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REVIEW

Benefits of Artificial Intelligence for Achieving Durable and Sustainable Building Design

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ABSTRACT: Artificial intelligence (AI) is transforming the building and construction sector, enabling enhanced design strategies for achieving durable and sustainable structures. Traditional methods of design and construction often struggle to adequately predict building longevity, optimize material use, and maintain sustainability throughout a building's lifecycle. AI technologies, including machine learning, deep learning, and digital twins, present advanced capabilities to overcome these limitations by providing precise predictive analytics, real-time monitoring, and proactive maintenance solutions. This study explores the benefits of integrating AI into building design and construction processes, highlighting key advantages such as improved durability, optimized resource efficiency, and heightened alignment with sustainability goals. As part of this study, the durability aspects are assessed through a strengths, weaknesses, opportunities, and threats analysis. In addition, a sustainability assessment is carried out, taking into account environmental, economic, and social factors, as well as alignment with the United Nations Sustainable Development Goals. Generally, AI-driven predictive models significantly enhance structural durability by forecasting material performance, corrosion risks, and building lifespans with high accuracy. Similarly, AI facilitates sustainable practices by optimizing energy consumption, integrating renewable energy systems efficiently, and significantly reducing carbon footprints. Despite these considerable benefits, implementing AI in the construction industry faces several challenges, including technological complexity, data management concerns, and industry readiness. Nonetheless, future directions emphasize continued development of user-friendly AI platforms, expanded industry collaboration, and rigorous exploration of AI's transformative potential in sustainable and resilient architecture. Overall, AI is expected to redefine the built environment, delivering buildings that are durable and sustainably integrated within their ecological and social contexts.

KEYWORDS: Artificial intelligence; building; durability; sustainability; architecture

1 Introduction

Artificial intelligence (AI) is rapidly becoming integral in the construction industry, significantly influencing building design, construction practices, and maintenance protocols (Fig. 1). Traditional building methods often involve extensive manual processes and estimations that lead to inefficiencies, unnecessary costs, and compromised sustainability [1–6]. Recent developments in finite element modeling and AI enable precise degradation forecasting and lifecycle optimization via advanced monitoring and data-driven decision-making [7–11]. Numerous studies have addressed AI's potential within construction, particularly regarding sustainability. For instance, Adewale et al. [12] systematically reviewed how AI methods streamline sustainable building life cycles. Similarly, Regona et al. [13] emphasized AI's alignment with sustainable development goals, highlighting its role in energy efficiency and resource optimization. Kar et al. [14] discussed AI's broad implications for sustainability, highlighting how predictive models contribute significantly to ecological goals. Specific AI applications have been explored, such as AI-enhanced construction materials [15–17], smart building management systems [18,19], and sustainable integration of renewable energy [20,21]. The integration of AI with 3D printing and IoT facilitates real-time quality control, material optimization, and automated system coordination, advancing the construction of eco-friendly residential buildings [13,22,23]. Furthermore, sophisticated AI-driven frameworks, such as digital twins and physics-informed neural networks, have shown potential in precise structural and thermal modeling, significantly contributing to sustainability and durability [24–27]. In this regard, recent vision-based pipelines extend this capability: deep learning-based 3D image reconstruction and damage mapping with neural radiance fields (Nerfacto) support dense façade and component capture for condition assessment, while 3D pixelwise damage mapping with a deep-attention, modified Nerfacto enables fine-grained crack and spall segmentation that can be synchronized with digital twin states [28,29]. Although the literature extensively covers sustainability, there has been a particular emphasis on AI's ability to predict structural performance and durability aspects. Ji et al. [7] and Gouda Mohamed and Marzouk [30] illustrated AI's role in lifecycle predictions and building condition assessments, respectively. Machine learning techniques, as discussed by Bhamare et al. [31] and Meshref et al. [32], are proven effective in thermal performance predictions and life-cycle cost analysis. Additional studies explored AI's application in corrosion prediction [33–35], fatigue life estimation [36], and concrete durability [37,38]. The implementation of smart vision systems and automated inspections has also shown significant improvements in infrastructure monitoring, aiding in early detection of structural defects such as cracks [39–42]. Meanwhile, digital twin technologies provided by Zhai et al. [11] and Hu et al. [43] facilitated real-time structural health monitoring, highlighting a shift toward proactive maintenance strategies in construction management. Sustainability-specific research includes comprehensive analyses of energy-efficient buildings through AI-driven optimizations and management systems. Studies by Debrah et al. [44], Xiang et al. [45], and Li et al. [46] have assessed AI's role in achieving net-zero emissions in construction, emphasizing its importance in sustainability evaluations. Furthermore, Mehmood et al. [47], Asif et al. [48], and Ogundiran et al. [49] reviewed AI's applications in enhancing indoor environmental quality and energy efficiency, reinforcing AI's positive influence in these domains. Integration of AI with building information modeling (BIM) for smarter city developments was explored by Li et al. [50], highlighting benefits in improved sustainability practices and urban planning efficiency. Despite extensive exploration, there remains a gap in the comprehensive understanding of AI's practical implications, specifically for integrating durability and sustainability effectively in building design. Although studies have focused individually on durability or sustainability, few have thoroughly investigated the joint benefits and application potential of AI technologies in these interconnected areas. Particularly limited is the literature providing an overview and benefit assessments of AI's combined effects on sustainable building practices and durability. Addressing this gap, this study aims to review and assess the dual potential of artificial intelligence comprehensively. The objective is to illustrate how AI technologies, from predictive analytics to smart monitoring systems, offer practical solutions that enhance both the sustainability and durability of building structures simultaneously. Furthermore, this research aims to clarify AI's role within the broader context of achieving sustainable development goals and to propose strategies for overcoming existing implementation barriers. Within the study context, a durability aspects assessment through strengths, weaknesses, opportunities, and threats (SWOT) analysis is performed along with a sustainability assessment considering environmental, economic, and social aspects, as well as United Nations sustainability development goals alignment. By focusing on durability and sustainability collectively, this study's novelty is represented by seeking to guide the construction industry toward more resilient, economically feasible, and environmentally responsible building practices. Accordingly, this study aims to contribute to both the state of the art and the state of the practice.

