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Review

Roles of Artificial Intelligence and Machine Learning in Enhancing Construction Processes and Sustainable Communities

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Abstract: Machine Learning (ML), a subset of Artificial Intelligence (AI), is gaining popularity in the architectural, engineering, and construction (AEC) sector. This systematic study aims to investigate the roles of AI and ML in improving construction processes and developing more sustainable communities. This study intends to determine the various roles played by AI and ML in the development of sustainable communities and construction practices via an in-depth assessment of the current literature. Furthermore, it intends to predict future research trends and practical applications of AI and ML in the built environment. Following the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines, this study highlights the roles that AI and ML technologies play in building sustainable communities, both indoors and out. In the interior environment, they contribute to energy management by optimizing energy usage, finding inefficiencies, and recommending modifications to minimize consumption. This contributes to reducing the environmental effect of energy generation. Similarly, AI and ML technologies aid in addressing environmental challenges. They can monitor air quality, noise levels, and waste management systems to quickly discover and minimize pollution sources. Likewise, AI and ML applications in construction processes enhance planning, scheduling, and facility management.

Keywords: artificial intelligence; communities; sustainable construction; machine learning; roles

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1. Introduction

Construction projects are complicated, and their success relies heavily on various factors [1]. Traditionally, construction projects have faced numerous challenges, including delays, cost overruns, and safety concerns. These issues often arise due to human error, inefficient resource allocation, and inadequate planning. Similarly, human activities become efficient in smart and sustainable communities [2]. Artificial Intelligence (AI) and Machine Learning (ML) have the potential to significantly enhance construction processes and contribute to the development of sustainable communities. Specifically, AI has the potential to increase labour efficiency by 40% and quadruple yearly economic growth rates by 2035 [3]. AI, a branch of computer science, focuses on creating intelligent machines capable of performing tasks that ordinarily need human intelligence. AI can find non-obvious patterns in data while also producing reliable forecasts of the expected future in previously unexplored circumstances [4]. ML is a key branch of AI [2] that allows a computer to learn from data, uncover patterns, and ultimately make judgments and predictions with minimal human intervention [5].

AI and ML are well-known for their effectiveness in construction automation [6]. AI technologies excel in data analysis and pattern recognition, allowing them to extract valuable insights from vast amounts of information. Additionally, AI plays a vital role in optimizing the allocation of resources in construction projects. In addition to enhancing project management and resource allocation, AI also facilitates the creation of smarter, more sustainable communities. Furthermore, AI-powered systems can enhance safety on construction sites by continuously monitoring and analyzing data from sensors, cameras, and wearable devices. These technologies empower project stakeholders with valuable insights, optimize resource allocation, and contribute to the development of energy-efficient infrastructure. The current study focuses on identifying the roles of AI and ML in improving construction processes and creating sustainable communities.

Emerging AI techniques, such as artificial neural networks (ANNs), can be used to generalize hidden patterns and implicit associations from historical data, resulting in a viable prediction model to assist the planner in analysing new cases in the issue area [4]. Artificial neural networks are a class of ML algorithms capable of modelling nonlinear relationships between input vectors and target values [7]. More so, digital twins (DTs) integrate AI, ML, and data analytics to create living digital simulation models that can learn and update from multiple sources as well as represent and predict the current and future conditions of physical counterparts [8]. Residential and commercial buildings account for a significant portion of global energy consumption; therefore, hourly predictions of electricity consumption in residential and commercial buildings are required to support operational decisions, demand response strategies, and the installation of distributed generation systems [7]. Thermal comfort is a key component of smart building control and operation, as well as building design and modelling [9]. Also, the building and construction sectors consume one-third of the total world's final energy consumption and emit roughly 15% of CO_2 [10].

Meanwhile, application programming interfaces (APIs) enable smart cities to share huge amounts of data [11]. Predicting occupant thermal experience is an essential target for architects, engineers, and facility managers in creating and maintaining pleasant interior settings [12]. Thus, to promote energy sustainability, it is necessary to focus on the consumer end rather than only the production end [13]. AI, particularly its ML branch, has the capacity and roles to make buildings and communities smarter and more sustainable [14].

