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AI in automated sustainable construction engineering management

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A R T I C L E I N F O

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A B S T R A C T

The construction industry is responsible for approximately 39 % of global carbon emissions. This paper presents a systematic literature review on the advancements and applications of Artificial Intelligence (AI) in Automated Sustainable Construction Engineering Management. It investigates the transformative role of AI in driving construction automation, sustainability, and improving operational efficiency. The review highlights key IoT, digital twins, and big data analytics developments for real-time construction site monitoring, carbon footprint reduction, and structural health monitoring. In addition, project management automation, including automatic quality control and cost-duration prediction using green AI is reviewed. The article explores the integration of AI in construction robotics, including 4D printing and smart robotics. It highlights the importance of electroencephalogram for human-centric safety, augmented reality for training, and energy-efficient Heating, Ventilation, and Air Conditioning (HVAC) control systems for green buildings. It addresses challenges, limitations, and future research directions for AI in fostering sustainable, efficient, and automated construction.

1. Introduction

This section introduces the concept of sustainable development and its importance in modern construction. It explores Sustainable Construction Engineering Management (SCEM) and the role of Artificial Intelligence (AI) in promoting sustainable practices within the industry. The problem statement identifies key challenges in achieving sustainability in construction, while the research objectives aim to address these issues. The structure of the paper is outlined to provide a clear framework for tackling the integration of AI into sustainable construction practice.

1.1. Concept and definition of sustainable development

Sustainability is defined as meeting current needs without compromising the ability of future generations to meet their own needs [1]. In 1969, the term “sustainability” first appeared in the United States with the National Energy Policy Act, which led to the emergence of the concept of “sustainable development.” Consequently, the timeline of the sustainable development timeline evolved as follows:

Abbreviations: ACS, Automated construction safety; ASCEM, Automated sustainable construction engineering management; AI, Artificial intelligence; ANNs, Artificial neural networks; AR, Augmented reality; BDA, Big data analytics; BIM, Building information modelling; BERT, Bidirectional encoder representations from transformers; CI, computational intelligence; CNNs, Convolutional neural networks; CO_2, Carbon dioxide; CEM, Construction engineering and management; DL, Deep learning; DRL, Deep reinforcement learning; DR, Demand response system; EEG, Electroencephalogram / Electroencephalography; EMS, Energy management system; ERVs, Energy recovery ventilators; fNIRS, functional near-infrared spectroscopy; FDD, Fault detection and diagnostics; GAI, Green artificial intelligence; GNNs, Generative neural networks; GA, Genetic algorithm; GPT, Generative pre-trained transformer; GRAN, Greedy ranking allocation; HVAC, Heating, ventilation, and air conditioning; IoT, Internet of things; LLM, Large language models; ML, Machine learning; POCO, Power conservation optimisation; PMA, Project management automation; ROUV, Remotely operated underwater vehicle; RFID, Radio-frequency identification; RL, Reinforcement learning; SA, Simulated annealing; SCEM, Sustainable construction engineering management; SDC, Speed-regulated compressors; SHM, Structural health monitoring; SLR, Systematic literature review; TES-AC, Thermal energy storage air conditioners; UAVs, Unmanned aerial vehicles; VRF, Variable refrigerant flow; XAI, Explainable AI.

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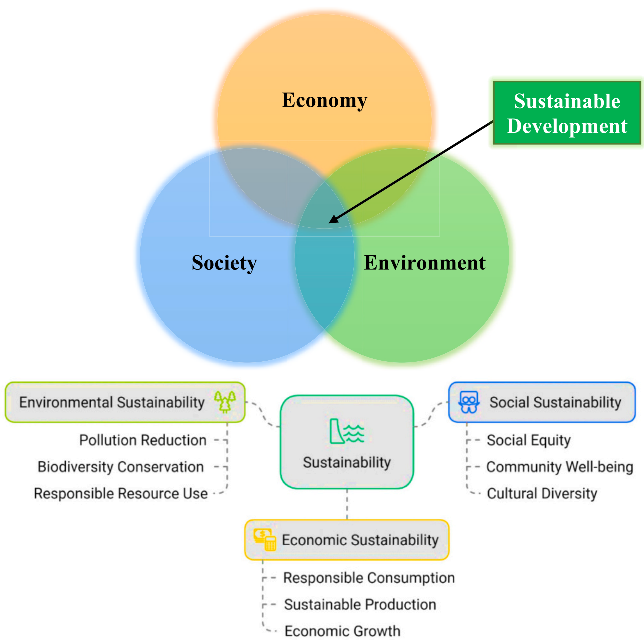

Fig. 1. Three dimensions harmonisation for sustainable development [2,3].

- 1987: Brundtland Report defined sustainable development.
- 1992: Earth Summit adopted Agenda 21, promoting global sustainable development.
- 2000: Millennium Development Goals (MDGs) set 8 global targets by 2015.
- 2012: Rio + 20 focused on advancing the green economy.
- 2015: The Paris Agreement aimed to limit global warming to below 2 °C.
- 2015: Sustainable Development Goals (SDGs) set 17 goals by 2030.
- 2021: COP26 saw nations commit to more ambitious climate actions.
- 2022: COP27 in Egypt focused on adaptation, loss, and damage funding.
- 2023: The Global Stocktake assessed collective progress toward the Paris Agreement.
- 2024: The world gears up for COP29, with a focus on scaling renewable energy solutions.
- 2025: COP30 is expected to assess the effectiveness of international climate agreements.

Deep decarbonisation and sustainable development aim to (1) enhance environmental quality, (2) improve social prosperity, and (3) boost economic performance. Achieving sustainable development goals requires balance and harmony among these three dimensions. The three pillars of sustainability and sustainable development are the environmental, social, and economic dimensions [2], as illustrated in Fig. 1. Environmental Sustainability focuses on conserving natural resources and minimising ecological impact; Social Sustainability, which emphasises social equity, well-being, and community resilience; and Economic Sustainability, which targets long-term economic growth, profitability, and efficient resource use. Together, these three pillars form the foundation of sustainable development, ensuring a balanced approach to environmental protection, societal welfare, and economic viability. (See Table 1.)

1.2. Sustainable construction engineering management (SCEM)

The construction industry is defined as the planning, designing, and building of infrastructure, including residential, commercial, and industrial projects. It involves a wide range of activities, such as civil engineering, architecture, project management, and skilled labour, to create physical structures. As a key driver of economic growth, the industry contributes significantly to national GDPs and employment, while facing challenges related to sustainability and resource efficiency [4].

The construction industry plays a pivotal dual role in sustainable development, contributing both positively and negatively across environmental, social, and economic dimensions. Environmentally, it supports sustainability through projects like wastewater treatment and waste-to-energy initiatives, however, remains a significant source of carbon emissions (30 %), air pollution (25 %), and water pollution (40 %), while heavily consuming natural resources. Socially, the sector

Table 1
Positive and negative impacts of construction industry on sustainability dimensions.

Impact / Dimension	Positive Impacts	Negative Impacts
Environment	The projects executed by the construction industry, such as wastewater treatment, solid waste, gas treatment, and waste-to-energy incineration projects, contribute significantly to protecting the environment from the wastes generated by human activities. Moreover, the construction industry is the key responsible for renewable energy projects execution such as wind farms, solar stations, and nuclear plants [5].	• Of produced emissions [6], including 30 % of carbon dioxide emissions [7]. • Air Pollution: the construction sector is responsible for 25 % of the total air pollution. • Water Pollution: the construction industry contributes to 40 % of water pollution [8]. • Natural Resources Consumption: the construction sector consumes 40 % of natural resources. • Water Consumption: the construction industry uses 12 % of the potable water supply [5].
Society	The construction industry is a labour-intensive sector [9], it assists in solving the unemployment problem by providing hundreds of thousands of jobs annually [4]. According to the International Labour Organization, in 2018, the number of employees in the construction industry worldwide was 111.9 million workers. Furthermore, this percentage increases annually by 1.30 % [10].	• Safety risks on worksites: the construction sector throughout the world is experienced as one of the risky, if not the riskiest fields that are fraught with the recurrent occurrence of severe accidents. • Health risks and mental health on worksites: the construction sector is full of severe health risks, such as mental fatigue, cement and dust inhalation, high noise, carrying overload, etc. These health risks can cause various diseases, such as asthma, coughing, deafness, and spinal cord damage [11].
Economy	Supporting the Gross Domestic Product (GDP) of the countries. Statistically, 4 to 19 % of the GDP of many national economies is associated with the construction industry [12]. This significant contribution highlights the sector's role in infrastructure development, urbanization, and economic growth.[13]	• Construction Wastes: the construction industry generates approximately 2 billion tons of building material waste annually. Depending on the type of material, between 8.47 % and 16.61 % of the materials delivered to construction sites become waste [13]. This waste contributes to project cost overruns of 20 to 30 %. • Construction hazards: the occurrence of construction hazards causes fatalities or hazardous injuries, leading to tragic impacts on the economic dimension of the countries [4].

Tabl. 2
Definitions of Sustainable Construction.

Reference	Definition
[14]	The principles of sustainable construction emphasis minimising environmental impact, maximising interaction with the natural environment, and enhancing amenities and health outcomes.
[15]	Sustainable construction involves a series of processes through which a profitable and competitive industry delivers built assets such as buildings, structures, supporting infrastructure, and their immediate surroundings that enhance the quality of life and customer satisfaction. These assets should offer flexibility to accommodate future user changes, support desirable natural and social environments, and maximise the efficient use of resources.
[16]	The use and/or promotion of (a) environmentally friendly materials, (b) energy efficiency in buildings, and (c) management of construction and demolition waste.
[17]	Sustainable construction applies sustainable development principles throughout a building's life cycle, encompassing planning, construction, raw material extraction and production, usage, demolition, and waste management. It is a holistic process that aims to maintain harmony between the natural and built environments by creating settlements that are conducive to human well-being and support economic equity.

provides over 111 million jobs globally, however, is plagued by safety risks, including workplace accidents and exposure to harmful substances. Economically, construction contributes between 4 % and 19 % to national GDPs, but inefficiencies in material use result in up to 16.61 % waste, leading to cost overruns of 20–30 %, while construction hazards further strain economic sustainability. These challenges underscore the need for more sustainable practices to balance growth with environmental responsibility and worker safety.

Sustainable construction is a multidimensional concept that integrates environmental, economic, and social principles to create and manage built environments in a resource-efficient and ecologically sound manner as in Table 2. Sustainable construction emphasises minimising environmental impacts while maximising interactions with the natural environment, human health, and well-being. Sustainable construction is concerned with the use of environmentally friendly materials, and energy-efficient practices considering the entire life cycle of a building, from planning and material extraction to construction, operation, and eventual demolition. The objective is to deliver built assets that enhance quality of life, support social and natural environments, and ensure the efficient use of resources. It is a holistic approach that balances ecological preservation with economic viability, ensuring that buildings contribute positively to the well-being of both current and future generations.

Sustainable construction principles can be distinguished according to the three dimensions of sustainable development: environmental, social, and economic as outlined in Fig. 2 and Table 3 [18]. The Venn diagram illustrates the intersections between the Environmental, Social, and Economic pillars of sustainable construction, with "Sustainable Construction" positioned at the core where these three domains overlap. The Environmental circle emphasises energy efficiency, green materials, waste reduction, and CO_2 reduction, reflecting the ecological focus of sustainable practices. The Social domain includes community well-being, social equity, and mental health, highlighting the human-centred aspects of sustainability, such as health, safety, and smart cities. The Economic circle covers job creation, economic resilience, and renewable energy investment, addressing the financial viability of sustainable construction. In the overlaps, we see areas such as affordable green housing, energy efficiency, and climate resilience, which require an integrated approach across all three spheres. At the core, SCEM embodies a balance of environmental preservation, social welfare, and economic feasibility, ensuring a long-term, holistic approach to building practices as in Fig. 2.

1.3. AI in sustainable construction

AI simulates human intelligence processes by machines, especially computer systems. AI encompasses intelligent robotics, reinforcement learning, machine learning, and deep learning. It involves various techniques, such as reinforcement learning, supervised/unsupervised machine learning, neural networks, deep learning, and generative AI algorithms, as in Fig. 3. Green AI is assessing the CO_2 emissions during computing AI to minimise environmental impact. Green AI or sustainable AI should be the new direction for AI to maintain computational sustainability. Integrating AI and green artificial intelligence (GAI) in sustainable construction engineering heralds a new transformative era, fostering innovation across various domains. In pursuing sustainable building materials design and optimisation, innovative materials such as green concrete, bamboo composite panels, recycled plastic bricks, solar-active glass, recyclable steel alloys, and transparent photovoltaic films are investigated [22]. Based on AI, researchers aim to optimise the composition and application of these materials to meet sustainability criteria while enhancing structural performance.

Green design optimisation represents another critical aspect of AI for construction engineering, as AI is employed to design and optimise structures with minimal environmental impact [23]. concepts such as

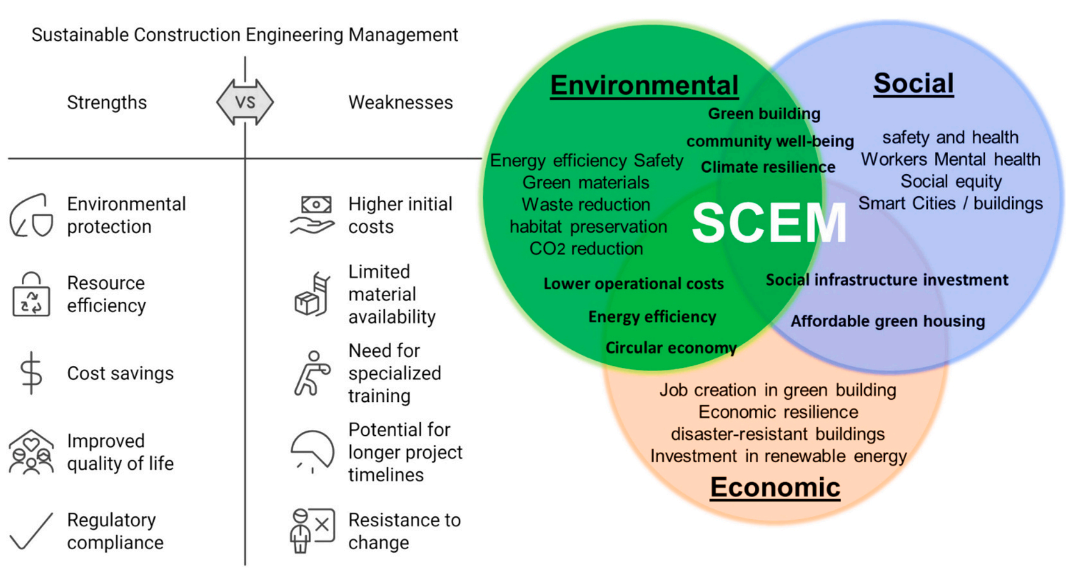

Fig. 2. Venn diagram of the three pillars of SCEM.

Table 3
Summary of Sustainable Construction Principles.

Environmental	Social	Economic
Efficient Use of Four Generic Resources: Energy, Water, Materials, and Land [18].	Promote Employment Creation, and in Some Situations, Labour Intensive Construction [19].	Construction Supports the Local Economy and Society [18].
Apply 3Rs Concept of Waste Management: Reduce, Reuse, Recycle [20].	Upskill Employees Capabilities by Advanced Training and Education [18].	Construction Optimises Outputs with Minimum Inputs [20].
Use Renewable Resources Instead of Non-Renewable Resources [18].	Protect Worker's Health mentally, psychologically, and physically through a Healthy and Safe Working Environment based on minimising mental stress and fatigue [20].	Construction Optimises Value for Money: (Optimum Combination of Whole Life Costs and Benefits) [18].
Minimise Pollution of Air, Water, and Land [19,21].	Preserve the Human Rights of Employees and the Surrounding Community [20].	Construction Optimises Financial Gains for Clients, Constructors, and the Government [19].
Create a Healthy and Non-Toxic Environment [18].	Promote Comfortable, Functional, and Safe Construction [19].	Reduced Operational Costs such as energy-efficient building designs and the use of renewable materials.
Minimise Damage to Natural Habitat [20].	Minimise Damage to Existing Societies and Sensitive Landscapes: Scenic, Cultural, Historical, and Architectural [19].	Increased Property Value due to their energy efficiency, lower utility costs

zero-energy buildings, green roofs, green facades, green walls, and zero-energy cities are at the forefront of this research, utilising AI-driven solutions to maximise energy efficiency, reduce carbon footprints, and create urban environments that harmonise with nature [2]. Focusing on construction materials reduction and recycling, such as water conservation and recycling, waste reduction and recycling, and the innovative approach to waste reduction, maintains sustainable development for the construction industry. By incorporating AI strategies, researchers seek to revolutionise construction practices, minimising resource consumption and promoting efficient recycling methods.

According to renewable energy-efficient design, AI is harnessed to integrate solar, wind, and biomass energy into building structures. Several publications work explored how AI-driven design and optimisation can create buildings that consume less energy and actively contribute to sustainable energy solutions, aligning with global efforts to address climate change [24]. The applications of building information modelling (BIM) and digital improve construction energy simulation and optimisation, where AI facilitates the modelling of energy performance and parametric design for efficiency, allowing for iterative design processes that maximise sustainable energy efficiency [25]. Integrating AI in BIM and digital twins enhances the precision and sustainability of construction projects. Integrating AI in infrastructure, natural disaster preparedness is pivotal for resilience [26]. Automatic quality control is enhanced by computer vision inspections, machine learning for defect recognition, and automated material testing, ensuring construction meets rigorous quality standards. According to smart transportation, AI is central to optimising and managing transportation systems, contributing to sustainable urban planning. These AI-driven applications collectively revolutionise construction management and execution, fostering a more sustainable, efficient, and resilient construction industry [27].

