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Framework for Leveraging Artificial Intelligence in Monitoring Environmental Impacts of Green Buildings

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Abstract
The transition toward green buildings has emerged as a pivotal strategy for mitigating climate change, reducing urban environmental footprints, and improving human well-being. However, one of the persistent challenges lies in effectively monitoring the environmental impacts of green buildings across their lifecycle. Conventional assessment tools, while useful, often rely on static datasets and periodic audits, limiting the ability to capture real-time performance dynamics and adaptive responses. This proposes a framework for leveraging Artificial Intelligence (AI) in monitoring the environmental impacts of green buildings, offering a comprehensive, data-driven, and adaptive solution. The framework is structured into four interrelated layers. The input layer encompasses sensor networks, Internet of Things (IoT) devices, and external datasets to gather information on energy consumption, water use, indoor air quality, carbon emissions, and waste generation. The decision layer employs AI tools—such as machine learning models, neural networks, and predictive analytics—to detect anomalies, conduct life-cycle impact assessments, and optimize building performance against multiple sustainability criteria. The implementation layer integrates AI outputs into building management systems and policy compliance mechanisms, providing actionable insights for facility managers, developers, and regulators. Finally, the feedback layer ensures continuous monitoring, adaptive learning, and replication, enabling real-time refinement of building operations and scaling across portfolios of green buildings. Application scenarios include optimizing energy performance in commercial complexes, enhancing water efficiency in urban housing estates, tracking carbon footprints in office buildings, and reducing waste during construction and operation. By bridging technological innovation, sustainability assessment, and governance, the proposed framework highlights how AI can move green building monitoring beyond static evaluations to dynamic, responsive systems. Future directions point to the convergence of AI with digital twins, blockchain-enabled reporting, and global standardization efforts, positioning AI-enabled monitoring as central to the next generation of sustainable built environments.

Keywords: Artificial Intelligence, Green Buildings, Environmental Monitoring, Sustainability Assessment, Energy Efficiency, Carbon Footprint Tracking, Smart Sensors, Data Analytics, Predictive Modeling, Lifecycle Assessment, Resource Optimization

1. Introduction

The accelerating pace of climate change and rapid urbanization has intensified the need for sustainable built environments, with green buildings emerging as a central strategy to reduce environmental impacts and promote urban resilience (Tushar *et al*., 2018; Qolomany *et al*., 2019 [43]). Green buildings are designed to optimize energy efficiency, minimize carbon emissions, conserve water resources, and improve indoor environmental quality, thereby contributing to both ecological preservation and human well-being (Alawneh *et al*., 2018 [5]; Prada *et al*., 2010). In regions experiencing rising urban populations and increasing resource constraints, the adoption of green buildings is no longer optional but a necessity to meet global climate targets, reduce environmental degradation, and support sustainable urban transformation (Deng *et al*., 2018; Zhang *et al*., 2019) [15, 60]. However, for green buildings to achieve their intended outcomes, effective mechanisms for monitoring and evaluating their environmental performance are essential (Lützkendorf, 2018; Zhang *et al*., 2019) [32, 60].

Despite the growing body of standards and certification frameworks—such as LEED, BREEAM, and EDGE—accurately monitoring environmental impacts remains a significant challenge. Conventional approaches often rely on static datasets, periodic audits, or post-construction evaluations, which may fail to capture dynamic changes in building performance over time (Mallela *et al*., 2018; Gupta *et al*., 2020) [33, 21]. Energy consumption patterns, carbon emissions, water use, and waste generation vary significantly depending on user behavior, climatic conditions, and operational efficiency. The absence of real-time, adaptive monitoring systems limits the ability of stakeholders to respond proactively to inefficiencies, underperformance, or changing environmental conditions (Barnett *et al*., 2019; Osho *et al*., 2020) [8, 38]. This gap risks undermining the transformative potential of green buildings, particularly in fast-growing cities where sustainability targets must be balanced with affordability and scalability.

Artificial Intelligence (AI) offers a transformative opportunity to overcome these limitations by enhancing data collection, analysis, and predictive capacity (Duan *et al*., 2019; Pencheva *et al*., 2020) [16, 40]. Through integration with Internet of Things (IoT) sensors, smart meters, and building management systems, AI can provide real-time insights into the environmental performance of buildings. Machine learning algorithms can detect anomalies in energy or water consumption, optimize heating and cooling systems, forecast maintenance needs, and assess lifecycle environmental impacts with greater precision (Petroșanu *et al*., 2019; Qolomany *et al*., 2019) [41, 43]. By moving beyond descriptive monitoring to predictive and prescriptive analytics, AI enables stakeholders not only to understand current performance but also to anticipate future challenges and opportunities. This capability aligns with the global shift toward digitalization in construction and urban management, where data-driven decision-making is becoming essential for achieving sustainability and resilience objectives (Engin *et al*., 2020; Hetemi *et al*., 2020) [18, 23].

