

Review

Generative AI for Sustainable Project Management in the Built Environment: Trends, Challenges, and Future Directions

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Abstract

Generative Artificial Intelligence (GAI) is gaining increasing attention as a catalyst for advancing sustainability within project management for buildings and infrastructure. This paper systematically reviews 173 peer-reviewed publications, including 142 journal and conference papers, to examine the current research landscape. Bibliometric mapping and thematic synthesis reveal expanding applications of GAI in project planning, design optimization, risk management, and sustainability assessment, but adoption remains fragmented across regions and domains. This review identifies persistent challenges that constrain large-scale implementation, including data variability and interoperability gaps, high computational demand, limited regulatory alignment, and ethical and governance concerns, coupled with the absence of standardized evaluation metrics. In response, this paper outlines future research prospects through a structured agenda that emphasizes scalable and generalizable AI models, real-time integration with IoT and digital twins, explainable and secure AI systems, and policy-aligned governance frameworks. These priorities aim to strengthen environmental, social, and economic sustainability outcomes in the built environment. By clarifying current progress and knowledge gaps, this review supports both scholars and practitioners in strengthening the role of GAI in the built environment.



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1. Introduction

Generative Artificial Intelligence (GAI), a subset of artificial intelligence as shown in Figure 1, focuses on producing new content from existing data using advanced machine learning models. Recent progress in deep learning, particularly large language models such as GPT-4 and Gemini, has accelerated the adoption of GAI across multiple industries [1]. In project management, GAI offers significant opportunities to automate routine tasks, generate reports and documentation [2], support predictive maintenance [3,4], and improve decision-making through data-driven insights [5]. These capabilities are increasingly relevant in the built environment, where efficiency, accuracy, and innovation are critical to delivering complex projects. Building on these developments, the evolution of GAI technologies provides the foundation for their emerging applications in architecture, engineering, and construction. Generative AI has developed through several technological milestones, beginning with early neural network research in the 1950s and progressing to

more sophisticated architectures such as Generative Adversarial Networks (GANs) [6], Variational Autoencoders (VAEs), and transformer models [7]. These advances underpin the capabilities of state-of-the-art systems like GPT-4, which have demonstrated unprecedented performance in generating realistic text, images, and design alternatives. Within the context of the built environment, such models are being explored for applications in design optimization [8], construction monitoring [4], risk assessment [9], and resource allocation and optimization [10], highlighting their transformative potential for sustainability-oriented project management.

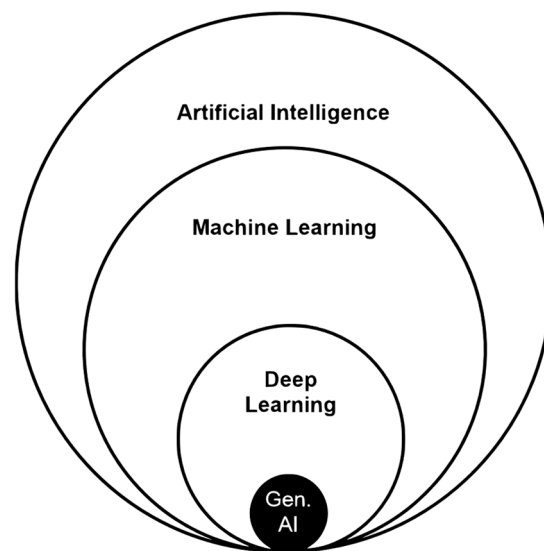


Figure 1. Artificial intelligence paradigm.

At the same time, sustainability has become a central priority in project management [11]. Organizations are expected to balance economic performance with environmental responsibility and social impact, aligning their operations with global benchmarks such as the United Nations Sustainable Development Goals (SDGs) [12]. Integrating sustainability principles into project management enables organizations to minimize environmental footprints, enhance resource efficiency, and improve stakeholder trust [13]. However, applying GAI to support these sustainability objectives remains limited and fragmented.

This paper seeks to address these issues by conducting a systematic literature review of 173 peer-reviewed journal articles and conference proceedings. Through bibliometric analysis and thematic categorization, it examines the contributions, challenges, and emerging applications of GAI in sustainable project management. This paper provides insights for academics, practitioners, and policymakers, positioning GAI as a potential enabler of resilient, efficient, and environmentally responsible built environment. To guide this investigation, the following research questions are posed:

- Research Question 1 (RQ1): What contributions has the existing literature made to sustainability and project management in buildings and infrastructure projects through the use of Generative AI (GAI)?
- Research Question 2 (RQ2): What are the main challenges and barriers identified in the literature regarding the implementation of GAI for sustainable practices in buildings and infrastructure projects?
- Research Question 3 (RQ3): What is the current state of applications of GAI with a sustainability focus in buildings and infrastructure projects, as reported in the literature?
- Research Question 4 (RQ4): What research gaps exist in the application of GAI for sustainable management of buildings and infrastructure projects, and what directions are proposed for future research?

The format of the article is intended to provide a thorough examination of the application of Gen. AI to advance sustainable practices within the field of project management. Section 2 describes the methodological strategy used for this paper. Section 3 examines the relevant literature on papers and summarizes its contributions. Section 4 showcases the analysis of the selected research papers. Section 5 discusses the selected research papers, providing an overview of the current state of the art. Section 6 delineates the identified challenges and future research directions. To conclude, Section 7 provides a summary of the paper's major discoveries, contributions, and implications.

2. Methods

This paper adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to guide a systematic and transparent process of literature selection [14]. This approach supports comprehensive coverage of relevant knowledge, reduces duplication, and improves the clarity and quality of reporting, while providing a standardized structure for conducting systematic reviews [14]. The application of this methodology was carried out through the steps illustrated in Figure 2.