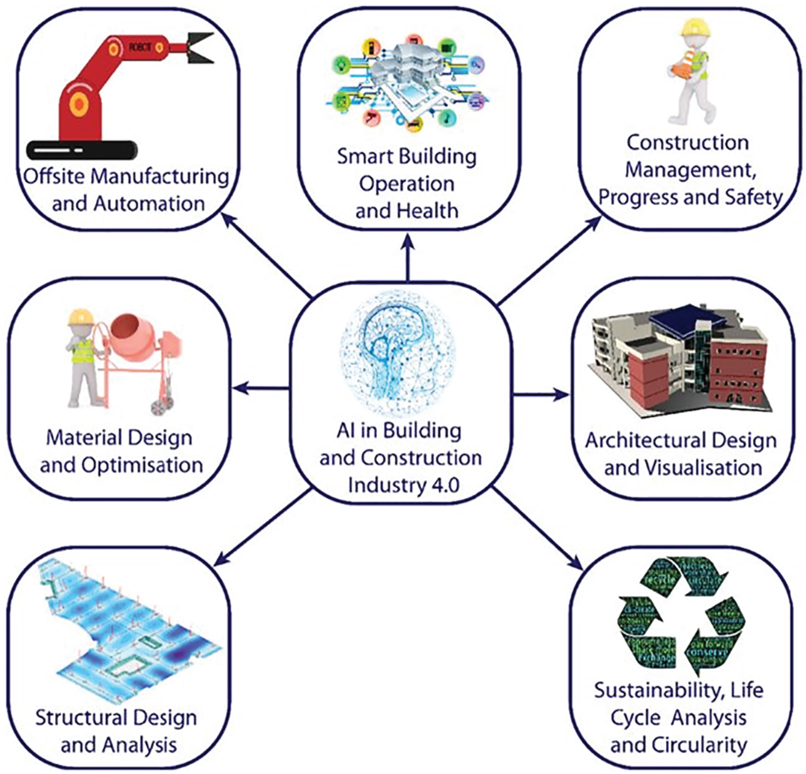

Figure 1: Various AI applications in the building and construction industry 4.0 (Adapted with permission from [8])

2 Bibliometric Analysis

The bibliometric analysis carried out in this study highlights the directions taken by researchers focusing on artificial intelligence within the context of sustainable and durable building design. A total of 375 publications were identified through Scopus, selected based on the presence of the terms "artificial intelligence," "building design," and either "sustainability" or "durability" in their titles, abstracts, or keywords. The publication date range was left as default to cover all available sources, and hence it was not limited to any specific range. This filtering ensured that the dataset was comprehensive while remaining directly aligned with the research scope, thereby reducing the inclusion of studies where AI was applied in unrelated construction contexts such as general project management or cost estimation. The data was processed using VOSViewer software, which allowed for visual and statistical representation of patterns in the literature. Specifically, VOSViewer was employed to generate co-authorship maps, keyword co-occurrence networks, and citation analyses, enabling the identification of influential researchers, research clusters, and thematic trends. The visualization also revealed how different AI techniques, such as machine learning, neural networks, and optimization algorithms, are distributed across applications in energy-efficient design, material durability, and lifecycle assessment. The classification of publication types shows that journal articles form the majority, with 212 out of the total 375, followed by 119 conference papers, 35 book chapters, and 8 books, as seen in Fig. 2. This suggests that peer-reviewed journals are the primary venue for disseminating research in this area, though conference proceedings also play a significant role, likely due to the evolving and experimental nature of AI technologies in design applications.

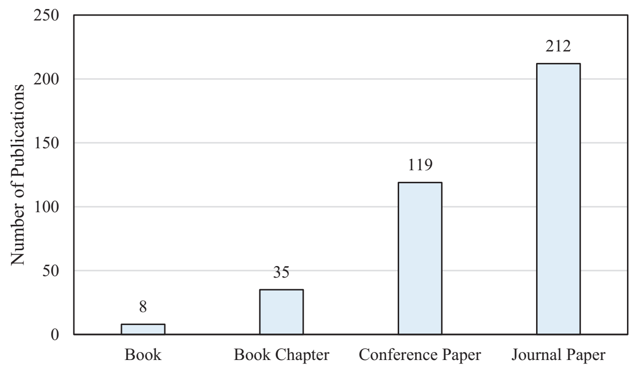

Figure 2: Types of journal articles and conference papers on AI applications for achieving sustainability and durability in building design

A review of publication trends over time, illustrated in Fig. 3, shows limited activity before 2015, with annual outputs generally below 10. A marked rise began around 2015 and gradually built-up momentum. The number of publications peaked in 2024 with 122 entries, while 2025 shows a high figure of 82, despite the year being incomplete. This pattern suggests that interest in the topic has expanded considerably in recent years, which may be linked to the increased accessibility of AI tools and heightened awareness of environmental and structural resilience in design practices.