The purpose of this, is to propose a structured AI-enabled framework for monitoring and improving green building performance, addressing the pressing need for dynamic, accurate, and adaptive monitoring systems. The framework is designed to integrate multiple layers: input mechanisms for data collection, decision-making through advanced AI analytics, implementation via integration with building systems and policy instruments, and continuous feedback for learning and refinement. By aligning technological innovation with sustainability goals, the framework seeks to bridge the gap between design intentions and real-world performance.

In doing so, this framework not only strengthens the accountability and transparency of green building practices but also provides actionable insights that can inform policy, guide investment decisions, and empower communities. Ultimately, leveraging AI for environmental monitoring enhances the capacity of green buildings to fulfill their promise as critical enablers of climate mitigation and sustainable urban futures.

2. Methodology

The development of this framework was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to ensure methodological rigor, transparency, and replicability. The process began with the formulation of a central research question: *How can Artificial Intelligence be leveraged to monitor and improve the environmental impacts of green buildings?* To address this, a systematic search of peer-reviewed and grey literature was conducted across major academic databases including Scopus, Web of Science, ScienceDirect, and IEEE Xplore, alongside institutional and policy repositories focusing on sustainability and digital technologies. The search strategy combined key terms such as “artificial intelligence,” “green buildings,” “environmental monitoring,” “sustainability assessment,” “IoT,” and “life-cycle analysis.”

The identification stage produced a broad pool of studies, which were screened to remove duplicates and irrelevant publications. Inclusion criteria prioritized literature published between 2000 and 2025 that explicitly addressed AI applications in environmental monitoring, building performance assessment, and sustainability reporting frameworks. Exclusion criteria were applied to studies lacking empirical grounding, focusing exclusively on non-environmental applications of AI, or addressing building performance without technological integration. Full-text reviews were then conducted at the eligibility stage to ensure methodological soundness, contextual relevance, and potential contribution to the conceptual framework.

The final selection included interdisciplinary sources spanning architecture, engineering, computer science, sustainability science, and policy analysis. Data extraction focused on identifying recurring themes such as the role of IoT-enabled data collection, AI-driven predictive analytics, lifecycle assessment integration, and the governance of smart building systems. The synthesis of this evidence informed the design of a multi-layered framework that encompasses input, decision, implementation, and feedback dimensions.

By following PRISMA guidelines, the methodology ensured that the proposed framework is grounded in a robust evidence base, capturing both technological advancements and sustainability imperatives. This systematic approach enhances the framework’s reliability and provides a structured foundation for applying AI in real-world green building contexts, bridging scientific research, policy development, and practical implementation.

2.1 Conceptual Foundations

The foundation for leveraging Artificial Intelligence (AI) in monitoring the environmental impacts of green buildings lies at the intersection of digital innovation, sustainability assessment frameworks, and life-cycle thinking. By integrating advanced computational techniques with established evaluation systems, AI can significantly enhance the accuracy, responsiveness, and adaptability of monitoring systems (Ahmed *et al*., 2020; Adir *et al*., 2020) [3, 2]. This explores the conceptual underpinnings of such a framework, focusing on AI applications in sustainable construction and facility management, green building assessment principles, and the integration of life-cycle assessment (LCA) with AI-driven analytics.

Artificial Intelligence has increasingly been applied in the construction sector, offering transformative potential for sustainability outcomes. In the context of green buildings, AI contributes to both the design and operational phases. During construction, AI-powered tools can optimize material selection, identify opportunities for waste reduction, and support predictive logistics, thereby reducing embodied carbon (Dash *et al*., 2019; Osho *et al*., 2020) [14, 38]. For instance, machine learning algorithms trained on historical project data can predict the environmental impact of material choices and suggest alternatives that minimize ecological footprints.

In facility management, AI becomes a critical enabler of real-time monitoring and adaptive operations. Integration with Internet of Things (IoT) devices and smart sensors allows continuous data collection on energy consumption, indoor air quality, water use, and waste generation. AI systems can process this high-frequency data to detect anomalies, optimize heating, ventilation, and air conditioning (HVAC) operations, and provide predictive maintenance schedules. Furthermore, reinforcement learning approaches can adapt control strategies dynamically, improving building performance under varying climatic and occupancy conditions (Brandi *et al*., 2020; Yang *et al*., 2020) [10, 57]. These applications not only improve environmental efficiency but also reduce operational costs, enhance occupant comfort, and extend the lifecycle of building systems.