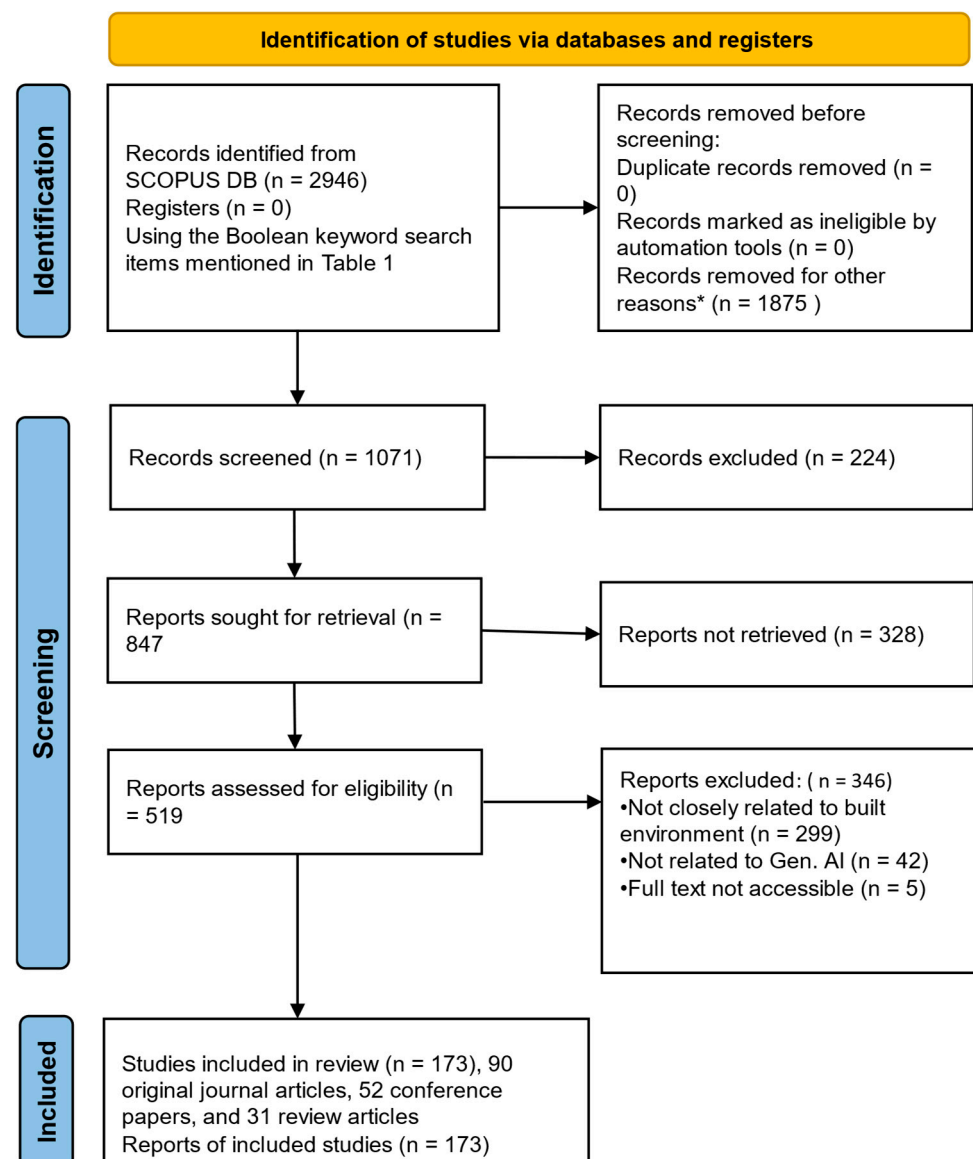


Figure 2. Article selection procedure—PRISMA steps.

In the first stage, the scope and objectives of the study are defined, including the establishment of inclusion and exclusion criteria and keyword selection. A literature search is performed using the Scopus database with the comprehensive list of terms in Table 1, which captures the most common keywords for the main concepts in the study (i.e., “Gen. AI” AND “Sustainability” AND “Management”), where the keywords were developed by two independent field experts and used to retrieve publications containing at least one keyword in the title, abstract, or keyword section. An asterisk (*) was included as a wildcard to capture variations of key terms (e.g., searching for “sustainability report*” retrieved results for “sustainability reporting” and “sustainability reports”). To maintain focus, the search was restricted to publications categorized under the “Engineering” research area within the Scopus Database, preventing an overly broad scope. Moreover, the search was limited to the publications since 2014, which was a landmark year due to the introduction of Generative Adversarial Networks (GANs) by Ian Goodfellow et al., which significantly advanced the field. This search was conducted on 6 January 2025. The selection of these keywords aimed to capture a comprehensive range of studies that explore the intersection of sustainability, Gen. AI, with buildings and infrastructure projects management over the past decade. The initial query generated 1071 publications, including but not limited to original research articles, conference proceedings, reviews, and editorials.

In Stage 2, a rigorous filtration process was applied to the initial 1071 publications. The selection criteria required documents to be classified as “Original Articles,” “Review,” or “Conference Paper”, with “Source type” limited to “Journal” or “Conference Proceedings”, “Publication stage” set to “Final”, and language restricted to English, resulting in 849 papers. Each journal article’s abstract was then manually reviewed to ensure its relevance to buildings and infrastructure projects within the context of sustainability and Generative AI or Deep Learning (DL) applications. This filtering process yielded 177 articles (91 journal articles, 55 conference papers, and 31 reviews). All selected papers were downloaded for further analysis in the next stage, except for four inaccessible papers, which were excluded, leaving a total of 173 publications included in the final dataset, comprising 90 journal articles, 52 conference papers, and 31 review papers. The detailed Stage 3 full-text analysis was conducted on the 142 journal and conference papers, as these works provide original empirical and theoretical contributions. The 31 review papers were excluded from the systematic coding framework to avoid duplication but were analyzed separately and are discussed in Section 2 (Related Works) to contextualize existing secondary studies. A systematic evaluation for the full text is conducted based on the following dimensions depicted in Table 2.

Potential reporting bias was addressed by documenting all inclusion and exclusion decisions in the PRISMA flow diagram and by applying broad Scopus search criteria to minimize missed studies. While statistical tests for publication bias were not applicable due to the qualitative synthesis, transparent reporting of exclusions reduces the risk of bias from missing results.

In the subsequent section a bibliometric analysis was carried out on the selected papers to gain more in-depth insight.

Table 1. Keyword search terms.

No.	Main Concept	Item	No.	Main Concept	Item	No.	Main Concept	Item
1.1	1. Generative AI	“Generative AI”	1.23	1. Generative AI	“Image generation”	2.14	2. Sustainability	“Environmental* responsib**”
1.2		“Generative Artificial Intelligence”	1.24		“image synthesis”	2.15		“Ecological* responsib**”
1.3		“GenAI ”	1.25		“Content creation”	2.16		“Social* responsib**”
1.4		“Generative model**”	1.26		“ AI-generated content”	2.17		“Responsible development”
1.5		“Foundation model**”	1.27		“Data augmentation”	2.18		“CSR”
1.6		“Large Language Model**”	1.28		“Deepfake**”	2.19		“Environmental* responsive**”
1.7		“LLM**”	1.29		“deep learning”	2.20		“Social* responsive**”
1.8		“Transformer model**”	1.30		“self-supervised learning”	2.21		“Ecological* responsive**”
1.9		“BERT”	1.31		“unsupervised learning”	2.22		“Green Building”
1.10		“GPT-**”	2.1	2. Sustainability	“Sustainability”	2.23		“Green Construction”
1.11		“GPT”	2.2		“Sustainable corporation**”	2.24		“Triple bottom line”
1.12		“ChatGPT”	2.3		“Sustainable organization**”	2.25		“Corporate citizenship”
1.13		“Language model**”	2.4		“Sustainable firm**”	2.26		“Eco-efficien**”
1.14		“Generative Adversarial Network**”	2.5		“Sustainable enterprise**”	2.27		“Environmental performance”
1.15		“GAN”	2.6		“Sustainable business**”	2.28		“Social performance”
1.16		“GAN architecture”	2.7		“Sustainable company**”	2.29		“Environmental management”
1.17		“GAN-based model**”	2.8		“Sustainability report**”	2.30		“Environmental protection”
1.18		“Diffusion model**”	2.9		“Environmental* sustainab**”	2.31		“Environmental report**”
1.19		“Stable Diffusion”	2.10		“Ecological* sustainab**”	2.32		“Natural environment”
1.20		“DALL-E”	2.11		“Social* sustainab**”	2.33		“Global warming”
1.21		“Text-to-image model**”	2.12		“Sustainable development”	2.34		“Climate change”
1.22		“Text generation”	2.13		“Sustainability-oriented”	3.1	3. Management	**Management**”
		Total retrieved results	=	2946 Articles				

Note: The asterisk (*) is used as a wildcard symbol in the search strings to capture variations of a keyword, such as plural forms, different suffixes, or related word endings (e.g., “responsib **” retrieves “responsible” and “responsibility”).

Table 2. Considered dimensions for stage 3 of the review process.