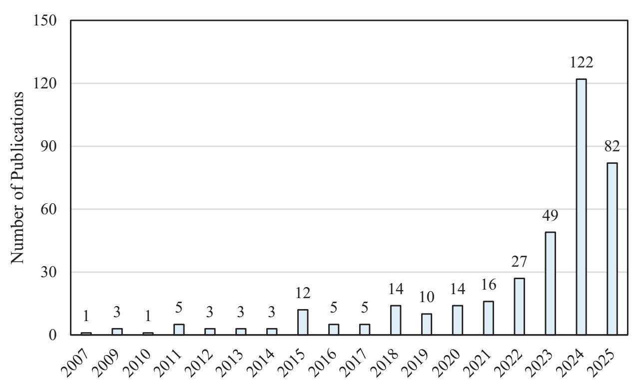

Figure 3: Number of yearly publications on AI applications for achieving sustainability and durability in building design

Keyword analysis further clarifies the focus of the published work. As shown in Fig. 4, terms such as "artificial intelligence," "energy efficiency," "machine learning," "building information modeling," and "optimization" frequently appear. These keywords reflect a concentration on computational methods used to improve energy use, structure performance, and decision-making processes in construction projects. Other recurring words, such as "smart city" and "project management," indicate that the literature often situates these technologies within broader planning and operational frameworks. In terms of geographic contributions, the visual map in Fig. 5 shows active involvement from several countries, with the United Kingdom, United States, and China appearing as the most productive. Other countries such as Saudi Arabia, Germany, South Africa, Australia, and the United Arab Emirates are also represented, suggesting a global interest in adapting AI to local design and construction needs. This wide participation points to the broad appeal of AI in addressing building performance goals, though the volume of output still varies significantly by region. Overall, the bibliometric findings suggest a growing and increasingly organized field, with distinct patterns of research focus, steady growth in publication numbers, and a globally distributed base of contributors. These patterns signal not just an interest in applying AI in building design, but also a recognition of its potential to address long-standing concerns related to efficiency, durability, and environmental goals.

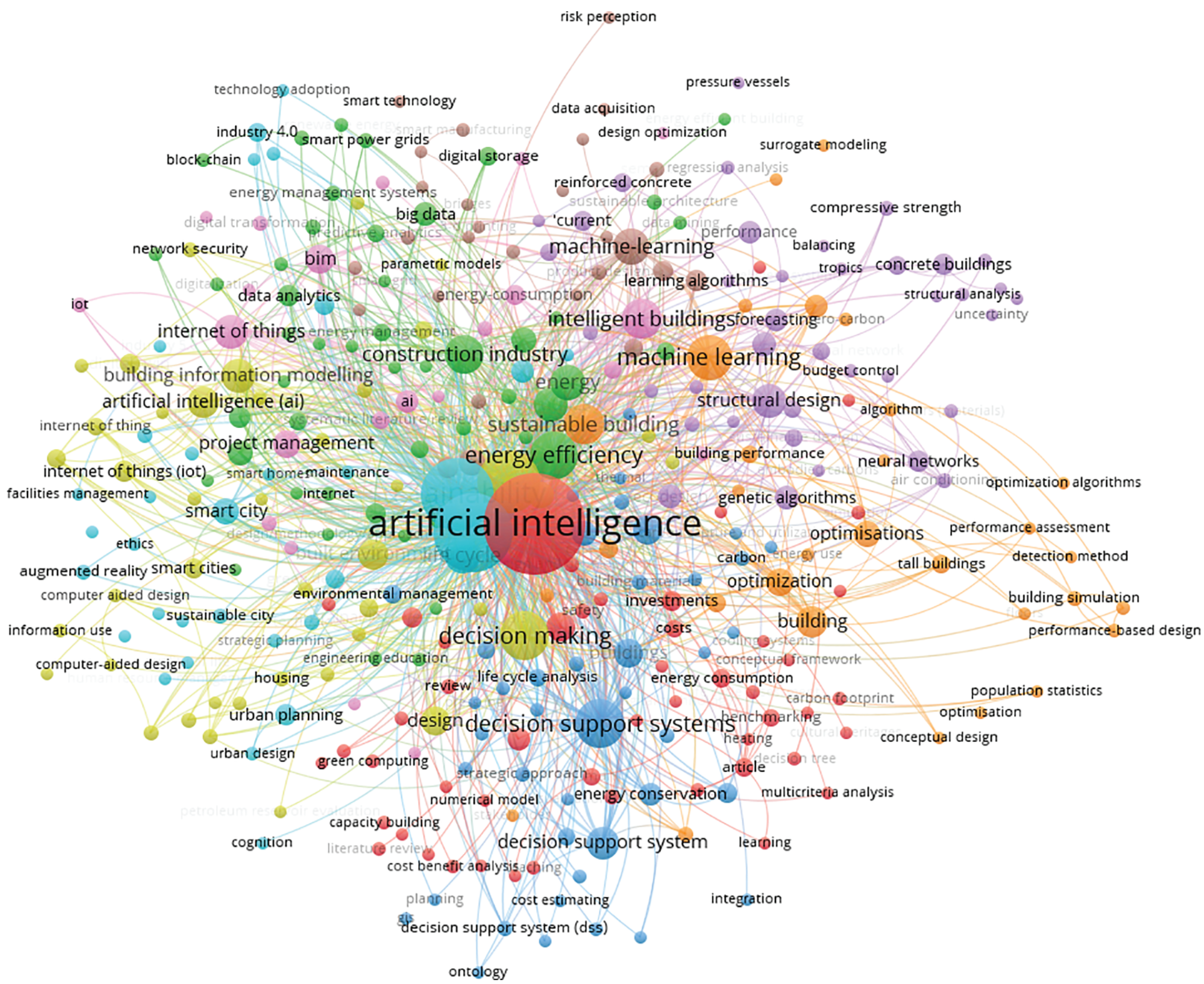

Figure 4: Co-occurrence of keywords in previous research on AI applications for achieving sustainability and durability in building design