Green building assessment frameworks such as LEED (Leadership in Energy and Environmental Design), BREEAM (Building Research Establishment Environmental Assessment Method), and EDGE (Excellence in Design for Greater Efficiencies) have established standardized benchmarks for evaluating building sustainability. These systems assess performance across multiple categories, including energy efficiency, water conservation, material sustainability, waste reduction, and indoor environmental quality. While highly influential in guiding sustainable design and construction, these frameworks often depend on periodic audits, static documentation, or modeled estimates rather than continuous, real-time data (Rašković *et al*., 2020; Zoghi and Kim, 2020) [46, 61].

AI can address this gap by enhancing the scope and accuracy of compliance monitoring. For instance, an AI-driven system linked with IoT devices can provide continuous evidence for certification credits, ensuring that performance targets are not only met at the design stage but also maintained during operation. By integrating AI with these assessment frameworks, certification processes can evolve from static evaluations into dynamic performance verification systems. Moreover, AI can support post-certification monitoring, ensuring that green buildings continue to deliver environmental benefits throughout their lifecycle rather than only during initial occupancy.

Life-Cycle Assessment (LCA) provides a comprehensive methodology for evaluating the environmental impacts of buildings and construction materials across their entire lifecycle—from raw material extraction to demolition or recycling. LCA highlights the embedded carbon, energy use, and environmental trade-offs associated with different construction and operational decisions. While robust, LCA can be data-intensive, complex, and time-consuming, often requiring extensive datasets and expert knowledge for meaningful application (Stephan *et al*., 2019; Durão *et al*., 2020) [50, 17].

AI has the potential to significantly advance LCA by automating data collection, streamlining analysis, and enabling predictive modeling. For example, natural language processing can be used to extract data from technical reports, while machine learning models can estimate missing environmental impact data for under-documented materials. Predictive analytics can model future environmental impacts under different scenarios, such as changing climate conditions, occupancy patterns, or energy supply sources. By integrating LCA with AI-driven analytics, decision-makers gain access to actionable insights that are faster, more precise, and adaptive to dynamic contexts.

This integration also enables scenario-based optimization. AI can simulate multiple design or operational strategies, quantifying their respective environmental footprints over the building's lifecycle. For example, an AI-augmented LCA can compare the long-term impacts of using geopolymer concrete versus traditional Portland cement, taking into account embodied emissions, durability, and maintenance requirements. This capability empowers architects, engineers, and policymakers to prioritize strategies that align with both short-term resource efficiency and long-term sustainability.

Together, these conceptual foundations demonstrate the necessity of bridging AI applications, green building assessment frameworks, and LCA methodologies. AI strengthens the responsiveness and efficiency of sustainable construction and facility management, turning buildings into adaptive, intelligent systems (Chew *et al*., 2020; Yigitcanlar *et al*., 2020) [11, 58]. Assessment frameworks such as LEED, BREEAM, and EDGE provide the normative structure for defining and measuring sustainability, while AI ensures that these standards are met dynamically and continuously. LCA, when enhanced through AI analytics, closes the loop by providing lifecycle-wide insights that capture both operational and embodied impacts.

In this synthesis, AI acts as a unifying force—connecting performance data from IoT-enabled monitoring with certification benchmarks and lifecycle analysis tools. This convergence creates a robust foundation for the proposed framework, enabling environmental monitoring of green buildings that is not only rigorous and evidence-based but also adaptive, predictive, and scalable.

2.2 Framework Components

The proposed framework for leveraging Artificial Intelligence (AI) in monitoring the environmental impacts of green buildings is organized into four interdependent layers: input, decision, implementation, and feedback. Each layer plays a distinct yet complementary role, ensuring that environmental monitoring evolves from static reporting to a dynamic, adaptive, and scalable system as shown in figure 1 (Asch *et al*., 2018; Raptis *et al*., 2019) [6, 45]. By combining real-time data acquisition, intelligent analytics, and user-focused decision support, the framework creates a holistic architecture capable of bridging technology, policy, and practice.

The foundation of the framework lies in robust and diverse data collection mechanisms. Sensor networks and Internet of Things (IoT) devices embedded within green buildings enable real-time measurement of critical parameters such as energy consumption, water use, indoor air quality, and waste generation (Tushar *et al*., 2018; Hayat *et al*., 2019 [22]). These sensors provide granular, continuous data streams that reflect both environmental performance and occupant behavior.