1.4. Problem statement

Construction Engineering and Management (CEM) is defined as the discipline that integrates engineering principles with project management techniques to oversee the design, planning, and execution of construction projects, ensuring efficiency, quality, and cost-effectiveness. It focuses on optimising resources, managing risks, and coordinating teams to deliver successful projects within set timelines and budgets. The key disciplines of Construction Engineering and Management include project planning and scheduling, cost estimation and control, quality management, risk management, safety management, contract administration, and resource allocation. These areas ensure the efficient execution of construction projects while maintaining

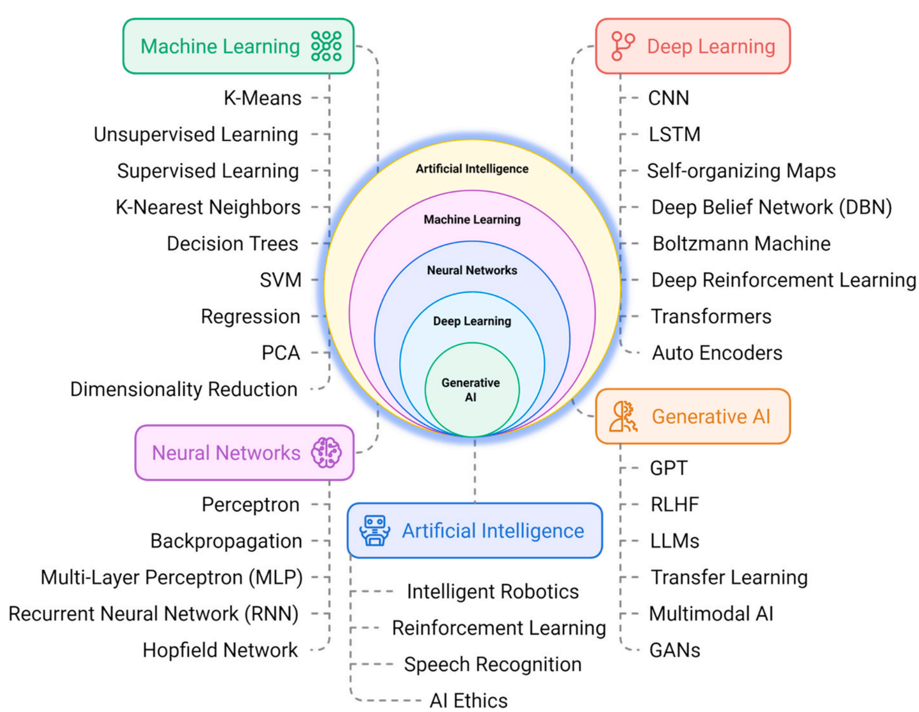

Fig. 3. Artificial Intelligence (AI) domains [21].

Table 4
Comparison of past literature review papers.

Reference	Main Objective	Year	Research Pillars			Future Perspectives and Limitations	SLR
			AI for Construction Engineering	AI for Construction management	SCEM		
[27]	SLR on ML for building	2023	√	√	×	×	√
[2]	Artificial intelligence and smart vision for building and construction	2022	√	√	√	×	×
[23]	ANNs for Sustainable Construction Industry	2022	√	√	×	×	×
[25]	Sustainable Development through the Perspective of Construction 4.0	2022	√	√	√	×	×
[28]	artificial intelligence in construction engineering and management	2021	√	√	×	√	×
[24]	Artificial intelligence in the construction industry	2021	√	√	×	√	×
[26]	Artificial intelligence in civil engineering toward sustainable development	2021	×	×	√	√	√
This paper	ASCEM	2024	√	√	√	√	√

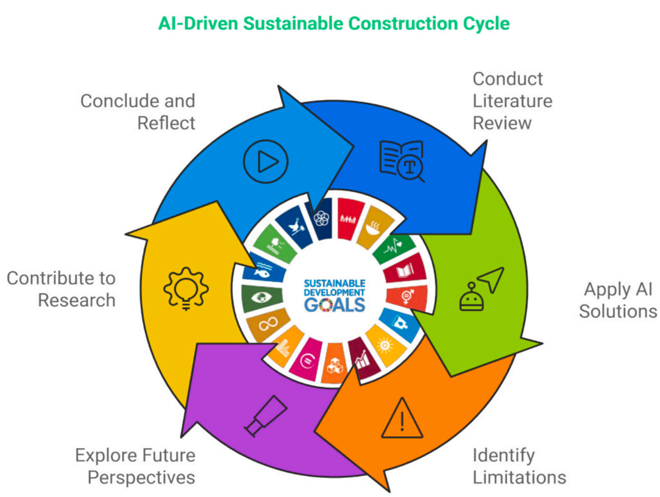

Fig. 4. AI-driven sustainable construction cycle.

budget, timeline, and quality standards [2]. AI for construction engineering, construction management, and sustainable construction is closely interconnected, each complementing the others. AI in construction engineering focuses on optimising technical tasks such as structural design and material efficiency, directly contributing to sustainability by promoting energy-efficient and resource-saving practices. In construction management, AI enhances project cost estimation, planning, budgeting, and resource allocation, reducing waste and delays, which align with sustainability goals. These AI-integrated applications foster sustainable construction by minimising the environmental impact and improving energy efficiency.

AI applications are rapidly evolving, with new advancements and updates emerging daily. Moreover, the identified gaps and limitations in the current literature on AI models for sustainable construction highlight the necessity of this research as in Table 4. Many prior studies are outdated, lacking recent developments and papers from 2024, which limits their relevance in the rapidly evolving field [24]. Furthermore, numerous publications are surveys rather than systematic literature reviews (SLRs), making it difficult to obtain a comprehensive and methodologically sound understanding of AI's applications in construction [2,23]. Additionally, most existing works cannot integrate sustainability practices within construction, an essential factor for addressing modern environmental challenges [23]. Ambiguities in research design, such as unclear inclusion and exclusion criteria, weaken the validity of various studies, and few papers focus on both construction engineering and management, which are critical for holistic AI implementation [25]. Moreover, the absence of discussions on limitations and future perspectives leaves gaps in understanding AI's long-term impact [23,25]. As a result, these issues make it necessary to provide an updated and systematic review that thoroughly addresses AI applications in construction engineering, management, and sustainability while considering future challenges.

1.5. *Research objectives and structure*

The article's objective is to address the interconnected issues of AI for sustainable construction engineering, construction management, and sustainability, providing a more comprehensive approach than previous studies. While some papers have focused on individual aspects such as machine learning (ML) for buildings or artificial neural networks (ANNs) for sustainable construction lacking a holistic integration of AI for sustainable construction domains. This research bridges that gap by linking AI applications in construction engineering and management to sustainability practices, offering a more complete understanding of how AI technologies can drive sustainable outcomes across the construction industry. Therefore, this paper responds to the gaps in prior research and emphasises the importance of integrating sustainability in AI applications for a more sustainable and efficient construction industry. This review paper aims to explore innovative ideas for applying AI to sustainable construction practices, focusing on machine and deep learning algorithms. The core significance of this review is as follows:

1. Comprehensive SLR: This paper conducts an in-depth systematic literature review, introducing recent AI applications in the construction industry and exploring their various applications in sustainable construction.
2. Identification of Gaps: The review systematically analyses a wide range of literature to identify gaps in the application of AI in the sustainable construction domain.
3. Quality Assessment of Research: This review critically evaluates the quality of research related to AI in the sustainable construction industry. It assesses the methodologies, strengths, and weaknesses of the included studies.
4. Future Research Directions: The review provides valuable insights into open issues and future directions for researchers. It highlights new challenges and demonstrates how AI can advance the field by addressing them.

This article contributes to the "AI-Driven Sustainable Construction Cycle" which illustrates a continuous process that integrates artificial intelligence (AI) into the construction industry to align with the United Nations' SDGs. The cycle begins with conducting a literature review to gather knowledge and identify relevant AI applications. Subsequently,

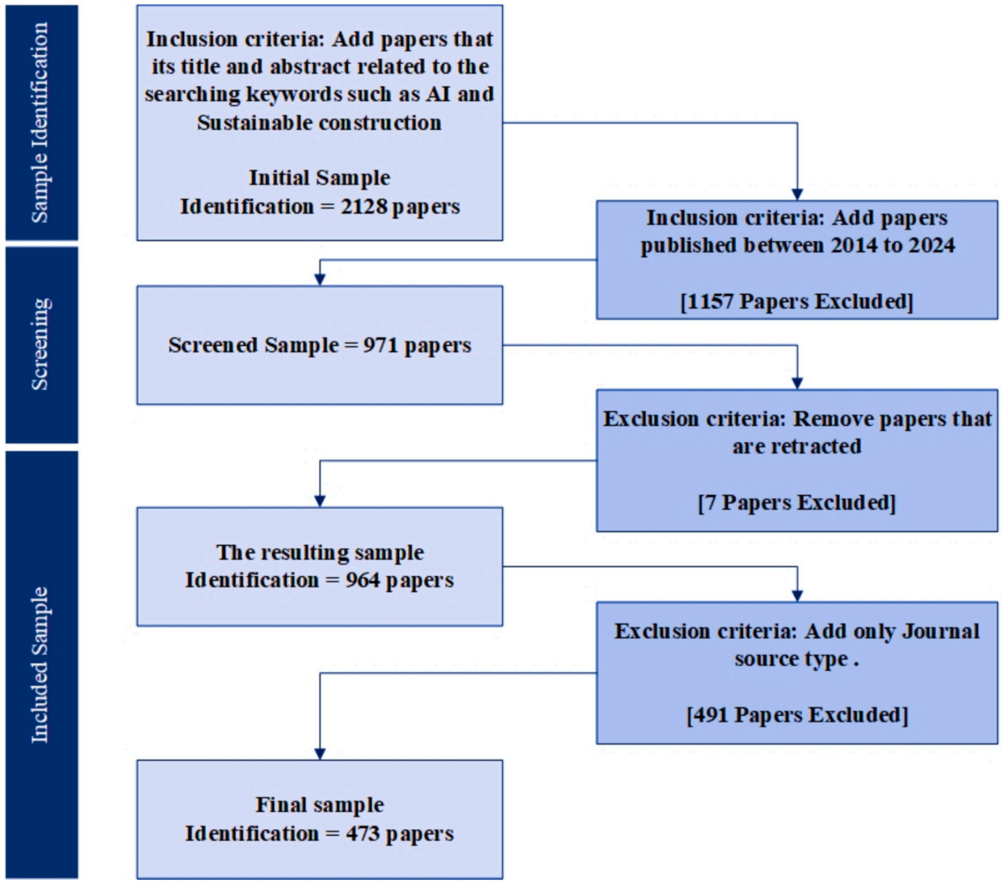

Fig. 5. Flow diagram of the search identification and selection process.

AI solutions are applied to construction processes, focusing on improving efficiency and sustainability. The next step involves identifying limitations and challenges in the AI application, which informs future research. The cycle then explores future perspectives, aiming to expand the role of AI in construction. The process culminates by contributing findings to the broader research community, concluding with reflections to enhance ongoing AI advancements. This cycle emphasises the iterative nature of integrating AI with sustainability goals in construction as in Fig. 4.

The structure of this paper follows the AI-driven sustainable construction cycle as follows: Section 1 introduces the research, outlining its scope and significance. Section 2 details the method employed for conducting the systematic literature review (SLR). Section 3 presents an in-depth analysis of AI applications in sustainable construction. In Section 4, the limitations of current AI integration and emerging future trends within the field are examined. Section 5 discusses the research contributions in response to the SLR questions, offering insights and practical implications. Finally, Section 6 concludes with key remarks and reflections on the study's findings.

2. Systematic literature review (SLR)

This article on the application of AI for sustainable construction management and engineering adopted an SLR method. Consequently, this investigation delved into the panorama of AI and deep learning in sustainable construction management and engineering using the SLR framework.

2.1. Formulation of questions

The following analytical questions (AQ) are discussed and answered in this work. The following research questions about AI applications in the sustainable construction industry form the basis of this study's method:

- AQ.1: What is the research production performance focused on AI applications in the sustainable construction industry?
- AQ.2: What are the most productive countries and funding institutes?
- AQ.3: What are the most repetitive keywords and their relations?
- AQ.4: What is AI for sustainable construction?
- AQ.5: What are the most cited papers and authors for AI for sustainable construction?
- AQ.6: How does AI enhance safety measures and risk management in the sustainable construction industry?
- AQ.7: What role does AI play in optimising sustainable construction processes?
- AQ.8: What are the recent challenges, limitations, and future perspectives?

2.2. Literature search strategy

The documents were selected using the selection strategy outlined in the flowchart depicted in Fig. 5. The papers are chosen based on two stages of selection. The first stage involved choosing a paper with an abstract or title that addressed AI and sustainable construction. The keywords used in the search query are: (sustainable construction) AND (artificial intelligence) in ten years from 2014 to 2024. Accordingly, the key scope is a bibliometric study of "Artificial intelligence and machine learning applications in the sustainable construction sector." More precise keywords (ML, DL, difficulties, constraints, supply chain,

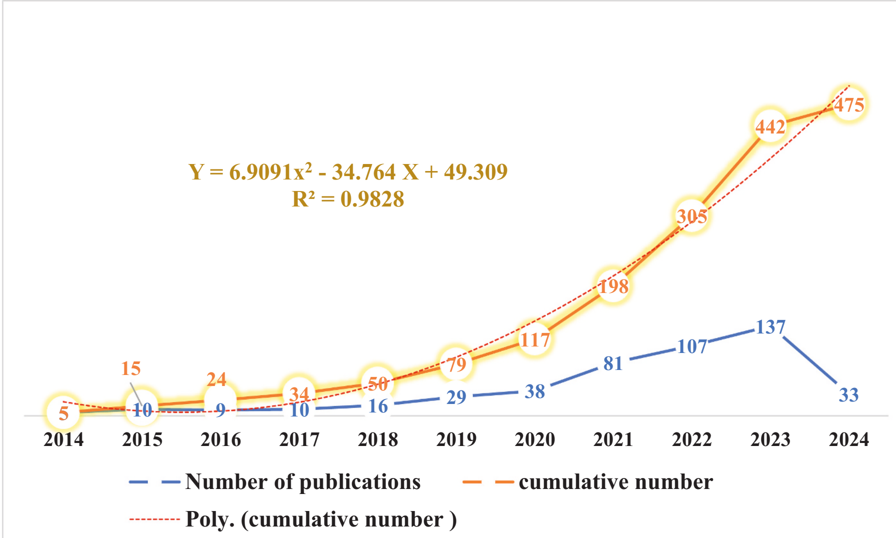

Fig. 6. Publications from 2014 to 2024 (473 papers).

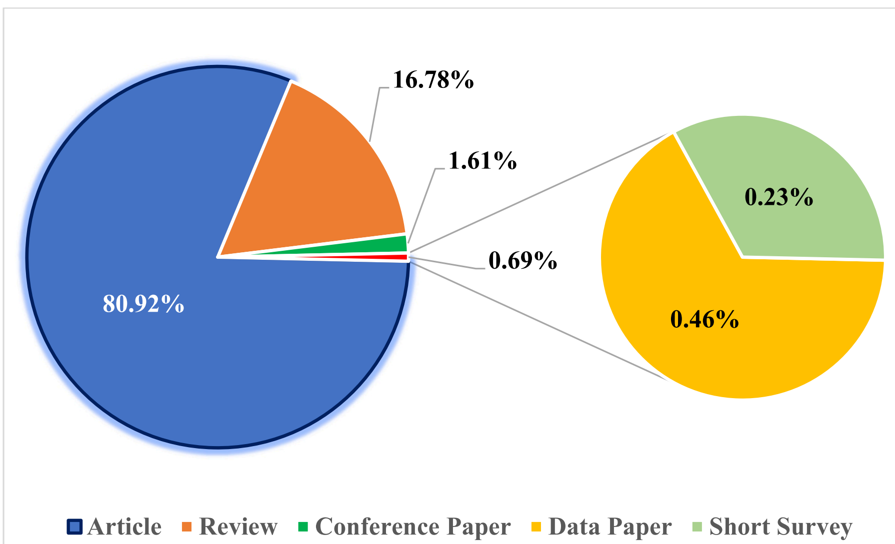

Fig. 7. Publication type of statistical publications (473 papers).

conversion technologies, sustainability, and future directions) are also used in the selection of the articles. The second stage is to include journal papers only to ensure the highest quality of given research papers and avoid retracted papers. Prestigious high-quality publishers such as Springer, American Society of Civil Engineers (ASCE), IEEE, Wiley, Elsevier, Taylor, and ACM are considered acquiring the papers and publications using The Web of Science (WoS) and Scopus library. As a result, only peer-reviewed articles published in books, journals, conferences, and formal reports were chosen. Subsequently, the most significant papers have been selected.

As shown in Fig. 5, the paper's titles and abstracts related to the search keywords such as (AI and sustainable construction) have been added as an initial sample of 2128 papers. The keywords were artificial intelligence AND sustainable construction) OR (artificial intelligence AND green buildings). The paper sample was screened based on publication years between 2014 and 2024. All publications outside the scope of [(Construction Industry) AND (Artificial Intelligence)] have been excluded. As a result, 1157 papers were excluded, and the remaining papers were 971 papers. All retracted papers (7 papers) were removed. Subsequently, the final sample was 473 papers. Articles that are written and published in English, where most of the papers were written in English (401 out of 473 articles). The other languages were Chinese (53 out of 473 articles), Korean (13 out of 473 articles), and Russian (8 out of 473 articles).

2.3. Quantitative meta-analysis

The distribution of the final collected papers over the last ten years is visualised in Fig. 6, where both curves display an increasing growth of publications production yearly. The fitting equation provided in Fig. 6 is a polynomial regression equation. The equation is designed to fit the relationship between the year (X) and the cumulative number of publications (Y) on AI for sustainable construction. Based on the equation and the R^2 value, the trend in publications on AI for sustainable construction from 2014 to 2024 is strongly upward and accelerating. A total of 473 publications were extracted, including five different types, including Articles (80.92 %), Reviews (16.78 %), Conference papers (1.61 %), short surveys (0.23 %), and Data Papers (0.46 %) as in Fig. 7.