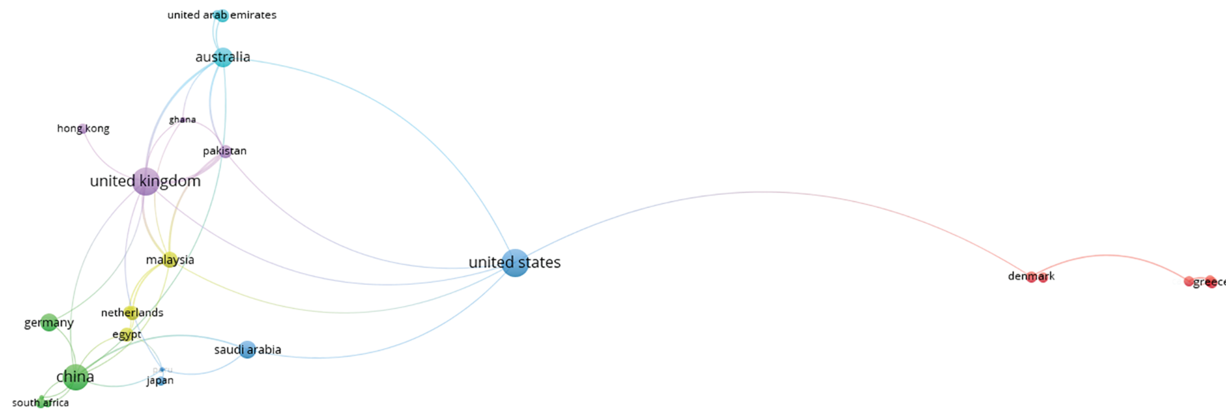

Figure 5: Most contributing countries to research on AI applications for achieving sustainability and durability in building design

3 AI Techniques for Durability

AI methods have become increasingly relevant in ensuring the durability of building structures, addressing long-standing challenges in accurately forecasting material performance and structural integrity [51–54]. Ji et al. [7] created predictive models for building lifespan assessment through advanced machine learning algorithms, considerably refining lifecycle management processes. Bhamare et al. [31] designed deep learning techniques predicting the thermal characteristics of buildings utilizing phase change materials, enhancing energy management and material durability. Gouda Mohamed and Marzouk [30] introduced artificial neural networks integrated with structural equations to evaluate building condition, providing precise and actionable condition assessments. Farrar and Worden [55] pioneered structural health monitoring methodologies utilizing machine learning, laying a foundational framework for subsequent durability assessments. Sun et al. [56] extensively reviewed machine learning methodologies applied to structural design and durability evaluation, highlighting their practical applications. Taffese and Espinosa-Leal [37] developed machine learning models specifically for chloride resistance prediction in concrete, directly influencing strategies for concrete durability enhancement. Aghabalaei Baghaei and Hadigheh [57] effectively utilized machine learning to assess the durability of FRP-to-concrete connections under moisture exposure, crucial for structural longevity. In green construction contexts, machine-learning models have enhanced project cost and schedule predictions, indirectly bolstering durability planning and sustainability by enabling more reliable lifecycle cost analyses [7,58]. Hafez et al. [38] devised a comprehensive machine learning system to forecast mechanical and durability properties of blended cement concrete, thus aiding robust construction practices. Meshref et al. [32] applied deep learning to lifecycle cost estimation, evaluating structural durability options in industrial buildings. Coelho et al. [33] systematically reviewed machine learning techniques for corrosion prediction, confirming their efficacy over conventional methods. Ossai [34] comparatively assessed machine learning approaches for corrosion risk management, validating their superior predictive accuracy. Hughes et al. [35] explored corrosion inhibitors using machine learning, significantly advancing predictive accuracy across different environments. Lunardi et al. [36] developed hybrid machine learning techniques predicting concrete fatigue under cyclic loads, critical for sustained structural performance. Baduge et al. [8] reviewed smart vision applications and highlighted that the potential of AI technologies for structural and construction material design, analysis, and optimization, significantly aiding timely maintenance strategies. Yeum and Dyke [39] introduced automated vision-based methods for detecting bridge cracks, improving inspection accuracy and timeliness. Jahanshahi and Masri [40] enhanced vision-based damage detection with three-dimensional scene reconstruction, ensuring precise assessments of structural conditions. Islam and Kim [41] developed convolutional neural networks for autonomous crack identification, enabling rapid evaluation of concrete structures. Rao et al. [42] implemented convolutional neural networks specifically for crack assessment in infrastructure, enhancing overall monitoring efficiency. Dang et al. [24] highlighted cloud-based digital twin technologies utilizing deep learning for continuous structural health monitoring. Zhai et al. [11] advanced digital twin frameworks quantifying seismic damage, improving response strategies for earthquake-prone structures. Hu et al. [43] designed intelligent BIM-integrated digital twin systems coupled with IoT sensors for enhanced real-time structural monitoring. Previously, physics-informed neural networks have demonstrated high fidelity in modeling building thermal dynamics, offering actionable insights for maintenance scheduling and durability enhancement [59,60]. Gokhale et al. [25] developed control-oriented PINN models, providing precise thermal modeling within buildings. Mai et al. [60] applied robust physics-informed neural networks to predict structural instability risks, substantially improving predictive accuracy compared to purely statistical methods. Chew et al. [61] reviewed physics-informed machine learning methods for urban infrastructure durability, confirming their high utility in managing structural resilience. Collectively, these studies underscore how AI-driven methods have reshaped durability research by introducing tools that enhance predictive precision and reliability. Their combined contributions reveal how machine learning, digital twins, and physics-informed models are not merely experimental but are becoming integral to evaluating material longevity, structural health, and lifecycle performance. Together, these advances establish AI as a cornerstone for building infrastructures that are not only more durable but also safer and better equipped to withstand future environmental and operational challenges. Table 1 summarizes the common AI applications for durability in buildings.

