimize resource use, monitor emissions, and support compliance with environmental regulations, promoting sustainable construction [27].

AI-driven machine learning and predictive analytics improve forecasting, maintenance, and performance optimization for renewable energy systems, reducing costs and enhancing efficiency. By analyzing large datasets, AI predicts energy outputs, assists in project planning, and identifies optimal locations for renewable infrastructure [34].

Smart building systems leverage AI to enhance occupant comfort and productivity through personalized environmental control, using sensors and real-time adjustments [2]. Additionally, AI-driven urban planning analyzes infrastructure, transportation, and public services to create inclusive, accessible cities. Smart sensors and algorithms optimize traffic flow, reducing congestion and improving mobility [27].

AI-Driven Digital Twins

Digital Twin (DT) was initially implemented in NASA's Apollo program in 2010, and since then, its use has expanded across various industries, including manufacturing, aviation, defense, and healthcare, enhancing automation and efficiency [35]. The convergence of Artificial Intelligence with Digital Twin technologies have sparked growing interest in their potential applications within the AEC sector. While Digital Twins offer a virtual replica of physical assets - such as buildings, infrastructure, or entire urban environments - the integration of AI enhances their functionality, rendering them more dynamic, predictive, and adaptive in response to real-time data and evolving conditions. The potential of a human-centric Digital Twin (DT) approach is envisioned to create adaptive, data-driven built environments that interact dynamically with users, facilitating more dynamic and personalized interactions. Its ecosystem consists of three core elements: the physical environment, its digital replica, and the system managing their interaction [36].

Modeling technologies create a virtual model that reflects the physical environment's parameters, such as structure, functionality, location, and performance, While IoT technologies enable bi-directional data exchange via communication protocols. High-volume, multi-source data is stored, integrated, and analyzed using advanced analytics, then presented to users through interactive visualizations supported by visualization technologies [35].

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4.2. Digital Twin System Architecture

The digital twin system is conceptualized in five development layers: data acquisition, data transmission, digital modeling, data/model integration, and service.

1. **Data Acquisition**: This layer collects dynamic data from the physical environment trought IoT sensors that detect changes in physical, chemical, and electrical properties of the surroundings (temperature, humidity, gas concentrations, light intensity, motion etc.), producing an electrical output in response. Input from various sensors can be collected by the more advanced control systems like Supervisory Control and Data Acquisition (SCADA) system for HVAC plants, Direct Digital Control (DDC) system etc. These technologies include ultrasonic and gyroscopic sensors, which are used to detect clashes, track machinery locations, and ensure accurate placement of resources on construction sites. While building surveillance systems with video streams detect pedestrians and measure environmental conditions like ambient brightness and surface temperatures using thermal imaging modules [35].
2. **Data Transmission**: Raw data from the data acquisition layer is transmitted to other system components via wired or wireless technologies (Wi-Fi, Bluetooth, WLAN and Ultra-Wideband (UWB)), following communication protocols like Message Queuing Telemetry Transport (MQTT) or Hypertext Transfer Protocol (HTTP). Building Management Systems (BMS) use the internet and Building Automation and Control Networks (BACnet) protocols for data communication between devices and sensors. Additionally, platforms like SophyAI and Gazebo-ROS are utilized for visualizing and processing sensor data [35].
3. **Digital Modeling**: Virtual models of the physical environment are created using technologies like laser scanning, photogrammetry, and software tools (Autodesk Revit, Navisworks, Solidworks etc) to capture and represent parameters such as geometry, functionality, location, and performance. Additionally, game development software like Unity 3D is employed for creating interactive 3D models, avatars, and virtual environments (e.g., Virtual Reality setups with Oculus devices) [33,34]. Specifically, Autodesk defines five levels of Digital Twins in the AEC sector, each with a distinct function: Descriptive, Informative, Predictive, Comprehensive and Autonomous. Currently, most DT applications are at Level 2 (Informative Twin), with some moving toward Level 3 (Predictive Twin) [36].

Figure 6. Primary data processing [36].