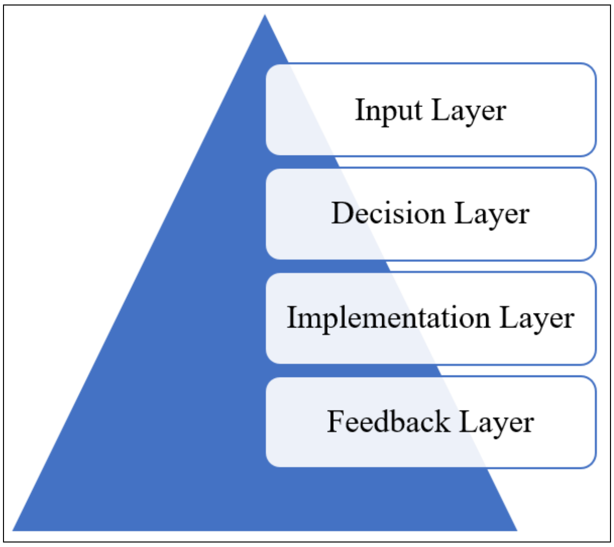

Fig 1: Framework Components

Complementing internal sensors, external datasets supply contextual information that influences building performance. Climate conditions, weather forecasts, and grid emissions factors are essential inputs for evaluating energy efficiency, carbon intensity, and resilience. For instance, integrating grid emissions data allows the system to quantify the carbon footprint of electricity consumption based on temporal variations in energy supply sources.

In addition, historical building performance records serve as benchmarks for identifying trends and anomalies. Past data on energy loads, maintenance logs, and occupancy patterns provide the baseline against which real-time performance is assessed (Pang *et al*., 2018; Bang *et al*., 2019) [39, 7]. Together, these input sources ensure that the framework is not only reactive to current conditions but also informed by contextual and historical insights.

Once data is collected, the decision layer employs AI-driven analytics to transform raw inputs into actionable knowledge. Machine learning models play a central role in detecting anomalies, optimizing resource use, and supporting predictive maintenance (Dalzochio *et al*., 2020; Gohel *et al*., 2020) [13, 20]. For example, algorithms trained on historical energy use can identify unexpected spikes in consumption, signaling potential equipment malfunctions or inefficient operations. Predictive maintenance models further minimize downtime by forecasting system failures before they occur.

Beyond operational efficiency, AI algorithms for life-cycle impact analysis extend the decision-making process to long-term sustainability outcomes. By integrating life-cycle assessment (LCA) principles, AI can estimate embodied carbon, resource depletion, and other environmental impacts across the building's lifespan. This enables stakeholders to evaluate trade-offs between short-term efficiency gains and long-term environmental impacts.

Finally, the decision layer incorporates multi-criteria evaluation frameworks to balance environmental, economic, and social metrics. AI supports weighting and ranking strategies, enabling facility managers, architects, and policymakers to prioritize interventions that maximize sustainability benefits while respecting budgetary and regulatory constraints. This layer transforms data into evidence-based guidance that supports both tactical and strategic decision-making.

The implementation layer ensures that the analytical outputs of the decision layer are translated into operational improvements and compliance mechanisms. A central feature of this layer is the integration with Building Management Systems (BMS), which allows AI insights to be applied directly to control building operations. Automated adjustments in HVAC systems, lighting schedules, or water management strategies can be enacted in real time, ensuring continuous alignment with sustainability targets.

AI-driven dashboards further enhance the usability of the system by presenting actionable insights in accessible formats for facility managers, policymakers, and other stakeholders. Visualizations of key performance indicators, predictive alerts, and benchmarking against green building certification standards facilitate informed decision-making and accountability.

In parallel, the implementation layer supports policy compliance and reporting automation. AI can standardize and streamline the process of reporting to certification schemes such as LEED, BREEAM, or EDGE. Automated reporting not only reduces administrative burdens but also enhances transparency and credibility in sustainability claims.

The final component of the framework is the feedback layer, which ensures continuous monitoring, learning, and scaling. By capturing and analyzing performance data over time, the system supports adaptive learning that refines predictive models and operational strategies (Martin *et al*., 2020; Kalusivalingam *et al*., 2020) [34, 27]. For instance, algorithms can adjust to changing climatic conditions or evolving occupant behaviors, maintaining relevance and accuracy.

A key innovation within this layer is the inclusion of user engagement platforms that promote behavioral change. Occupants can receive personalized feedback on their energy or water use, empowering them to participate actively in sustainability efforts. Gamification elements, such as rewards for reducing energy use, can further enhance engagement and ownership.

Finally, the feedback layer enables scaling and replication across green building portfolios. Lessons learned from one building or project can be generalized and applied to others, creating a knowledge network that accelerates the diffusion of best practices. This scalability is crucial for maximizing the impact of AI-enabled monitoring on urban sustainability and climate mitigation goals.

Collectively, the four layers establish a comprehensive framework that moves beyond fragmented monitoring approaches. The input layer ensures diverse and reliable data; the decision layer transforms data into intelligent insights; the implementation layer operationalizes these insights; and the feedback layer promotes continuous improvement and scalability. Together, they create an adaptive, evidence-based system that strengthens the ability of green buildings to achieve their environmental promises while bridging technology, policy, and human behavior.