Group	Dimension	Description
Research Scope and Methodology	Research Aim/Purpose	Summarizes the core objective: e.g., “optimizing energy consumption,” “predictive maintenance,” “life-cycle assessment,” etc.
	Research Method	Quantitative, Qualitative, Mixed-Methods, Case Study, Simulation, etc.
	Data Sources	Sensor data, building operation data, public datasets, survey data, etc.
GenAI/DL-Specific Details	Type of AI/ML Technique	Distinguish between generative methods (e.g., GANs, large language models) vs. classical deep learning (CNNs, RNNs, LSTM, Transformers, etc.)
	Performance Metrics	E.g., accuracy, F1-score, RMSE, MAPE, or domain-specific metrics (energy savings, cost reduction)
	Model Explainability & Ethical Considerations	Whether the study discusses interpretability (e.g., SHAP, LIME) or responsible AI aspects (bias, fairness, transparency)
Sustainability & Management Context	Sustainability Domain	Environmental, Social, Economic, Governance/Policy, Technological
	Sustainability Sub-domain	E.g., energy efficiency, carbon emissions, resource management, health and safety, etc.
	Mapped SDGs	Map explicitly to Sustainability Development Goals SDGs as indexed in Scopus database (e.g., SDG 7 on Affordable and Clean Energy, SDG 9 on Industry, Innovation and Infrastructure)
	Management Aspect	Project management, operations management, asset management, facility management, etc.
	Stage in the Building/Infrastructure Life Cycle	Design, construction, operation, maintenance, retrofit, demolition
Project/Case Study Characteristics	Type of Building or Infrastructure	Residential, commercial, industrial, or specific infrastructure (bridges, roads, etc.)
	Scale or Size of the Project	Single-building, neighborhood, city-wide, national infrastructure
	Implementation Status	Conceptual, Pilot, Full Deployment
Outcomes, Impacts, and Limitations	Challenges and Limitations	Data availability, regulatory constraints, model generalizability, ethical concerns, etc.
	Recommendations & Future Work	Key suggestions for practitioners, policymakers, or future researchers

3. Related Works

The existing body of research primarily addresses general applications of artificial intelligence in construction or sustainability, but structured investigations into the intersection of GAI, sustainability, and project management are lacking. This gap is significant because sustainable infrastructure and building delivery requires both advanced digital solutions and robust management frameworks. Moreover, challenges such as data quality, interoperability, ethical concerns, and regulatory constraints hinder the large-scale implementation of GAI in real-world projects.

The pursuit of sustainability within the realm of project management has catalyzed a substantial body of research. However, the application of Gen. AI toward the advancement of sustainability and green building practices remains nascent.

A systematic literature review (SLR) framework is crucial for comprehensively understanding this emergent research paradigm. This section addresses RQ1 and provides an in-depth analysis of the literature on this subject.

More specifically, this section thoroughly examines 31 recent review studies on the topic, emphasizing the scarcity of reviews centered around research conducted on the use of Gen. AI to promote sustainability in buildings and infrastructure projects management. Table 3 summarizes these studies, presenting each identified paper’s publication year, Used Database, Aim of the study, Gen. AI/DL focus areas, Application Area, Time Coverage, and number of reviewed articles. It also provides an overview of recent literature reviews on AI in construction with a focus on various aspects, such as emerging digital technologies, AI adoption challenges, and specific AI applications like natural language processing (NLP) and digital twins.

Several review papers have addressed artificial intelligence in construction and project management, yet they remain limited in scope with respect to Generative AI. For example, prior reviews have broadly examined applications of AI in construction management or sustainability assessment, but they often emphasize traditional machine learning or optimization approaches rather than generative models. Other works have focused on digital transformation in the Architecture, Engineering, and Construction (AEC) sector, but they do not explicitly analyze how Generative AI contributes to sustainability-oriented project management practices. Moreover, existing reviews seldom combine bibliometric analysis with systematic thematic synthesis, resulting in partial coverage of publication patterns, research hotspots, and collaborative networks. Compared to these studies, the present paper makes three distinctive contributions: (i) it specifically investigates the intersection of Generative AI, sustainability, and project management, (ii) it integrates bibliometric mapping with qualitative analysis to provide a more comprehensive overview, and (iii) it proposes a structured research framework that unites dimensional perspectives (application domains and methods) with directional perspectives (emerging priorities). In doing so, this review not only situates current knowledge but also identifies concrete pathways for advancing research and practice.

Table 3. Overview of Literature Review on AI in Construction.

Ref.	Year	Used Database	Type of the Review	Aim of the Study	Gen. AI/DL Focus Areas	Application Area	Time Coverage	No. of Reviewed Articles
[15]	2025	Not Explicitly Mentioned	Review	Explore the use of large AI models in optimizing virtual power plants and energy management.	Large-scale AI models like GPT and BERT for energy optimization, predictive load balancing.	Virtual power plant management, renewable energy integration, smart grid optimization.	Open ended 2025	80
[16]	2024	Scopus	Bibliometric Analysis	Analyze key players in renewable energy and AI research, focusing on global scientific production and collaboration.	Deep learning, neural networks for renewable energy optimization and predictive analytics.	Renewable energy production, AI-driven automation, predictive maintenance.	2013–2023	822
[17]	2024	IEEE Xplore, ACM Digital Library, MDPI, Springer, ScienceDirect	Systematic Review (PRISMA methodology)	Explore the role of AI-enabled metaverse in sustainable smart cities, addressing technologies, applications, and challenges.	Generative AI (GAI), Large Language Models (LLMs), AI-driven digital twins, big data analytics.	Smart city governance, urban mobility, environmental monitoring, digital infrastructure.	2014–2024	284

Table 3. Cont.

Ref.	Year	Used Database	Type of the Review	Aim of the Study	Gen. AI/DL Focus Areas	Application Area	Time Coverage	No. of Reviewed Articles
[18]	2024	Multiple databases (not explicitly mentioned)	Systematic Review (PRISMA framework)	Examine AI-driven energy prediction techniques in healthcare buildings and their role in sustainability.	Artificial Neural Networks (ANNs), deep learning models for hospital energy consumption prediction.	Healthcare facility energy management, occupancy-based energy optimization, intelligent HVAC control.	2014–2024	35
[19]	2024	ScienceDirect, SpringerLink, ACM Digital Library, IEEE Xplore	Systematic Literature Review (SLR)	Review the role of transformer-based AI models for optimizing traffic flow in sustainable cities.	Transformer-based models (BERT, GPT, XLNet, T5, RoBERTa) for traffic prediction and optimization.	Traffic congestion prediction, urban mobility optimization, intelligent traffic coordination.	Articles were selected from four different periods.,	120
[20]	2024	Springer, MDPI, Google Scholar, Scopus, ScienceDirect, Taylor & Francis	Review	Analyze AI-based techniques for flood susceptibility assessment and disaster management.	Generative AI (GAI), GPT-4 for real-time flood forecasting, AI-driven flood mapping and risk assessment.	Climate change adaptation, disaster response, urban flood management.	Open ended 2024	52
[21]	2024	Scopus	Systematic Review	Analyze AI applications in energy efficiency and its impact on climate change.	AI for energy optimization, renewable energy integration, carbon footprint reduction.	Smart energy management, sustainability in industrial sectors, AI for climate resilience.	2010–2025	237
[22]	2024	Not Mentioned	Comparative Review	Evaluate AI techniques for optimizing wastewater treatment processes.	ANN, SVM, Random Forest, LSTM for pollutant identification, process optimization.	Wastewater treatment plant operations, pollution detection, process optimization.	Open ended 2024	104
[23]	2024	Web of Science, SCOPUS	Systematic Review (PRISMA methodology)	Investigate AI-driven methods in membrane separation technologies for water purification and resource recovery.	Deep learning (CNNs, RNNs, GANs) applied in filtration modeling and membrane optimization.	Membrane filtration, reverse osmosis, ultrafiltration, fouling reduction, real-time monitoring.	2013–2023	204
[24]	2024	Not Mentioned	Review Article	Review ANN techniques for predicting air pollutant levels.	ANN, CNN, LSTM, Random Forest for air quality prediction.	Air pollution monitoring, environmental impact assessment.	Open ended 2024	177
[25]	2024	Scopus	Systematic Review	Review ML/DL applications in forecasting building energy performance and optimization.	Deep Learning (ANNs, CNNs, LSTMs, GRUs), ML (Decision Trees, SVM, RF, Kriging).	Building energy simulation, heating/cooling management, renewable energy system control, fault detection.	2018–2023	70
[26]	2024	MDPI, ScienceDirect	Review	Examine reinforcement learning applications in energy system optimization.	Deep Reinforcement Learning (DRL), Q-learning, Actor-Critic models for energy management.	Grid optimization, renewable energy integration, real-time energy demand balancing.	Open ended 2024	40

Table 3. Cont.