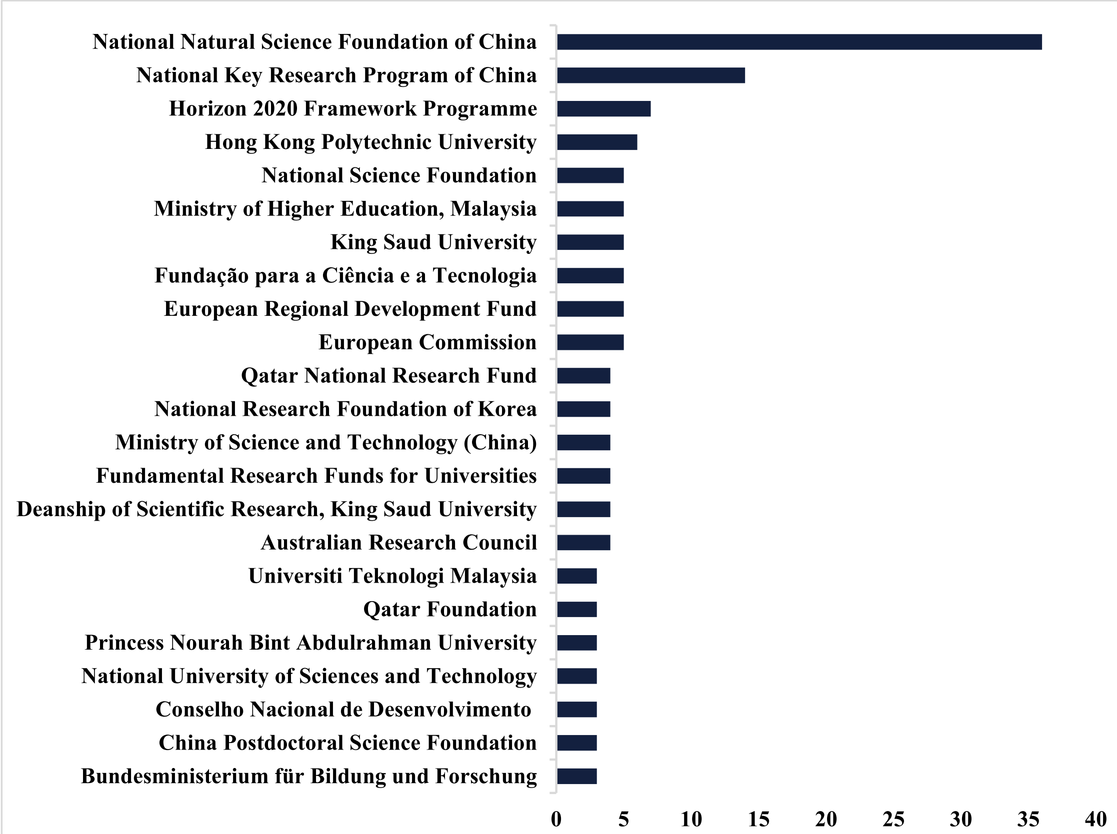

Fig. 8. Affiliations of the final screened sample (473 papers).

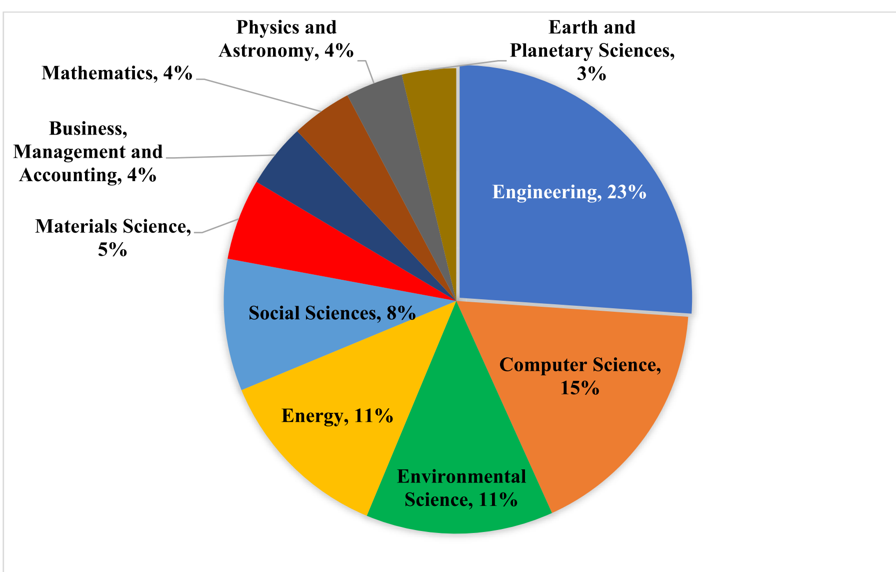

Fig. 9. Subject area by percentages of the publications (473 papers).

The research output of the individual affiliations demonstrates a diverse range of contributions to scientific knowledge. Leading the list is the National Natural Science Foundation of China with 36 papers, highlighting its pivotal role in funding fundamental research endeavours within the country. Following closely is the National Key Research Program of China, emphasising China's strategic investment in key areas of innovation and technological advancement. Horizon 2020 Framework Program represents collaborative efforts across European nations, evident in its significant impact with 7 papers. The Hong Kong Polytechnic University showcases its commitment to academic excellence with 6 papers, while institutions like King Saud University and the Ministry of Higher Education in Malaysia reflect the global nature of research with 5 papers each. Additionally, entities like the European Commission, the European Regional Development Fund, and the National Science Foundation contribute to the international scientific landscape, collectively emphasising the interconnectedness and

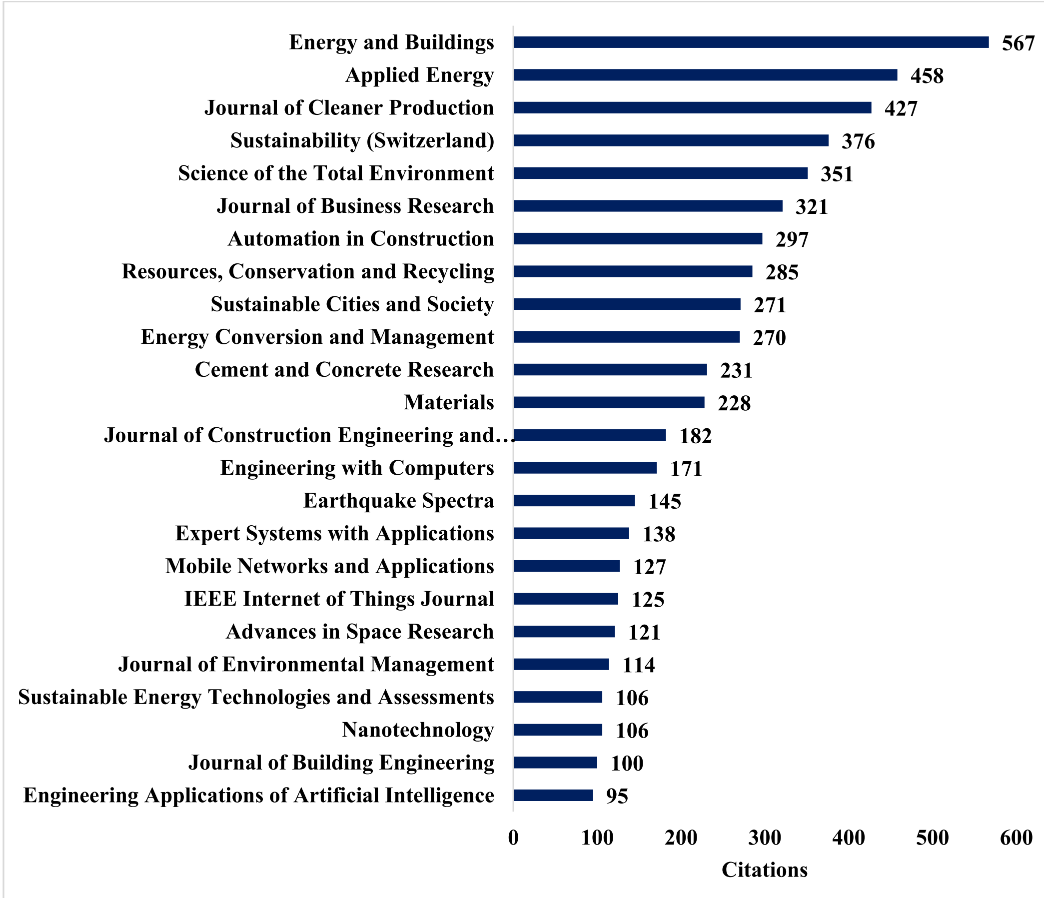

Fig. 10. Number of citations according to the paper source (473 papers) where these top 25 sources out of 266 sources contribute to 60 % of the total citations (5612 of 9238 citations).

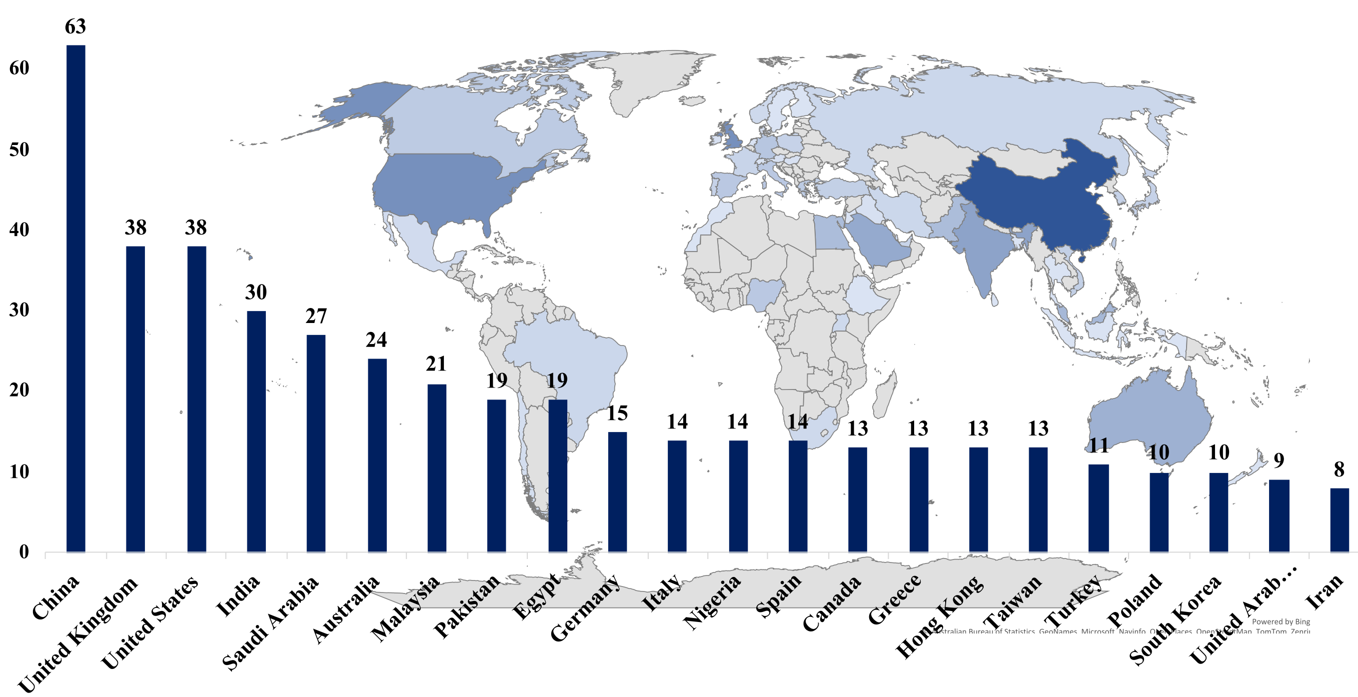

Fig. 11. Most productive country based on the final screened sample (473 papers).

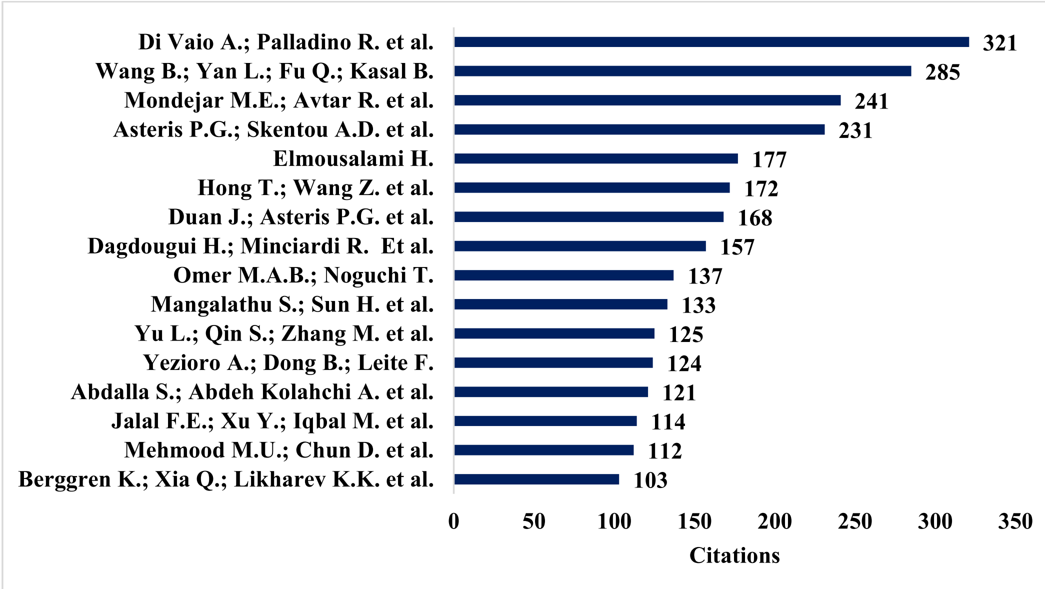

Fig. 12. Top-cited authors (473 papers).

Table 5
Most cited papers.

Reference	Citations	Year	Key objective	Document Type
[29]	321	2020	A systematic review of AI and business models for SDGs.	Article
[30]	285	2021	Review on recycled aggregate and concrete applications.	Review
[31]	241	2021	Digitalization's role in achieving a Smart Green Planet.	Review
[32]	231	2021	Ensembling models for concrete strength prediction.	Article
[21]	177	2020	Automated project cost prediction using AI algorithms.	Review
[33]	172	2020	Machine learning applications in building life cycle.	Review
[34]	168	2021	XGBoost model for predicting recycled concrete strength.	Article
[5]	137	2020	Building materials' contribution to achieving SDGs.	Review
[35]	133	2020	Machine learning for earthquake damage classification.	Article
[36]	125	2021	Deep reinforcement learning in smart building energy.	Review
[37]	114	2021	AI approaches for expansive soil swell-strength prediction.	Article
[38]	112	2019	AI and big data applications in energy-efficient buildings.	Review
[39]	107	2020	AI algorithms comparison for project conceptual cost prediction.	Article
[40]	95	2017	Neutrosophic method for residential house selection.	Article
[41]	89	2021	Framework for a circular digital built environment.	Article
[42]	89	2017	Smart home system powered by botanical IoT.	Article
[43]	88	2018	IoT and AI innovations for green building management.	Article
[44]	88	2019	Deep learning for drought monitoring with remote sensing	Article
[45]	87	2019	Energy benchmarking using city building data.	Article
[46]	82	2016	Office building optimisation for energy conservation.	Article

collaborative spirit driving advancements in various fields of study, as shown in Fig. 8.

The distribution of paper percentages across different subject areas is as follows: Engineering holds the majority with 23 %, followed by Computer Science at 15 %, Environmental Science and Energy both contributing 11 %. Social Sciences make up 8 %, while Materials Science, Business Management and Accounting, Mathematics, Physics, and Astronomy each account for 5 %, 4 %, 4 %, and 4 % respectively. Earth and Planetary Sciences round out the distribution with 3 %. This breakdown reflects a multidisciplinary approach to the research, showcasing the intersection and collaboration of various fields in addressing topics related to the subject matter as shown in Fig. 9.

The bar chart presents the top 25 journals publishing research on "AI in sustainable construction" and their corresponding citation counts, as in Fig. 10. Leading journals include "Energy and Buildings" with 567 citations, followed by "Applied Energy" and "Journal of Cleaner Production." These journals' high citation counts highlight their significance in the field. While the remaining journals contribute to the knowledge base, their citation levels vary. Analysing the citation distribution across these journals reveals the most frequently cited research areas and their influence on the field. This information is valuable for researchers seeking relevant literature and identifying emerging trends in AI for sustainable construction. For instance, the prominence of journals such as "Automation in Construction" suggests a growing impact and interest in integrating AI with construction processes to enhance efficiency and sustainability.

The distribution of publications across different countries or territories in this dataset showcases a diverse global engagement in research endeavours. China emerges as a substantial contributor, representing approximately 18.73 % of the total papers. Following closely are the United Kingdom and the United States, each contributing around 5.32 %. India, with a percentage of 4.43 %, and Saudi Arabia with 3.80 %, also demonstrate significant involvement. Australia, Malaysia, and Pakistan contribute approximately 3.42 %, 3.04 %, and 2.79 %, respectively. Egypt, Germany, and Italy round out the list with percentages of 2.66 %, 2.28 %, and 2.15 %, highlighting a widespread and collaborative international effort in the exploration of diverse subject areas represented in the dataset, as shown in Fig. 11.

