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Intelligent Risk Identification and Mitigation in Green Construction: A Lifecycle Framework

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ABSTRACT

Construction industry is highly rated among the high consumers of energy and greenhouse gases in the world, raising continuous pressure to balance the economic development and the goals of sustainability. Although traditional methods of green buildings have provided quantifiable environmental outcomes, many provide a narrow range of solutions to the complexity and interdependence of factors related to climate resiliency, resource-saving, and long-term operation capabilities. Recent developments in artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and Building Information Modeling (BIM) may provide new ways of contributing to the risk identification and mitigation throughout the building lifecycle. The paper develops a lifecycle-based framework that incorporates intelligent technologies with sustainable building concepts at critical points, such as design, the selection of materials, construction, operation and maintenance, and recovery of post-damages. The framework groups the biggest risk categories, namely seismic, climatic, financial, environmental, and operational and then maps them in the right intelligent mitigation strategies, including optimization algorithms, predictive analytics, and AIoT enabled monitoring systems. By relying on evidence synthesized based on a systematic mapping review, the study points to the role that techniques such as genetic algorithms, deep learning models, fuzzy logic, and sensor-based systems can play in ensuring enhanced structural safety, better cost prediction, lesser environmental effects, and decision-making capacity. Based on the results, the implementation of intelligent technologies and green building strategies does not only improve the environmental performance and energy efficiency but also increases the resiliency and well-being of the occupants. The proposed framework provides a methodological and mobile foundation on the researchers, practitioners and policymakers who seek to align the green-smart building (GSB) practices with the global climate and sustainability goals, of which intelligent, lifecycle based construction is one of the major streams to low-carbon and resilient built environment.

1. INTRODUCTION

The growing concern over greenhouse gas emissions has brought heightened global attention to sustainability, prompting many corporations to take on environmental responsibilities and advocate for ecological transformation. Among the sectors requiring urgent intervention, the construction industry known for its high energy consumption stands out as a significant contributor to global emissions. According to researchers, buildings use a large amount of energy and release a lot of greenhouse gases [1]. Since the number of people around the world keeps increasing, it is crucial to build energy-saving buildings for the support of a sustainable economy [2]. To support the aims of the Paris Agreement and reduce harm to the environment [3, 4], using eco-friendly technologies and ideas in construction is necessary.

Due to the climate crisis and the wish of many nations to become carbon neutral, different countries have passed policies promoting green building to help save energy and reduce emissions. Buildings are considered green when technology such as renewable energies and low-carbon systems is put in place. Developers plan these structures guided by sustainability rules, always ensuring safety, usefulness, and comfort, and reducing the harm they cause to the environment. Gilbert and others early on described a green building as one that minimizes resources and follows environmental ethics in its design [5]. Green buildings not only hold together safely, but they foster good health and new ideas. They can be located in residential, commercial and office premises and show how technology and sustainability intersect.

The philosophy behind green building is governed by some main principles. First of all, conservation of energy and reduction of carbon emissions is essential in reducing the environmental issues as well as improving on how resources are utilized [6, 7]. Second, green architecture is focused on recycling in design processes and the building materials, more sustainable resources, and developing strategies on waste handling throughout the whole construction process [8]. In addition, the development plans are supposed to protect the environment by protecting the ecosystems and minimizing their impact during constructions.

In this case, it is logical to enhance green buildings into smart buildings. Smart building concept has gained momentum due to development of computational and communication technologies which bring about smart buildings to act as smart environments. These structures use automated control systems, sensors and microcontrollers to control processes like lighting, HVAC and security. By doing this, they would make power consumption more efficient and a positive impact to the environment results [9]. Smart technologies such as predictive analytics and smart grid integration also enable the building to optimize the use of power and enhance the process of planning and energy distribution [10]. The AI integration also adds functionality in the form of ability to identify users and monitor the environment [11], further broadening the range of smart building applications.

Green-smart building (GSB) systems will ensure that the energy consumption and pollution are significantly cut down, human well-being is enhanced and the environment and the society live in harmony with one another. Such buildings serve as systems that are integrated both in terms of design, building, operation, maintenance and recycling. This paper starts with the discussion of fundamental principles of green building and how smart technologies upgrade every phase of building lifecycle. It is devoted to five interrelated spheres, such as design, materials, building, renovation and management, and assessment of structural damage. In every sphere, the implementation of such technologies as AI and IoT is addressed in detail.

The paper ends with a discussion of sustainability initiatives at all the phases of a lifecycle and gives a synthesized general overview of the technologies that will be used to enable them.

2. METHODOLOGY

This research paper uses a systematic mapping review and conceptual method development to research the subject of intelligent risk identification and mitigation of GSB projects throughout the building lifecycle. The methodology is intended not only to synthesize the existing evidence but also to come up with a structured, lifecycle-oriented approach to risk identification, based on the literature reviewed.

The proposed approach, as shown in Figure 1, conceptualizes GSB as a combined socio-technical system where risks are created in the intersection of environmental conditions, building systems, regulatory conditions, and intelligent technologies. The approach starts with identification of the most fundamental risk types such as natural calamities, safety risks, and compliance risks. These fundamental risks are converted to risk aspects that display building-specific vulnerabilities and performance issues. In order to have a holistic approach, the risk aspects identified are mapped to the architectural life cycle, which includes design, construction, operation, renovation, and post-damage phases. This phase-based risk detection and avoids non-dynamic or piecemeal risk assessment is facilitated by this lifecycle embedding. The GSB system is the primary analytical unit, with the inputs of lifecycle risks being subjected to an organized risk analysis phase, with the aim of producing standardized and easily understandable risk assessments.