Ref.	Year	Used Database	Type of the Review	Aim of the Study	Gen. AI/DL Focus Areas	Application Area	Time Coverage	No. of Reviewed Articles
[27]	2024	Not Explicitly Mentioned	Comprehensive Review	Examine machine learning applications in water resource management, covering sustainability, water quality, and flood management.	LSTM, Hybrid ML techniques, AI-driven decision support systems.	Groundwater management, water quality monitoring, flood management, wastewater treatment.	2014–2024	250
[28]	2024	Not Explicitly Mentioned	Review	Analyze how deep learning techniques contribute to urban environmental hazard monitoring and disaster mitigation.	Self-supervised learning, transformer architectures, adversarial robustness, multimodal learning.	Urban environmental monitoring, disaster prediction, resilience planning, hazard mitigation.	2008–2024	167
[3]	2024	Not Explicitly Mentioned	Comprehensive Review	Analyze AI-driven asset management in electric power systems, focusing on predictive maintenance and optimization.	Machine learning models, reinforcement learning for asset maintenance and performance forecasting.	Smart grid management, predictive maintenance in power transmission and distribution.	Open ended 2024	100
[29]	2024	IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar	Systematic Review	Explore AI-based computational intelligence methods for microgrid energy management.	Deep reinforcement learning, supervised/unsupervised learning for microgrid optimization.	Energy storage, demand-side management, smart grid optimization.	Open ended 2024	109
[30]	2023	Not Explicitly Mentioned	Systematic Review	Analyze deep learning applications in land use and land cover classification.	CNNs, GANs, Autoencoders, RNNs for remote sensing and classification tasks.	Urban planning, environmental monitoring, land resource management.	Open ended 2023	95
[31]	2023	Not Explicitly Mentioned	Survey	Review ML methodologies for water management, emphasizing prediction, clustering, and reinforcement learning.	AI for irrigation optimization, flood forecasting, water quality assessment.	Smart irrigation, water demand forecasting, desalination plant management.	Open ended 2023	302
[32]	2023	Not Explicitly Mentioned	Comprehensive Review	Investigate the role of Industry 5.0 technologies in smart cities.	AI-driven decision-making, machine learning, deep learning, automation frameworks.	Smart city infrastructure, AI-enabled urban services, cybersecurity, intelligent transportation.	Open ended 2023	104
[33]	2023	Scopus, Web of Science, ScienceDirect, TRID, Wiley Online Library	Systematic Review (PRISMA methodology)	Analyze the integration of ML and remote sensing in urban sustainability studies and propose an integrative framework.	Supervised and unsupervised ML techniques, deep learning for urban sustainability analysis.	Land use classification, disaster risk management, pollution monitoring, built infrastructure analysis.	Open ended 2022	107

Table 3. Cont.

Ref.	Year	Used Database	Type of the Review	Aim of the Study	Gen. AI/DL Focus Areas	Application Area	Time Coverage	No. of Reviewed Articles
[34]	2022	Scopus	Content Analysis and Topic Modeling	Identify key research themes in AI-driven sustainable energy studies.	BERT, LDA-based topic modeling, deep learning for energy efficiency.	Smart energy systems, AI-based optimization, renewable energy management.	2004–2022	182
[35]	2022	IEEE Xplore, ScienceDirect, Scopus, ACM Digital Library	Survey	Review deep learning applications in waste detection and classification, analyzing datasets and methods.	Deep learning for image classification and object detection in waste management.	Waste sorting, environmental sustainability, automated recycling.	Open ended 2022	102
[36]	2022	Not Mentioned	Systematic Literature Review	Analyze ML/DL applications in smart city management and sustainability.	CNN, LSTM, AI-driven IoT applications in smart city operations.	Energy management, traffic optimization, surveillance, air quality monitoring.	Open ended 2022	33
[37]	2022	Bibliometric Analysis of 578 Papers	State-of-the-Art Review	Examine AI applications in building asset management, focusing on efficiency, risk, and sustainability.	GANs for synthetic data generation, Deep Reinforcement Learning for asset optimization, AI-driven Digital Twin models.	Energy management, facility maintenance, lifecycle cost optimization, project risk assessment.	2012–2022	578
[38]	2022	ScienceDirect	Comprehensive Review	Review AI applications in energy supply, storage, demand management, and energy optimization.	Supervised, Unsupervised, and Reinforcement Learning in smart energy trading, optimization, and adaptive control.	Energy storage, renewable energy transition, microgrid adaptive control, smart trading, and carbon neutrality.	Open ended 2022	208
[39]	2022	Scopus, Google Scholar	Review	Investigate deep learning applications in facility management, particularly HVAC maintenance.	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) for predictive maintenance.	Facility management, predictive maintenance of HVAC systems, automation in construction.	Open ended 2022	100
[40]	2021	Not Explicitly Mentioned	Comprehensive Review	Assess deep learning models for solar irradiance prediction and renewable energy forecasting.	CNN, LSTM, Deep Belief Networks (DBN), Echo State Networks (ESN) for solar forecasting.	Solar power integration, smart grid forecasting, energy storage management.	Open ended 2021	174
[41]	2021	Not Explicitly Mentioned	Review	Assess deep learning applications for energy forecasting in buildings.	Neural networks, recurrent neural networks (RNN), deep learning-based energy forecasting.	Building energy management, energy efficiency optimization, smart building automation.	2011–2021	99
[42]	2020	Scopus, Web of Science	Systematic Review	Summarize the use of big data in urban sustainability research, including its applications and challenges.	Big Data analytics, deep learning for pattern recognition in urban mobility and environmental sustainability.	Urban planning, environmental monitoring, public health, and smart cities.	Open ended 2018	224

Table 3. *Cont.*

Ref.	Year	Used Database	Type of the Review	Aim of the Study	Gen. AI/DL Focus Areas	Application Area	Time Coverage	No. of Reviewed Articles
[43]	2020	Not Explicitly Mentioned	Comprehensive Review	Investigate the role of AI, IoT, and Blockchain in modernizing smart grids and integrating renewable energy resources.	Machine learning, deep learning, AI-based optimization for smart grid operations.	Smart microgrids, energy resilience, renewable energy integration.	Open ended 2020	181
[44]	2019	Web of Science, Scopus	Systematic Review	Review ML models used in energy systems, categorize them, and discuss their advancements and challenges.	Hybrid ML models, deep learning, ensemble techniques, AI-driven energy forecasting.	Energy demand prediction, renewable energy forecasting, smart grid optimization.	Open ended 2019	70

4. Analysis of Results

4.1. Bibliometric and Descriptive Analysis

The software VOSviewer (version 1.6.20, Centre for Science and Technology Studies, Leiden University, The Netherlands), utilized for generating and visualizing bibliometric maps, was employed to import citation, bibliographical, and author keyword data from 142 articles and conference papers. Maps generated by VOSviewer comprise elements. This paper focuses specifically on nations or author keywords as the subjects of interest. Any two items may possess a link, connection, or relationship with one other. The strength of each link is represented by a positive integer. The greater the link, the higher this value becomes.

In co-authorship analysis, total link strength indicates the overall robustness of a country's co-authorship connections with other nations, whereas link strength between countries reflects the quantity of publications co-authored by the two affiliated countries. In co-occurrence analysis, the link intensity between author keywords indicates the frequency of articles in which two keywords appear together.

4.1.1. Publication Output and Growth of Research Interest

It is interesting to note that although Generative Adversarial Networks (GANs) were first introduced in 2014 [6], their application to sustainability in buildings and infrastructure projects did not appear in the literature until 2017, when the earliest journal article on the subject was published by [45]. Moreover, there was another two-year delay before the first conference paper emerged in 2019 by [46]. As illustrated by Figure 3, the volume of both journal articles and conference papers began to climb steadily after that point, culminating in a marked surge through 2024. This trend signals a growing enthusiasm for harnessing GenAI techniques to address sustainability challenges in the built environment.