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4. **Data/Model Integration**: Multi-source, high-volume data is stored in cloud platforms like Google Cloud Microsoft Azure and Amazon Web service (AWS). Some systems also use mirrored databases to store data from existing building systems like BMS. Data fusion techniques integrate various data types (e.g., sensor, mechanical, and image/video data) into a unified digital twin model, often utilizing customized Application Programming Interfaces (APIs). Platforms like Autodesk Revit, Unity 3D, and Midas Gen are used for this integration, enabling real-time updates and the fusion of multi-form data into BIM or other virtual environments. Advanced AI technologies process this data for insights and predictive analysis. The processed data then is visualized in digital twin systems through various software platforms, primarily 3D modeling tools like Autodesk Revit, Autodesk Navisworks, Unity 3D, Virtual and Augmented Reality [35].
5. **Service:** Represents the range of services it provides to users, and these services vary depending on the specific application context. It enables real-time monitoring, predictive analytics, early issue detection, and data visualization, supporting decision-making and operational efficiency. It tracks structural assets, construction activities, and environmental conditions (e.g., temperature, energy consumption, occupancy) while identifying faults in building systems, forecasting failures, and triggering alarms for anomalies. Additionally, digital twins facilitate scenario simulations, robotic control, and smart home management [35].

These layers work together to provide a comprehensive view of the physical and virtual systems in real-time, allowing stakeholders to monitor, analyze, and make data-driven decisions in the built environment.

4.3. The Role of Digital Twins in Bioclimatic Design

The advent of Digital Twin technologies has revolutionized the approach to building design, construction, and urban planning, particularly in the context of bioclimatic design. By using Digital Twins designers and engineers can create precise virtual models of buildings or urban areas that integrate real-time environmental data, sensor feedback, and predictive simulations. This technology facilitates continuous performance monitoring and optimization, ensuring adaptive responses to climatic conditions. By linking physical assets with virtual counterparts, Digital Twins incorporate Building Information Modeling, IoT, and sensor networks to implement climate-responsive features such as solar shading, natural ventilation, and energy-efficient building envelopes. Real-time sensor data on indoor and outdoor conditions supports adaptive design modifications, reducing energy consumption and enhancing occupant comfort [35,37].

An increasing interest in optimizing building envelope systems to reduce energy consumption and enhance occupant comfort, driving research into advanced technologies. For example, a data-driven approach to the digital twinning and optimization of a naturally ventilated solar façades with phase-changing materials (PCMs) and double-façade systems integrated with active air conditioning system scan improve thermal performance, energy efficiency of buildings and offer a viable solution for low-income communities facing challenges related to energy costs and indoor air quality. The role of digital twins in monitoring, analyzing, and optimizing the façade system's behavior in real-time under various climate scenarios, providing valuable insights for sustainable building design and reducing energy demand, particularly for low-income communities [38,39].

Monitoring indoor thermal comfort has also gained increasing attention as it plays a key role in optimizing building energy use while maintaining desired indoor conditions. Recent advances integrate BIM, IoT, and immersive VR to provide real-time, interactive visualizations of comfort indicators such as Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD). These systems allow users to navigate virtual building models, access live sensor data, and adjust parameters like metabolic rate or clothing insulation to simulate various scenarios, enabling more intuitive and efficient comfort assessment [40].

In urban environments, Digital Twins are being explored in the multi-energy system digitalization. By integrating data from IoT sensors, building management systems, and grid

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infrastructure, DTs provide a dynamic and accurate virtual representation of the physical energy systems, enabling stakeholders to model, simulate, and analyze energy flows and system behavior. By modeling and analyzing energy flows, cities can optimize the integration of renewable sources like solar, wind, and geothermal, reducing reliance on non-renewable energy and enhancing sustainability [41].

AI-driven Digital Twins also can play a crucial role in stormwater management, addressing urbanization and climate change challenges. Using machine learning, they process vast datasets from sensors, weather forecasts, and monitoring systems to simulate stormwater behavior, predict flooding, and optimize drainage performance, reducing the need for costly infrastructure upgrades [42,43]. By integrating real-time sensor data with hydraulic models, digital twins enhance stormwater depth estimation, improve near-term forecasts, and detect sensor faults with over 99% accuracy, minimizing false flood alarms. Enabled by low-power sensing and wireless communication, they support street-level flood warnings, sewer blockage detection, and active control of valves and gates, ultimately mitigating flooding and pollution risks [43].

Additionally, Digital Twins aid in fire risk management in urban and wildland-urban areas by integrating temperature sensors, smoke detectors, and satellite imagery to detect and simulate fire behavior. They support bioclimatic design by assessing fire risks and optimizing mitigation strategies, including design of fire-resistant materials, building layouts, and vegetation planning [44].