Table 1: Summary of common AI applications for durability in buildings

Application	Core principle	Key inputs	Outputs & insights	Durability role	Typical use cases	Implementation challenges
Supervised machine learning	Statistical learning (regression, classification)	Historical performance logs; material test results	Degradation curves; remaining useful life	Quantifies expected lifespan; prioritizes repairs	Lifespan estimation; maintenance scheduling	Requires labeled data; risk of overfitting
Deep learning	Hierarchical feature extraction via neural networks	High-frequency sensor streams; imagery	Anomaly scores; latent damage indicators	Detects subtle patterns before visible damage	Vibration analysis; fatigue crack detection	Data-hungry; opaque "black-box" models
Digital twin & simulation	Coupled real-time feedback in virtual replica	Live IoT feeds; as-built BIM geometry	Virtual state updates; scenario forecasts	Enables "what-if" testing; predicts failure under loads	Seismic response simulation; load redistribution	Integration complexity; model drift over time
Physics-informed neural networks	Hybrid of physical laws and data-driven approximators	Material properties; boundary conditions; sensors	Physically consistent state predictions	Ensures interpretability; respects conservation laws	Thermal stress modeling; moisture ingress impact	Requires precise physics formulation
Vision-based inspection	Computer vision for pattern recognition	High-res images/video of surfaces	Defect heatmaps; crack dimension measurements	Automates visual inspection; quantifies crack metrics	Facade crack mapping; corrosion spot detection	Lighting/angle sensitivity; preprocessing needs
Unsupervised anomaly detection	Pattern recognition without labeled faults	Continuous operational data; multivariate metrics	Outlier alerts; change-point detection	Flags novel damage modes; supports proactive alerts	Structural health monitoring; sensor drift alerts	Tuning false-alarm rates; interpretability

(Continued)

Table 1 (continued)

Application	Core principle	Key inputs	Outputs & insights	Durability role	Typical use cases	Implementation challenges
Transfer learning	Leveraging pre-trained models on new but related tasks	Pre-trained network weights; small new datasets	Rapid deployment; refined feature extraction	Speeds up model build for new structures	New site inspections where data are scarce	Domain mismatch; negative transfer risk

4 AI Techniques for Sustainability

In general, sustainability in buildings means the capacity of a building to deliver high-quality performance over its life while minimizing environmental burdens, maintaining economic feasibility, and supporting occupant health and social equity. In this regard, AI has gained significant attention as a tool for promoting sustainability within the built environment, addressing key challenges related to environmental impacts, energy efficiency, and resource optimization [62,63]. Debrah et al. [44] discussed the integration of AI in green building practices, illustrating various successful implementations in enhancing environmental outcomes. Xiang et al. [45] presented methodologies for evaluating sustainability in construction, demonstrating how AI significantly influences energy consumption optimization. Adio-Moses and Asaolu [64] examined AI applications for intelligent buildings, emphasizing its contribution to sustainable urban development. Bajwa et al. [18] systematically reviewed AI-driven smart management systems in buildings, highlighting their potential for improved energy efficiency and sustainability outcomes. Gilner et al. [65] focused on AI-driven optimization methods in sustainable building design, showing clear benefits in achieving better resource utilization. Elwy and Hagishima [66] reviewed surrogate models in AI-supported sustainable building designs, pointing to improvements in the optimization process and sustainability performance. Hanafi et al. [19] comprehensively surveyed AI methods for energy management in sustainable buildings, detailing significant advancements in energy use optimization. Adewale et al. [12] systematically reviewed AI applications in the lifecycle management of sustainable buildings, highlighting improvements in efficiency and environmental sustainability. Mehmood et al. [47] explored big data and AI-driven energy efficiency measures in buildings, emphasizing the positive impact on indoor environmental comfort. Asif et al. [48] discussed digital technologies' roles in sustainable building management, addressing their effectiveness in energy conservation and resource optimization. Alijoyo [67] demonstrated the significance of deep learning techniques within industry 4.0 frameworks, enhancing sustainability through better energy management in smart buildings. Vattano [68] provided insights into smart building technologies and their role in promoting sustainable development through intelligent resource management. Ogundiran et al. [49] reviewed AI's impact on improving energy efficiency and indoor environment quality, highlighting positive outcomes in sustainable building design. Li et al. [46] presented a comprehensive review on AI strategies toward achieving net-zero carbon emissions, showing significant contributions to sustainability goals. Prasad [69] discussed optimization strategies involving deep learning in smart building practices, highlighting significant improvements in sustainable outcomes. Li et al. [50] explored the relationship between AI and Building Information Modeling (BIM), illustrating advancements in smart cities and sustainable buildings. Farzaneh et al. [70] described how AI evolved in smart buildings, significantly influencing energy efficiency measures. Aguilar et al. [71] reviewed AI applications for energy self-management in smart buildings, providing evidence of improved sustainability performance. Dounis [72] investigated AI methodologies for energy conservation, highlighting their effectiveness in reducing energy consumption in buildings. Alnaser et al. [23] explored AI-powered digital twins and IoT applications, demonstrating their effectiveness in smart city sustainability initiatives. Tariq et al. [73] discussed complex AI models for enhancing energy sustainability in educational buildings, showing notable improvements in energy efficiency. Krausková and Pifko [74] examined AI applications in sustainable architecture, summarizing key technological developments and their impact. Ajayi et al. [75] highlighted AI's capability in reducing building carbon emissions through predictive analytics, substantially contributing to sustainability. Al-Haddad et al. [76] focused on AI-enhanced aerodynamic façades, highlighting their potential in advancing sustainable architectural designs. Pasupuleti et al. [77] discussed AI's role in navigating sustainable construction practices, highlighting practical implementations that enhance building sustainability. Ekici et al. [78] detailed AI methodologies for multi-zone optimization in high-rise buildings, significantly improving sustainability. Kazeem et al. [79] explored AI's contributions to sustainable construction processes, focusing on improved efficiency and community benefits. Manmatharasan et al. [80] reviewed AI-driven design optimization for sustainable buildings, illustrating marked improvements in resource efficiency. Gilner et al. [81] discussed AI applications in sustainable building design, highlighting optimization techniques beneficial for environmental outcomes. Alotaibi [82] demonstrated the integration of AI and machine learning for enhancing energy efficiency in residential buildings, significantly contributing to sustainable construction practices. Saliu and Elezi [83] reviewed AI integration in architectural practice, emphasizing its significant role in sustainable design performance. Elmousalami et al. [84] examined automated AI frameworks in sustainable construction management, underscoring substantial improvements in project efficiency. Gadalla et al. [85] addressed the effective role of AI in sustainable architectural designs, presenting clear benefits in efficiency and sustainability outcomes. Dagadkar et al. [86] reviewed AI techniques in sustainable construction, detailing practical impacts and solutions contributing to sustainability objectives. Michalakopoulos et al. [26] presented physics-informed neural networks predicting building energy efficiency, highlighting improvements in sustainability management. Naeini et al. [27] discussed hybrid AI frameworks combining physics-informed neural networks and blockchain security, showing enhanced sustainability through optimized energy consumption. Collectively, these contributions illustrate AI's extensive potential in promoting sustainability in the construction industry, demonstrating varied methodologies that effectively address ecological, economic, and social sustainability.