4.1.2. Preferred Conferences

To further underscore this progression, Table 4 highlights the top 10 international conferences that have contributed the most publications to this rapidly evolving field, weighted by the total number of citations per conference in the selected dataset. It highlights the most cited conferences contributing to the research landscape at the intersection of Generative AI (GAI), sustainability, and project management. The data reveals a diverse range of conferences spanning topics in humanitarian technology, urban planning, robotics, sustainable infrastructure, and AI-driven environmental management. Notably, the IEEE Global Humanitarian Technology Conference (GHTC 2019) leads with the highest citation count, reflecting a strong interest in AI

applications for sustainability and waste management. The presence of multiple IEEE-sponsored conferences (ICIVC, SusTech, EPEC, ICCES) underscores the dominant role of IEEE in advancing AI-driven sustainability research. The International Conference on Sustainable Infrastructure with Smart Technology for Energy and Environmental Management (FIC-SISTEEM 2020) and CAADRIA 2021 further demonstrate the growing emphasis on smart cities, energy efficiency, and automation in construction. The inclusion of conferences such as ISCRAM 2020 and GTSD 2020 indicates the increasing role of AI in disaster response, crisis management, and energy forecasting. The geographical diversity—spanning Seattle, Xiamen, Dhaka, Hong Kong, and various locations in India and Vietnam—shows a global effort in integrating AI for sustainable infrastructure. These conferences provide a strong foundation for emerging research and foster interdisciplinary collaborations between AI, engineering, and sustainability experts, positioning GAI as a critical tool for addressing challenges in sustainable project management.

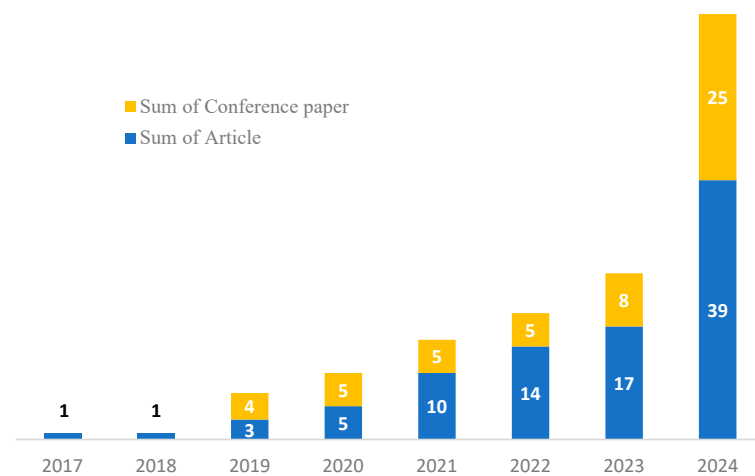


Figure 3. Number of publications per year, 2014–2024.

Table 4. Top 10 Conferences by sum of citations.

Conference Name	Year	Conference Location	Sum of Citations	The Most Cited Article
9th Annual IEEE Global Humanitarian Technology Conference, GHTC 2019	2019	Seattle	32	[47]
4th IEEE International Conference on Image, Vision and Computing, ICIVC 2019	2019	Xiamen	27	[48]
3rd International Conference on Robotics, Electrical and Signal Processing Techniques, ICREST 2023	2023	Dhaka	22	[49]
26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia: Projections, CAADRIA 2021	2021	Hong Kong	16	[50]
7th IEEE Conference on Technologies for Sustainability, SusTech 2020	2020	Santa Ana, Orange County	15	[51]
1st International Conference on Sustainable Infrastructure with Smart Technology for Energy and Environmental Management, FIC-SISTEEM 2020	2020	Tamil Nadu	13	[52]
2019 IEEE Electrical Power and Energy Conference, EPEC 2019	2019	Montreal	12	[53]
4th International Conference on Communication and Electronics Systems, ICCES 2019	2019	Coimbatore	10	[46]
17th Annual International Conference on Information Systems for Crisis Response and Management, ISCRAM 2020	2020	Blacksburg	8	[54]
5th International Conference on Green Technology and Sustainable Development, GTSD 2020	2020	Virtual, Ho Chi Minh City	8	[55]

4.1.3. Journal Citation Network

The findings indicated that the ten most prolific journals in the domain of GAI, sustainability, and project management for buildings and infrastructure projects are published by three distinct publishers (Table 5). The most productive journal was published by the Institute of Electrical and Electronics Engineers Inc. (IEEE). Elsevier published the second journal, contributing to a total of seven, while the other two journals were published by the Multidisciplinary Digital Publishing Institute (MDPI).

Table 5. Top 10 source journals of the intersection of Gen.AI, Sustainability, and Project management research 2014–2024.

Journal Name	Publisher	Count	Cited By	The Most Cited Article
IEEE Access	IEEE	12	404	[56]
Sustainable Cities and Society	Elsevier	12	301	[33]
Energies	MDPI	9	723	[43]
Sensors	MDPI	6	157	[57]
Energy and Buildings	Elsevier	5	175	[58]
Journal of Cleaner Production	Elsevier	4	423	[59]
Automation in Construction	Elsevier	4	132	[60]
Applied Energy	Elsevier	3	119	[61]
ISPRS Journal of Photogrammetry and Remote Sensing	Elsevier	3	51	[62]
Sustainable Computing: Informatics and Systems	Elsevier	1	72	[34]

The most productive journals were IEEE Access and Sustainable Cities and Society, each with 12 articles (8.2%), followed by Energies (9 articles, 6.1%), Sensors (6 articles, 4.1%), and Energy and Buildings (5 articles, 3.4%). The citation analysis for sources of the intersection of GAI, Sustainability, and Project management research 2014–2024 using VOSviewer is also captured at Figure 4.

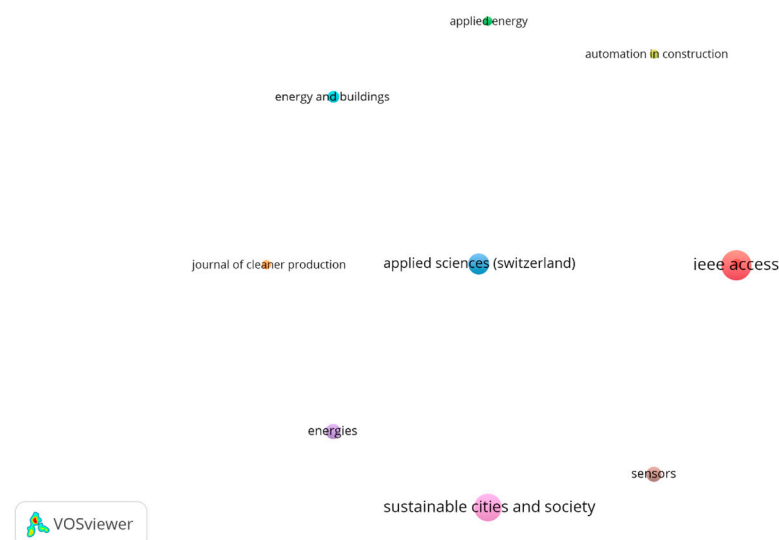


Figure 4. Citation Analysis for sources of the intersection of GAI, Sustainability, and Project management research 2014–2024.

Beyond publication counts, citation analysis provides insights into the influence and interconnection of journals in this field. Figure 5 illustrates the co-citation network of journals publishing research at the intersection of Generative AI, sustainability, and project management between 2014 and 2024. Larger nodes indicate journals with higher

citation counts, while stronger linkages reflect frequent co-citations, signifying intellectual connectivity across research communities. The visualization highlights IEEE Access and Sustainable Cities and Society as central sources, frequently co-cited with other outlets such as Energies, Energy and Buildings, and the Journal of Cleaner Production, indicating their pivotal role in shaping scholarly discourse.