2.3 Application Scenarios

The application of Artificial Intelligence (AI) to monitor and improve the environmental impacts of green buildings extends across multiple domains of building performance and lifecycle management. From energy use to waste generation, AI-enabled systems transform static monitoring into dynamic, adaptive, and predictive processes that significantly enhance sustainability outcomes (Yigitcanlar *et* *al*., 2020; Stevens *et al*., 2020) [58, 51]. This illustrates four critical scenarios where the proposed framework can be applied: energy optimization, water efficiency monitoring, carbon footprint tracking, and waste reduction.

Energy consumption represents one of the most significant contributors to the environmental footprint of buildings, particularly in urban contexts where demand for lighting, heating, ventilation, and cooling is continuous. AI offers substantial potential for optimizing energy performance in both office and residential buildings. By integrating data from smart meters, IoT sensors, and Building Management Systems (BMS), AI algorithms can analyze usage patterns, detect inefficiencies, and recommend corrective measures in real time.

For example, machine learning models can forecast energy demand based on occupancy, weather conditions, and historical performance, enabling dynamic adjustments in HVAC operations or lighting systems. Reinforcement learning techniques can further optimize system control by continuously adapting to feedback, balancing occupant comfort with energy savings. In residential settings, AI can provide tailored recommendations to households, such as shifting energy use to off-peak hours or adjusting appliance settings, thereby lowering costs and reducing strain on the grid. In commercial office buildings, predictive analytics can anticipate peak load demands and suggest strategies for load shifting or renewable energy integration, contributing to both carbon reduction and operational cost savings.

Water scarcity is an escalating challenge in many urban areas, making efficient management a central sustainability priority. AI-enabled monitoring systems in housing estates can provide granular insights into water consumption, leak detection, and reuse opportunities. IoT-enabled flow sensors capture data at multiple points within a building or estate, while AI algorithms analyze these data streams to identify anomalies and inefficiencies (Adi *et al*., 2020; Kalusivalingam *et al*., 2020) [1, 27].

Machine learning models, for instance, can detect unusual spikes in consumption that may indicate leaks or faulty fixtures, allowing for rapid intervention. Beyond anomaly detection, AI can optimize water distribution by aligning usage with occupancy patterns or climatic conditions, such as adjusting irrigation schedules based on rainfall forecasts. AI-driven decision systems can also evaluate opportunities for water reuse, such as greywater recycling or rainwater harvesting, by assessing cost-benefit trade-offs under different scenarios.

In large-scale urban housing estates, these applications not only reduce water waste but also lower operational costs and enhance resilience to droughts or supply disruptions. By integrating water efficiency monitoring into broader building sustainability frameworks, AI contributes to holistic resource conservation strategies.

Accurately accounting for carbon emissions across the lifecycle of buildings is critical for aligning with global climate targets. In large commercial complexes, where operations involve complex energy use patterns and supply chain dependencies, AI offers a powerful tool for carbon footprint tracking and management.

By combining data from energy meters, procurement records, and external datasets such as grid emissions factors, AI can provide a real-time estimate of operational carbon emissions. Natural language processing (NLP) techniques can further extract emissions-related information from technical documents and supplier disclosures, filling gaps in traditional reporting processes. Predictive models allow facility managers to forecast future emissions under different scenarios, such as changes in occupancy, equipment upgrades, or energy supply mixes.

Moreover, AI can support decision-making by simulating the impact of interventions—such as retrofitting with energy-efficient equipment, integrating on-site renewable energy, or procuring low-carbon materials—on long-term carbon performance. These insights are vital for ensuring compliance with carbon disclosure requirements, achieving corporate sustainability targets, and enhancing the credibility of green building certifications.

Waste generation during both construction and building operation phases presents another critical sustainability challenge. AI-enabled systems can play a significant role in minimizing waste, enhancing recycling, and supporting circular economy practices (Zainal *et al*., 2021; Jose *et al*., 2020 [26]).

During construction, computer vision technologies combined with AI can monitor material usage on-site, identify inefficiencies, and reduce over-ordering or misuse of resources. Predictive analytics can optimize supply chain logistics to align deliveries with project schedules, minimizing material wastage. At the operational stage, smart waste bins equipped with sensors can classify waste streams, while AI algorithms analyze usage patterns to enhance recycling rates and reduce landfill contributions.

AI also enables the development of material passports and digital twins, which track materials throughout the building lifecycle. This provides valuable data for future renovation or demolition phases, where materials can be reclaimed and reused. Such applications are aligned with circular economy principles, transforming waste management from a reactive process into a proactive, resource-efficient system.