5 AI Potential Assessment for Achieving Building Durability and Sustainability

As mentioned before, AI presents a complex and increasingly central role in reshaping both durability and sustainability outcomes in building design. Although the architectural and construction industries have historically relied on standardized methodologies for structural design and maintenance, the entrance of AI has shifted the focus toward adaptive and data-driven solutions that account for change over time, environmental variability, and operational unpredictability.

5.1 Durability Aspects

Evaluating AI within the durability context of buildings reveals several applications, Table 2, and strengths, weaknesses, opportunities, and threats (SWOT) analysis, Table 3. AI's strength in predicting degradation is not just an incremental improvement over conventional monitoring; it represents a redefinition of how buildings can be maintained and evaluated. Machine learning models, when supplied with high-resolution historical and sensor data, are capable of forecasting deterioration at a level of precision that manual inspections often miss. Such forecasting allows for targeted interventions rather than reactive responses, which reduces long-term maintenance costs and prevents cascading failures. In systems where fatigue or cyclic loading plays a central role, such as in bridges or high-rise constructions, traditional lifetime estimations fall short due to their rigid reliance on linear deterioration models. The application of hybrid learning systems offers an alternative where models adjust continuously based on newly acquired performance data. This represents a decisive shift toward condition-based lifecycle modeling rather than assumption-based design, which, despite being embedded in many engineering codes, remains relatively inflexible. Despite these strengths, the application of AI in assessing durability remains constrained by several technical limitations.

Table 2: Summary of common AI applications for sustainability in buildings

Application	Core principle	Key inputs	Outputs & insights	Sustainability focus	Typical use cases	Implementation challenges
Predictive optimization	Surrogate modeling + operations research	Design parameters; energy/resource metrics	Optimal control schedules; resource plans	Minimizes waste; balances trade-offs	HVAC sequencing; daylight harvesting schedules	Multi-objective complexity; computation intensity
Reinforcement learning	Trial-and-error with reward feedback	Real-time performance; control signals	Adaptive control policies	Learns dynamic strategies for peak efficiency	HVAC setpoint tuning; lighting automation	Convergence time; reward design
Digital twin + IoT analytics	Real-time data assimilation in dynamic simulation	Continuous sensor streams; weather forecasts	Scenario-based energy forecasts	Enables adaptive operations under varying conditions	Microgrid management; demand response	Data integration; latency management
Multi-objective evolutionary algorithms	Evolutionary search for Pareto-optimal sets	Cost, comfort, emission functions	Pareto fronts of design/configuration	Balances cost vs. carbon vs. comfort	Envelope optimization; material selection	Large search spaces; convergence guarantees
Physics-informed neural networks	Embedding conservation laws into neural approximators	Environmental physics parameters; sensor feeds	Physically consistent energy models	Ensures model fidelity; supports robust energy forecasts	Thermal load forecasting; seasonal control	Complex loss formulation; solver stability
Occupant behavior modeling	Statistical inference of human patterns	Occupancy logs; environmental sensor histories	Usage patterns; peak demand predictions	Reduces over-conditioning; aligns with real needs	Automated ventilation control; lighting schemes	Privacy concerns; behavior variability
Waste & water efficiency analytics	Pattern mining for resource anomalies	Procurement records; water-use meters	Waste hotspots; water-use inefficiencies	Identifies root causes of resource overuse	Construction waste reduction; rainwater use	Data granularity; cross-system integration

(Continued)

Table 2 (continued)

Application	Core principle	Key inputs	Outputs & insights	Sustainability focus	Typical use cases	Implementation challenges
Federated learning	Decentralized model training across multiple sites	Local datasets; model parameter exchanges	Aggregate insights; preserves data privacy	Enables collaboration without sharing raw data	Cross-project energy benchmarking; material models	Communication overhead; heterogeneity of data

A recurring issue is the inconsistency and incompleteness of datasets. Structural health monitoring systems are often deployed after construction, meaning data from earlier stages are missing. This data scarcity introduces blind spots in the model's understanding of early-stage material behavior and makes long-term predictions less reliable. Furthermore, the efficacy of deep learning models, particularly convolutional neural networks for defect detection, depends not only on data quantity but on data quality, which varies significantly across projects. Financial constraints further compound the problem. While large-scale infrastructure projects may justify the upfront investment in AI platforms and sensor systems, smaller-scale or budget-limited constructions often lack the resources to integrate these technologies. This imbalance may contribute to a widening gap in the longevity and performance of buildings based on economic context. The situation is not simply a matter of availability but of policy and institutional inertia. Many construction codes remain prescriptive rather than performance-based, delaying the adoption of adaptable AI-supported monitoring tools. The threat of cybersecurity breaches should not be considered an afterthought. AI-integrated digital twins rely heavily on continuous data exchange between on-site sensors and centralized databases. If not adequately protected, these systems become vulnerable points in the digital infrastructure of cities. Unlike physical failures that degrade gradually, digital intrusions can compromise systems instantaneously and without warning. Nevertheless, there are considerable opportunities. Integration with BIM and the IoT enables the formation of intelligent maintenance regimes where buildings effectively monitor themselves and initiate inspection or maintenance protocols as required. Such autonomy in infrastructure operation has the potential to shift responsibilities from manual inspections toward decision-making informed by real-time analytics, ultimately lowering operational inefficiencies.