Finally, the use of Digital Twins in the field of heritage conservation is emerging as a vital tool for sustainable and effective cultural heritage preservation. Photogrammetry and laser scanning have revolutionized documentation by enabling the rapid acquisition of detailed 3D point clouds. Heritage assets, subject to natural decay and external factors, require ongoing monitoring and maintenance, as emphasized by international organizations like ICOMOS and UNESCO. Heritage Building Information Modeling (HBIM) applies BIM techniques to built heritage, using digital surveys to create accurate models for conservation. Traditionally reliant on visual inspections, monitoring is now enhanced by sensors and scanning technologies. Digital Twins integrate these advancements with AI and Machine Learning to predict deterioration and simulate conservation needs, though research in this area remains limited. The Heritage Digital Twin (HDT) framework applies DT concepts to heritage sites, assessing them through four key attributes: Fidelity (model accuracy), Synchronization (real-time interaction), Intelligence (data and AI integration), and Autonomy (automation in conservation tasks) [45].

AI-driven digital restoration is also gaining importance, particularly in detecting and repairing damage to ancient heritage. Deep learning algorithms can identify cracks in murals with high precision, while Generative Adversarial Networks (GANs) simulate and restore original colors and textures. Integrated with 3D modeling and virtual reality, these technologies enable precise digital reconstruction, improving restoration accuracy and efficiency [46].

Future Perspectives of AI in AEC Industry and Sustainable Building Design

The integration of Artificial Intelligence into the AEC industry presents significant opportunities for advancing technology and promoting sustainability. AI-powered systems offer innovative solutions to optimize energy use, minimize waste, and streamline resource allocation, ultimately reducing carbon emissions and conserving natural resources. By leveraging AI in BIM, IoT, Big Data, and predictive systems, the industry can improve efficiency, sustainability, and safety while progressing toward Sustainable Development Goals such as SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 11 (Sustainable Cities and Communities). AI-driven innovations in predictive analytics, supply chain optimization, and data-driven communication further foster economic growth and environmental preservation, supporting a holistic approach to sustainable construction [3].

However, despite AI's potential, adoption in the construction sector remains slow due to traditional industry practices, project complexity, and a limited understanding of AI's potential benefits [2]. Key challenges affecting AI integration include:

- **High Initial Costs:** AI-driven tools such as BIM, generative design, and automation demand substantial upfront investment, posing financial challenges. Adopting tools like BIM integrated with AI, deploying AI-powered energy management systems like urban multi-energy systems (UMES) DTs, or investing in robotic construction technologies involve significant costs for hardware, software, and training. These financial barriers can be especially challenging for small and medium-sized enterprises (SMEs). Financial incentives, government subsidies, and demonstrated long-term return on investment (ROI) could facilitate wider adoption. However, the hidden costs associated with AI adoption, such as system customization, integration with existing infrastructure, and ongoing maintenance, must also be considered [2,27].
- **Data Transmission and Security:** AI applications in construction heavily rely on data from various sources, including sensor networks, environmental data, construction schedules, and building materials. The data generated in these systems often includes heterogeneous types, such as image data, video data, mechanical data, and environmental data. In terms of data transmission, most studies nowadays have focused on short-range wireless technologies, such as Wi-Fi, Bluetooth, and UWB. Moreover, ensuring secure data transmission is a key consideration. Many construction-related data are confidential, and the transmission of such sensitive information can expose the system to cyber-attacks. A breach in these systems could have far-reaching consequences, including compromising building safety, exposing sensitive data, or disrupting critical infrastructure. Future research should focus on privacy-preserving network models and secure data exchange mechanisms [35].
- **Data Integration and Compatibility:** The AEC industry struggles with fragmented inconsistent, and siloed data across across various stages of a building's lifecycle. Construction projects typically involve numerous stakeholders using different software platforms, which complicates system interoperability [27]. This data often comes from multiple sources, including design models (e.g., BIM), building materials, construction schedules, sensor networks, and environmental data from IoT devices, which can be incompatible or poorly organized. This lack of integration often leads to delays, cost overruns, and project disruptions. Open-source platforms, standardized interfaces, and semantic web technologies can enhance interoperability. Additionally, collaborative approaches, such as BIM and Integrated Project Delivery (IPD), can streamline workflows, improve coordination, and enhance overall project delivery)[1,2,35].
- **Integration of AR and VR for Data Processing and Visualization:** In terms of data visualization, the use of 3D modeling platforms, along with immersive technologies like Virtual and Augmented Reality, has advanced the visualization and interaction with digital twin data, driving increasing interest in their integration within Intelligent DSS for construction engineering. These technologies provide interactive and immersive experiences that improve spatial comprehension, collaboration and enhance decision-making but face usability and cost barriers. User-friendly solutions, real-time synchronization with BIM and cost-effective solutions are needed for widespread adoption in the AEC sector [1,35].
- **Scalability and Standardization:** While AI-driven solutions show significant potential in individual construction projects, scaling these solutions across entire industries and supply chains presents a distinct challenge. The construction industry's diversity, characterized by varying regulations, building codes, materials, and construction techniques, complicates the widespread implementation of AI solutions without considerable customization. AI adoption is hindered by industry diversity, varying regulations, and a lack of standardized protocols. Unlike industries such as healthcare, which have established broad standards like HL7, or manufacturing with ISO 9000, the construction sector lacks cohesive frameworks for data exchange, interoperability, and quality assurance. Establishing industry-wide frameworks is essential for interoperability and efficiency [1,27].
- **Continuous Learning and Adaptation:** Studies have shown benefits of DSS in areas like project scheduling, risk management, and material selection. Online learning algorithms in risk management, allowing the system to adjust to evolving risk profiles and enhance decision-