These application scenarios highlight the versatility of AI in advancing green building sustainability. Energy optimization reduces both costs and carbon emissions, water efficiency safeguards critical resources, carbon footprint tracking enhances accountability and compliance, and waste reduction promotes circular practices. Importantly, these scenarios demonstrate how AI-enabled monitoring shifts environmental management from fragmented interventions to integrated, systemic solutions. By embedding predictive, adaptive, and real-time capabilities into building performance monitoring, AI not only strengthens the environmental credentials of green buildings but also contributes to broader urban resilience and sustainability goals (Olaseni, 2020; Radanliev *et al*., 2020) [37, 44].

2.4 Implementation Challenges and Enablers

The integration of Artificial Intelligence (AI) into monitoring environmental impacts of green buildings promises significant advances in sustainability, resilience, and operational efficiency. However, the realization of these benefits is neither automatic nor uniform. Successful implementation depends on navigating a complex landscape of challenges while leveraging critical enablers that can accelerate adoption as shown in figure 2 (Sivakumar and Kumar, 2019; Inaganti *et al*., 2020) [49, 25]. This analyzes the barriers—such as high costs, data privacy risks, limited technical capacity, and fragmented standards—and contrasts them with enablers, including digital twin technologies, government incentives, cross-sector partnerships, and open data ecosystems.

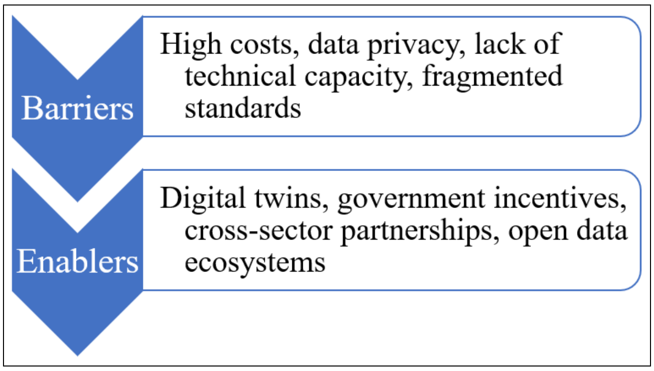

Fig 2: Implementation Challenges and Enablers

One of the foremost barriers to AI-enabled green building monitoring is the significant financial investment required for deployment. The upfront costs associated with IoT sensors, advanced data infrastructure, and AI platforms can deter adoption, particularly in developing economies or small-scale projects with limited budgets. While long-term savings through energy efficiency and reduced operational costs are well-documented, stakeholders often struggle to justify the initial capital expenditure. Additionally, the return on investment (ROI) of AI systems may be uncertain, as benefits depend on scale, data quality, and integration with existing infrastructure.

AI-enabled monitoring relies heavily on vast quantities of data collected from sensors, building management systems, and external sources. These datasets often include sensitive information, such as occupancy patterns and energy consumption linked to specific users or tenants. Without robust safeguards, there is a heightened risk of data breaches or misuse. Privacy regulations, such as the European Union's GDPR, impose stringent requirements on data collection, processing, and storage, complicating the design of AI-driven solutions. Building trust among occupants and stakeholders thus becomes a critical challenge.

Deploying AI systems for green building monitoring requires specialized expertise in machine learning, data analytics, IoT integration, and sustainable construction. Many stakeholders—such as facility managers, developers, or local governments—lack the technical capacity to design, operate, and maintain these systems effectively (Sacks *et al*., 2018; Hu *et al*., 2019) [47, 24]. Skills gaps can lead to underutilization of technologies, misinterpretation of results, or outright project failures. Furthermore, limited training opportunities and the absence of clear career pathways in AI-enabled green construction exacerbate the problem, particularly in regions where technical education systems lag behind global advancements.

The lack of standardized frameworks for integrating AI into green building monitoring is another critical barrier. Existing green certification schemes such as LEED, BREEAM, or EDGE provide criteria for sustainability performance but do not systematically incorporate AI-driven data analytics. Similarly, interoperability issues across platforms and proprietary systems hinder the seamless exchange of data between stakeholders. Fragmented standards result in inefficiencies, increase implementation costs, and discourage widespread adoption of AI solutions in the building sector.

Digital twin technology, which creates virtual replicas of physical assets, acts as a powerful enabler for AI-enabled monitoring. By simulating building performance in real time, digital twins allow stakeholders to test interventions, forecast outcomes, and optimize environmental impacts without disrupting operations. Coupled with AI algorithms, digital twins provide predictive insights into energy use, water consumption, and waste generation, enabling proactive management strategies. The ability to visualize and interact with complex datasets enhances decision-making and fosters collaboration among architects, engineers, and facility managers.

Policy support and financial incentives play a pivotal role in reducing the financial barriers to AI deployment. Governments can promote adoption by offering tax credits, subsidies, or grants for green building projects that integrate advanced monitoring technologies. Additionally, updating building codes and climate action plans to include AI-based monitoring requirements creates regulatory drivers for adoption (Fathi *et al*., 2020; Mehmood *et al*., 2020) [19, 36]. By aligning national sustainability goals with AI-enabled innovations, governments can stimulate demand while lowering risks for early adopters.