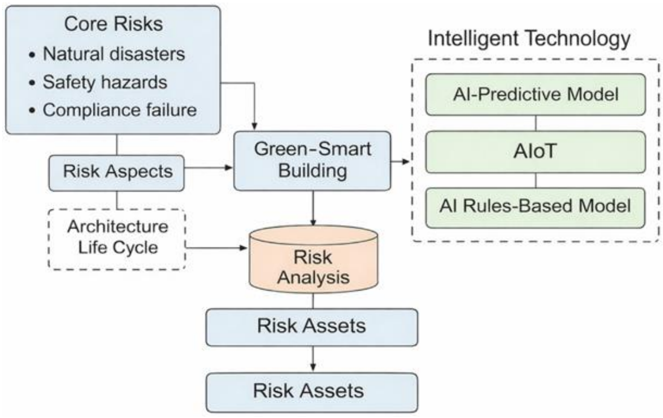

Figure 1. Research framework

The incorporation of intelligent technologies is the characteristic of the proposed methodology and a major enabling factor of risk detection throughout the building lifecycle. The strategy integrates three layers of complementary technologies, namely AI-based predictive models to aid in forecasting and early identification of risks, AIoT-enabled sensing and connectivity to enable real-time data collection and continuous monitoring, and AI rule-based models to support structured reasoning, compliance testing, and decision support. The combination of these layers creates a logic of operation, which connects sources of risks and lifecycle stages with the proper analytical mechanisms. In order to justify and substantiate this methodological framework, the research uses a systematic mapping review to integrate the existing studies related to intelligent risk detection and mitigation in green construction, but not statistically sum up the effect sizes.

2.1 Literature search strategy

Four large scientific databases, including Scopus, Web of Science, ScienceDirect, and IEEE Xplore, were systematically searched to make certain that all credible peer-reviewed studies in the area of engineering, construction management, sustainability, and computational intelligence were covered. The search was limited to those studies that were published in 2015-2024, which is a timeframe that signifies the swift development and growing popularity of AI, IoT, and Building Information Modeling (BIM) in green building. The search strategy was a keyword-based search strategy that included Boolean operators to facilitate the combination of sustainability, risk, and intelligent technologies keywords, namely: (green building or sustainable construction) and (risk / resilience) and (artificial intelligence / machine learning / IoT / BIM /). Where needed, variants of the key words were used as the equivalent and database specific query syntax was used to make the search results complete and consistent.

2.2 Inclusion and exclusion criteria

In order to achieve relevance and technical rigor, pre-defined inclusion and exclusion criteria were used to select the studies. Qualified articles included peer-reviewed journal articles, or conference proceedings that explicitly used intelligent technologies, including AI, ML, IoT, or BIM and directly applicable to risk identification, assessment, or mitigation at any or more phases of the building lifecycle, which are design, construction, operation, renovation, or post-damage management. The exclusion criteria were that the studies were either too conceptual or policy-based and had no technical or methodological implementation or the study was about non-building infrastructure, like transportation networks or pipelines or power transmission systems, or were duplicate records or publications without adequate methodological description.

2.3 Study selection process

The selection of the study was done according to two stages of screening. First, titles and abstracts have been checked so that obviously irrelevant studies could be excluded. Second, full-text screening was conducted to determine the eligibility on the inclusion and exclusion criteria. The review was performed in cycles to eliminate any ambiguities, which guaranteed uniformity in the decision made with regard to selection. Figure 2 is a PRISMA-style flow diagram, which describes the stages of identifying, screening, eligibility and inclusion of the review process.

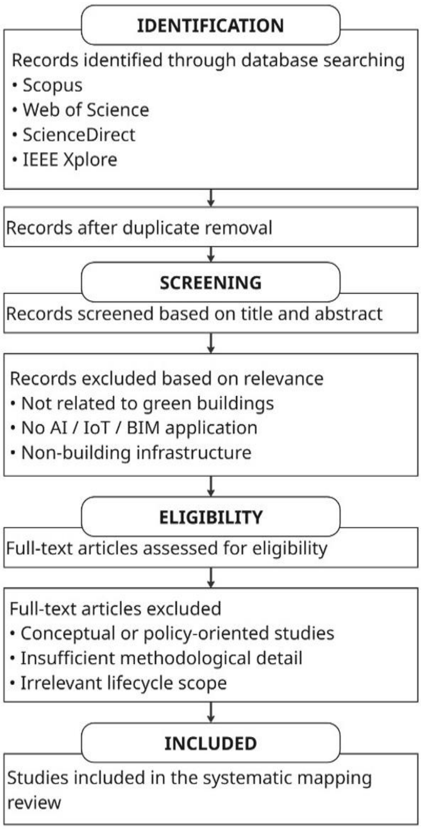

Figure 2. PRISMA flow diagram of the study selection process

2.4 Review scope and synthesis approach

The quantitative meta-analysis was not possible, because of the high heterogeneity of the reviewed studies in terms of datasets, performance measures, type of building, climatic conditions, and modeling techniques. Thus, the proposed study uses a systematic mapping and narrative synthesis, with the main emphasis on the determination of the prevalent risk categories, smart mitigation methods, and their correspondence to the lifecycle phases and international standards. The process can be used to make a systematic comparison of approaches and their uses as well as contribute to the creation of the suggested lifecycle-based risk identification and mitigation framework. According to the systematic mapping review, it is suggested to create a lifecycle risk-technology decision pipeline to convert the synthesized evidence into a smart practice on intelligent risk mitigation.

2.5 Lifecycle risk–technology decision pipeline

The paper has operationalized the suggested lifecycle-oriented model using a systematic risk technology decision pipeline, which converts the perceived threats into practical risk mitigation processes. The pipeline has four main inputs, namely risk type (e.g., flood, seismic, operational or cybersecurity risk), lifecycle phase (design, construction, operation, renovation or post-damage management), data accessibility (sensor data, historical data, BIM models, or remote-sensing data) and regulatory limitations. These contributions define the contextual frames within which the intelligent technologies could be selected and implemented accordingly so that the mitigation measures could be both technically possible and institutionally acceptable.

A rule-based mapping mechanism is combined with curated model and standards libraries to form the processing within the pipeline. The rule-based layer is used to filter the candidate solutions, which is achieved by associating risk types and life cycle stages to an appropriate set of intelligent methods, whereas the model library offers the AI-, ML-, and AIoT-enabled techniques based on the data properties and operational limitations. Simultaneously, the standards library provides the assurances in the compliance with the appropriate sustainability, safety, and governance standards. The resultant products are prescribed analysis or control models, concomitant compliance checks, and a monitoring plan that defines the way in which risks are monitored and revised as time goes on. As an illustration, real-time sensor data and historical records may prompt the use of predictive time-series and image-based models based on AIoT monitoring and facilitated by constant compliance checks and adaptive facility management responses in such a situation as flood risk in the operation stage. This pipeline makes the proposed framework more deployable and transparent, and allows unified and risk-sensitive decision-making throughout the green construction projects.