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making. While, machine learning for material selection, enabling the system to learn and refine recommendations based on feedback and new data. DSS enhance project management but require reliable data access and scalable algorithms [1].

- **Explainability and Transparency:** AI models, particularly those using deep learning, often operate as "black boxes," where their decision-making processes are not transparent or understandable to humans. AI decision-making must be interpretable to ensure trust and accountability. The field of Explainable Artificial Intelligence aims to address this issue by creating models that provide clear, understandable explanations for their decisions. XAI frameworks should balance accuracy and interpretability [19].
- **Environmental Impact:** As AI systems grow in sophistication, they require massive computational resources, which translates to a substantial environmental impact. AI models require significant computational resources, contributing to a high energy demand and carbon footprint. Sustainable AI practices, data optimization, and governance frameworks should be prioritized [47,48]. In this context, the concept of Net Zero Energy Data Centers (NZEDC) encapsulates key sustainability strategies, defined by the RenewIT project (Deliverable 4.5) as data centers that achieve a net-zero balance by exclusively consuming renewable energy while generating an equivalent amount of electrical and thermal energy over their operational lifespan [16].
- **Regulatory and Ethical Considerations:** AI systems, which can significantly impact society, the economy, and individual lives, require robust frameworks to ensure they are developed and deployed responsibly. Design teams often lack regulatory support documents with performance benchmarks for non-mechanical solutions, unlike mechanical systems (e.g., HVAC, heat pumps) validated by European standards (Delegated Regulation 2022/759; Commission, 2014). These benchmarks are crucial for assessing energy savings and comfort across climates [10]. Moreover, AI governance must address fairness, transparency, and human oversight. According to the AI Index Report 2024, in 2023, policymakers in both the European Union and the United States made significant strides in AI regulation [20]. The European Union's AI Act and similar frameworks emphasize ethical AI development [23].
- **Skill Gaps and Workforce Adaptation:** AI adoption in the AEC sector requires significant workforce reskilling to bridge the technical expertise gap. While AI can greatly enhance efficiency, it may reduce the need for certain manual tasks, leading to potential workforce displacement. This raises important ethical concerns about balancing the benefits of automation with the preservation of employment opportunities [31]. In addition, Many professionals in construction lack the technical expertise required to effectively use AI tools, which demand knowledge in areas like machine learning, data analytics, robotics, and programming. Building and deploying AI solutions in construction require specialized knowledge, and there is currently a large gap between the demand for AI talent and the availability of qualified professionals.Talent development and collaborative training programs are essential to prepare professionals for AI-driven roles [2,27].

To fully realize AI's potential in sustainable construction, industry stakeholders must address these challenges through policy support, investment, and technological advancements. Future research should focus on scalable, cost-effective AI solutions that enhance efficiency, safety, and sustainability while ensuring ethical and responsible implementation.