Fig. 12 illustrates the top-cited authors from a pool of 473 papers, showcasing the influence of their work in the field. Di Vaio A., Palladino R., Hassan R., and Escobar O. lead with 321 citations, indicating their

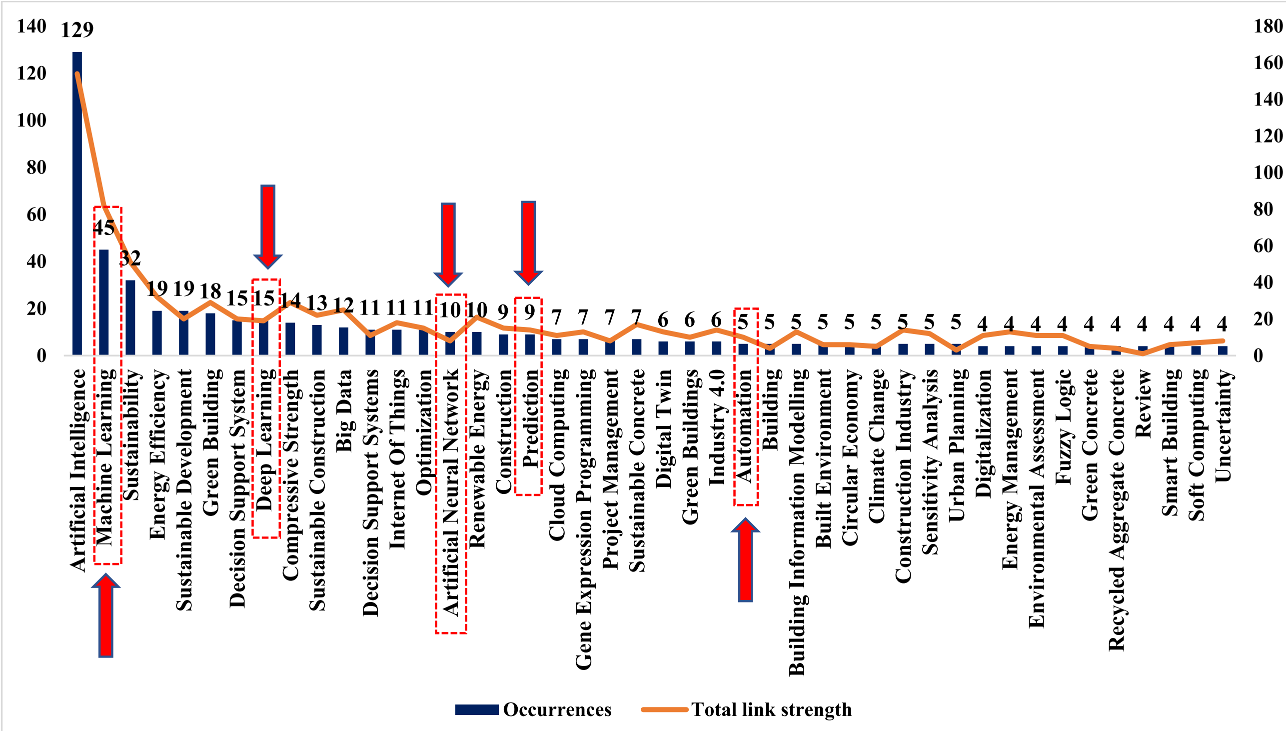

Fig. 13. Occurrences and total link strength of top keywords based on the final screened sample (473 papers) where the red-bordered keywords have a key focus on this paper as AI models. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

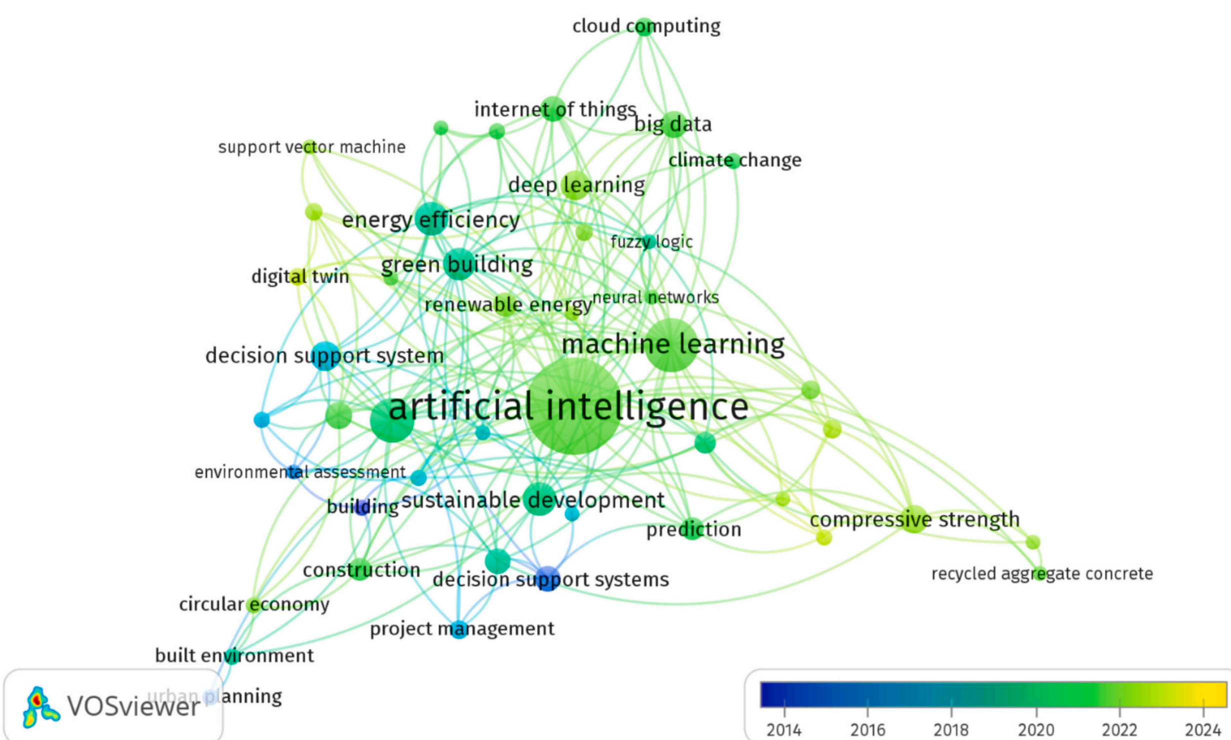

Fig. 14. Keyword co-occurrence network map based on year of publication based on the final screened sample (473 papers).

prominent role in the literature. Wang B., Yan L., Fu Q., and Kasal B. follow closely with 285 citations. Mondejar M.E., Avtar R., and Diaz H.L. B. also feature significantly with 241 citations. Authors such as Okolo C. C., Prasad K.A., and She Q., as well as Asteris P.G., Skentou A.D., and Elmousalami H., have also made substantial contributions, with citation counts of 231 and 177, respectively. The chart highlights a range of authors who have significantly impacted the field, with citation numbers reflecting their scholarly influence, ranging from over 300 citations to just 100 for the most cited works.

Table 5 presents the most cited papers in the field, highlighting

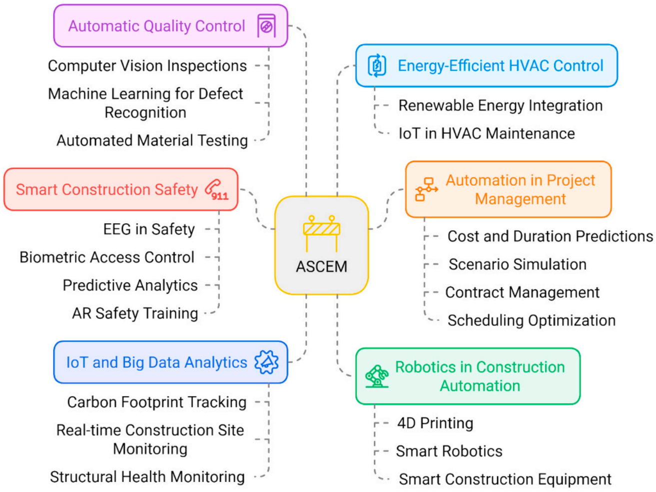

Fig. 15. ASCEM structure.

influential research across various areas. The highest-cited paper, with 321 citations, is from 2020 and focuses on a systematic review of AI and business models for achieving the SDGs [29]. Other significant papers include a 2021 review on recycled aggregate and concrete applications (285 citations) [30], a review on digitalisation's role in achieving Smart Green Planet SDGs with 241 citations [33], and research on ensemble models for concrete strength prediction (231 citations) [34]. Key papers address project cost prediction using AI algorithms (177 citations and 107 citations) [21,39], machine learning applications in building life cycles (172 citations) [33], and deep reinforcement learning in smart building energy management (125 citations) [36]. The table underscores the increasing relevance of AI, machine learning, and sustainability in construction research.

2.4. Keyword co-occurrence analysis

A comprehensive overview of keywords' weight within the context offers insights into the frequency of occurrence and the associated total link strength for various key terms as in Fig. 13. "Artificial Intelligence" emerges as the most prominent keyword, appearing 129 times with a total link strength of 135, reflecting its significant presence and influence. "Machine Learning" follows with 45 occurrences and a link strength of 76, emphasising its relevance. Sustainability-related terms such as "Sustainability" and " Green Building" exhibit considerable importance, appearing 32 and 31 times, with total link strengths of 44 and 28, respectively. In addition, Fig. 13 highlights key technological concepts such as "Decision Support System," "Deep Learning," and "Big Data," indicating their significance in the studied domain. Additionally, terms associated with sustainable construction, renewable energy, and smart technologies, such as "Sustainable Construction," "Renewable Energy," and "Internet of Things," are significant, suggesting a focus on environmentally conscious and technologically advanced practices in the field. The occurrences and link strengths provide a quantitative representation of the emphasis on specific topics within the dataset, offering valuable insights into the thematic landscape of the associated research.

Fig. 14 presents a keyword co-occurrence network map derived from

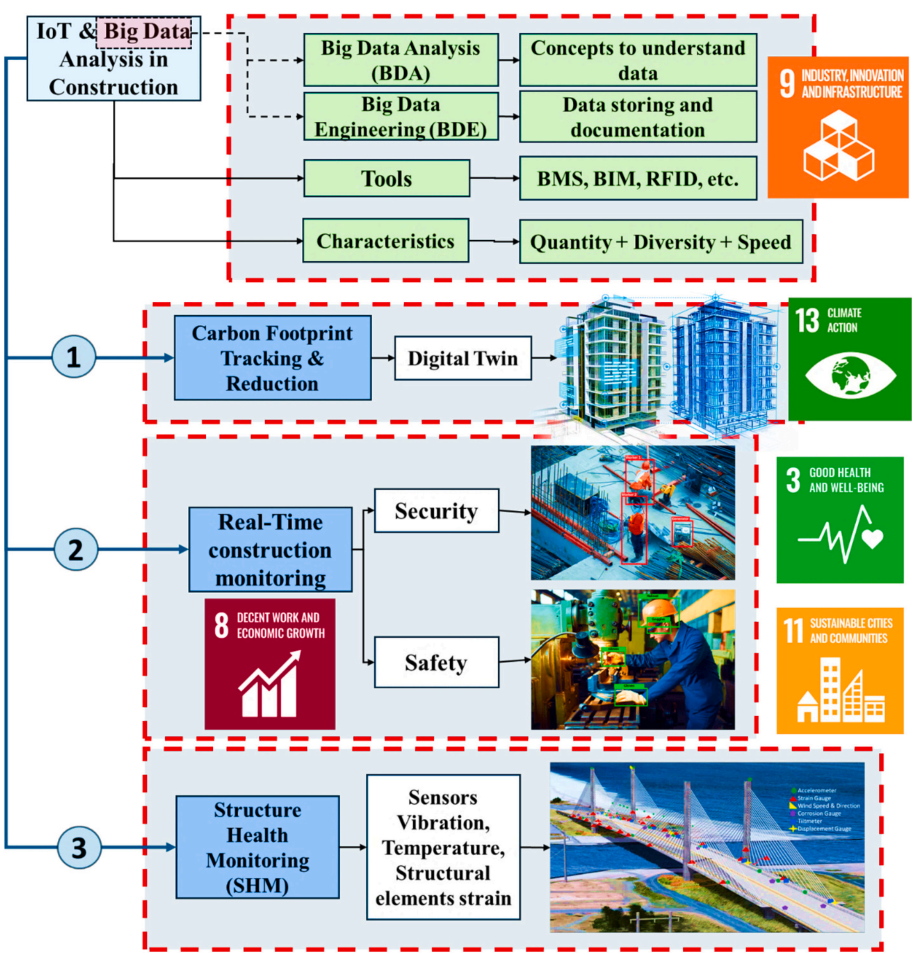

Fig. 16. IoT and Big Data Analytics for ASCEM.

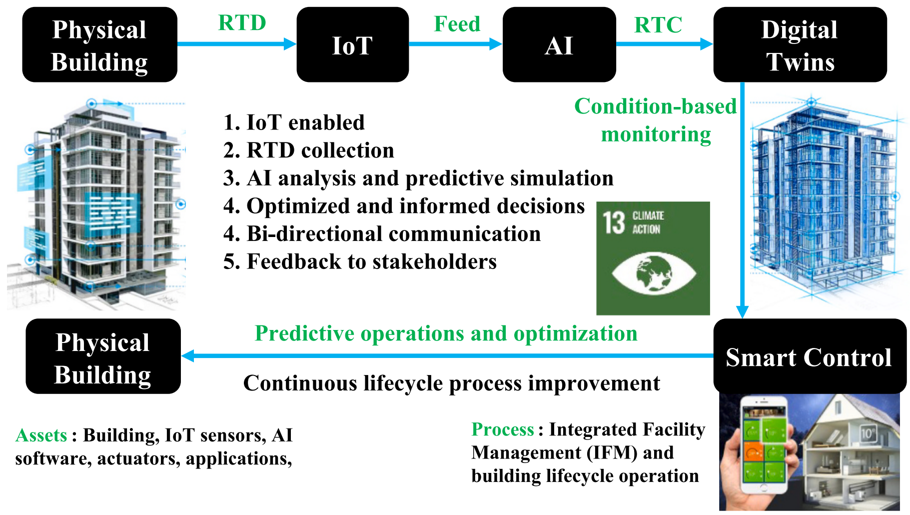

Fig. 17. IoT and Big Data Analytics for Sustainable Green Buildings. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

473 papers, showcasing the relationships between key terms in AI-related research in construction, arranged by the year of publication. The map highlights "artificial intelligence" and "machine learning" as the most central and frequently co-occurring terms, especially in recent years (depicted in green and yellow). Key emerging topics include "deep learning," "big data," "internet of things," and "energy efficiency," reflecting the growing integration of AI technologies in areas such as "green building," "renewable energy," and "sustainable development." Other significant clusters involve terms such as "decision support systems," "compressive strength," and "recycled aggregate concrete," indicating the application of AI in optimising building materials and sustainable practices. The map shows the evolving focus from earlier topics such as "support vector machines" and "fuzzy logic" to more recent trends, such as "cloud computing" and "climate change."

3. Automated Sustainable Construction Engineering Management (ASCEM)

Automated Sustainable Construction Engineering Management (ASCEM) is an AI-driven framework of automated applications designed to optimise construction processes focusing on sustainability, efficiency, and environmental impact. ASCEM integrates automation technologies, smart data analytics, and predictive models to enhance decision-making and project management. ASCEM promotes resource-efficient construction practices while ensuring safety and minimising carbon emissions. The key applications for ASCEM are organised into six main categories, each with specific sub-categories as in Fig. 15. Automatic Quality Control focuses on leveraging computer vision, machine learning for defect recognition, and automated material testing to ensure high-quality outcomes. Smart Construction Safety incorporates technologies, such as EEG in safety monitoring, biometric access control, predictive hazard analytics, and Augmented Reality (AR) training to improve worker safety. IoT and Big Data Analytics enhance sustainability through carbon footprint tracking, real-time site monitoring, and structural health monitoring. Energy-efficient HVAC Control integrates renewable energy and IoT for smarter, more sustainable heating, ventilation, and air conditioning systems. Automation in Project Management covers cost and duration predictions, scenario simulation, contract management, and resource optimisation to streamline construction processes. Finally, Robotics in Construction Automation includes advanced technologies, such as 4D printing, smart robotics, and smart equipment, to enhance efficiency and precision in construction tasks. Together, these innovations aim to promote sustainability, safety, and efficiency in the construction industry.

3.1. IoT and big data analytics

AI for sustainable construction management and execution involves leveraging advanced algorithms and machine learning to optimise resource use, enhance energy efficiency, and reduce waste [47]. By analysing vast amounts of data, AI can improve Sustainable Construction Engineering Management (SCEM) project planning, monitor environmental impact, and ensure compliance with sustainability standards. This technology supports the construction industry in achieving its sustainability goals through smarter, data-driven decision-making and operations. AI has the potential in the fields of forecasting, optimisation, and decision-making to help the traditional construction sector keep up with the quick speed of automation and digitalisation [48]. The various advantages of AI in SCEM are summarised in Fig. 16.

The Internet of Things (IoT)'s main goal is to create a network of interconnected devices that can communicate and exchange data with each other [49]. Combining these dynamic digital and physical worlds is opening amazing growth prospects. IoT applications are widely used in various industries, including energy, defence, logistics, transportation, asset tracking, smart buildings, smart homes, and agriculture [50]. Radio Frequency Identification (RFID) application for quality assurance and construction monitoring was showed by Elghamrawy et al. [51]. Meadati et al. [52] used RFID technology with asset 3D BIM documents to provide fast object search and location. An IoT-based framework for building energy monitoring was proposed by Wei and Yi [53]. To define the concept of Smart Cities, Zanella et al. [54] provided urban IoT requirements. The technological details of the smart object for the petrochemical and road-building industries were covered by Kortuem et al. [55]. Curry et al.'s study [56] focused on how energy sensor data was processed and stored utilising a cloud-based data management system. IoT applications are complex and can use thousands or even hundreds of sensor units to gather data. On the other hand, Big Data is a captivating subject because the building industry offers countless IoT use cases. Big Data and IoT are complementary developments; the former generates vast amounts of data, while the latter stores and analyses it in real-time for applications specific to the construction industry. The industry works with massive amounts of data from multiple disciplines during all phases of a facility's existence. Building information modelling (BIM) aims to help stakeholders collaborate across disciplines by methodically gathering multi-dimensional computer-aided design (CAD) data [57]. Typically, BIM data is compressed, in a variety of proprietary formats,

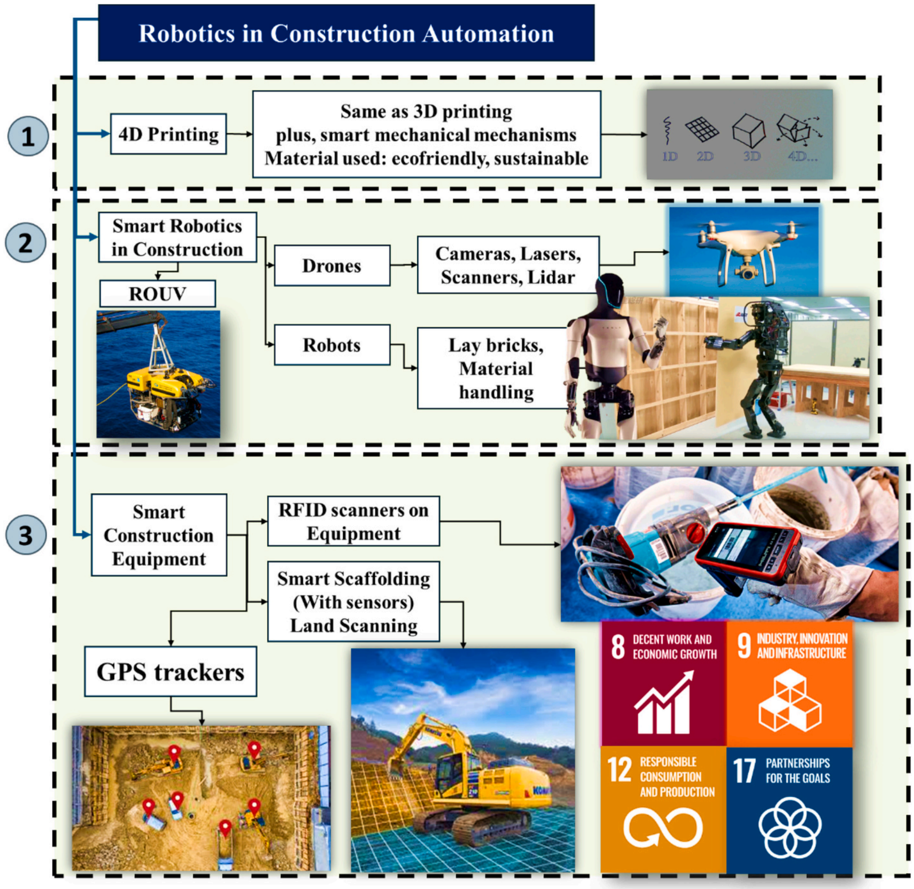

Fig. 18. IoT and Big Data Analytics for Sustainable Construction.

interconnected, 3D geometric encoded, and computationally heavy (including graphics and Boolean computations). Consequently, this heterogeneous data is assembled into common BIM models, which are then continuously improved and preserved even after the facilities' lifespan has ended. Therefore, the performance of the industry benefits directly from this data in all forms and shapes.