3. RISK IDENTIFICATION IN GREEN-SMART BUILDING PROJECTS

Identifying risks is a critical initial step in the lifecycle of GSB projects. These projects, which integrate sustainability principles with intelligent technologies, inherently involve complex systems and interdependencies. Therefore, comprehensive risk identification is essential to ensure successful project outcomes, operational efficiency, and long-term sustainability.

Integrating both environmental and technological targets poorly at the design stage may result in risks. A bad choice or wrong placement of photovoltaic panels or wind turbines can cause them to work poorly or break apart over time. Not considering how the environment will affect the project site or unique climactic risks can put both sustainability and practical construction at risk. While construction is happening, several possible risks need to be taken into account. Sometimes, these problems appear when eco-friendly products are used incorrectly, energy-efficient construction is inconsistently followed, the arrival of key parts is postponed or no one is skilled enough to install smart upgrades. Also, if the team does not always supervise energy use or waste, the project may not uphold the standards for being called a green building.

During operation, important risks come from possible cybersecurity issues, problems relating to how sensor data is handled by the algorithms and system outages due to poor maintenance. Adding smart systems to buildings can make them more complex which without proper management might lead to wasting energy, privacy leaks or unhappy occupants.

The type of material used can bring certain dangers. If we use resources with big embodied energy or limited thermal effects, it may reduce our efforts to be sustainable. Misunderstanding how selected materials and smart systems could interfere with each other may also decrease the effectiveness of the automated systems.

A strong risk identification framework makes GSB more viable and helps deal with challenges at every stage of their development. Key risks that can appear at the various stages of GSB projects are shown in Figure 3.

Figure 3. Types of risks involved in design, building and running green-smart building (GSB)

3.1 Integrated risk identification and mitigation in green building design and construction

The early phases of GSB projects spanning both design and construction are critical for ensuring long-term sustainability, safety, and resilience. These stages concentrate a large share of risks, as they involve extensive material deployment, structural decisions, technological integration, and financial commitments. To secure reliable outcomes, risks must be systematically identified and mitigated through the application of intelligent technologies.

Natural hazard and climate-related risks are among the most significant. In seismic regions, inappropriate structural configurations heighten vulnerability to earthquake damage. To counter this, Calledda et al. [12] proposed seismic-resistant design strategies using network inversion and optimization, while Cetin et al. [13] demonstrated that Differential Evolution (DE)-optimized Tuned Mass Dampers (TMDs) reduce structural vibrations. Flood-related hazards have also been investigated with AI-based predictive models: Zabihi et al. [14] applied Support Vector Machines (SVMs) and multi-criteria frameworks for real-time monitoring, Wang et al. [15] combined Long Short-Term Memory (LSTM) models with the Analytic Hierarchy Process (AHP) to predict flood risks, and Hussain et al. [16] applied Convolutional Neural Networks (CNNs) for flood severity classification. For hurricane-prone regions, Bayesian networks and image analysis supported damage estimation [17], while Patel et al. [18] developed AI-enabled irrigation systems for resilient landscape management in arid climates.

Financial risks remain central to green building construction, largely due to limited historical data and uncertainty in ecological standards. Conventional cost estimation methods often underperform. Artificial Neural Networks (ANNs) have been shown to improve predictive accuracy in cost estimation [19, 20], and Alshboul et al. [21] integrated Deep Neural Networks (DNNs) with XGBoost to enhance financial forecasting for environmentally responsible projects. Multi-output regression models have been applied to construction cost prediction by jointly estimating multiple cost components, offering an alternative to single-output forecasting approaches [22]. Environmental and operational risks frequently arise during construction and early operation. HVAC system malfunctions or inconsistent energy use can degrade indoor air quality and energy efficiency. Zhu et al. [23] developed lightweight ANN-based ventilation models for energy-efficient air quality management. Wang et al. [24] combined life cycle assessment (LCA), BIM, and XGBoost to model and reduce carbon emissions during foundation construction, while BIM itself has been recognized as a collaborative platform for risk-aware decision-making [25]. Complementary approaches include deep learning–based models for operational monitoring and lightweight load-based ventilation models (LLVMs) for energy-efficient system optimization, as demonstrated in recent studies on deep reinforcement learning control of HVAC systems [26] and IoT/deep learning–enhanced building energy monitoring [27].

Design-stage risks introduce additional vulnerabilities. Poor placement of reinforcement or structural elements increases the likelihood of wind or seismic failure. Alanani and Elshaer [28] applied genetic algorithms for optimal shear wall placement, while Zhao et al. [29] employed Graph Neural Networks (GNNs) for adaptive beam configuration and real-time risk identification. Multi-objective optimization is commonly used to manage trade-offs related to occupant comfort and energy efficiency; Baumann and Kramer [30] demonstrated the effectiveness of evolutionary approaches for such optimization problems. Prefabrication is also a risk in terms of scheduling and logistics which is becoming more efficient and has less impact on the environment. Yin et al. [31] employed an advanced genetic algorithm to aim at the optimization of prefabrication and transportation schedules, and Sun [32] showed that digital twins, with the help of the BIM and AIoT, would allow predicting and preventing risks related to prefabricated parts.

Altogether, the risks that can be identified during the design and building stages include natural risk, financial risk, operational risks, and structural weaknesses. These risks can be identified and addressed systematically using AI-based prediction models, optimization algorithms, and BIM-based simulations and enhance the resilience and sustainability of GSB projects.

As Figure 4 shows, the categories of risks, including seismic, flood, financial, and environmental risks, are accurately mapped to intelligent mitigation techniques, including DE as a structural optimization algorithm, LSTM and CNN as predictive hazard detection algorithms, ANN and XGBoost as cost prediction algorithms, and BIM-enhanced ANN as environmental and operational efficiency algorithms. This visualization underscores the role of AI-driven technologies in supporting comprehensive risk management across the early phases of GSB projects.