7. Conclusions

Amid growing environmental challenges like climate change and resource depletion, bioclimatic design has emerged as a key strategy for creating energy-efficient, climate-responsive buildings, aligning with global sustainability goals. Simultaneously, AI technologies are transforming decision-making across various domains, driving the development of intelligent, eco-friendly infrastructure. This review explores the intersection of bioclimatic design and AI, highlighting their integration as a solution to sustainability and efficiency challenges in the AEC industry.

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AI is transforming bioclimatic design across the building lifecycle, enhancing energy efficiency and performance through tools like generative design algorithms and surrogate models. Among these advancements, Digital Twin technologies stand out, enabling real-time monitoring, simulation, and optimization by integrating AI, IoT, and BIM. Their applications in façade optimization, energy flow analysis, and risk assessment highlight their potential in sustainability and energy efficiency. Looking ahead, DTs are expected to drive autonomous, human-centric design under Construction 5.0 and Industry 5.0, with applications extending to heritage conservation and resource-efficient construction. However, challenges such as computational and energy demands, interoperability, and regulatory constraints must be addressed for broader adoption. Future research should prioritize scalable, ethical, and transparent implementations to maximize AI's impact. By integrating AI, DTs, and emerging technologies, the AEC industry can set new benchmarks for sustainable, adaptive, and intelligent built environments.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AEC	Architecture, Engineering and Construction
DT	Digital Twin
SDG	Sustainable Development Goals
ML	Machine Learning
DL	Deep Learning
EPBD	Revised Energy Performance of Buildings Directive
GAN	Generative Adversal Networks
IoT	Internet of Things
GPU	Graphic Processing Units
TPU	Tensor Processing Units
XAI	Explainable Artificial Intelligence
EU	Europian Union
kNN	k-Nearest Neighbours
BIRCH	Balanced Iterative Reducing and Clustering using Hierarchies
NLP	Natural Language Processing
ANN	Artificial Neural Networks
MLP	Multi-Layer Perception
CNN	Convolutional Neural Networks
RNN	Recurent Neural Networks
GM	Generative Models
GAN	Generative Adversal Network
RBM	Restricted Boltzman Machine
DBN	Deep Belief Network
NHE	Natural Hazards Engineering
CAD	Computer-Aided Design
BIM	Building Information Modeling
DSS	Decision Support Systems
RFID	Radio-Frequency Identification
BPM	Building Performance Monitoring
SHM	Structural Health Monitoring
KBE	Knowledge-Based Engineering
SM	Surrogate model

HVAC	Heating, Ventilation and Air Conditionig
AR	Augmented Reality
VR	Vurtual Reality
SCADA	Supervisory Control and Data Acquistion
DDC	Direct Digital Control
WLAN	Wireless Local Area Network
UWB	Ultra-Wideband
MQTT	Message Queuing Telemetry Transport
HTTP	Hypertext Transfer Protocol
BMS	Building Management Systems
AWS	Amazon Web Service
API	Application Programming Interface
PCM	Phase-Changing Material
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
HBIM	Heritage Building Information Modeling
UMES	Urban Multi-Energy Systems
SME	Medium-Sized Enterprise
ROI	Return on Investment
IPD	Integrated Project Delivery
NZEDC	Net Zero Energy Data Center