The second essential component, Big Data Analytics (BDA), deals with the duties involved in gathering information to inform decisions [58]. BDA is primarily focused on concepts, practices, and strategies for understanding Big Data. The foundation of BDA is identifying hidden patterns in vast amounts of data and leveraging those patterns to produce insights that can be put into practice. These insights have the potential to change the future paths of many different industries significantly when combined with data-driven decision-making.

3.1.1. Carbon footprint tracking and reduction

Carbon footprint tracking and reduction, alongside sustainable construction, are integral components of modern environmental management in the construction industry. Carbon footprint tracking involves measuring and analysing the greenhouse gas emissions (GHG) associated with construction activities, including material production, transportation, and on-site operations [59]. With this real-time data (RTD) stored as a comprehensive dataset, AI models could leverage it for training, providing valuable insights for carbon footprint reduction. This approach shifts the monitoring phase from the occupancy period to the early stages of a building's lifecycle. These AI models would enable predictive assessments of a structure's resource consumption, offering a forward-looking analysis. Consequently, the first application of the IoT-powered “digital twin” concept was established, paving the way for enhanced sustainability in the construction and management of buildings [60,61].

The framework for intelligent building management that integrates IoT, real-time computing, and AI. IoT-enabled devices collect real-time data (RTD) from the physical building. This data is then processed by real-time computing (RTC) to enable condition-based monitoring and identify potential issues. AI algorithms are employed to analyse the data and generate predictive simulations, allowing for optimised decision-making and proactive maintenance strategies. This integrated approach contributes to the efficient and sustainable operation of the building as in Fig. 17. As a result, digital twins pave the way for more sustainable building and infrastructure by tracking and minimising energy and GHG emissions [62].

3.1.2. Real-time construction site monitoring

Real-time Construction Site Monitoring involves the use of advanced technologies, such as IoT sensors, drones, and AI-driven analytics to continuously track and assess various activities on a construction site. It enables real-time data collection on safety, productivity, equipment usage, and environmental conditions, allowing for immediate decision-making and proactive risk management [63]. This enhances site efficiency, safety, and overall project performance. By utilising state-of-the-art technologies, the sustainable construction industry can handle real-time Big Data by using iterative assessments that reflect the structures' actual consumption patterns. The identification of excessive utilisation in a variety of systems, such as HVAC, electromechanical, and structural systems, is one of the major advantages of this innovation [64]. By cutting down on the time required to identify and fix any problems, these capabilities are essential to improving the safety and integrity of structures, which would be the second application of IoT in construction. This technique optimises construction efficiency and plays an essential part in the preventive management of potential problems, protecting the structure's general functionality and durability.

3.1.3. Structural health monitoring (SHM) using sensor networks

SHM using sensor networks plays a critical role in sustainable construction by ensuring the safety, longevity, and performance of structures. SHM involves deploying sensors to monitor the structural integrity of buildings and infrastructure continuously, detecting issues such as stress, strain, and potential damage in real-time. This proactive approach enables early detection of problems, allowing for timely maintenance and repairs that extend the lifespan of structures and prevent catastrophic failures [65].

By optimising maintenance schedules and minimising unnecessary repairs, SHM reduces resource consumption and waste, contributing to more sustainable construction practices [65]. The data collected from SHM systems can inform the design of more resilient and efficient structures in future projects, enhancing overall sustainability in the construction industry. The ability of the sensor networks to continuously collect massive amounts of data regarding the state of a structure in real-time is the basic component of this integration which is the third application for IoT in construction.

3.2. Robotics in construction automation

Robotics in construction automation is a key result of integrating AI and construction industry including 4D printing, smart robotics, drones, and advanced sensing equipment. These technologies are used for tasks such as material handling, construction equipment automation, and site monitoring. The image also emphasises the potential benefits of robotics in construction, including improved efficiency, safety, and sustainability. By automating repetitive and hazardous tasks, robotics can enhance productivity and reduce risks to human workers. Additionally, the use of sustainable materials and technologies can contribute to a more environmentally friendly construction industry, as in Fig. 18.

3.2.1. 4D Printing

The first application of robotics in sustainable construction is 4D printing. With the advent of 4D printing technology, 3D-printed objects can now respond to external stimuli such as heat, light, and temperature, altering their shape and behaviour over time. This temporal change introduces a fourth dimension to the process. Thus, 4D printing, known as continuous manufacturing, combines all the benefits of 3D printing with an added technological advantage. Like 3D printing, it uses computer-controlled equipment to produce objects layer by layer based on digital 3D models. Promising advancements in this emerging technology include its potential for adaptive materials, self-repairing structures, and responsive designs in various industries [66].

First, a 3D printer can operate efficiently and autonomously with minimal human intervention, significantly reducing project timelines from several weeks or months to just hours or days. Second, 3D printing technology enhances the ability to produce curved roofs, walls, and other non-standard designs with greater precision. This increased geometric flexibility allows for the seamless construction and customisation of complex shapes and structures, unbounded by the constraints of traditional building methods.

Thirdly, 3D printing allows for incorporating unique material properties, such as high tensile strength, corrosion resistance, and heat tolerance, resulting in enhanced construction durability. These mechanically optimised materials contribute to longer-lasting structures. Additionally, many of the materials used, including eco-friendly, organic, and recycled options, support sustainable construction practices. The precise determination of material quantities further reduces waste and lowers costs. Since 2012, the use of 3D printing in construction projects involving concrete, polymers, and metals has grown, though a significant portion of these projects are still experimental rather than commercial [67].

To advance the practical use of 3D printing, it is imperative to address issues related to structural safety regulation, architectural perspective shifts, and the creation of a digital and logical design workflow. Significantly, 4D printing, which incorporates the temporal dimension and intelligent behaviour, is rapidly displacing 3D printing. Intelligent behaviour in altering configurations for self-assembly, multi-functionality, and self-repair is the main innovation of 4D printing over 3D printing. Currently, in its experimental stage, 4D printing in construction has brought forth several new issues, including the increased need for engineers with a strong digital background, sophisticated computational analysis, and innovative concepts for design and structure verification [68].

3.2.2. Smart robotics in construction

Rapid advancements in smart robots have made a versatile range of semi-autonomous or completely autonomous construction applications possible. Aerial, a remotely operated underwater vehicle (ROUV) and ground robots are the two main categories of robotics. For example, a wide range of construction robots with varying functionalities have been created in response to human needs. These robots can do repetitive operations and automate certain manual processes, such as bricklaying, masonry, prefabrication, model generation, rebar tying, demolition, and more [69]. Stated differently, robots facilitate the conversion of low-level materials (such as steel, wood, concrete, etc.) into high-level building pieces. Furthermore, certain dangerous jobs can be delegated to robots to shield employees from accidents and injuries sustained at work. Consequently, there are several expected advantages to these robots, such as mitigating labour shortages, reducing operating expenses, and guaranteeing general quality, accuracy, and security, which is considered the second application of robotics in construction.

Unmanned aerial vehicles (UAVs) equipped with image capture devices (cameras, laser scanners, go-pros) are common examples of aerial robots (Drones) [70]. They are becoming increasingly common in land surveying, site monitoring, and structural health monitoring. Since they can reduce complexity, secure, expedite, and lower the cost of the process. Instead of manual inspection, Unmanned Aerial Vehicles (UAVs) fly over the construction site or even inside the building structure to collect high-resolution photos, record live videos, and use remote laser scanning to find structural defects (such as cracks, erosion, blisters, spalls, etc.) and guarantee worker safety [71]. Additionally, machine learning can train robots, allowing talented robots to operate more intelligently by collecting skills from a simulation. One problem at the moment is that smart robotics adoption has not caught on, and construction automation techniques are still in their early stages [72]. Consequently, ongoing work is required to improve robot utilisation by giving robot systems enhanced capabilities and integrating them into the built environment. Robots will perform more professional jobs in unstructured situations as robot technology becomes more prevalent, which is expected to create prospects for future construction automation [73].

A Remotely Operated Underwater Vehicle (ROUV) has a crucial role in offshore construction, particularly for projects such as marine construction works, offshore wind farms, gas and oil platforms, pipelines, jetties, and ports. These vehicles are used for underwater inspection, maintenance, and installation tasks in environments that are difficult or dangerous for human divers to access [74]. In offshore wind farms, ROUVs help lay subsea cables, inspecting turbine foundations, and monitoring underwater infrastructure. For oil and gas platforms, they are essential for inspecting and maintaining pipelines, detecting leaks, and ensuring the integrity of subsea structures. Additionally, ROUVs support the construction and upkeep of jetties and ports by conducting underwater surveys and inspections, helping to prevent damage and ensure safe operations. Their precision and ability to operate in challenging conditions make them indispensable in ensuring the efficiency, safety, and sustainability of offshore construction projects [75].

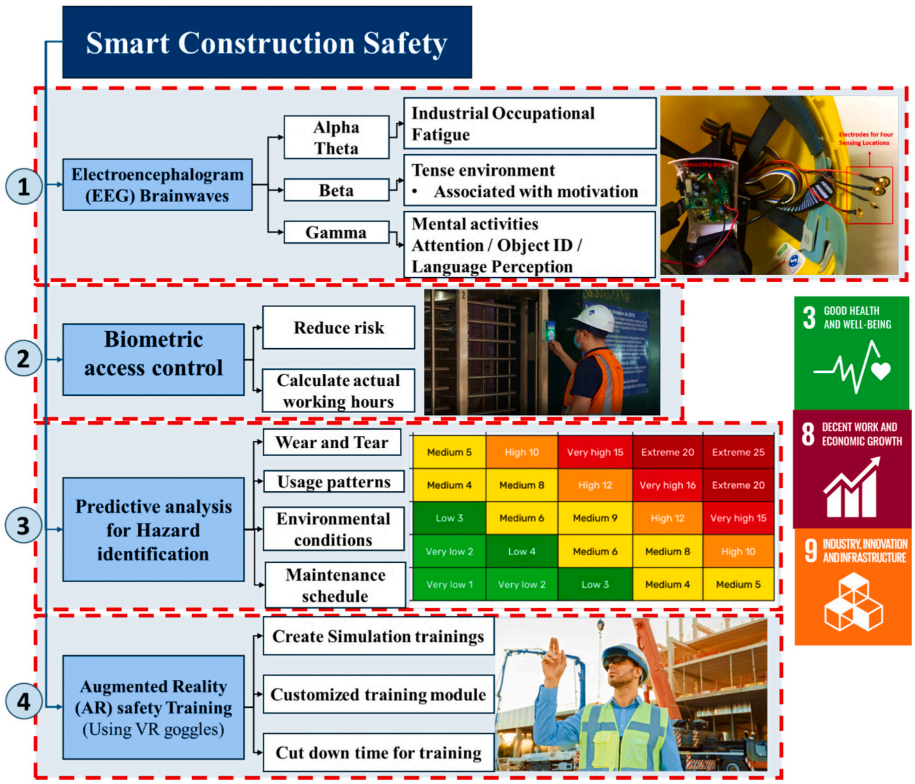

Fig. 19. Automated Construction Safety (ACS).

3.2.3. Smart construction equipment

The tracking of powered equipment in the construction industry is very important and effective in the overall management of the project. However, little attention was given to the non-powered construction assets such as scaffolding, formwork and temporary work. Where these could be equipped with sensors and IoT-based devices to monitor their condition and location. This would delve into asset management and safety, respectively. For instance, sensors could detect weight or weaknesses in any of the equipment, altering supervisors to potential hazards. Moreover, this could be very beneficial for security and theft prevention, as it could provide an exact location in case of any sabotaging attempts via GPS trackers. Moreover, these sensors could track the maintenance schedule for these assets, which could be conducted via RFID tags. In addition, environmental monitoring by utilising sensors on temporary structures that can monitor air quality, allowing for ventilation adjustment to improve worker comfort and reduce greenhouse gas (GHG) emissions [76].

3.3. Smart construction safety

Risk reduction and safety management have always been major concerns in the sustainable construction industry. Compared to workers in other industries, construction workers are more likely to get injured or die two or three times as frequently, accordingly. Risk management and safety management have become crucial issues Throughout their regular duties, construction workers are subjected to unexpected risks and hazards, particularly when they are handling physically and mentally demanding tasks [77]. Thus, maintaining a close watch on the physical and mental well-being of construction workers would be crucial to reducing risks associated with the job site. Smart construction safety solutions outline four key strategies: 1) EEG brainwave monitoring to assess fatigue levels and identify potential risks; 2) biometric access control to regulate site access and ensure only authorised personnel are present; 3) predictive analysis for hazard identification using data on wear and tear, usage patterns, and environmental conditions to optimise maintenance schedules; and 4) augmented reality safety training to provide immersive and customised training experiences, reducing training time and enhancing learning outcomes as in Fig. 19.

3.3.1. Electroencephalogram (EEG) in construction safety

Self-report survey instruments, brainwave, and biofeedback (heart rate and skin temperature)-based instruments have been extensively used on construction sites to measure the physical, psychological, and mental states of workers. However, reflecting a person's mental state using trustworthy, unbiased methods has proven difficult. Recently, wearable electroencephalogram (EEG) helmets have overcome many technical obstacles and have been integrated into relevant research. These EEG devices, which can be fixed under the site helmet, differentiate between each brainwave, offering a more accurate and real-time assessment of workers' mental states. In the context of Industry 5.0, integrating EEG technology with AI and automation can enhance worker safety and neuro-safety, providing data-driven insights that promote well-being, reduce risks, and prevent cognitive overload or stress on construction sites. This human-centric approach aligns with the goals of Industry 5.0, fostering a safer and more efficient work environment.

Monitoring the emotional and psychological well-being of workers during construction operations is an important challenge. However, physiological indicators are successful in reflecting the physical exertion of workers. As a safe neuroimaging method, EEG can give precise, quantitative measurements of brain activity [78]. The start of voluntary movements is mediated by the brain. As a result, EEG-detected brain activity is predictive of related behaviours. Additionally, a person's behaviour is greatly influenced by their mental and cognitive health. Since variations in EEG components can indicate the activation of cognitive systems, EEG is currently used to study cognitive performance [79]. Safety managers can determine which employees are at more risk by analysing minute variations in their EEG-based behavioural and cognitive status, as suggested by the direct brain-behaviour relationship. The essential steps can be performed ahead of time to stop risky behaviour and reduce on-site dangers with the help of the EEG

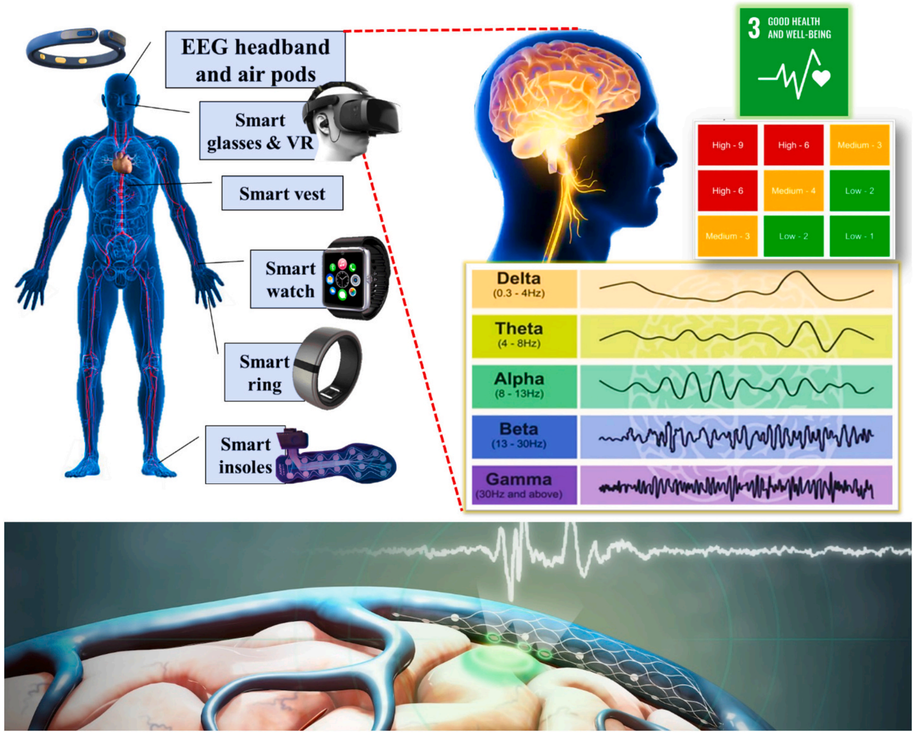

Fig. 20. Wearable devices and brainwaves (EEG) for workers health monitoring and neuro-safety.

approach. Due to its benefits in terms of mobility, portability, and movement tolerance, EEG has been regarded as the ideal neuroimaging technique for construction [80]. The EEG-based monitoring method is even expected to bring about a fundamental shift in building safety, according to researchers [81]. Researchers and practitioners are becoming more interested in using EEG on construction sites because of its prospective influence in improving safety.