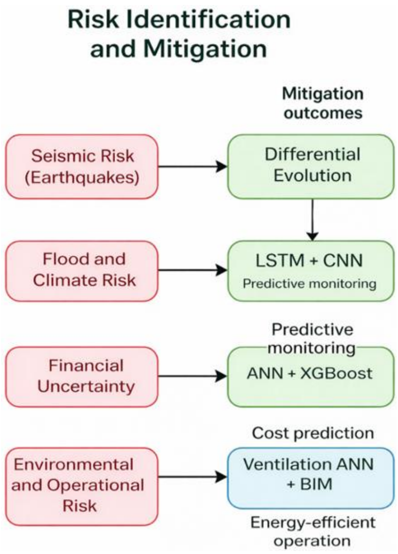

Figure 4. Diagram linking risks to intelligent mitigation strategies in green construction projects

3.2 Risk identification and mitigation in building operation, management, and energy systems

The operation and management phases of GSB are increasingly characterized by the adoption of intelligent automation, advanced energy systems, and smart control technologies. These innovations enhance energy performance, sustainability, and user satisfaction, but they also introduce complex risks that must be identified and mitigated. The primary challenges fall into three categories: operational and monitoring risks, cyber-physical vulnerabilities, and energy cost control uncertainties. Together, these risks shape the resilience, efficiency, and long-term viability of green buildings. Table 1 summarizes the main categories of risks identified in building operation, management, and energy systems, along with the intelligent techniques applied in the literature to mitigate them.

Operational and monitoring risks arise from the reliance on smart meters, occupancy detectors, and temperature sensors. Device malfunctions or communication delays can compromise control accuracy and increase energy consumption, thereby undermining sustainability objectives [33]. Intelligent solutions have been developed to address these challenges. For instance, Gomaa et al. [34] applied AI-based systems to detect fire risks, forecast fire propagation, and optimize evacuation planning. Similarly, Kim et al. [35] employed CNNs with grayscale surveillance for anomaly detection in real time. Despite these advances, cyber-physical vulnerabilities remain a major concern. With the widespread integration of IoT, building management systems (BMS) face heightened risks of data breaches, unauthorized control, and network overload. Misconfiguration or interruptions in IoT-enabled control systems for air quality, lighting, and HVAC can compromise both safety and user comfort [36].

Electrical hazards also remain critical. Ren et al. [37] demonstrated the potential of Fuzzy Logic Reasoning (FLR) to identify low-voltage arc faults, while transfer learning and expert systems further improved fault classification and predictive maintenance reliability [38, 39]. Beyond technical hazards, user dissatisfaction and regulatory misalignment constitute reputational risks. Guo et al. [40] applied natural language processing (NLP) to social media data to identify patterns of occupant dissatisfaction in LEED-certified buildings, while Xiao et al. [41] used Latent Dirichlet Allocation (LDA) and Semantic Network Analysis (SNA) to reveal mismatches between national green building policies and user expectations.

Energy cost control represents another major dimension of risk. The building sector accounts for nearly 40% of global energy use and over 75% of electricity demand [42], with cooling requirements expected to triple by 2050 [43]. While smart technologies support predictive energy optimization, they are also sensitive to data inaccuracies, model drift, and integration failures. ANN–GA scheduling frameworks [44], deep reinforcement learning models [45], and temporal convolutional networks (TCNs) [46, 47] have demonstrated potential in load forecasting but remain vulnerable to sensor noise and behavioral shifts. Attention-based deep learning models provide higher accuracy but risk misinterpreting feature importance under unseen climatic extremes [48]. IoT-enabled controllers for hybrid renewable systems [49] improve dispatching but remain exposed to failures from data overload or network instability.

Risks are also evident in renewable energy subsystems. Rooftop solar designs face spatial estimation errors: Li et al. [50] applied U2-Net with GIS, while Ibnelouad et al. [51] leveraged Particle Swarm Optimization (PSO) to improve system sizing, though both approaches remain sensitive to parameter variability. Water and resource monitoring, as explored by Mohammed et al. [52], shows vulnerability to misclassification in arid climates using MLP and SVR. Wind energy management introduces additional risks: Vives [53] employed KNN and SVM for turbine fault diagnosis, while Zhang et al. [54] used LSTM-based variational autoencoders, which risk misdiagnosis under incomplete datasets. Integrated renewable systems compound these risks, as IoT-enabled hybrids combining SVM, RF, and ANN architectures remain vulnerable to synchronization failures and controller malfunctions [55-58].

In summary, the operation, management, and energy systems of GSB must address intertwined risks that include sensor reliability, cybersecurity, predictive accuracy, and renewable integration. Intelligent technologies such as CNNs, NLP, ANN–GA hybrids, reinforcement learning, BIM, and IoT-based controllers demonstrate strong potential for mitigation. However, their effectiveness depends on overcoming data scarcity, ensuring interoperability, and building trust through robust governance and policy alignment.

Table 1. Risk identification and mitigation in building operation, management, and energy systems

Risk Category	Applied Intelligent Techniques	References
Operational and monitoring risks	CNNs; IoT-based sensing; DRL; DNNs; real-time sensing; edge processing	[35, 36, 59-61]
Fault detection and electrical hazards	Fuzzy Logic Reasoning (FLR); transfer learning; rule-based expert systems; arc-fault recognition	[37-39]
Occupant experience and policy risks	NLP; LDA; SNA; sentiment mining	[40, 41]
Forecasting and load management errors	ANN-GA; DRL; TCN; attention-based deep learning; IoT-enabled dispatching	[44-49]
Solar efficiency and system design risks	U2-Net + GIS; ANN-PSO; hybrid PSO-GA models	[50, 51, 62]
Water and resource quality risks	MLP; SVR; remote monitoring and prediction models	[52]
Turbine operation and fault misdiagnosis	KNN; SVM; LSTM-based variational autoencoders	[53, 54]
Integrated renewable control failures	IoT platforms; BATCN; hybrid SVM-RF-ANN controllers; real-time monitoring systems	[55-58]

Note: CNN = Convolutional Neural Network; DRL = Deep Reinforcement Learning; DNN = Deep Neural Network; FLR = Fuzzy Logic Reasoning; NLP = Natural Language Processing; LDA = Latent Dirichlet Allocation; SNA = Semantic Network Analysis; ANN = Artificial Neural Network; GA = Genetic Algorithm; PSO = Particle Swarm Optimization; MLP = Multi-Layer Perceptron; SVR = Support Vector Regression; KNN = k-Nearest Neighbors; SVM = Support Vector Machine; LSTM = Long Short-Term Memory; RF = Random Forest; BATCN = Bayesian-Augmented Temporal Convolutional Network. Applicability depends on data availability and quality, climate zone, building type, and operating regime.

3.3 Material integrity, damage assessment, and waste management in green construction

Performance of the materials, structural integrity, and recovery of the damages are vital aspects of sustainable building. Other than environmental impact, construction materials and waste management plans define resilience, safety of operations, and adherence to sustainability goals. Smart technologies offer additional possibilities to assess, forecast, and reduce risks through the selection of materials, structural damage, and waste treatment after damage, but also create doubts that need to be thoroughly considered.