Collaboration between academia, industry, government, and civil society is essential for overcoming knowledge gaps and resource constraints. Cross-sector partnerships enable the sharing of expertise, data, and infrastructure while fostering innovation ecosystems. For example, universities can provide training and research support, while private firms supply cutting-edge technologies and governments ensure regulatory alignment. Public-private partnerships also expand opportunities for pilot projects, demonstrating the feasibility and benefits of AI-enabled monitoring in real-world settings.

The development of open data ecosystems is another enabler that can transform the scalability of AI-enabled monitoring systems. Access to high-quality, standardized datasets enhances the training and performance of AI algorithms, while interoperability across platforms ensures broader usability. Open data initiatives reduce duplication of effort, lower costs, and accelerate innovation by allowing multiple stakeholders to build upon shared resources (Kassen, 2018; Ahn *et al*., 2019) [28, 4]. Moreover, transparency in data exchange fosters accountability and trust among stakeholders, addressing one of the critical barriers related to data privacy concerns.

The implementation of AI in monitoring green building performance exists at the intersection of promise and constraint. High costs, privacy concerns, skill gaps, and fragmented standards present significant hurdles, particularly for widespread and equitable adoption. Yet these barriers can be mitigated by leveraging enablers such as digital twins, supportive government policies, collaborative partnerships, and open data ecosystems. The interplay between these factors underscores the need for a systemic approach that combines technological innovation with policy, education, and governance interventions.

By aligning financial, technical, and regulatory mechanisms, stakeholders can move beyond pilot projects toward mainstream adoption of AI-enabled monitoring frameworks. Such integration not only enhances environmental outcomes—through reduced emissions, resource efficiency, and waste minimization—but also contributes to broader societal goals of resilience, equity, and climate adaptation (Lehmann, 2018; Bhattacharya *et al*., 2019) [31, 9].

2.5 Outcomes and Impacts

The integration of Artificial Intelligence (AI) into monitoring environmental impacts of green buildings represents a transformative step in the evolution of sustainable construction and facility management. By embedding advanced data-driven capabilities into building systems, stakeholders can achieve measurable environmental, economic, and social gains that extend across the life cycle of green buildings. The outcomes and impacts of such a framework can be classified into three interrelated dimensions: environmental benefits, economic advantages, and social contributions (Sehnem *et al*., 2019; Taliento *et al*., 2019) [48, 52]. Together, these outcomes underscore the significance of AI as both a technological enabler and a catalyst for broader sustainability transitions.

A key outcome of AI-enabled monitoring lies in the reduction of greenhouse gas emissions. Real-time tracking of energy consumption allows building managers to detect inefficiencies and optimize operations, thereby lowering reliance on carbon-intensive electricity. AI-driven predictive models can recommend demand-response strategies, renewable energy integration, and energy storage solutions that collectively reduce the carbon footprint of buildings. Similarly, the capacity of AI to monitor and forecast water use contributes to efficient resource management, ensuring that consumption aligns with availability and reducing strain on urban water infrastructure.

AI frameworks also enhance compliance with green building standards such as LEED, BREEAM, and EDGE. By continuously collecting and analyzing performance data, AI systems can provide transparent evidence for certification processes and ensure buildings remain compliant beyond the initial design stage. For instance, anomaly detection algorithms can alert managers when indoor air quality or energy performance begins to deviate from certification thresholds, prompting timely interventions. This dynamic compliance ensures that green buildings maintain their intended environmental performance, rather than regressing due to poor maintenance or changing operational conditions.

In addition, AI-driven waste reduction mechanisms extend the environmental outcomes by tracking material flows during construction and operations. By identifying opportunities for reuse, recycling, or remanufacturing, AI reduces the volume of waste sent to landfills and supports the circular economy transition in the built environment. Collectively, these environmental outcomes contribute to urban sustainability, climate change mitigation, and resilience against resource scarcity.

The economic impacts of AI-enabled monitoring are equally significant. Cost savings represent one of the most immediate benefits, as AI can identify operational inefficiencies that lead to excessive energy and water use. Predictive maintenance, powered by machine learning models, minimizes unplanned downtime and reduces repair costs by detecting early signs of equipment failure (Lee *et al*., 2020; Çınar *et al*., 2020) [30, 12]. Over time, these savings offset the high initial investment in AI technologies and demonstrate favorable returns on investment.

Another economic advantage lies in optimized maintenance strategies. Traditional preventive maintenance approaches often result in unnecessary expenditures, as equipment may be serviced regardless of actual need. AI introduces condition-based and predictive maintenance, ensuring that resources are allocated only when performance data indicates a genuine requirement. This optimization extends equipment lifespan and reduces material waste, lowering both direct and indirect costs.