However, EEG is prone to several artifacts and noisy waves. Therefore, it is recommended to integrate more than neuroimaging techniques together such as functional near-infrared spectroscopy (fNIRS) or bio-wearable devices to improve the accuracy of EEG and biofeedback. Various wearable devices, including smart glasses, VR headsets, vests, watches, rings, and foot insoles, are integrated to collect physiological data. EEG headbands or EEG-air pods monitor brainwave activity, providing insights into mental states and cognitive function. The collected biodata is analysed to assess factors such as mental and physical fatigue, stress, and overall well-being. This information can be used to optimise work schedules, identify potential health risks, and implement interventions to promote worker health and prevent injuries, as in Fig. 20.

EEG analysis takes advantage of the computing power of frequency bands, such as delta, theta, alpha, beta, and gamma, or ratios between these frequencies [82]. Arousal, vigilance, mental effort, valence, and other psychological states can all be reflected in different frequency bands of EEG data. The gamma band is linked to perception. Gamma frequency range is associated with mental activities, including attention [83] arousal, object identification, and language perception. Low-frequency bands, such as theta and alpha waves, were primarily used in earlier studies on industrial and occupational fatigue [84]. In a tense environment with detail and activity are highly required, the beta band is predominant. A condition that increases focus, motivation, emotion, and mental activity is frequently linked to an elevation in the beta band [85]. Therefore, during construction jobs, an increase in the mental workload and attention level might be linked to an increase in the work involvement index [86]. On the other hand, a lower beta power density indicates a less active state brought on by weariness. According to neurological research, mentally demanding jobs weaken awareness, leaving construction workers open to unanticipated risks [81]. Places where complicated operations are conducted need to have the appropriate safety measures in place, such as electric shock prevention, falling object protection, and trip and fall protection.

3.3.2. *Biometric access control*

A wide range of gadgets, including wearable technology, smartphones, tablets, personal digital assistants, and personal computers, are part of the IoT. These devices, which are composed of embedded sensors and processors that can manage both their internal states and the external environment around them, have become a daily requirement for people due to their increasing processing capacity, decreased cost, and enhanced mobility. IoT is a vast network of intelligent gadgets that collaborate to enhance people's lives by increasing convenience and accessibility. Moreover, biometric access control helps in closing the gap with sustainability, as using biometrics in construction sites reduces the use of plastic conventional cards, thus reducing the associated GHG emissions [87].

Due to the widespread use of smartphones, biometric authentication is becoming more widely accepted because of the successful consumer market combination of mobile phones and biometrics. In 2013, using biometrics has grown significantly since Apple introduced Touch ID, an exceedingly user-friendly biometric recognition system. Now, biometric module-mounted IoT devices are stand-alone items on the market. Biometric recognition uses the features of an individual, including their face and fingerprints, to verify or identify them. It circumvents the limitation of password-based authentication [88] and is growing in popularity as the technology advances in its sensing power. As a result, biometric recognition could be very beneficial in the construction industry to regulate and monitor the amount and the selected personnel access in certain areas. This technique could reduce the risk of injuries and create a localised focused group of labour for certain tasks. Moreover, biometric recognition could be connected to a smart sensing system to calculate a more accurate amount of actual working hours, and fast identify the individuals responsible for any hazardous events.

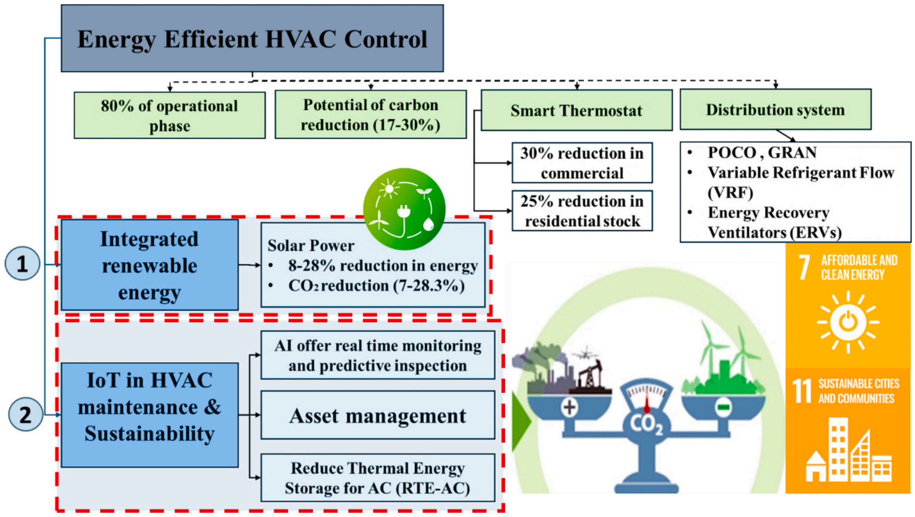

Fig. 21. Automated HVAC energy management.

3.3.3. Predictive analytics for Hazard identification

The third application of smart construction safety is a predictive hazard. Powered or non-powered equipment can benefit from predictive maintenance schedules based on real-time data collection from sensors. By monitoring factors such as wear and tear, usage patterns, and environmental conditions, maintenance can be scheduled proactively to avoid costly downtime and extend the lifespan of the asset [89]. For example, sensors on temporary lighting structures can monitor bulb lifespan and automatically schedule replacements before they fail, ensuring continuous illumination on the construction site. This could be extended to expecting the number of materials or equipment to be procured and tracking the best time to buy the equipment, which could be very beneficial in fluctuating periods and economically unstable countries.

3.3.4. Augmented reality (AR) safety training

The fourth application of smart construction safety is augmented reality oriented to training. AR in construction overlays digital models onto physical environments, enabling real-time visualisation and enhanced precision in design, planning, and execution. Virtual hazard simulation is one of the various applications AI could provide in safety training, by analysing data from previous accidents or near-missed events [90]. AR could create a simulation of hazards to be worked upon in training and safety protocols. AR in safety training with the help of AI could personalise safety training modules based on individual worker's learning pace and experience level to be trained for future hazards and based on the results, the data could determine which personnel is the best fit to be placed in a relatively more dangerous location for example at higher levels, etc. This interactive safety demonstration allows workers to engage with safety concepts and protocols in a hands-on manner. The outcome of such technology usage would cut down the time required for safety training and skill-enhancing protocols [91].

3.4. Energy-efficient HVAC control

Air conditioning, heating, cooling, lighting, appliances, and other operational energy services account for over 80 % of the energy utilised in a structure across its lifetime. Over half of the energy consumed is used by Heating, Ventilation, and Air Conditioning (HVAC) systems. Designing these systems to achieve increased energy efficiency and lower energy consumption has become essential. Recently, several research has concentrated on improving the HVAC systems' operational control and efficiency. Enhancing the building systems' energy efficiency can be a useful strategy for reducing the amount of energy used in buildings. Even though they may increase a building's original cost, efficient technologies ultimately save energy costs and lower carbon emissions.

Energy efficiency techniques reduce energy use, which reduces carbon emissions. Numerous studies have shown that modernising buildings can significantly reduce energy use and, consequently, GHG emissions. Galvin et al. [92], found that energy-retrofitted commercial buildings in the UK reduce carbon emissions by 17–30 %. According to Tang et al. [93], modernising China's residential buildings can reduce carbon emissions by 17–33 %. The efficiency of energy-saving measures is determined by the cost of the retrofit as well as the quantity of energy saved. Vázquez et al. [94] evaluated the financial viability of renovating Spanish public buildings. According to the data, there is a payback period that varies from 8 to 14 years. Retrofitting was economical for a significant percentage of buildings. Recent innovations in energy retrofitting techniques include the use of contemporary technology, such as energy storage, building automation, and smart building systems. These technologies have the potential to reduce the payback period and improve the efficacy of energy retrofitting techniques as conducted by Kim et al. [95] in evaluating the effectiveness of upgrading commercial buildings in South Korea.

Recently, HVAC efficiency became a growing demand to be delved into to reach the proposed sustainability level. The latest key technological innovations are smart thermostats, Variable Refrigerant Flow (VRF) systems, Energy Recovery Ventilators (ERVs), and advanced Building Management Systems (BMS). Smart Thermostats have revolutionised HVAC energy management by combining AI, and occupancy sensing, thus, reducing energy consumption by up to 30 % in commercial settings and 25 % in residential stock. By modelling user behaviour and HVAC dynamics, approaches like Power Conservation Optimisation (POCO) and Greedy Ranking AllocatioN (GRAN) automatically modify thermostat settings to reduce consumption.

Variable Refrigerant Flow (VRF) systems operate by modelling the flow of refrigerant based on energy demand in the structure. The advantage of this system is its variety as its application along with speed-regulated compressors (SDC) allows efficient coverage of changeable heat loads without delay, also, the development of the VRF module within EnergyPlus showed potential energy saving of 22.2 % compared to conventional systems. Energy Recovery Ventilators (ERVs) facilitate energy-efficient ventilation by transferring moisture and heat from entering to exiting air streams. According to [96] the integration of fuzzy logic controllers within BMS for HVAC systems in smart buildings showed promising results in reducing energy consumption and costs,

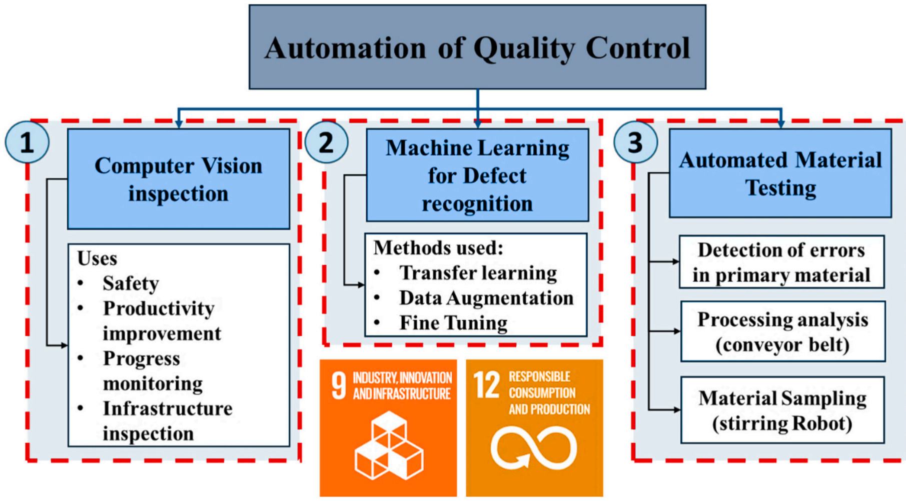

Fig. 22. AI contribution to quality control.

thus all contributing to a better BMS as in Fig. 21.

3.4.1. *Integrating renewable energy sources with HVAC*

Integrating renewable energy sources with HVAC systems enhances energy efficiency and reduces reliance on fossil fuels in building environments and operations. By utilising solar, wind, or geothermal power, HVAC systems can operate sustainably while minimising carbon emissions. This integration supports urban deep-decarbonisation policies, and zero-energy buildings to promote long-term environmental and economic benefits. An experimental study conducted by [97], where solar-powered Air Conditioning (AC) systems were compared with conventional systems, showed an energy saving range of (8–28 %) and GHG emission reduction of (7–28.3 %). An AI-based system must be utilised to regulate the operation of this hybrid system such as a predictive control system, reinforced learning for HVAC control, Energy Management System (EMS), Demand Response (DR) system, Fault Detection and Diagnostics (FDD) [98].

3.4.2. *IoT in HVAC maintenance and sustainability*

IoT plays a crucial role in HVAC maintenance, offering real-time monitoring and predictive inspection for any deficiencies. By using sensors and smart systems, HVAC can be monitored by collecting data on temperature, humidity, and system status. Thus, by running these data using AI tools, IoT could monitor its status and be tailored based on the user behaviour. This sensing intervention could be very beneficial in asset management, as it could prolong the lifetime of the HVAC system in structures. Dominguez et al. [99] highlighted the usage of AI in predictive maintenance for HVAC systems and applied their work to a five-star hotel system. The AI model reduces the amount of energy required for the system to run. Implementing AI tools in HVAC design will lead to more sustainable infrastructure assets by using lessened energy or optimised usage based on the inhibitor's usage. Thus, the load charge for thermal energy storage air conditioners (TES-AC) will be reduced.

3.5. *Automatic quality control (AQC)*

Industry 4.0 refers to automation, digitalisation, and data utilisation in industrial processes to enhance efficiency and quality. In the construction industry, utilising AI in its process has become very important. This utilisation aims to enhance technical innovation, sustainability, and efficiency. In the same context, many studies have valued AI methods for automating quality control. Plastic closed-loop injection is a good example of the application of AI in quality control for plastic manufacturing. Sensors in closed-loop injection modelling can measure a variety of parameters such as pressure, temperature, and flow rate. These measurements help ensure that materials such as plastics, insulation, etc. are all produced with the same consistency and specifications for strength, and durability [100]. As a result, AQC in construction utilises AI and sensor technologies to monitor and assess construction processes in real-time, ensuring compliance with standards. It enhances accuracy, reduces errors, and minimises the need for manual inspections, leading to improved project efficiency and quality, as in Fig. 22.

3.5.1. *Computer vision inspections (CVI)*

CVI has become increasingly popular in the construction industry for safety monitoring, productivity improvement, progress monitoring, and infrastructure quality inspection. Alateeq et al. [101] employed *You Only Look Once* model version 5 (YOLO-v5) to monitor construction safety by gathering data from construction workers using computer vision from closed-circuit television (CCTV) footage and the workers' protective equipment (PPE). However, there were some drawbacks in identifying relatively small objects, such as helmets and safety belts. CVI could identify building defects such as concrete cracks and ensure quality control during the maintenance phase, thus ensuring the safety and high quality of the structure that could prolong its lifetime. This will last the usability of the structure longer relative to regular inspection techniques, which impact the environment. Preserving the assets, there is no need to demolish or rebuild the structure, which would serve sustainable development goals (9 and 12) [102].

On the other hand, for productivity improvement, CVI plays a vital role. By automating tasks such as waste analysis, and human productivity measurement [133], CVI can calculate the rate of work and material consumption which could expect and identify the completion date of an individual task, and if it is on the critical path of the project, the completion date of the project could be determined as well. Moreover, automate the procurement process of the material by identifying the amount of consumption in construction. CVI could have its impact by automating the auditing of the construction process, such as keeping track of the amount of material consumed on the site would eventually expedite the cost estimation process [134].

3.5.2. *Machine learning for defect recognition*

Machine learning, particularly deep learning, and pattern recognition, has a vital role in defect recognition in construction materials. For defect recognition, numerous methods are used. From these methods: transfer learning, data augmentation, and fine-tuning. Visual automated non-destructive testing uses neural networks that showcase high accuracy levels [103]. Construction elements can be classified, and defects can be localised using deep learning models; ResNet-50 has achieved

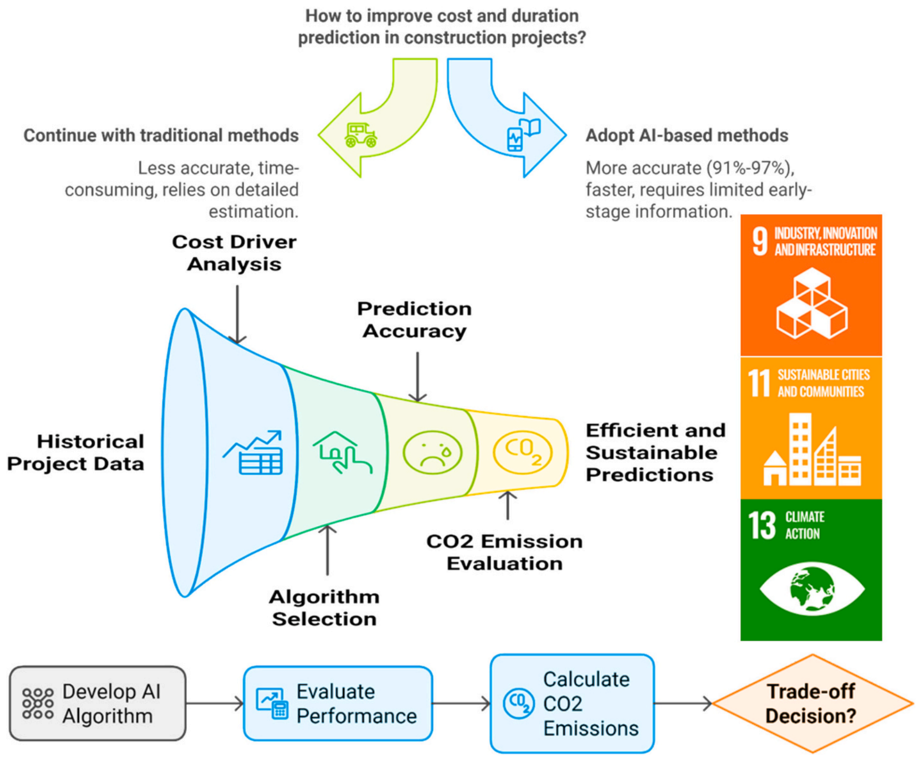

Fig. 23. GAI strengths and development of sustainable (green) predictions [21,39,107]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

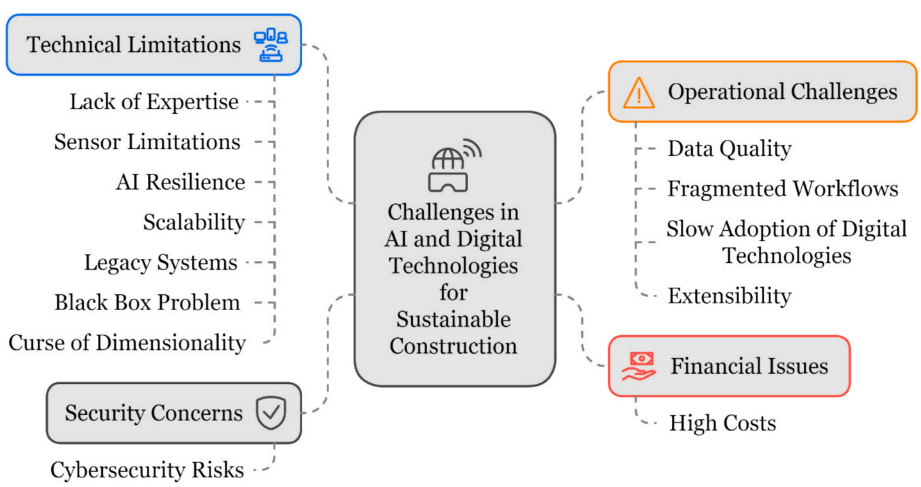

Fig. 24. Categorization of research gaps and challenges.