Advanced insulation, phase change materials (PCMs), and smart glazing have a high potential in the field of functional and adaptive materials to have impact on reducing the amount of energy demanded. However, such materials also have long-term threats in terms of reliability, fatigue and interaction with users. Hai et al. [63] demonstrated the use of ANNs to model the thermal behavior of PCM-based radiant heating systems, highlighting risks of phase instability over repeated heating cycles. Deliktaş and Şahinöz [64] applied fuzzy multi-criteria decision-making for insulation optimization, though mis-weighting of factors may result in poor thermal performance. Openings such as windows remain a critical source of inefficiency, responsible for up to 50% of thermal losses [65]. Aburas et al. [66] proposed dynamic coatings and smart windows for solar regulation, while Tien et al. [67] employed deep learning (DLIP) to evaluate manual window operation, underscoring behavioral uncertainties in automation.

Sustainable and recyclable materials, while reducing embodied energy, introduce risks of durability and compliance. May Tzuc et al. [68] evaluated vegetated concrete walls, noting risks of mold growth and structural degradation under moisture. Gogineni et al. [69] applied XGBoost to predict compressive strength in fly-ash concrete, showing variability linked to feedstock composition. Similarly, Xiong et al. [70] used KNN to assess fatigue in recycled steel, finding that external load variations compromise safety margins. ANN-GA systems have modeled acoustic absorption in recycled carpets [71], though issues of fire resistance and aging remain unresolved. Bio-based alternatives such as bamboo, rammed earth, and fungal composites present renewable solutions but face challenges in standardization and mechanical validation [72, 73].

Structural damage caused by environmental hazards introduces another layer of complexity. Earthquakes, floods, hurricanes, and tsunamis can compromise load-bearing systems or cause partial collapses. Termite infestations and biological degradation further weaken structural components [74]. Intelligent systems have been developed to support rapid assessment. Song et al. [75] combined genetic algorithms (GA), ANNs, and SVMs for real-time damage detection. Li and Tang [76] applied decision tree classifiers to multi-temporal remote sensing for seismic damage classification, while Oh et al. [77] designed an unsupervised CNN-based anomaly detection framework to identify deviations from baseline structural states. Deep residual networks (ResNet) have further improved hidden risk localization [78].

Equally important is the management of waste following demolition or natural disasters. Inefficient logistics and improper disposal of hazardous debris can exacerbate environmental impacts. Khan et al. [79] illustrated how recycled PET can be applied in construction, with ANN models predicting pavement performance risks. Elshaboury and Marzouk [80] optimized waste fleet operations with multi-objective models to reduce emissions and delays, while Na et al. [81] used transfer learning for real-time debris detection and classification. Additional research confirms the value of intelligent image recognition and optimization frameworks in reducing post-damage risks and improving resource recovery [82].

Overall, intelligent technologies support the assessment of material reliability, damage diagnostics, and sustainable waste management. However, risks linked to degradation, mechanical uncertainty, data dependency, and operational variability must be addressed to ensure resilience and environmental compliance in green construction.

3.4 Data governance and cybersecurity in AI-enabled green-smart buildings

The growth of the dependency on AI-based analytics, AIoT sensing, and Building Management Systems (BMS) in GSB requires effective data governance and cybersecurity mechanisms. The first step in risk mitigation is to minimize data meaning that only the data needed to achieve the required operational and safety goals should be collected and stored. A hybrid edge-cloud processing model can be suggested to increase the resilience and privacy of any architecture where the inputs that are latency-sensitive and those that are privacy-sensitive are processed at the edge, and long-term analytics and optimization are aided with cloud computing. Zero-trust segmentation should be embraced in cybersecurity architectures, to isolate subsystems in the building, with constant authentication of access to mitigate the spread of lateral attacks. Adaptive security management is supported by an incident response lifecycle, which consists of detection, containment, recovery, and post incident learning. The correspondence to the international standards goes even further to provide responsibilities: according to NIST Cybersecurity Framework (CSF) and IEC 62443, the asset owners establish governance and risk tolerance, operators establish secure configurations and monitoring, and technology vendors establish secure-by-design hardware, software, and update protocols. A combination of these measures offers a systematic way of ensuring the integrity of data, the accessibility of the system, and the confidence of the occupants in AI-enabled GSB.

4. RISK IDENTIFICATION AND MITIGATION

Table 2. Intelligent technologies for material performance, damage assessment, and waste management in green construction

Risk Area	Applied Intelligent Techniques	References
PCM and thermal material risks	ANN-based thermal modeling; fuzzy MCDM insulation selection; DLIP for window/occupant behavior inference	[63, 64, 67]
Smart windows and glazing reliability	Stimulus-responsive coatings; AI-informed feedback and control strategies	[65, 66]
Concrete, steel, and sustainable materials	XGBoost strength prediction; KNN fatigue modeling; hygrothermal simulation; ANN-GA acoustics modeling	[68-71]
Bio-based material challenges	ML and simulation-based evaluation of bamboo, rammed earth, fungal composites	[72, 73]
Structural damage detection	GA; ANN; SVM; decision trees; CNN anomaly detection; ResNet-based assessment	[75-78]
Post-damage waste management	ANN for recycled PET; multi-objective logistics optimization; transfer learning for debris detection	[79-82]

Notes: PCM = Phase Change Material; MCDM = Multi-Criteria Decision-Making; DLIP = Deep Learning-based Image Processing for Window State Recognition; XGBoost = Extreme Gradient Boosting; GA = Genetic Algorithm; CNN = Convolutional Neural Network; ResNet = Residual Neural Network; PET = Polyethylene Terephthalate. Applicability depends on material aging, environmental exposure, data quality, and climate conditions.

Although green construction helps people, it also includes new problems that must be noticed and handled properly. Table 2 summarizes the main material-related risks in green construction, including material performance, structural damage detection, and post-damage waste management, together with the intelligent technologies applied to mitigate these challenges. Together with other risks, technical, environmental, economic and social, the impact of new materials, technologies and green rules can lead to higher risk. As a result, project managers need to notice and address risks to increase the success of a project.