AI-enabled monitoring also contributes to higher property values and market competitiveness. Green buildings equipped with advanced monitoring systems offer enhanced transparency and reliability in performance reporting, making them attractive to investors, tenants, and buyers. As sustainability considerations increasingly influence real estate markets, AI-driven monitoring frameworks provide a competitive edge by ensuring measurable and verifiable performance outcomes. In commercial contexts, this can translate into higher rental yields and stronger occupancy rates.

Beyond environmental and economic gains, AI frameworks deliver significant social benefits. Chief among these is the creation of healthier indoor environments. By continuously monitoring parameters such as indoor air quality, humidity, and thermal comfort, AI systems safeguard occupant well-being and productivity. This is particularly important in office buildings, schools, and healthcare facilities, where indoor environmental quality directly impacts cognitive performance, learning outcomes, and recovery rates.

AI-enabled monitoring also fosters stakeholder engagement by providing accessible dashboards and visualizations that communicate environmental performance in real time. Tenants and occupants can be empowered to modify their behaviors—such as adjusting energy use or waste disposal practices—based on feedback from AI platforms. This participatory approach enhances awareness, accountability, and collective responsibility for sustainability outcomes.

Another social impact lies in knowledge sharing and capacity building. AI-generated data not only benefits individual buildings but can also inform larger networks of practitioners, policymakers, and researchers. Aggregated performance data across portfolios of green buildings creates opportunities for benchmarking, policy learning, and continuous improvement. As these insights circulate, they strengthen the collective capacity of societies to design and manage more sustainable built environments (Lawrence, 2020; Megahed and Ghoneim, 2020) [29, 35].

The environmental, economic, and social outcomes of AI-enabled monitoring reinforce one another in a synergistic manner. Reduced emissions and efficient resource use lower costs, while economic savings create incentives for wider adoption. Social benefits, such as healthier indoor environments and improved engagement, build legitimacy and foster public trust in green building initiatives. Together, these impacts advance the overarching goals of sustainable urban development, aligning with global agendas such as the Sustainable Development Goals (SDGs) and national climate action commitments.

Nevertheless, the realization of these outcomes depends on addressing barriers such as high costs, privacy risks, and fragmented standards. The presence of enabling factors—digital twins, supportive policies, open data ecosystems, and cross-sector partnerships—remains critical in translating theoretical benefits into measurable practice. As adoption scales, the outcomes are expected to expand beyond individual buildings to city-wide portfolios and eventually to

regional or global networks of green buildings.
The outcomes and impacts of AI-enabled monitoring extend far beyond incremental improvements in building performance. They represent a holistic transformation of how the built environment is designed, operated, and evaluated, ensuring that environmental sustainability, economic efficiency, and social well-being are pursued in tandem (Wang *et al*., 2019; Toli and Murtagh, 2020) [56, 53]. By aligning advanced technologies with sustainability goals, this framework creates the conditions for a resilient, low-carbon, and inclusive future in urban development.

3. Conclusion

Artificial Intelligence (AI) has emerged as a transformative enabler for advancing the sustainability of green buildings, addressing long-standing challenges in monitoring and managing environmental impacts. By leveraging real-time data, predictive analytics, and intelligent decision-making, AI strengthens the ability of buildings to reduce emissions, optimize energy and water use, and comply with green certification standards over their entire life cycle. In a context where climate change, rapid urbanization, and resource scarcity are reshaping the built environment, AI provides the analytical and adaptive capacity necessary to ensure that green buildings achieve their intended environmental, economic, and social outcomes.
The proposed framework demonstrates how AI can serve as a bridge between technology, design, and policy, integrating sensor networks, machine learning models, building management systems, and compliance mechanisms into a coherent structure. This multi-layered approach ensures that sustainability principles are not confined to design intentions but are actively embedded into daily operations and long-term management. Furthermore, by connecting digital tools with policy requirements, the framework enhances transparency, accountability, and alignment with broader climate and sustainability agendas.
Looking ahead, several future directions hold promise for expanding the effectiveness of AI in green building monitoring. AI-augmented digital twins will enable real-time simulation and optimization of building performance, creating dynamic feedback loops for adaptive management. Blockchain-enabled reporting can strengthen trust and transparency in environmental performance claims by providing immutable and verifiable records of resource use and emissions. Finally, efforts toward global standardization will be critical to harmonize data formats, metrics, and governance mechanisms, ensuring scalability across regions and markets.
AI-enabled monitoring represents not only a technological innovation but also a paradigm shift in sustainable construction, offering a pathway toward resilient, low-carbon, and socially inclusive built environments.

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