90.68 % accuracy in defect recognition. Furthermore, defect detection is achieved by acoustic-laser (sound-light) techniques. To improve defect identification, a machine learning strategy based on K-singular value decomposition (K-SVD) and Orthogonal Matching Pursuit (OMP) algorithm effectively reconstructs missing data in data collection [104].

3.5.3. *Automated material testing*

Automated material testing has seen significant advancements in construction sectors because of AI [105]. In this context, material testing was developed in material sampling, processing, analysis, and detection. Automated material sampling in the construction industry is important in quality control. A concrete stirring robot with an automated sampling function ensures precise control over concrete quality and provides samples for evidence and inspection. Moreover, the automatic collection systems to sample from conveyor belts have been developed to improve the quality of the sample, which optimises the process for better quality control and reduces the manual documentation time required for this process. Wong et al. [106] emphasised the advantage potential of deep learning in defect detection regarding construction materials, a video-based deep learning approach to be used in automatic material counting, enhancing the on-site management process.

3.6. *Project Management Automation (PMA)*

Project Management Automation (PMA) refers to the use of AI, machine learning, and software tools to streamline, optimise, and automate various project management tasks, such as scheduling, budgeting, resource allocation, risk management, and reporting. PMA

Table 6
Research gaps and challenges examples.

Challenge	Description of the challenge	Examples of the challenge	References
System Integration	Integrating AI and IoT with traditional construction industry practices is difficult due to resistance to change and existing workflows, software, and hardware.	Implementing AI-based project management tools in a company that relies heavily on manual processes and spreadsheets.	[4,123]
	Integrating AI with legacy construction industry systems is difficult due to reliance on outdated tools, fragmented workflows, and slow adoption of digital technologies.	Compatibility issues between different platforms and technologies used by various stakeholders.	
High Costs	Significant upfront investment is required for infrastructure upgrades, training, and technology implementation.	Implementing a complex IoT system for real-time monitoring on a construction site.	[2,124]
Lack of Expertise	Shortage of skilled professionals with expertise in digital twins, AI, IoT, and their applications in construction.	Difficulty in finding qualified personnel to develop and implement AI-driven solutions for predictive maintenance.	[48,125]
Cybersecurity Risks	Increased vulnerability to cyberattacks, data breaches, and privacy concerns due to the growing use of digital technologies.	Potential for hackers to access sensitive project data through unsecured IoT devices or cloud-based platforms.	[126,127]
Data Quality	Challenges in ensuring data accuracy, reliability, and consistency for AI, digital twins, and IoT applications.	Inaccurate sensor readings or incomplete datasets hinder the effectiveness of predictive analytics models.	[43,110]
	Limited availability of high-quality, labelled datasets, especially for tasks such as project cost prediction, predictive maintenance, or energy efficiency optimization.	Lack of sufficient labelled data for training AI models to accurately predict project outcomes or identify potential maintenance issues.	
	Construction projects generate unstructured or incomplete data, hindering AI model performance and accuracy.		
Sensor Limitations	Need for improved sensor systems for hazard identification and accurate data collection.	Limited sensitivity in detecting subtle changes in structural health or environmental conditions.	[4,128]
AI Resilience	Ensuring AI models can adapt to changing conditions and maintain performance in dynamic construction environments.	Challenges in training AI algorithms to handle unexpected events or variations in project parameters.	[110,129]
Scalability	AI solutions developed for small-scale projects struggle to adapt to larger, more complex constructions.	Difficulty in scaling up AI-based project management tools to handle large-scale infrastructure projects with thousands of data points.	[130]
Legacy Systems	Many construction companies still rely on outdated project management tools and manual data entry processes, limiting the adoption of AI technologies.	Using spreadsheets or paper-based systems for tracking project progress and resource allocation, instead of modern digital tools.	[1,123]
Fragmented Workflows	Construction projects involve various stakeholders using different software systems, creating data silos, and hindering AI analysis.	Difficulty in accessing and analysing comprehensive project data when information is stored in multiple, incompatible systems.	[131]
Slow Adoption of Digital Technologies	The construction industry's slow adoption of digital transformation due to cost concerns and resistance to change hampers the scaling of AI innovations.	Reluctance to invest in new AI technologies due to perceived risks and uncertainties, or resistance from employees who are comfortable with traditional methods.	[4,132]
Extensibility	The ability of AI solutions to adapt to new or unforeseen scenarios and challenges in sustainable construction projects.	Difficulty in adapting AI-based energy efficiency models to changing building codes or variations in energy consumption patterns.	[133,134]
Black Box Problem	The lack of transparency and interpretability in AI models makes it difficult to understand how they arrive at their decisions and whether they are making unbiased and ethical judgments.	Difficulty in explaining the rationale behind AI-generated recommendations for sustainable material selection or waste management strategies.	[134]
Curse of Dimensionality	The challenge of working with large datasets containing numerous features or variables can lead to overfitting, noise, and computational inefficiency.	Difficulty in training AI models to accurately predict the environmental impact of construction projects based on a vast number of input parameters.	[21,135]

enhances efficiency, reduces human error, and enables data-driven decision-making throughout the project lifecycle [21].

3.6.1. Cost and duration automation using green AI (GAI)

The role of AI in cost and duration prediction is transformative for PMA, particularly in construction projects [107,108]. Machine learning algorithms analyse historical project data to forecast potential cost overruns and timeline delays more accurately than detailed construction cost and duration estimation, as in Fig. 23. Cost drivers have been explored and ranked based on qualitative and structural equation models [4,109]. The conceptual cost estimation can be predicted with accuracy ranging from 91 % to 97 % based on only limited information of the early stage of the project life cycle [39]. Elmousalami has investigated different computational intelligence (CI) algorithms and models, such as Fuzzy Logic, ANNs, and ensemble machine learning for construction cost and duration prediction [21].

Furthermore, Green AI (GAI) has been conducted to develop an Automated Cost-Duration Variance Prediction (CDVP) system by Haytham Elmousalami [110] where Eq. 1 is a novel evaluation metric for the developed AI algorithms to make a trade-off between algorithm accuracy and computational CO_2 equivalent emission [110].

$$\mathrm{E_{total}} = (\mathrm{N_u} \times \mathrm{T_u}) \times \mathrm{E_t} \tag{1}$$

E_{total}: Total generated CO_2 emissions.
N_u: Number of system users.
T_u: Computational time in hours per user.
E_t: CO_2 emissions of each computational hour in the computational system.

3.6.2. Scenario simulation and risk forecasting

Generative neural networks (GNNs) are powerful tools for scenario simulation and risk forecasting in PMA. By analysing historical project data and real-time inputs, these models can simulate various future project scenarios, considering different variables, such as resource availability, task dependencies, budget fluctuations, and external risks. GNNs generate a range of possible outcomes, allowing project managers to explore "what-if" scenarios and assess the impact of different decisions before committing to a course of action. This capability enhances risk forecasting by identifying potential challenges, such as delays or cost overruns, and providing early warnings. With these insights, managers can develop more robust contingency plans, optimise resource allocation, and make data-driven decisions to mitigate risks and improve project success rates [111].

On the other hand, Generative Neural Networks (GNNs) play a foundational role in models such as ChatGPT or Google Gemini, which are based on generative pre-trained transformers (GPTs). While GNNs

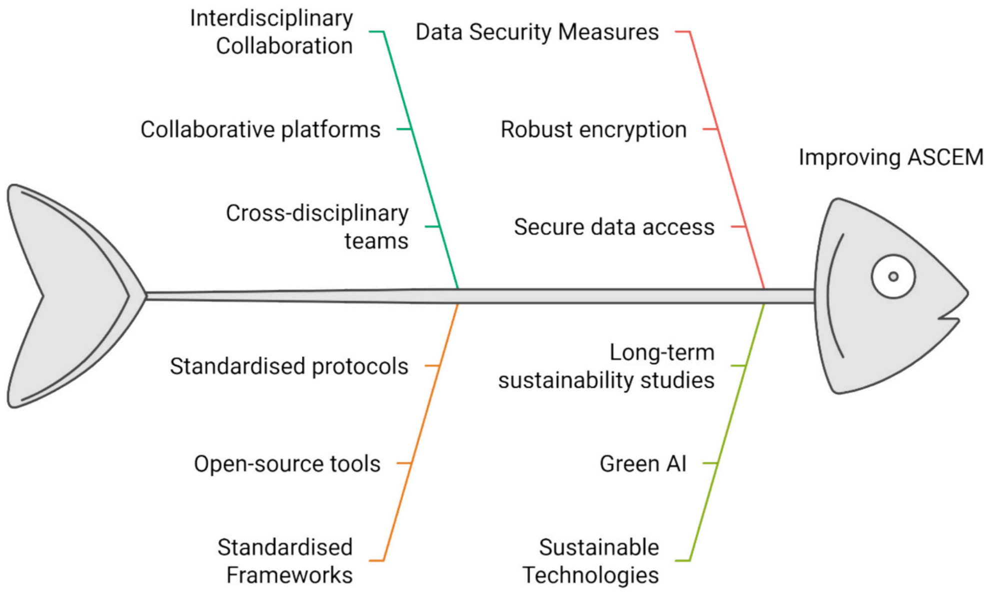

Fig. 25. Future research direction to improve ASCEM.

broadly refer to neural networks capable of generating data (such as images, text, or audio), the specific architecture behind ChatGPT involves transformer-based networks, which are specialized types of neural networks used for natural language generation and understanding. GPT models can automate project management by generating insights from project data, predicting outcomes such as risk analysis, Monti Carlo simulation, budget, and schedule variance, and offering data-driven recommendations. They enhance decision-making through natural language interfaces, enabling seamless communication and reporting [112].

3.6.3. Contract and documentation management

By automating and optimising different project phases, Natural Language Processing (NLP) and large language models (LLM) improves AI-based sustainable construction management systems. Better decision-making, increased efficiency, and simpler procedures result from this integration. NLP accelerates documentation procedures that have historically required considerable amounts of human work, such as risk assessment and contract analysis. NLP makes it easier to handle project information by transforming unstructured data into organised formats, which enhances project performance and overall risks [113].

NLP significantly enhances contract and documentation management by automating tasks, such as extraction, analysis, and compliance checking in project management. NLP algorithms can efficiently process large volumes of contractual documents, identifying key clauses, obligations, deadlines, and risks. This automation reduces the time spent on manual review, ensuring that project managers are alerted to critical terms, potential conflicts, or compliance issues early on. NLP can streamline version control, comparing different iterations of contracts to highlight changes, and extracting relevant information for reporting or audits. By making contract management more efficient and accurate, NLP reduces legal risks and administrative burdens, while enhancing decision-making based on real-time document insights [114].

Moreover, NLP approaches help with risk classification and requirement validation by enabling the extraction of crucial insights from large amounts of text data. Construction projects benefit from the application of sophisticated models such as Bidirectional Encoder Representations from Transformers (BERT), which have been demonstrated to achieve good accuracy in risk classification tasks. To improve data-driven decision-making in construction, further study is needed to explore the possibilities of integrating NLP with BIM, as shown by ongoing research. Even though NLP has various advantages, there are still obstacles to incorporating these technologies into current construction workflows, which calls for continued research and development [115].

3.6.4. Scheduling and resource optimisation

Reinforcement learning (RL) and deep reinforcement learning (DRL) are highly effective for dynamic scheduling optimisation in project management, especially in complex and uncertain environments. RL approaches learn optimal scheduling policies by interacting with the project environment and receiving feedback in the form of rewards based on schedule performance, such as minimising delays or maximising resource utilisation. DRL, which combines RL with deep neural networks, enhances this capability by handling high-dimensional data, making it suitable for large, complex projects with numerous interdependent tasks and constraints. By continuously learning and adapting to real-time project conditions, DRL can optimise task sequencing, resource allocation, and timeline adjustments in ways that traditional scheduling methods cannot, leading to more resilient and efficient project management outcomes [116].

Moreover, RL and DRL offer advanced solutions for efficient resource optimization in project management by continuously learning how to allocate resources (e.g., personnel, equipment, and materials) more effectively. RL algorithms optimise resource usage by interacting with the project environment, experimenting with different allocation strategies, and receiving rewards based on how well the resources are used, considering factors such as cost, time, and availability. DRL enhances this process by using deep neural networks to handle complex, high-dimensional data for large-scale projects with numerous interrelated resources and constraints. By learning from historical data and real-time feedback, DRL systems can predict optimal resource allocation patterns and adapt to dynamic changes in demand or availability, leading to improved efficiency, reduced costs, and minimized resource bottlenecks [117].

4. Research limitations and future perspectives

This section addresses the key limitations encountered in the research and explores future directions for advancement. It outlines the challenges faced in integrating AI and IoT technologies within the construction industry, as discussed in Section 4.1. Based on these challenges, Section 4.2 presents recommendations for future research, focusing on enhancing interdisciplinary collaboration, developing

Table 7
Answering the analytical questions.

Analytical Question (AQ)	Finding
AQ.1: What is the research production performance focused on AI applications in the sustainable construction industry?	The research production performance has been significant, with numerous studies exploring various aspects of AI in sustainable construction. This includes the development of AI-driven models for optimising building materials, enhancing energy efficiency, and improving overall sustainability in construction practices. The literature shows a growing trend in publications, highlighting the increasing importance of AI in this field as showed in Fig. 6.
AQ.2: What are the most productive countries and funding institutes?	The most productive countries in AI applications in sustainable construction are the USA, China, and various European countries. Key funding institutes include national science foundations, governmental bodies, and international organisations dedicated to sustainable development and technological innovation in the construction sector as showed in Fig. 11.
AQ.3: What are the most repetitive keywords and their relations?	The most repetitive keywords in the research include 'AI,' 'machine learning,' 'sustainable construction,' and 'energy efficiency. These keywords often relate to topics such as optimisation, safety, resource management, and environmental impact, indicating a strong focus on integrating AI to achieve sustainability goals in construction as showed in Fig. 13.
AQ.4: What is AI for sustainable construction?	Automated Sustainable Construction Engineering Management (ASCEM) is an AI-driven framework of automated applications designed to optimise construction processes focusing on sustainability, efficiency, and environmental impact. The key applications for ASCEM are organised into six main categories, each with specific sub-categories as in Fig. 15.
AQ.5: What are the most cited papers and authors for AI for sustainable construction?	Fig. 12. is for top-cited authors and Table 5 is for most cited papers.
AQ.6: How does AI enhance safety measures and risk management in the sustainable construction industry?	AI enhances safety measures and risk management by using real-time data analytics and predictive models to identify potential hazards and prevent accidents. Technologies such as EEG helmets, sensor networks, wearable devices, and AI-driven safety protocols improve site monitoring and ensure compliance with safety standards. Additionally, AI applications in risk assessment help in proactive decision-making and risk mitigation as discussed in section 4.
AQ.7: What role does AI play in optimising sustainable construction processes?	AI plays a crucial role in optimising sustainable construction processes by automating design and planning, improving resource allocation, and enhancing energy efficiency. Optimisation algorithms also assist in achieving better project outcomes with minimal environmental impact as discussed in section 3.3
AQ.8: What are the recent challenges, limitations, and future perspectives?	Recent challenges in AI applications in sustainable construction include data privacy concerns, high initial implementation costs, and the need for skilled personnel. Limitations also arise from the variability in construction environments, making standardisation difficult. Future perspectives suggest a growing adoption of AI-driven technologies as costs decrease and AI systems become more robust and user-friendly. Continuous advancements in AI, along with the increased emphasis on sustainability, are expected to drive further innovation in the construction industry as discussed in section 4.1.

standardised frameworks, promoting sustainability, and ensuring robust data security to drive the continued evolution of construction practices.

4.1. Research challenges

The goals of Construction 4.0 efforts are to improve project management, safety, and efficiency by combining technologies such as Digital Twins, IoT, and AI [118]. However, obstacles, including high expenses for implementation, inexperience, and worries about technical assistance prevent IoT for safety in construction from being widely used. The construction industry has to adopt IoT technologies, despite their potential benefits in streamlining construction site stages, sharing information, and improving structural monitoring [119]. These technologies are widely used in other industries. To overcome the industry's resistance to change, funding educational initiatives, and emphasising the benefits of implementing these innovative technologies are all necessary to overcome these obstacles.

In addition, because of high initial costs and the need for significant investments in infrastructure upgrades and training to integrate AI and IoT technologies in traditional construction contexts, presents obstacles. The adoption of IoT for safety improvements struggles in the construction industry, which is notably dangerous due to concerns about the large investment required and the availability of technical support [120]. In addition, problems including a lack of case studies and standards, data quality challenges, and a labour scarcity with experienced workers all impede the adoption of AI in the construction industry and raise perceptions of high prices and training requirements. To overcome these challenges, a deeper comprehension of the benefits of implementing AI and IoT technologies is needed, such as feasibility studies, besides specially designed training courses that will make integration with conventional construction methods easier [121].