During earthquakes and floods, buildings built using green methods must be able to withstand serious shaking without slowing down their appropriate level of sustainability. As part of their work, Calledda et al. [12] introduce an algorithm to develop safe buildings that require less money. Cetin et al. [13] also carried out tests using DE in order to find the best configuration for TMD, showing that DE can decrease the impact of seismic vibrations on green buildings.

Predictive analysis and selection frameworks have been integrated into systems to improve the mitigation of flood risks observed in the Poyang Lake region of China. Using SVM and MCDA, Zabihi et al. [14] created a system of green infrastructure that can deal with floods. The team of Wang et al. [15] used LSTM networks together with AHP to estimate the flood risk and plan appropriate actions.

Due to hurricanes and hot temperatures caused by climate, companies have started using various new technologies for risk management. Wang et al. [17] relied on Bayesian inference and aerial pictures to quickly determine how badly buildings had been affected by hurricanes, helping with immediate response and recovery efforts. Patel et al. [18] came up with an irrigation management system for green rooftops that uses AI and fuzzy logic to help reduce the use of water while managing the thermal regulation of urban green buildings.

Apart from risks related to the environment, budget problems and uncertainty about costs can be major issues in green projects due to the newness of green technology and the lack of available records. For this purpose, ML approaches are applied to make the predictions of costs more accurate. Alshboul et al. [21] suggested a model that uses XGBoost and both hard and soft cost indicators to predict the costs of building projects. Such models support risk mitigation through better financial planning and informed decision-making during the early stages of the project lifecycle.

The environmental monitoring hazards associated with emissions of pollutants, waste disposal, or unexpected ecological effects can be controlled with the help of sophisticated sensing and control systems. A model to track the quality of indoor environment and energy consumption was proposed by Zhu et al. [23] using artificial neural networks as a part of LLVM, optimizing HVAC operation. Wang et al. [24] intertwined (LCA) tools with ML (XGBoost) and BIM to monitor and minimize carbon emissions in the construction of the foundation.

All these instances have highlighted the need to ensure that intelligent risk identification capabilities are combined with proactive mitigation measures at the design, construction, and operation stages of green buildings. Using AI, data-driven model, and real-time monitoring, green construction projects can be more resilient, cost-efficient and green.

On the first level, the number 4 illustrates three elements of environmental and physical risks, including Seismic risk, Flood risk, and Climate-related risk. The reduction of seismic risks is aimed at optimization of earthquake-resistant designs with the help of algorithmic techniques network inversion algorithm and difference evolution algorithm, which are proved by Calledda et al. [12] and Cetin et al. [13]. Flood risk is tackled by using predictive systems, which combine models such as LSTM and CNN, as put forward by Wang et al. [15] and Hussain et al. [16]. The risks associated with climate, including hurricanes and heatwaves, are addressed with the help of AI-based disaster damage assessment methods, such as Bayesian networks and fuzzy logic methods [17, 18].

The second framework layer includes systemic and operational risks: Economic risk, Environmental monitoring risk, and Monitoring and control systems. The (ML) models applied to handle economic risk, namely uncertainty of construction cost in green projects, include linear regression, DNN, and XGBoost, which were discussed in previous works [19-21]. Environmental monitoring risks are mitigated using data-driven techniques such as ANN and BIM for real-time pollutant tracking and lifecycle analysis [23, 24]. Lastly, intelligent Monitoring and control systems rely on embedded IoT devices and automated control mechanisms to provide continuous supervision and optimization of building systems, as described in the works of Wang et al. [24] and Gomaa et al. [34].

Having these categories in Table 3 illustrates that introducing intelligent technology is vital for tackling and managing the multiple risks of green construction projects and maintaining their durability.

Table 3. Risk-mitigation mapping in GSB projects

Risk Category	Intelligent Technology / Method	Key References
Flood and climate risk	LSTM networks; CNN-based image analysis; MCDA decision support	[15, 16]
Seismic risk	Differential Evolution (DE) for TMD optimization; network inversion algorithms	[12, 13]
Cost uncertainty	XGBoost; DNN; ANN cost prediction models	[19-21]
Cybersecurity risk	IoT anomaly detection; secure BMS; IEC 62443 and NIST CSF-aligned controls	[34, 36]
Environmental monitoring	BIM-LCA integration; ANN for IAQ; ML-based carbon tracking	[23-25]

Notes: MCDA = Multi-Criteria Decision Analysis; DE = Differential Evolution; TMD = Tuned Mass Damper; DNN = Deep Neural Network; IAQ = Indoor Air Quality; NIST CSF = NIST Cybersecurity Framework; IEC 62443 = Industrial Cybersecurity Standards. Applicability depends on hazard type, sensing infrastructure, and operational constraints.

4.1 Risk mitigation mapping

One of the most important contributions of this review is the direct mapping between important categories of risks in GSB projects and the intelligent technologies, which can reduce the risk. Through a systematic connection between each category of risk to predictive models, optimization methods and intelligent control systems, the project stakeholders will acquire a viable structure of making risk-aware decisions. These relationships are summarized in Table 3.

As an example, the risks of flooding are effectively reduced with the help of hybrid deep learning systems like LSTM networks and CNN predictive flood models and real-time hazards identification [15, 16]. On the same note, DE algorithms can be used to minimize the seismic risks through optimization of Tuned Mass Dampers (TMD) in a way that the structural vibrations during earthquakes can be minimized [12, 13].

Green projects are not well accounted in terms of financial risks especially construction cost uncertainty because historical datasets are unavailable. The high-order AI algorithms, like Extreme Gradient Boosting (XGBoost) and DNN, have demonstrated good results in cost estimation by being able to offer more accurate budgeting and resource allocation [19-21].

Within the sphere of cybersecurity threats that are the results of integrating IoT-enabled solutions, IoT-based anomaly detection systems and adherence to standards, including IEC 62443 and NIST CSF, play a vital role in protecting BMS against data breaches and functional failures [34, 36]. The functions of environmental and operational risks, including carbon emissions and air quality, are alleviated with the help of the (BIM, LCA), and AI-based monitoring tools, which will give real-time feedback and optimize the work of the HVAC [23-25].

Based on this mapping, it can be seen that AI, IoT, and BIM are not tools to operate more efficiently but the key enablers of risk mitigation throughout the building lifecycle.

In order to make sure that the risk identification and mitigation strategies in GSB are not only technically competent but also consistent with the best practices at the global level, the strategies in question have to be anchored into the existing international standards and certification schemes. These frameworks offer performance standards, performance compliance indicators and performance guidelines that create the gap between theory and practice.