References

1. Waqar, A. Intelligent decision support systems in construction engineering: An artificial intelligence and machine learning approach. Expert Syst. Appl. 2024, 249(A), 123503. https://doi.org/10.1016/j.eswa.2024.123503
2. Adewale, B.A.; Ene, V.O.; Ogunbayo, B.F.; Aigbavboa, C.O. A Systematic Review of the Applications of AI in a Sustainable Building's Lifecycle. Buildings 2024, 14, 2137. https://doi.org/10.3390/buildings14072137
3. Regona, M.; Yigitcanlar, T.; Hon, C.; Teo, M. Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. Sustain. Cities Soc. 2024, 108, 105499. https://doi.org/10.1016/j.scs.2024.105499
4. Mejía-Parada, C.; Mora-Ruiz, V.; Attia, S. Bioclimatic design recommendations for novel cluster analysis-based mapping for humid climates with altitudinal gradient variations. J. Build. Eng. 2024, 82, 108262. https://doi.org/10.1016/j.jobe.2023.108262
5. Elaouzy, Y.; El Fadar, A. Impact of key bioclimatic design strategies on buildings' performance in dominant climates worldwide. Energy Sustain. Dev. 2022, 68, 532–549. https://doi.org/10.1016/j.esd.2022.05.006
6. Global Alliance for Buildings and Construction. Global Status Report for Buildings and Construction 2020; United Nations Environment Programme (UNEP): Nairobi, Kenya, 2020. Available online: https://globalabc.org/resources/publications/2020-global-status-report-buildings-and-construction (accessed on [05.11.2024])
7. Barea, G.; Mercado, M. V.; Filippín, C.; Monteoliva, J. M.; Villalba, A. New paradigms in bioclimatic design toward climatic change in arid environments. Energy Build. 2022, 266, 112100. https://doi.org/10.1016/j.enbuild.2022.112100
8. Elaouzy, Y.; El Fadar, A. Sustainability of building-integrated bioclimatic design strategies depending on energy affordability. Renew. Sustain. Energy Rev. 2023, 179, 113295. https://doi.org/10.1016/j.rser.2023.113295
9. European Union. Directive (EU) 2024/XXX of the European Parliament and of the Council on the Energy Performance of Buildings (Recast); Official Journal of the European Union, 2024. Available online: https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/energy-performance-buildings-directive_en (accessed on [05.11.2024])
10. López Plazas, F.; Crespo Sánchez, E.; González Ruiz, P. Bioclimatic strategies in existing multifamily buildings to achieve cities decarbonization goals: Potential and relevance for Catalonia climates. Cities 2024, 154, 105335. https://doi.org/10.1016/j.cities.2024.105335

11. Ozarisoy, B.; Altan, H. Systematic literature review of bioclimatic design elements: Theories, methodologies, and cases in the South-Eastern Mediterranean climate. Energy Build. 2021, 250, 111281. https://doi.org/10.1016/j.enbuild.2021.111281
12. Couvelas, A. Bioclimatic building design theory and application. Procedia Manuf. 2020, 44, 326–333. https://doi.org/10.1016/j.promfg.2020.02.238
13. Xhexhi, K.; Aliaj, B. Modular construction and bioclimatic strategies: A sustainable approach to building design. In Proceedings of the 4th International Conference on Scientific and Academic Research; All Sciences Academy: Konya, Turkey, 19–20 July 2024. https://www.researchgate.net/publication/382561521