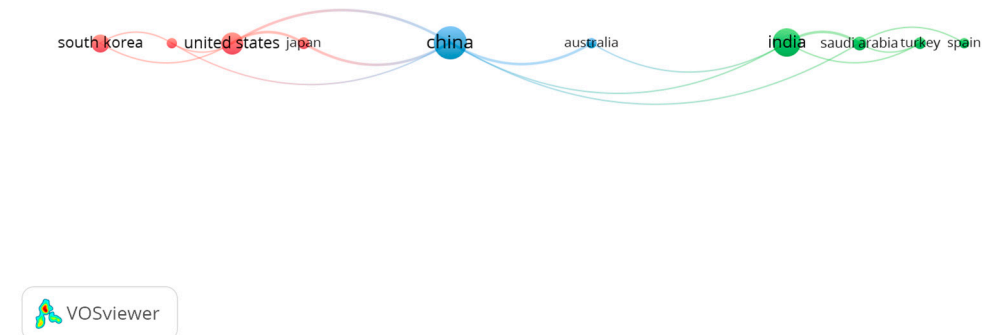


Figure 5. Co-Authorship Author—Countries.

4.1.4. Leading Countries and International Collaboration

Country-level analysis highlights the geographic distribution and collaborative intensity of research in this field. In the Co-Authorship Author–Countries analysis, a minimum document threshold of four and a minimum citation requirement of 21 were applied, resulting in 10 countries meeting the criteria. As shown in Table 6, China, India, the United States, and South Korea dominate in terms of publication volume. China leads with 39 documents and 573 citations, followed by South Korea (319 citations) and the United States (317 citations). Together, China, the USA, India, and South Korea account for approximately 77% of all publications in the dataset, underscoring their pivotal role in advancing research on Generative AI, sustainability, and project management.

Table 6. Top 10 most cited documents by country.

Rank	Country	Documents	Country	Citations
1	China	39	China	573
2	India	29	South Korea	319
3	United States	18	United States	317
4	South Korea	12	Spain	122
5	Saudi Arabia	7	India	106
6	Japan	5	Saudi Arabia	104
7	Turkey	5	Turkey	69
8	Australia	4	Australia	65
9	United Kingdom	4	Japan	55
10	Spain	4	United Kingdom	28

Figure 5 provides a visualization of the international collaboration network based on co-authorship analysis. Node size represents the number of publications per country, while link strength indicates the intensity of co-authorship ties. The visualization reveals three distinct clusters: (1) the United States, South Korea, Japan, and the United Kingdom; (2) China and Australia; and (3) Spain, Turkey, Saudi Arabia, and India. These clusters demonstrate that while leading nations dominate publication output, there is also meaningful cross-regional collaboration emerging between Asia, Europe, and the Middle East.

Together, Table 6 and Figure 5 highlight two key insights: research activity is highly concentrated in a few leading countries, and at the same time, international partnerships are becoming increasingly important in shaping the development of this field.

Overall, the bibliometric analysis demonstrates that Generative AI research in sustainable project management is still at a formative stage, characterized by concentration in a few journals and geographic regions. While this reflects the leadership of specific countries and institutions, it also highlights the need for greater diversification of publication outlets and broader geographic representation. The prominence of certain venues suggests that the discourse is emerging within established sustainability and engineering management platforms, but its relatively low dispersion underscores that the field has not yet matured into a mainstream research domain. These findings provide an important backdrop for the thematic analysis by clarifying both the strengths and imbalances in the current knowledge base.

5. Trends in the Literature

The bibliometric and content analysis was conducted on 142 primary studies, consisting of 90 journal articles and 52 conference papers. These publications were included in the full-text analysis to directly address RQ3, as they provide original empirical and theoretical contributions at the intersection of Generative AI, sustainability, and project management. In addition, 31 review papers were identified in the dataset; these were not subjected to the detailed coding process in order to avoid duplication with secondary studies. Instead, they were examined separately and are discussed in Section 3 (Related Works) to provide a broader contextual understanding of the field.

The relationship between sustainability requirements and Gen. AI in the context of project management revealed several key themes. The following are the observed embedded themes presented in Figure 6, followed by a discussion of each theme.

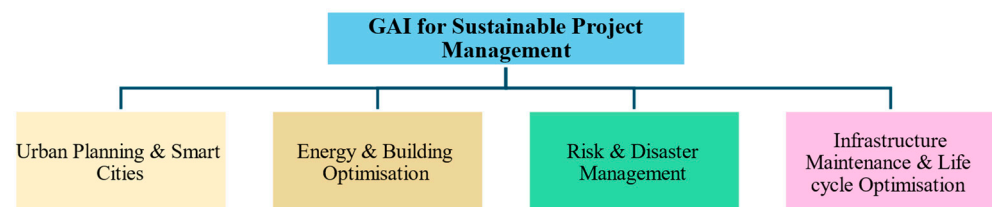


Figure 6. Mapping of the current trends.

5.1. Urban Planning and Smart Cities

Generative AI (GenAI) is transforming urban planning and smart city development by improving land use planning, infrastructure optimization, and disaster resilience [63,64]. AI-powered models analyze large-scale urban datasets to predict expansion patterns and optimize transportation networks, ensuring more sustainable and adaptive urban environments [65–67]. The integration of remote sensing and satellite imagery with AI has enhanced pollution monitoring, zoning regulations, and land use assessments [68–70]. Moreover, AI-driven simulations enable real-time urban scenario modeling, allowing planners to make data-driven decisions that align with sustainability goals [71,72]. Some studies highlight that AI-driven environmental monitoring and infrastructure planning can significantly reduce urban congestion, flooding risks, and inefficient land allocation [62,73,74]. However, challenges remain, including data integration issues, regulatory barriers, and the need for real-time AI analytics to make these solutions more actionable [75,76]. Future research should focus on developing AI-driven decision-support tools for policymakers to enhance data-driven urban governance and develop truly adaptive smart cities [60,77,78].

5.2. Energy and Building Optimization

AI is revolutionizing energy efficiency and smart building management by optimizing HVAC systems, lighting automation, and energy storage solutions [79]. Generative AI models are being integrated into demand-response mechanisms, allowing for dynamic load balancing and peak-hour energy conservation, which is crucial for modern smart grids [80,81]. Some studies show that AI-driven energy forecasting enhances grid resilience by predicting fluctuations in energy demand and adjusting energy distribution accordingly [82,83]. The application of digital twins in smart building management allows real-time simulation of energy consumption patterns, helping optimize sustainability efforts [84,85]. Additionally, AI-based adaptive learning models continuously improve HVAC control and energy optimization strategies based on occupant behavior and environmental conditions [86–88]. However, computational complexity, interoperability challenges, and lack of standardization across energy management systems hinder large-scale AI adoption [89–91]. Researchers suggest developing more computationally efficient AI models and improving interoperability standards, ensuring AI solutions can be integrated across diverse building types and energy networks [92–94]. Addressing these concerns will further enable AI-driven net-zero energy buildings and carbon-neutral cities [61,95–100].

5.3. Risk and Disaster Management

Risk and disaster management is a critical area where AI-driven predictive models can enhance infrastructure resilience and disaster response efficiency [72,101]. AI is increasingly being used for flood forecasting, structural health monitoring, and climate risk prediction, helping urban planners proactively address disaster risks [102,103]. For example, machine learning models trained on geospatial and weather data can predict flood-prone areas and enable early warning systems, minimizing damage and casualties [59,104]. AI is also improving structural safety assessments by analyzing material degradation patterns in buildings and bridges, allowing for preventive maintenance [73,105]. However, many challenges persist, including data uncertainty, real-time processing limitations, and lack of integration with policy frameworks, which reduce the effectiveness of AI-driven disaster management [106,107]. Some studies highlight the need for more interpretable AI models in risk assessments, as black-box AI solutions often fail to provide clear explanations for their predictions, making it difficult for decision-makers to trust their outputs [108,109]. Future research should focus on enhancing AI explainability in disaster risk modeling, integrating real-time climate simulation data, and fostering cross-agency collaboration to ensure AI solutions are effectively incorporated into national and global disaster response strategies [60].