As an example, the Leadership in Energy and Environmental Design (LEED) certification program focuses on energy use, indoor air quality, and building material durability and provides performance credits that directly relate to risk mitigation in such areas as carbon reduction and occupant health [83]. In the same vein, BREEAM (Building Research Establishment Environmental Assessment Method) is an assessment scheme which is lifecycle-based and considers environmental risk assessment under energy, water, waste, and resilience categories [84].

The ISO 19650 standard can also provide internationally accepted principles of BIM regarding digital workflows and data governance, such that intelligent risk management systems are capable of delivering data consistency, interoperability, and traceability across the project lifecycle [85]. The ASHRAE Standard 55 occupant comfort and ASHRAE Standard 90.1 energy-efficient design are benchmarked as technical risks associated with thermal comfort and energy use, respectively, and define the occupant comfort and energy-efficient design thresholds, respectively as value-based performance standards on smart building control systems [86]. The operational health and safety hazards are also solved with the help of the WELL Building Standard that includes the air quality, water quality, thermal regulation criteria, and user well-being that ensure some guidelines on how to apply AI-based monitoring to the occupant-based system [87]. In the case of cyber-physical risks, the international standards NIST CSF and IEC 62443 are defined to address the requirements of this area, i.e., IoT device security, network segmentation, and anomaly detection procedures in BMS [88, 89]. These frameworks make sure that the smart systems of risk identification comply with both the cybersecurity and privacy requirements as well.

The framework provided in the current review is made more practical in its use as well as its policy applicability by clearly mapping the intelligent risk mitigation techniques to these international standards. The connections between the risk types, mitigation types, and benchmarks applicable are summarized in Table 4.

Table 4. Mapping of risks and mitigation methods to international standards

Risk Category	Mitigation Methods	Relevant Standards / Benchmarks
Energy and comfort risks	AI-based HVAC optimization; predictive thermal comfort modeling	ASHRAE 55; ASHRAE 90.1; LEED; BREEAM
Material and environmental risks	BIM-LCA integration; sustainable material evaluation	ISO 19650; LEED; BREEAM
Occupant health and well-being	IoT air/water quality monitoring; NLP-based feedback analysis	WELL Building Standard; LEED
Cybersecurity and operational risks	Intrusion detection; secure BMS; IoT anomaly monitoring	NIST CSF; IEC 62443
Lifecycle management risks	Digital twins; BIM-enabled monitoring; risk-aware scheduling	ISO 19650; BREEAM

Notes: ASHRAE 55/90.1 = Thermal Comfort and Energy Standards; LEED = Leadership in Energy and Environmental Design; BREEAM = Building Research Establishment Environmental Assessment Method (BRE Global); ISO 19650 = BIM Information Management Standard; WELL = WELL Building Standard; NIST CSF = NIST Cybersecurity Framework; IEC 62443 = Industrial Automation Cybersecurity Standard. Standard applicability depends on jurisdiction, certification scope, and project delivery model.

Table 5. Quantitative effect summary of intelligent risk mitigation methods in green construction

Ref.	Application Domain	Metric	Baseline Comparator	Direction of Effect (↑/↓)	Context (Climate Zone, Building Type)
[46, 47]	HVAC optimization and building energy management	Energy use intensity / energy consumption (EUI/energy demand)	Rule-based / conventional control strategies	↓(reported reductions)	Buildings across varying operational conditions; climate zone and building type vary by study
[19-21]	Construction cost prediction	Prediction error / forecasting accuracy	Linear regression / traditional statistical models	↓ error, ↑ accuracy	Project datasets vary; building type and regional context depend on source dataset
[23-25]	Environmental monitoring and carbon assessment (BIM-LCA)	Emission prediction accuracy / carbon estimation reliability	Conventional estimation methods and/or non-ML baselines	↑(demonstrated improvements)	Case-study settings; context varies (public buildings and project-specific scenarios reported)
[12, 13]	Seismic risk mitigation and vibration control	Peak displacement / structural response indicators	Non-optimized or conventional TMD configurations	↓ (relative gains vs baseline)	Earthquake simulation/structural case studies; location and building type vary by study
[34, 36]	Cybersecurity and operational resilience in BMS/IoT	Intrusion/anomaly detection performance and security monitoring capability	Conventional monitoring / non-intelligent detection approaches	↑ (improved detection)	IoT-enabled (BMS); evaluated in testbed or case-study contexts

4.2 Narrative evidence synthesis

Although the qualitative evidence points to the promise of innovative technologies in risk alleviation, the results of the literature reviewed show that the use of such methods is reported to be linked to decreased risks, proven increases, and relative advantages over the conventional techniques in various aspects of performance. Table 5 summarizes the quantitative evidence reported in the literature, highlighting the performance improvements achieved by intelligent risk mitigation methods across different application domains. Some reports state the enhancement of energy efficiency, accuracy of cost prediction, and structural and environmental risk management, which indicates that the use of AI and smart systems may provide concrete performance gains when implemented on green constructions. As an example, it has been related to the reported decrease in the energy use intensity due to AI-based reinforcement learning-based HVAC optimization and predictive control, compared to traditional rule-based control methods [46, 47]. Equally, ANN-cost predictive models show enhanced accuracy in estimating costs as compared to the conventional linear regression methods in construction cost forecasting activities [19-21]. The XGBoost and CNNs (ML) algorithms have been demonstrated to improve the quality and stability of the results in environmental monitoring concerning prediction of emissions across a range of climatic conditions [23, 24]. In structural risk reduction, DE-optimized TMD have shown comparative improvements in the minimization of the peak structural responses as compared to the non-optimized design, in seismic conditions [12, 13].

Overall, the quantitative evidence underscores the added value of intelligent risk mitigation technologies. While effect sizes vary depending on project type, data quality, and model configuration, the majority of studies report consistent improvements in efficiency, accuracy, and resilience compared to conventional approaches.