14. Mazzeo, D.; Matera, N.; Peri, G.; Scaccianoce, G. Forecasting green roofs' potential in improving building thermal performance and mitigating urban heat island in the Mediterranean area: An artificial intelligence-based approach. Appl. Therm. Eng. 2023, 222, 119879.https://doi.org/10.1016/j.applthermaleng.2022.119879
15. Skandalos, N.; Karamanis, D. Decarbonizing Operational Emissions in Urban Neighborhoods with the Integration of Rooftop Photovoltaics and Green Infrastructure under Current and Future Climate Conditions. Energy Build. 2025, 329, 115306. https://doi.org/10.1016/j.enbuild.2025.115306
16. Manganelli, M.; Soldati, A.; Martirano, L.; Ramakrishna, S. Strategies for Improving the Sustainability of Data Centers via Energy Mix, Energy Conservation, and Circular Energy. Sustainability 2021, 13, 6114. https://doi.org/10.3390/su13116114
17. Hoffmann, C. H. Is AI intelligent? An assessment of artificial intelligence, 70 years after Turing. Technol. Soc. 2022, 68, 101893. https://doi.org/10.1016/j.techsoc.2022.101893
18. Padmaja-Chinimilli, V. R.; Sadasivuni, L. N.; Gouthami, L. A.; Priyanka, K. B. The rise of AI: A comprehensive research review. IAES Int. J. Artif. Intell. 2024, 13(2), 2226–2235. http://dx.doi.org/10.11591/ijai.v13.i2.pp2226-2235
19. Longo, L.; Brcic, M.; Cabitza, F.; Choi, J.; Confalonieri, R.; Del Ser, J.; Guidotti, R.; Hayashi, Y.; Herrera, F.; Holzinger, A.; Jiang, R.; Khosravi, H.; Lecue, F.; Malgieri, G.; Páez, A.; Samek, W.; Schneider, J.; Speith, T.; Stumpf, S. Explainable Artificial Intelligence (XAI) 2.0: A manifesto of open challenges and interdisciplinary research directions. Inf. Fusion2024, 106, 102301. https://doi.org/10.1016/j.inffus.2024.102301
20. HAI, Stanford University. Artificial Intelligence Index Report; Stanford University, 2024. Available online: https://aiindex.stanford.edu/report/ (accessed on [02.12.2024]).
21. European Commission. Ethics Guidelines for Trustworthy AI; European Commission, 2019. Available online: https://ec.europa.eu/digital-strategy/our-policies/ethics-guidelines-trustworthy-ai (accessed on [10.12.2024]).
22. European Commission. Artificial Intelligence Act 2024; European Commission, 2024. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206 (accessed on [10.12.2024]).
23. Díaz-Rodríguez, N.; Del Ser, J.; Coeckelbergh, M.; López de Prado, M.; Herrera-Viedma, E.; Herrera, F. Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation. Inf. Fusion 2023, 99, 101896. https://doi.org/10.1016/j.inffus.2023.101896
24. Bellini, V.; Cascella, M.; Cutugno, F.; Bignami, E. G.; et al. Understanding basic principles of Artificial Intelligence: A practical guide for intensivists. Acta Bio Med. 2022, 93(5). https://doi.org/10.23750/abm.v93i5.13626
25. Krausková, V.; Pifko, H. Use of Artificial Intelligence in the Field of Sustainable Architecture: Current Knowledge. Archit. Pap. Fac. Archit. Des. STU 2021, 26(1), 20–29. https://doi.org/10.2478/alfa-2021-0004
26. Mortezapour Shiri, F.; Perumal, T.; Mustapha, N.; Mohamed, R. A comprehensive overview and comparative analysis on deep learning models. J. Artif. Intell. 2024, 6(1), 301–360. https://doi.org/10.32604/jai.2024.054314
27. Rane, N. Integrating Leading-Edge Artificial Intelligence (AI), Internet of Things (IoT), and Big Data Technologies for Smart and Sustainable Architecture, Engineering and Construction (AEC) Industry: Challenges and Future Directions. SSRN Electron. J. 2023. https://doi.org/10.2139/ssrn.4616049