5.4. Infrastructure Maintenance and Lifecycle Optimization

Generative AI is also playing a significant role in infrastructure maintenance and lifecycle management, improving structural durability, predictive maintenance, and sustainable construction practices [110,111]. AI-powered monitoring systems now assess material degradation and detect structural faults in buildings and roads, reducing maintenance costs and improving public safety [103,112]. By analyzing historical maintenance records, sensor data, and construction materials, AI models can predict the lifespan of infrastructure components, helping policymakers allocate resources more efficiently [90,94]. AI-driven optimization techniques are also being leveraged in sustainable construction, allowing engineers to minimize material waste and carbon footprints while maximizing energy efficiency [113,114]. However, data variability, lack of standardization in predictive maintenance models, and high implementation costs remain barriers to large-scale adoption [76,115]. Some studies suggest that AI-powered digital twins, combined with Building Information Modeling (BIM), can improve lifecycle assessments and long-term

sustainability strategies [109]. Future research should focus on enhancing AI-powered predictive maintenance tools, integrating AI-driven BIM platforms, and developing cost-effective AI-driven construction monitoring solutions, ensuring sustainable and resilient infrastructure management [109].

Taken together, the reviewed studies illustrate both the diversity and fragmentation of Generative AI applications in sustainable project management. Contributions span domains such as design optimization, resource planning, and risk management, yet most remain isolated demonstrations rather than components of an integrated framework. This fragmentation limits the transferability of findings and makes it difficult to assess long-term impact on sustainability outcomes. Nevertheless, the breadth of exploratory efforts reflects growing recognition of the potential of Generative AI and provides a foundation for more systematic inquiry. These insights reinforce the necessity of the framework proposed in this paper, which aims to consolidate and align scattered contributions into a coherent research agenda.

6. Challenges and Future Research Directions

The literature on Generative AI for sustainable project management identifies both persistent challenges and opportunities for future exploration. This section consolidates these insights by first outlining the key challenges and barriers that hinder practical implementation and then proposing future research directions that can help address these limitations and advance the field.

6.1. Challenges

The deployment of GAI to enhance sustainability within project management revealed a multitude of challenges. These challenges encompass organizational, technical, and human-centric dimensions. The principal obstacles are delineated in the following subsections and illustrated in Figure 7, addressing RQ2.

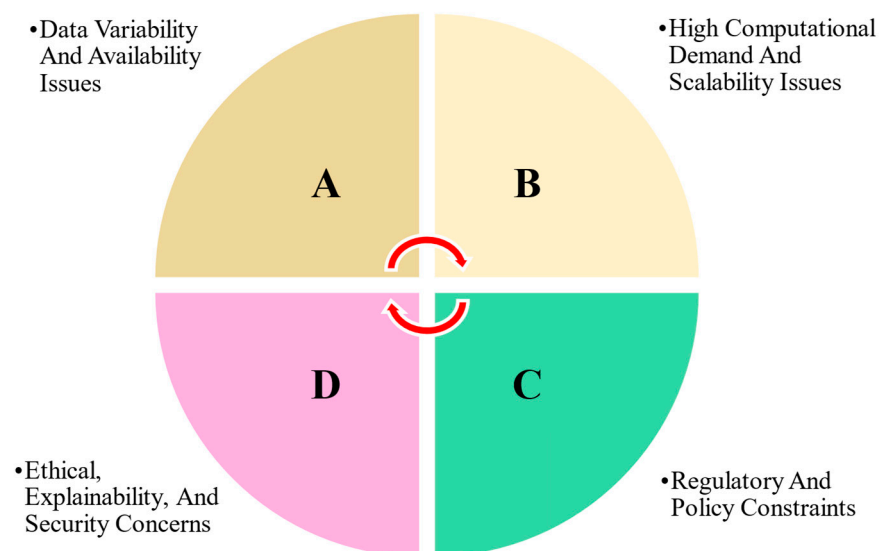


Figure 7. Mapping of identified adoption challenges.

6.1.1. Data Variability and Availability Issues

One of the most pressing challenges in applying Generative AI (GenAI) for sustainability in built environment management is data variability and availability. Many studies highlight concerns about data sparsity and inconsistent labeling in urban datasets, which reduce AI model accuracy and generalizability [63,66,116]. Seasonal fluctuations further exacerbate these issues, making predictive models unreliable across different envi-

ronmental conditions [67,68]. Integrating heterogeneous data sources, such as real-time urban monitoring, satellite imagery, and IoT sensor networks, is also problematic due to a lack of data standardization [72,80,82,83,101]. Additionally, AI models often rely on historical datasets, which fail to reflect evolving urban dynamics, leading to poor adaptability [75,86–88]. Addressing these challenges requires improved data curation strategies, cross-regional dataset integration, and federated learning approaches to enhance data diversity and model robustness [60,73,98,106,107,117–119].

6.1.2. High Computational Demand and Scalability Issues

GenAI models, particularly deep learning-based architectures, require significant computational resources, making their real-time implementation difficult [64,80,81]. In urban applications such as energy forecasting, transportation optimization, and climate resilience planning, the high computational demand restricts scalability and accessibility [83,120–122]. This challenge is especially critical for small-scale cities and developing regions, where high-performance computing infrastructure is limited [76,123,124]. AI-based predictive maintenance solutions also suffer from high processing costs and latency issues, limiting their ability to provide real-time insights [92,103,125]. To address these concerns, researchers suggest integrating edge computing, hybrid AI architectures, and lightweight AI models, which could reduce the computational burden and energy consumption [74,126].

6.1.3. Regulatory and Policy Constraints

The lack of harmonized regulatory frameworks and AI governance policies remains a significant barrier to AI-driven sustainability solutions [67,69,116]. Legal and policy constraints often hinder the large-scale implementation of AI-based decision-making in urban planning, energy distribution, and environmental monitoring [85,127]. Many sustainability-focused AI solutions must comply with existing environmental laws, urban zoning regulations, and data governance policies, yet these laws often fail to accommodate AI-driven automation [59]. Additionally, the absence of clear accountability measures raises concerns among policymakers about data privacy, liability, and ethical risks, further slowing AI adoption [108]. Future research should focus on AI-aligned policy development that ensures compliance while allowing for innovation in sustainability applications.

6.1.4. Ethical, Explainability, and Security Concerns

Several studies emphasize that AI explainability, fairness, and security risks present major challenges in sustainability applications [81,128,129]. AI models often function as black-box systems, making their decision-making processes difficult to interpret and validate [59,121,125]. This lack of transparency raises concerns about bias, accountability, and potential social inequalities in AI-driven sustainability solutions [106,113,130]. Furthermore, AI-driven urban infrastructure systems are vulnerable to cybersecurity threats, including adversarial attacks, data breaches, and model manipulation [131]. Without robust explainability frameworks, ethical safeguards, and enhanced cybersecurity protocols, AI-driven sustainability initiatives risk facing public and institutional resistance [131].

6.2. Future Research Directions

This section showcases propositions for potential future research directions to mitigate the existing challenges and knowledge gaps concerning the interplay between sustainability requirements and GAI. Emphasis is placed on green building practices, as derived from the qualitative analysis of the scrutinized literature.

Figure 8 presents a comprehensive framework for future research directions in Generative AI (GAI) for Sustainable Project Management. It consists of four core research themes

interconnected with three enabling dimensions that influence AI adoption and effectiveness in sustainability contexts.