Cyberattacks, data breaches, and privacy concerns are among the risks associated with the growing use of digital technologies in construction projects. These risks include breaching passwords, viruses, and hacking, all of which are common threats to data management in the building sector. In addition, there are vulnerabilities associated with the use of BIM and Cloud-Based BIM technologies that result in the disclosure of private project information and intellectual property. Furthermore, the use of autonomous machinery on building sites brings up cybersecurity issues because cyberattacks have the potential to compromise project data, cause disruptions to work, and even endanger people's safety. Thus, to protect sensitive data and guarantee the safe handling of data on construction sites, it is imperative that experts in the construction industry are aware of these risks and put strong cybersecurity measures and protection safety layers. There are still challenges to be resolved, such as the requirement for improved hazard identification sensor systems and implementation barriers for AI-enhanced health and safety procedures [122]. To overcome these constraints, more research is needed to improve sensor accuracy, guarantee AI resilience in changing conditions, and enable smooth system integration across multiple suppliers in the construction industry.

The key challenges in implementing AI and digital technologies for sustainable construction have been visualised in Fig. 24. The challenges and barriers have been categorised into four primary categories:

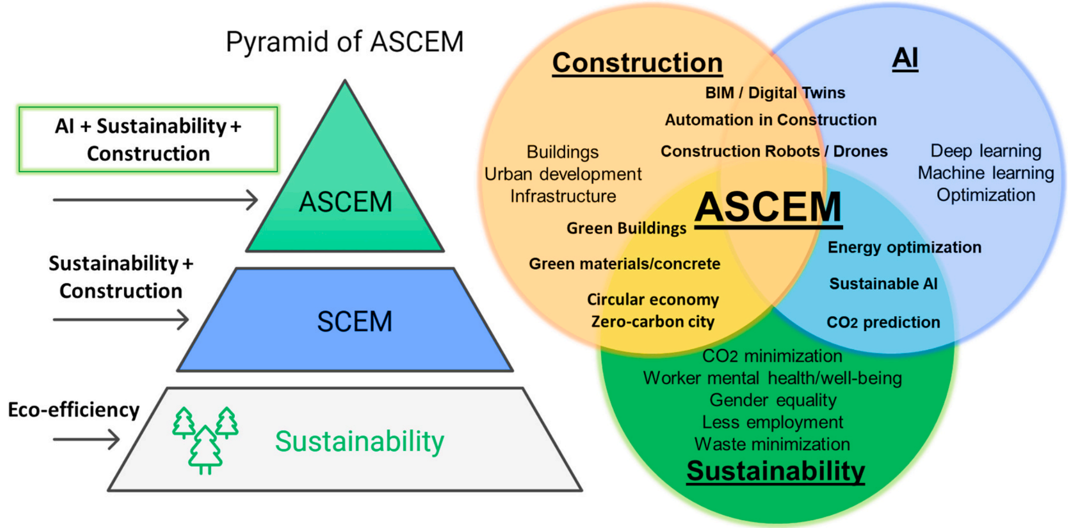

Fig. 26. Pyramid and Venn diagram of ASCEM.

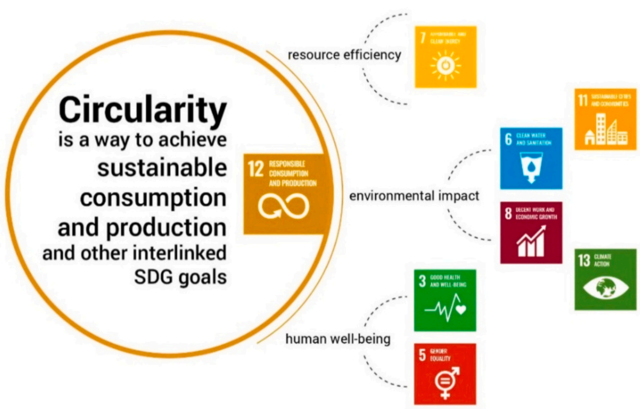

Fig. 27. Impact of ASCEM on circularity and other SDGs.

technical limitations, operational challenges, security concerns, and financial issues. Technical limitations refer to constraints in technology, such as insufficient data infrastructure or lack of advanced tools. Operational challenges include the difficulties in integrating new systems into existing workflows and managing their practical implementation. Security concerns focus on vulnerabilities related to data privacy and cybersecurity risks. Financial issues emphasise the high costs of adopting and maintaining advanced technologies, which can hinder widespread adoption in the construction industry. These challenges highlight the complexities that must be addressed to fully realise the potential of AI in sustainable construction. Table 6 provides descriptions and examples of each sub-category.

4.2. *Recommendations for the future research*

Future research in the construction industry should focus on enhancing interdisciplinary collaboration, fostering integration between AI, IoT, and traditional building systems. Developing standardised, open-source frameworks can streamline technology adoption. Sustainability and green technologies must be prioritized, including energy-efficient AI and environmentally friendly solutions. Robust data security measures are essential to protect sensitive project information. Additionally, the emphasis on explainable AI (XAI) will ensure transparency and fairness. Moreover, long-term studies and generalized models are crucial to ensure the adaptability, reliability, and effectiveness of AI-driven solutions across various construction scenarios.

4.2.1. *Enhanced interdisciplinary collaboration*

Developing more resilient, scalable, and efficient integrated systems requires more cooperation between architects, engineers, developers, and policymakers. Research indicates that interdisciplinary cooperation is important [136], emphasising the need for creative pedagogies to improve teamwork. It is possible to maximise energy efficiency and occupant well-being by integrating AI/ML and IoT technologies with traditional building systems [137]. Transdisciplinary research in catastrophe risk management also emphasises how important strong governance frameworks are to putting knowledge-based solutions into practice. Diverse partnerships are advantageous for large-scale projects because they produce flexible integration structures that foster creativity and innovation.

4.2.2. *Development of standardised and open-source frameworks*

The development of open-source platforms and standardised protocols makes it easier to incorporate AI and IoT into construction projects. These developments make it possible to view project sites holistically, monitor environmental variables and construction equipment, and provide operational management and safety decision support. Construction stakeholders can optimise design methods, boost safety management, and promote human-robot collaboration by utilising AI technologies. The seamless integration of these technologies into project workflows can be further ensured by the use of intelligent frameworks and top-level design theories, which emphasise automatic data gathering and real-time upload for improved project quality management [138]. With all factors considered, these advancements present novel opportunities to change construction methods, lower hazards, and boost industry operational effectiveness.

4.2.3. *Focus on sustainability and green technologies*

In line with global sustainability goals, more research should be done on technologies such as Green AI, BIM, Modern Methods of Construction (MMC), or modular construction which can improve efficiency and lower the carbon footprint of construction projects [137,139]. On the other hand, Sustainable AI focuses on developing energy-efficient and environmentally friendly AI technologies that minimise carbon emissions and resource usage [110]. Construction processes can be optimised to minimise waste, cut down on energy use, and cut carbon emissions by integrating BIM with MMC. The benefits of these technologies include

Table 8
Contribution Examples of ASCEM to SDGs.

SDG	Contribution Example of ASCEM	Role of AI and automation	References
1 NO POVERTY	Affordable housing projects that address housing needs for low-income communities.	AI-driven cost optimization in construction projects to reduce expenses and make housing more affordable.	[110]
2 ZERO HUNGER	Construction and management of infrastructure supporting sustainable agriculture and food supply chains.	AI-based precision agriculture systems integrated into construction projects to manage and enhance food production.	[132]
3 GOOD HEALTH AND WELL-BEING	Design and construction of healthcare facilities and promoting safe construction practices for workers and mental health.	AI-enabled health and neuro-safety monitoring systems to prevent accidents and ensure worker well-being during the construction of hospitals.	[133]
4 QUALITY EDUCATION	Construction and maintenance of educational facilities, creating safe and accessible learning environments.	AI-assisted personalized learning environments within educational buildings to enhance the quality of education.	[2]
5 GENDER EQUALITY	Inclusive design and construction practices that consider the needs of all genders and promoting diversity in the construction industry.	AI-driven diversity and inclusion programs to address gender disparities within the construction sector.	[3]
6 CLEAN WATER AND SANITATION	Infrastructure development for water supply and sanitation systems, and sustainable water management in construction projects.	AI-based water management systems to optimise water usage and monitor water quality in construction projects.	[134]
7 AFFORDABLE AND CLEAN ENERGY	Implementation of deep decarbonisation pathways, energy-efficient technologies, and renewable energy sources in construction projects.	AI for optimising energy consumption in buildings, managing renewable energy sources, and enhancing energy efficiency and the built environment.	[135]
8 DECENT WORK AND ECONOMIC GROWTH	Providing safe working conditions and fair wages for workers and supporting economic development through construction projects.	AI-driven predictive maintenance for machinery, ensuring safer working conditions and promoting economic efficiency.	[2]
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE	Innovations in construction methods, technologies, and the development of sustainable infrastructure projects.	Integration of AI for smart construction, using robotics and EEG automation to enhance efficiency and innovation advancing Industry 5.0	[110]
10 REDUCED INEQUALITIES	Inclusive urban planning and affordable housing projects that reduce disparities in living conditions.	AI-driven algorithms for fair and equitable resource allocation in construction projects to reduce inequality between workers.	[3]
11 SUSTAINABLE CITIES AND COMMUNITIES	Urban planning, smart city initiatives, and construction of sustainable infrastructure for resilient and inclusive communities.	AI in city planning for optimising traffic flow, waste management, and enhancing the development of smart and negative-carbon cities.	[136]
12 RESPONSIBLE CONSUMPTION AND PRODUCTION	Implementation of sustainable construction practices, waste reduction, circular economy, and the use of eco-friendly materials.	AI for optimising material usage, waste reduction, and ensuring responsible sourcing in construction projects as construction circular economy.	[2]
13 CLIMATE ACTION	Construction of resilient infrastructure, green buildings, and projects that mitigate and adapt to climate change.	AI for climate modelling, predicting environmental impacts such as floods and meteorological conditions, and optimising construction practices for climate resilience.	[110]
14 LIFE BELOW WATER	Sustainable construction practices that protect coastal areas, prevent pollution, and preserve marine ecosystems.	AI-powered monitoring and alarming systems to prevent marine environmental damage during construction operations of offshore oil and gas platforms or floating wind turbines.	[137]
15 LIFE ON LAND	Biodiversity-friendly construction practices, reforestation projects, and protection of natural habitats during construction.	AI for ecological impact assessments and ensuring minimal disruption to natural habitats during construction.	[138]
16 PEACE, JUSTICE AND STRONG INSTITUTIONS	Compliance with ethical and legal standards in construction projects and promoting transparency and accountability.	AI-powered systems for regulatory compliance, ensuring ethical and legal standards are met in construction activities.	[26]
17 PARTNERSHIPS FOR THE GOALS	Collaborative efforts between governments, businesses, and communities for sustainable construction projects and development initiatives.	AI-driven data sharing and collaboration platforms to facilitate partnerships and information exchange in construction projects.	[139,140]

increased resource conservation, decreased energy and carbon emissions, and increased productivity. Putting these methods into practice helps to conserve energy, cut down on emissions, and maintain the environment besides promoting sustainable development [137].

4.2.4. *Robust data security measures*

Developing more robust cybersecurity measures to protect sensitive data generated from construction sites is crucial for the future of the industry. Research highlights how construction activities are more vulnerable to cyberattacks because of the growing digitalisation of industry 4.0. Existing literature highlights the need for further research investment in cybersecurity within the construction sector, focusing on areas beyond BIM and digital twins to include other digital systems such as construction robots and prefabrication platforms [140]. Furthermore, before using autonomous equipment on-site, cybersecurity risks can be identified and addressed with the use of vulnerability assessment tools, such as the Common Vulnerability Scoring System (CVSS). Improving cybersecurity helps to safeguard project data, private information, and avoids potential harm to individuals [130].

4.2.5. Green and explainable AI

Explainable AI (XAI) refers to AI systems designed to make their decision-making processes transparent and understandable to humans. By providing clear justifications for their actions, XAI enhances trust, accountability, and interpretability in AI-driven applications. Green and explainable AI combines energy-efficient AI technologies with transparent decision-making processes to promote sustainability and accountability in AI applications [110]. On the other hand, green and explainable AI should consider the following criteria:

- Clarity and Reliability: Future AI model development should prioritise enhancing model transparency and dependability, ensuring that outputs are easily interpretable and trustworthy for users across diverse applications.
- Context-Aware Techniques: AI research should focus on incorporating advanced context-aware methods, enabling models to better understand and process relevant contextual information, ultimately improving the precision and quality of recommendations.
- Ethical and Efficient Decision-Making: Advancing AI to support decision-making in complex environments is essential, with an emphasis on ethical considerations to ensure responsible AI integration, achieving higher performance, robustness, and societal acceptance.

4.2.6. Generalisation and long-term studies

Generalisation in construction automation research refers to developing adaptable AI systems that can perform consistently across various construction environments, project types, and tasks with minimal reconfiguration. Assessing the long-term impact of incorporating the latest innovations in the construction sector should be the main goal of upcoming longitudinal studies [142]. These studies should aim to follow the development of technology adoption and its long-term consequences on project efficiency, quality, and safety. Researchers can assess the long-term advantages and possible disadvantages of technologies such as BIM, AR, AI, Machine Learning, and Big Data by examining data from different phases of construction projects. The scalability, cost-effectiveness, and overall industrial transformation brought about by technology integration can all be understood through longitudinal research. These studies can also aid in identifying obstacles, hurdles, and best practices for the long-term, sustainable deployment of innovative construction technologies. Consequently, the future research direction to improve ASCEM can be visualised in Fig. 25.

5. Research contribution

This section highlights the key contributions of the paper to the field of construction engineering management. It begins with an analysis of the analytical questions (AQs) posed in Section 2.1, providing a comprehensive breakdown of AI applications in the construction industry. The discussion extends to the contribution of the ASCEM framework, which integrates advanced technologies such as BIM, Digital Twins, and AI tools to promote sustainability in construction. Through the automation and optimization of construction processes, ASCEM aims to improve energy efficiency, reduce environmental impact, and address important social aspects such as worker well-being and gender equality.

5.1. Discussion of analytical questions (AQs)

This section summarizes how the paper tackles the AQs outlined in section 2.1. It presents a statistical breakdown of the diverse categories of AI applications coupled with the construction industry. Table 7 shows the responses to the 10 research questions of this study.

5.2. Contribution to sustainability

ASCEM integrates construction innovations and AI advantages to promote sustainability, as in Fig. 26. ASCEM leverages technologies such as BIM, Digital Twins, and construction robots from the construction sector, alongside AI tools such as deep learning and optimisation, to automate and optimise construction processes. This approach enhances energy efficiency, reduces CO_2 emissions, and minimises waste, supporting sustainable construction practices. Additionally, ASCEM contributes to developing green buildings, circular economies, and zero-carbon cities, while addressing worker mental health, gender equality, and overall well-being. By combining automation, AI, and sustainability goals, ASCEM has a crucial direct impact on advancing sustainable construction engineering management.

For example, circularity, as a concept, aligns with the achievement of SDGs, particularly through enhancing resource efficiency, reducing environmental impact, and improving human well-being. In the context of ASCEM, AI can optimise construction resources by improving energy efficiency, material utilisation, and waste reduction, thereby supporting SDG 7 (Affordable and Clean Energy) and SDG 11 (Sustainable Cities and Communities). AI-driven solutions can mitigate environmental impacts, aiding goals such as SDG 6 (Clean Water and Sanitation) and SDG 13 (Climate Action). Furthermore, by enhancing safety, productivity, and inclusivity in construction, AI contributes to human well-being and SDG 3 (Good Health and Well-Being) and SDG 5 (Gender Equality), ensuring more equitable and sustainable industry practices as in Fig. 27. Table 8 provides examples and the role of AI in sustainable construction contribution to SDGs.

6. Concluding remarks

This article has provided a comprehensive overview of the current status and potential of AI in promoting sustainable construction. This research direction develops a term "Automated Sustainable Construction Engineering Management (ASCEM)". ASCEM advances industry 4.0 concepts and deep decarbonisation strategies to automate construction practices toward sustainability. Integrating AI tools and techniques in construction practices offers significant opportunities for enhancing efficiency, reducing environmental impact, and improving safety and quality control. The SLR yielded the following key insights and implications:

- Significant growth in AI research for sustainable construction, focusing on construction safety, Project Management Automation (PMA), energy efficiency, and material optimisation.
- Frequent keywords include 'AI,' 'machine learning,' and 'energy efficiency,' highlighting focus research areas.
- ML applications involve energy consumption prediction, schedule optimisation, and quality control.
- DL applications enhance safety monitoring by EEG and defect detection using CNNs and RNNs.
- AI improves safety through real-time hazard identification and proactive risk management tools.
- Advancements in Generative AI and Green AI drive Project Management Automation (PMA). Green AI minimises the computational GHG emissions for big data analyses. As a result, ASCEM drives Industry 5.0 by integrating AI, automation, and sustainability in construction processes.

By leveraging digitalisation, the construction industry can achieve higher levels of resource conservation, lower energy consumption, and reduced carbon emissions, thus aligning with global sustainability goals. The findings indicate that, while there are promising advancements in AI applications for sustainable construction, several challenges remain. These include high initial costs, resistance to change within the industry, and the need for substantial investments in infrastructure and training. Additionally, concerns about data security and privacy, especially with the increasing use of digital technologies and autonomous systems.

ASCEM is the future of the construction industry. Future research should focus on addressing these challenges by developing cost-effective solutions, enhancing educational initiatives, and conducting feasibility studies to demonstrate the long-term benefits of AI integration. Furthermore, interdisciplinary collaboration and the development of standardised frameworks and best practices will be crucial in facilitating the widespread adoption of AI technologies in construction. Therefore, AI has the potential to transform the sustainable construction industry by making it more sustainable, efficient, and safe. However, realising this potential requires continued research, investment, and a willingness to embrace change. By overcoming the existing barriers, the construction industry can fully leverage AI to achieve its sustainability objectives and contribute to a more automated and sustainable future.

CRediT authorship contribution statement

Haytham Elmousalami: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Mina Maxy:** Writing – original draft, Visualization. **Felix Kin Peng Hui:** Writing – review & editing, Supervision, Investigation. **Lu Aye:** Writing – review & editing, Supervision, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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