4.3 Barriers to mitigation

Despite the significant promising nature of intelligent technologies in reducing risks in GSB projects, some obstacles act as hampering factors to successful implementation. All these challenges are experienced due to the limitations of the data, technical issues, and financial aspects, as well as socio-regulatory factors that determine any type of scalability and reliability of smart risk management strategies. Data-related barriers. The quality and availability of input data is crucial to the performance of AI and ML models. The sensor networks that are installed in buildings are usually susceptible to noise, drift and calibration errors and this can lower prediction accuracy and raise false alarms [46, 47]. Alongside, the issue of the scarcity of datasets is also a major drawback because in some cases, especially in developing areas, there is no long-term, high-resolution building performance data. This limits the generalization capabilities of models like DNNs, LSTMs and XGBoost to different climatic and operational conditions [19, 23].

Technical barriers. There is concept drift vulnerability to AI models, where the conditions surrounding the environment or the behaviour of occupants change over time and the model becomes less precise. Likewise, interoperability is also problematic because there are heterogeneous data formats, vendor-driven (BMS), and no single digital frameworks [85]. The absence of effective data exchange protocols will relegate even a well-constructed predictive model to silo, even though they cannot fully offer risk mitigation.

Financial barriers. Initial capital expenditure CAPEX on the deployment of superior IoT infrastructure, digital twins, or AI-powered control system may be too high to be readily affordable to small- and medium-scale projects. Although operational expenditure OPEX savings can be substantial in the long term, uncertainty in payback periods, and in return on investment ROI will have discouraging impacts on greater adoption [83, 84]. Besides, the necessity of constant maintenance and training of skilled labor force adds to life-cycle expenses further.

Regulatory and social restrictions. The introduction of intelligent technologies in the mainstream building activities is frequently delayed by policy gaps and fragmented building codes. Even though such a certification as LEED, BREEAM, and WELL offer high-quality sustainability standards, these standards are not practically aligned with AI- and IoT-based solutions [83, 87]. Meanwhile, user trust is threatened by privacy and cybersecurity issues especially when the occupant data is gathered to model comfort or optimize energy usage. Social acceptance is one of the most important social aspects of mitigating risks that cannot be ignored [34, 36].

In conclusion, these barriers can be resolved through a multi-pronged approach: enhancing open-access data sets and data quality of sensors, creating interoperable standards (e.g., ISO 19650, IFC, Brick Schema), introducing financial incentives to de-risk investments, and enhancing regulatory frameworks that would create a balance between innovation and protection of users.

5. DISCUSSION

Intelligent technology in green construction is opening up new paths for the construction sector to become more sustainable, strong, and efficient over time. According to this study, smart systems, varying from AI used for cost prediction to advanced tools for monitoring the environment, help solve the challenges of green building development.

It has been found that AI and ML [12, 13] play key roles in predicting and managing risks. By using TMD and optimization for earthquakes and LSTM networks and decision-making systems for floods [14, 15], they allow for forward planning and on-the-spot decision-making support. Also, using predictive technologies and optimizing energy resources both support greater building performance and a longer lifespan for major infrastructure elements.

Even so, a few challenges remain for these groups. To start, using past data and information from sensors may not allow self-driving cars to adapt as well. For instance, cost prediction models such as DNN or XGBoost require extensive, high-quality datasets to function effectively [21], which may not always be available, particularly in developing regions. Similarly, intelligent systems embedded in BMS must be carefully calibrated to local climatic and socio-economic conditions to avoid misalignment with user needs and sustainability goals.

The other problem is the issue of striking the right balance between innovation and feasibility. Although the advantages of prefabricated buildings and new materials in terms of sustainability are impressive, they have not yet been implemented on a large scale due to regulatory barriers, cost-plus, and issues with the supply chain [31, 32]. Moreover, to guarantee the safety and privacy of the gathered building and occupant data especially in IoT-based systems and analytics on the cloud, strong governance mechanisms are needed to ensure that they are not abused to compromise user confidence.

The role of interdisciplinary collaboration is also important in the framework of the discussion in terms of systems view. Planning of smart green buildings requires the collaboration of data scientists, policymakers, end users, architects, and engineers. Also, the policy incentives and green certification programs, including LEED v5 [83], may be required to facilitate the massive implementation of the intelligent and sustainable building practices.

Moving forward, a greater number of studies ought to be conducted on hybrid frameworks combinatorial of AI and domain-specific knowledge to bring about better interpretability and robustness. It is also important in the creation of open access datasets and benchmarking tools which allow for innovation and performance comparison of green construction projects among the internationally green construction projects. Lastly, the introduction of equity and inclusivity within the design of GSB will support the use of the sustainability and technology advantages such that all socio-economic groups are allowed to enjoy them.

To sum up, intelligent technologies provide a good way to overcome most of the structural and operational barriers of green construction. With the help of smart innovations and by aligning them with sustainability goals, the construction industry can go to the place where the future would become not only more efficient and resilient, but also more equitable and environmentally friendly.

6. CONCLUSION

This study explored the convergence of intelligent technologies and green building strategies across the entire architectural lifecycle from design and construction to operation, renewal, and damage management. Since buildings are responsible for a lot of worldwide energy and carbon emission, using smart and sustainable methods in construction is necessary. Accepting AI, ML, IoT, and other technologies can greatly improve green construction projects' energy use, cost-efficiency, and responsibility to the environment.

A step-by-step discussion was used in the paper to demonstrate how various intelligent technologies are adapted to specific challenges in every stage. Genetic algorithms, neural networks, XGBoost, DNNs, ANN, and BIM platforms were used to generate useful results and influence how construction decisions were made. Also, by using prefabricated material, eco-friendly construction, and reviewing damage with data, architecture is now focused on sustainability throughout the building's lifespan.

It was also seen that smart monitoring of possible risks and effective management of uncertainty are vital for project dependability. Predicting risk from floods with LSTM, making buildings more seismically safe through optimization, and automatically tracking pollutants all show the abilities of AI to keep ahead of environmental and operational issues. They are designed to maintain the performance of a building and meet key sustainability targets included in the Paris Agreement and green certifications such as LEED.

Nevertheless, the document has articulated that there are still some problems, such as data access, model flexibility, costs of implementation, and system regulation. To mitigate these problems, further interdisciplinary work will be necessary, digital infrastructure will need investment, and supportive policy environments that prefer sustainable innovation will have to be developed.

Conclusively, green construction can take place through the incorporation of smart technology in buildings, as it provides a proper route towards the development of high-performance, low-impact buildings, and buildings in the future. With the continuous development of scientific and technological innovations, the construction sector is now in a position to take the forefront in responding to the issue of climate change, scarcity of resources, and resilience of cities through a smart sustainable design.

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