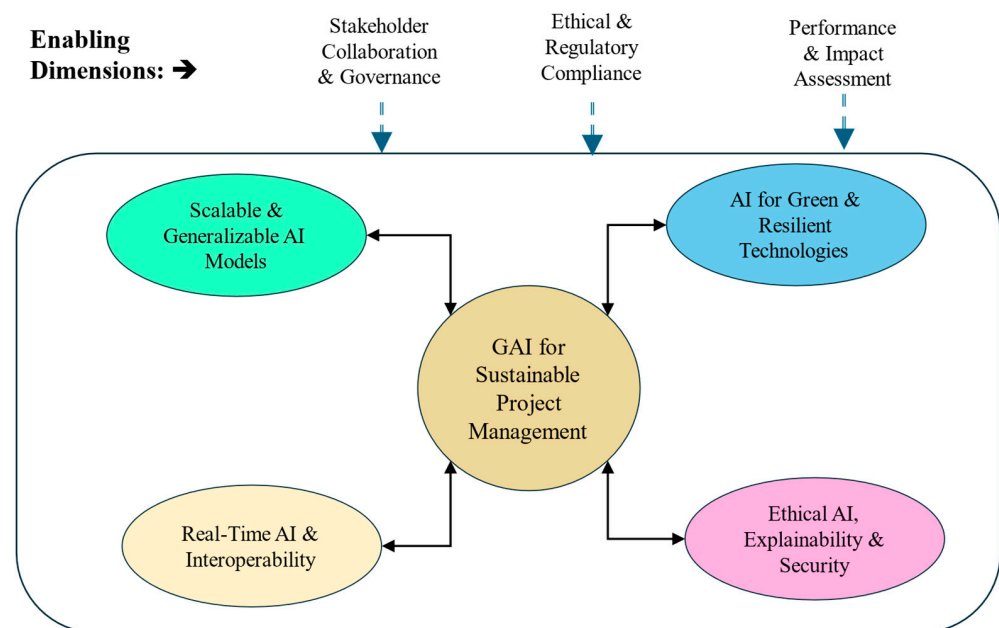


Figure 8. Proposed framework for future research directions.

At the heart of the framework lies GAI for Sustainable Project Management, which guides the development of AI-driven solutions aimed at achieving environmental, economic, and social sustainability. Surrounding this core are four key research themes that define the primary areas for AI advancement: Scalable and Generalizable AI Models, which promote adaptability across diverse regions, infrastructure types, and environmental conditions; AI for Green and Resilient Technologies, which integrates AI into renewable energy management, climate adaptation, and low-carbon infrastructure; Real-Time AI and Interoperability, which enables dynamic decision-making through IoT, digital twins, and smart infrastructure networks; and Ethical AI, Explainability, and Security, which addresses transparency, fairness, bias mitigation, and cybersecurity. Supporting these themes are three enabling dimensions that shape their success: Stakeholder Collaboration and Governance ensures alignment with policy frameworks and fosters multi-sector partnerships; Ethical and Regulatory Compliance enforces responsible AI deployment while addressing legal and ethical concerns; and Performance and Impact Assessment evaluates improvements in carbon reduction, energy efficiency, and environmental resilience. Together, these elements form a cohesive system that ensures AI solutions are effective, scalable, and ethically grounded.

By integrating these research priorities with enabling dimensions, Figure 8 provides a structured roadmap for advancing GAI in sustainable infrastructure management. The subsections that follow elaborate on the specific research directions derived from this framework, examining each theme and its implications in detail.

6.2.1. Real-Time AI Integration and Predictive Modeling

Future research should focus on real-time AI integration to improve sustainability applications such as waste detection, stormwater prediction, and HVAC system optimization [63,64]. Studies suggest that real-time AI models, combined with IoT sensor networks, can significantly enhance urban planning, energy efficiency, and resource allocation [66,80,132]. AI-driven predictive analytics should also be incorporated into disaster response planning, traffic management, and smart grid operations, ensuring faster response times and improved sustainability outcomes [82,83,101,111]. These solutions require seam-

less data flow, adaptive learning models, and cross-domain AI integration, which remain key areas for improvement [86,87,90,133,134]. Strengthening real-time AI applications in energy demand forecasting and environmental risk assessments is another major research priority [61,91,93,104,118,119].

6.2.2. AI Model Generalization and Scalability

A major limitation in current AI-driven sustainability research is the lack of model generalization across diverse geographic and environmental conditions [67,110,112]. AI models trained on specific climate zones, building types, or urban layouts often fail to adapt to different regions without extensive retraining [70–72]. Studies suggest that federated learning and transfer learning techniques could help improve cross-regional AI model adaptability [73,75,124]. Additionally, expanding training datasets to include heterogeneous urban landscapes, diverse construction materials, and varying climate conditions will improve AI scalability [74,98]. Future research should focus on hybrid AI architectures that combine simulation-driven insights with real-world empirical data, ensuring better generalization across different sustainability domains [77].

6.2.3. AI for Climate Adaptation and Resilience

Several studies emphasize the role of AI-driven climate adaptation models in air quality forecasting, hazard risk assessment, and climate resilience planning [64,80,132]. AI-powered models can significantly enhance flood mitigation strategies, optimize urban cooling solutions, and develop adaptive climate policies [59,102,104]. The integration of machine learning with real-time climate simulations can further improve predictive capabilities for extreme weather events [105,119]. Future research should explore hybrid AI models that combine historical climate data, geospatial analysis, and policy-driven adaptation strategies to develop more resilient and sustainable urban ecosystems [56,60,109].

6.2.4. Explainability, Ethics, and Security in AI

To increase trust in AI-driven sustainability applications, future work should focus on improving AI explainability, ethical fairness, and security protocols [125,127,129]. Studies highlight the need for neuro-symbolic AI and explainable AI (XAI) frameworks to ensure that AI models provide transparent and interpretable results [107]. Additionally, federated learning and decentralized AI models could enhance privacy-preserving AI applications for smart city projects [130]. Strengthening AI security through adversarial defense mechanisms and secure AI architectures is also essential to protect sustainability models from cyber threats [131,135]. Future research should prioritize AI fairness auditing, bias mitigation techniques, and inclusive AI model training to promote ethical sustainability solutions [135].

Synthesizing the challenges and future research directions makes clear that the most urgent priorities center on four interrelated themes. First, improving data quality, diversity, and interoperability is essential to overcome fragmented datasets and enable reliable model training. Second, the development of standardized evaluation metrics is required to ensure comparability of outcomes across different contexts and applications. Third, addressing ethical, regulatory, and governance concerns is critical to build trust and accountability in the use of Generative AI for sustainability. Finally, advancing cross-sector empirical validation through interdisciplinary collaboration will help move research beyond conceptual demonstrations toward practical, scalable adoption. By explicitly linking these barriers with actionable research pathways, the field can progress from exploratory applications toward systematic and impactful integration of Generative AI in sustainable project management.

7. Conclusions

This systematic literature review examined 175 peer-reviewed publications to evaluate the current state of Generative AI for sustainable project management in the built environment. From a quantitative perspective, the bibliometric analysis highlighted a marked increase in research activity since 2017, with significant contributions concentrated in China, India, the United States, and South Korea. The analysis also revealed clustering around a limited number of journals and conferences, indicating the field is still at a formative stage with growing but uneven global participation.

From a qualitative perspective, the thematic synthesis identified four major application domains: urban planning and smart cities, energy and building optimization, risk and disaster management, and infrastructure maintenance and lifecycle optimization. Across these domains, GAI has demonstrated potential to support sustainability-oriented project management by automating tasks, improving resource efficiency, enhancing predictive capabilities, and strengthening data-driven decision-making. However, this review also highlighted persistent barriers, including data variability, interoperability gaps, high computational demand, and limited regulatory and ethical frameworks.

Looking ahead, future research should focus on addressing these challenges through scalable and generalizable AI models, real-time integration with IoT and digital twins, explainable and secure AI approaches, and policy-aligned governance frameworks. Advancing these priorities will enhance the contribution of Generative AI to environmental, social, and economic sustainability objectives and support the transition toward more intelligent, resilient, and sustainable built environments.

This study is constrained by the extent of database coverage and the rapid evolution within the area. Future research should broaden multi-context case studies, develop evaluation criteria, and ensure that Generative AI solutions comply with regulatory and sustainability standards, emphasizing replicability across diverse areas and asset categories. Rectifying these deficiencies will facilitate the transition of the sector from promising demonstrations to credible, scalable practices in sustainable project management.

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