Table 3: SWOT analysis for durability

Strengths	Weaknesses
• High-precision degradation forecasting from multi-sensor fusion • Condition-based lifecycle modeling enabling just-in-time maintenance • Self-adapting models that incorporate new performance data • Early detection of hidden faults reduces risk of catastrophic failure • Scalability across asset portfolios via cloud platforms	• Incomplete historical datasets lead to blind spots • Quality and consistency of data vary widely between sites • Significant upfront investment in sensors, software, and training • "Black-box" model opacity can hinder regulatory and stakeholder acceptance • Requires specialized workforce for deployment and ongoing management

(Continued)

Table 3 (continued)

Opportunities	Threats
• Seamless BIM and IoT integration for fully autonomous monitoring • Democratization of AI through low-code/no-code platforms • Cross-project transfer learning to leverage insights from multiple structures • Regulatory shifts toward performance-based standards that reward proactive durability management • Use of edge computing to enable on-device analytics in areas with limited connectivity	• Cybersecurity vulnerabilities in connected digital twins and data pipelines • Institutional inertia; slow revision of prescriptive codes • Unequal access: smaller firms may lag, widening performance gaps • Liability concerns over AI-driven maintenance decisions • Data privacy regulations restricting sensor deployment

5.2 Sustainability Aspects

5.2.1 Environmental Benefits

AI's relevance to environmental sustainability lies primarily in its capacity to reconfigure how energy and resources are allocated within the building lifecycle, Table 4. Contrary to design philosophies that depend on static models, AI systems can recalibrate building performance strategies based on external inputs, such as seasonal variability, energy pricing, and occupancy patterns. This dynamism allows for continuous adjustment and minimization of waste, which is particularly relevant in the context of energy-intensive operations like HVAC systems. Thermal modeling has traditionally relied on simplified simulations, often unable to handle irregularities in building usage or climate shifts. PINNs offer an alternative that fuses physical laws with machine learning structures, producing outcomes that are both interpretable and adaptive. These models adjust to discrepancies between predicted and actual performance, refining future projections and encouraging low-waste energy regimes. Material waste remains a neglected variable in environmental assessments, yet AI offers pathways for preemptive identification of inefficiencies in procurement and construction stages. For instance, AI-supported simulations can flag mismatches between structural requirements and material allocations, which helps prevent overuse, reduce waste, and keep construction output consistent with the intended design. At the operational phase, smart systems monitor deterioration and signal optimal points for intervention, reducing the need for full-scale replacements.

5.2.2 Economic Benefits

The assumption that sustainable architecture necessarily implies increased expenditure has been gradually overturned through AI's intervention in project management and lifecycle cost modeling. It is demonstrated that AI-supported forecasts offer a more precise understanding of long-term costs associated with different structural configurations. This allows designers and contractors to make decisions that align with both budget constraints and environmental goals. In green construction, projects often suffer from delays due to the complexity of integrating novel materials or unfamiliar energy systems. AI applications streamline construction sequencing, resource scheduling, and supply chain coordination. The cost savings associated with delay reductions are substantial, and such economic efficiencies strengthen the case for integrating sustainability measures at the design stage rather than retrofitting them later. The economic benefits also extend into operational phases. Smart energy systems dynamically adjust building consumption patterns based on real-time variables. This realignment leads to significant reductions in utility costs. Over time, these savings often surpass the additional upfront costs associated with AI-enabled infrastructure.

5.2.3 Social Benefits

AI systems influence more than the physical environment, they shape the social quality of life within and around buildings. Indoor environmental quality, especially in dense urban areas, has direct consequences on health and well-being. AI-powered ventilation and filtration systems can respond dynamically to pollutants or occupancy patterns, avoiding blanket ventilation that wastes energy or fails to address localized conditions. Equally important is the role of AI in improving accessibility and inclusivity. Adaptive systems that recognize patterns of use among different demographic groups can modify building operations to support the needs of elderly individuals, children, or persons with disabilities. Public engagement in the construction process has long suffered from lack of transparency, often resulting in mistrust or resistance. AI-integrated platforms enable real-time feedback mechanisms where stakeholders can assess sustainability indicators without relying on abstract technical reports.

Table 4: Summary of the sustainability aspect benefits

Aspect	Benefit category	Benefit description	Applications/Examples
Environmental	Energy efficiency	Continuous calibration of HVAC, lighting, and solar gains to minimize consumption	PINNs for adaptive HVAC; RL for lighting schedules
	Emissions reduction	Predictive load balancing to shift energy use to low-carbon periods	Digital twins for demand response; optimization of backup generators
	Material & waste optimization	Pre-construction simulation to prevent material over-ordering; on-site monitoring to reduce spoilage	Surrogate models in procurement; vision-based waste sorting
Economic	Lifecycle cost management	Precise forecasting of total cost of ownership enables selection of cost-effective and durable design options	ML cost-prediction models; evolutionary algorithms for budget vs. performance
	Schedule & supply-chain streamlining	Dynamic rescheduling to avoid delays and reduce idle resources	RL agents for crane scheduling; optimization of delivery windows

(Continued)

Table 4 (continued)