 doi:10.20944/preprints202506.0008.v1

28. Deierlein, G. G.; Zsarnóczay, Á.; Govindjee, S.; Taciroglu, E.; et al. State of the Art in Computational Simulation for Natural Hazards Engineering - Second Edition. Report No. 2021-01, 2021. https://doi.org/10.5281/zenodo.4558106
29. Olawade, D. B.; Wada, O. Z.; Ige, A. O.; Egbewole, B. I.; Olajo, A.; Oladapo, B. I. Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. Hyg. Environ. Health Adv. 2024, 12, 100114. https://doi.org/10.1016/j.heha.2024.100114
30. Castro Pena, M. L.; Carballal, A.; Rodríguez-Fernández, N.; Santos, I.; Romero, J. Artificial intelligence applied to conceptual design: A review of its use in architecture. Autom. Constr. 2021, 124, 103550. https://doi.org/10.1016/j.autcon.2021.103550
31. Huang, S.; Wang, B.; Li, X.; Zheng, P.; Mourtzis, D.; Wang, L. Industry 5.0 and Society 5.0—Comparison, complementation and co-evolution. J. Manuf. Syst. 2022, 64, 424–428. https://doi.org/10.1016/j.jmsy.2022.07.010
32. Gilner, E.; Galuszka, A.; Grychowski, T. Application of Artificial Intelligence in Sustainable Building Design - Optimisation Methods. 24th Int. Conf. Methods Models Autom. Robot. 2019. https://doi.org/10.1109/mmar.2019.8864698
33. Elwy, I.; Hagishima, A. The artificial intelligence reformation of sustainable building design approach: A systematic review on building design optimization methods using surrogate models. Energy Build. 2024, 323, 114769. https://doi.org/10.1016/j.enbuild.2024.114769
34. Ziarati, T.; Hedayat, S.; Moscatiello, C.; Sappa, G.; Manganelli, M. Overview of the Impact of Artificial Intelligence on the Future of Renewable Energy. IEEE Int. Conf. Environ. Electr. Eng. IEEE Ind. Commer. Power Syst. Eur. 2024, 1-6. https://doi.org/10.1109/EEEIC/ICPSEurope61470.2024.10751553
35. Tuhaise, V. V.; Tah, J. H. M.; Abanda, F. H. Technologies for digital twin applications in construction. Autom. Constr.2023, 152, 104931. https://doi.org/10.1016/j.autcon.2023.104931
36. Osama, Z. The digital twin framework: A roadmap to the development of user-centred digital twin in the built environment. J. Build. Eng. 2024, 98, 111081. https://doi.org/10.1016/j.jobe.2024.111081
37. Shahinmoghadam, M.; Natephra, W.; Motamedi, A. BIM- and IoT-based virtual reality tool for real-time thermal comfort assessment in building enclosures. Build. Environ. 2021, 199, 107905. https://doi.org/10.1016/j.buildenv.2021.107905
38. Tariq, R.; Bassam, A.; Orozco-del-Castillo, M. G.; Ricalde, L. J.; Carvente, O. Sustainability framework of intelligent social houses with a synergy of double-façade architecture and active air conditioning systems. Energy Convers. Manag. 2023, 288, 117120. https://doi.org/10.1016/j.enconman.2023.117120
39. Tariq, R.; Torres-Aguilar, C. E.; Sheikh, N. A.; Ahmad, T.; Xamán, J.; Bassam, A. Data engineering for digital twining and optimization of naturally ventilated solar façade with phase changing material under global projection scenarios. Renew. Energy 2022, 187, 1184–1203. https://doi.org/10.1016/j.renene.2022.01.044
40. Shahinmoghadam, M.; Natephra, W.; Motamedi, A. BIM- and IoT-based virtual reality tool for real-time thermal comfort assessment in building enclosures. Build. Environ. 2021, 199, 107905. https://doi.org/10.1016/j.buildenv.2021.107905
41. Koirala, B.; Cai, H.; Khayatian, F.; Munoz, E.; An, J. G.; Mutschler, R.; Sulzer, M.; De Wolf, C.; Orehounig, K. Digitalization of urban multi-energy systems – Advances in digital twin applications across life-cycle phases. Adv. Appl. Energy 2024, 16, 100196. https://doi.org/10.1016/j.adapen.2024.100196
42. Kim, Y.; Oh, J.; Bartos, M. Stormwater digital twin with online quality control detects urban flood hazards under uncertainty. Sustain. Cities Soc. 2025, 118, 105982. https://doi.org/10.1016/j.scs.2024.105982
43. Sharifi, A.; Tarlani Beris, A.; Sharifzadeh Javidi, A.; Nouri, M.; Gholizadeh Lonbar, A.; Ahmadi, M. Application of artificial intelligence in digital twin models for stormwater infrastructure systems in smart cities. Adv. Eng. Inform. 2024, 61, 102485. https://doi.org/10.1016/j.aei.2024.102485
44. Yang, S.; Huang, Q.; Yu, M. Advancements in remote sensing for active fire detection: A review of datasets and methods. Sci. Total Environ. 2024, 943, 173273. https://doi.org/10.1016/j.scitotenv.2024.173273
45. Sugiyama, G.; Bourgeois, I.; Rodrigues, H. A holistic methodology for the assessment of Heritage Digital Twin applied to Portuguese case studies. Digit. Appl. Archaeol. Cult. Herit. 2025, 36, e00390. https://doi.org/10.1016/j.daach.2024.e00390

doi:10.20944/preprints202506.0008.v1

46. Yan, Y.; Chai, B.; Li, J. ArtDiff: Integrating IoT and AI to enhance precision in ancient mural restoration. Alex. Eng. J.2025, 111, 511–520. https://doi.org/10.1016/j.aej.2024.09.120
47. Van Wynsberghe, A. Sustainable AI: AI for sustainability and the sustainability of AI. AI Ethics 2021, 1(3), 213–218. https://doi.org/10.1007/s43681-021-00043-6
48. Wu, C. J.; Raghavendra, R.; Gupta, U.; Acun, B.; Maeng, K.; Chang, G.; Aga, F.; Huang, J.; Bai, C.; Gschwind, M.; Gupta, A.; Ott, M.; Melnikov, A.; Candido, S.; Brooks, D.; Chauhan, G.; Lee, B.; Lee, H. H.; Akyildiz, B.; ... Hazelwood, K. Sustainable AI: Environmental Implications, Challenges and Opportunities. Proc. Mach. Learn. Syst. 2022, 4. https://proceedings.mlsys.org/paper_files/paper/2022/hash/462211f67c7d858f663355eff93b745e-Abstract.html