Aspect	Benefit category	Benefit description	Applications/Examples
	Operational expense reduction	Smart energy systems that adapt to tariff changes and occupancy patterns, yielding utility bill savings	Federated learning across sites for tariff negotiation insights
Social	Health & comfort	Real-time air-quality control and personalized thermal comfort zones, improving occupant well-being	Occupant behavior models; IoT-driven ventilation control
	Accessibility & inclusivity	Adaptive wayfinding and environment settings (lighting, acoustics) for people with different mobility or sensory needs	Vision-based gesture recognition for controls; RL-driven acoustic adjustments
	Community engagement & transparency	Public dashboards and alerts on building sustainability performance, fostering trust and collaborative decision-making	Web portals fed by digital-twin data; dashboard analytics with automated reports

5.2.4 UN SDG Alignment

AI's application in building design aligns closely with several United Nations SDGs, Table 5, notably SDG 11 on Sustainable Cities and Communities through promoting resilient infrastructure and sustainable urban development. AI-enhanced energy efficiency directly supports SDG 7 (Affordable and Clean Energy) by facilitating sustainable energy management in buildings. Moreover, predictive maintenance and improved material durability align with SDG 9 (Industry, Innovation, and Infrastructure), ensuring resilient and sustainable. Additionally, AI technologies significantly contribute to SDG 13 (Climate Action) by accurately predicting and mitigating environmental impacts from construction activities. The optimization of resource usage and waste management supported by AI addresses SDG 12 (Responsible Consumption and Production), ensuring more sustainable construction practices. Lastly, the deployment of intelligent, sustainable buildings supports SDG 3 (Good Health and Well-being), particularly through improved indoor air quality and overall environmental health. In conclusion, AI demonstrates considerable potential for enhancing building durability and promoting sustainability. By systematically addressing identified weaknesses and threats, the construction industry can effectively maximize the benefits and opportunities presented by AI technologies, thus supporting a sustainable and resilient built environment. This requires targeted strategies such as improving data quality and availability, reducing implementation costs, strengthening cybersecurity, and updating regulatory frameworks to accommodate performance-based approaches. When these challenges are managed, AI's strengths in predictive maintenance, resource optimization, and digital-twin integration can be fully realized, enabling the sector to reduce waste, lower carbon emissions, and enhance the longevity and adaptability of buildings in line with global sustainability goals.

Table 5: UN SDG alignment analysis

SDG	Description	AI contribution
SDG 3	Good health and well-being	• AI-enabled indoor-air monitoring and control • Improved environmental health outcomes
SDG 7	Affordable and clean energy	• Smart energy management in buildings • Predictive demand response
SDG 9	Industry, innovation, and infrastructure	• Digital twins and predictive maintenance for infrastructure resilience
SDG 11	Sustainable cities and communities	• AI-driven resilient infrastructure design • Real-time monitoring for urban resilience
SDG 12	Responsible consumption and production	• Resource-use optimization • Waste-minimization simulations
SDG 13	Climate action	• Forecasting environmental impacts • Adaptive operation strategies for reducing carbon footprint

6 Challenges & Future Directions

Integrating AI within the building industry faces several practical challenges and obstacles. One key challenge arises from the significant initial investments required, making AI technologies inaccessible to smaller enterprises or firms operating under constrained budgets. Additionally, the construction industry traditionally relies on conventional methodologies, and resistance to adopting newer technologies like AI can significantly hinder their broader acceptance. Data management presents another substantial hurdle, as the efficacy of AI tools depends heavily on extensive, high-quality datasets, which can be difficult to obtain consistently. Data privacy concerns and cybersecurity threats also remain prominent, especially with increasing digitalization and network connectivity in construction processes, potentially deterring stakeholders from fully embracing AI solutions. Moreover, the complexity of AI systems necessitates a specialized workforce capable of managing and operating these advanced technologies. Currently, there exists a significant skill gap within the construction industry, limiting the effective deployment and management of sophisticated AI-driven solutions. Training personnel to operate these systems efficiently represents an ongoing, resource-intensive effort that companies must adequately prepare for. Despite these barriers, several promising avenues indicate strong potential for future AI integration within the construction sector. Continuous advancements in AI methodologies, particularly machine learning and digital twin technologies, show promise for overcoming many existing challenges by simplifying implementation processes and reducing the overall cost of adoption. Further research focusing on enhancing algorithm robustness, reducing data dependency, and improving user interfaces will likely aid in making these technologies accessible to a wider range of industry stakeholders. Regulatory frameworks supporting innovation and addressing data privacy and cybersecurity could significantly encourage broader acceptance of AI technologies within construction. Collaboration between academia, industry, and policymakers could streamline processes, enabling quicker adaptation and smoother integration into standard practices. Future directions could include expanding the application of AI into areas such as automated compliance checking, predictive urban planning, and adaptive reuse of existing structures, effectively managing resources and achieving sustainability goals more efficiently. Ongoing technological advancements will also likely result in more intuitive, user-friendly AI solutions, lowering the barrier to entry for smaller enterprises and facilitating broader industry uptake.

7 Conclusion

Artificial intelligence demonstrates significant potential to advance durability and sustainability within building design and construction. AI technologies contribute substantially to durability through predictive maintenance capabilities, enabling timely interventions that extend the lifecycle of structures. Moreover, AI applications facilitate optimized resource management, improved energy efficiency, and enhanced environmental outcomes, directly aligning with global sustainability objectives. Nevertheless, integrating AI within the construction sector faces challenges such as high initial costs, industry resistance to new technologies, data management complexities, and workforce skill gaps. Overcoming these barriers requires coordinated efforts among industry leaders, academic institutions, and policymakers, emphasizing targeted education, robust regulatory support, and ongoing technological innovation. Ultimately, continued advancements in AI technologies hold considerable promise for fostering a sustainable and resilient built environment, significantly benefiting both industry stakeholders and the broader community. Finally, this study is limited to assessing the role of artificial intelligence in achieving durability and sustainability in building design, without extending its scope to other emerging technologies, such as blockchain, that are also critical to the field.

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