According to [15], knowledge discovery in databases (KDD) and data mining (DM) are techniques that enable construction managers to identify valid, valuable, and previously unknown patterns in massive amounts of construction project data. Sadly, construction is one of the most dangerous industries in many nations [16]. Construction accidents are widespread; thus, developing prediction algorithms to detect severe accidents would be beneficial [17]. Relatedly, contractors are responsible for the whole engineering, procurement, and construction (EPC) project execution and are subject to many risks as a result of various imbalanced contracting techniques such as lump-sum, turn-key, and low-bid selection [18]. In the early stages of construction projects, estimating the project cost is critical [19]. Optimization algorithms and ML approaches can be employed to design and construct sustainably [20], focusing on all phases, from design to construction and operation.

Several studies have reviewed the current applications and future directions of AI in different domains of knowledge. On a broad note, the study [21] investigated the potential uses of AI in health systems. Meanwhile, review [22] focused on ML applications in neuroimaging. In the AEC domain, the scientometric study [23] on AI applications in the AEC industry was based on science mapping.

Furthermore, Ref. [5] investigated potential research prospects in AI and robotics for prefabricated and modular construction. However, additional research into the roles of AI and ML in optimising construction processes and establishing more sustainable communities is required. The current study, therefore, is unique in its approach to assessing current practical applications of AI and ML in that it adopts SR methodology to identify and expatiate the roles of AI and ML technologies in construction processes and sustainable communities.

Therefore, this research aims to investigate the roles of AI and ML in improving construction processes and creating more sustainable communities through a systematic review (SR). The evaluation intends to identify not only the roles of AI and ML in the development of sustainable communities and construction processes but also future research trends and practical applications of AI and ML in the built environment. Following the introduction, this study discusses the research context, the materials and procedures for review. The article then reports on the findings of the profile and content analysis. First, the roles of AI and ML in developing sustainable communities are categorized as indoor and outdoor communities [24] and discussed. The roles of AI and ML are then examined in the preconstruction, construction, and post-construction phases [25]. Future directions for using AI and ML to improve construction processes and sustainable communities are investigated and discussed, and conclusions are drawn. Meanwhile, the major research questions addressed in this study are as follows: (i) what is the primary emphasis and application of AI and ML in the construction domain? (ii) how are AI and ML employed in construction processes? (iii) what roles do AI and ML play toward ensuring sustainable communities? (iv) what are the future trends for AI and ML in the construction industry?

2. Methods and Materials

In contrast to traditional literature reviews, SR examines current research, evaluates scientific contributions, and synthesizes important data [26]. SR aids in comprehending the best available evidence on a particular topic [27]. SR also undertakes a methodical examination of the relevant literature to discover and discuss contemporary applications of the subject area [28]. Furthermore, SR aids in presenting a comprehensive summary of previously published investigations [29]. Finally, SR is a rigorous but time-consuming and resource-intensive procedure [30]. As a result, the described technique (SR) is appropriate for comprehensively determining the roles of AI and ML in improving construction processes and sustainable communities. To minimize poor reporting, this study followed five SR stages: question formulation, study identification, study screening, study critical assessment, and data extraction and synthesis of studies [31]. This method is similar to the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines mentioned in [32] and was used to meet the study's aim. The PRISMA records selection flow chart utilized in this study is depicted in Figure 1. The exact search queries and the overall research flowchart are shown in Figure 2.

The inclusion and exclusion criteria must be specified to filter the retrieved research and preserve the relevant ones [33]. Articles concentrating purely on mobility, remote sensing, and smart cities without a practical connection to the construction sector were eliminated from the current research. Studies based primarily on experiments, questionnaire surveys, scientometric analyses, and reviews were also removed. Non-English articles were similarly excluded. The study ensured that the query was not confined to certain journals, and the date range was selected to collect all relevant publications. The selection of keywords and databases in SR impacts the comprehensiveness of research trends findings [34]. Hence, the keywords and databases for this review have been carefully chosen to ensure their completeness. The articles for this study were retrieved from the Web of Science (WoS) and Scopus databases. While WoS is considered the most comprehensive and has the most significant and influential journals in its record [35], the Scopus database encompasses a wide range of articles [36] relevant to this study. The Scopus database's "Advanced search" tool was used. This function contains pre-generated searches that return articles relating to UN Sustainable Development Goal 11: "Sustainable Cities and Communities". Through the Scopus and Web of Science databases, these pre-generated search queries were utilized to obtain papers on the roles of AI and ML in enhancing sustainable communities.

Content analysis is a research approach that uses a series of procedures to draw meaningful conclusions from text [37]. An in-depth content analysis of the included articles was carried out to find publications that particularly explore the roles of AI and ML in improving processes for construction and creating sustainable communities.

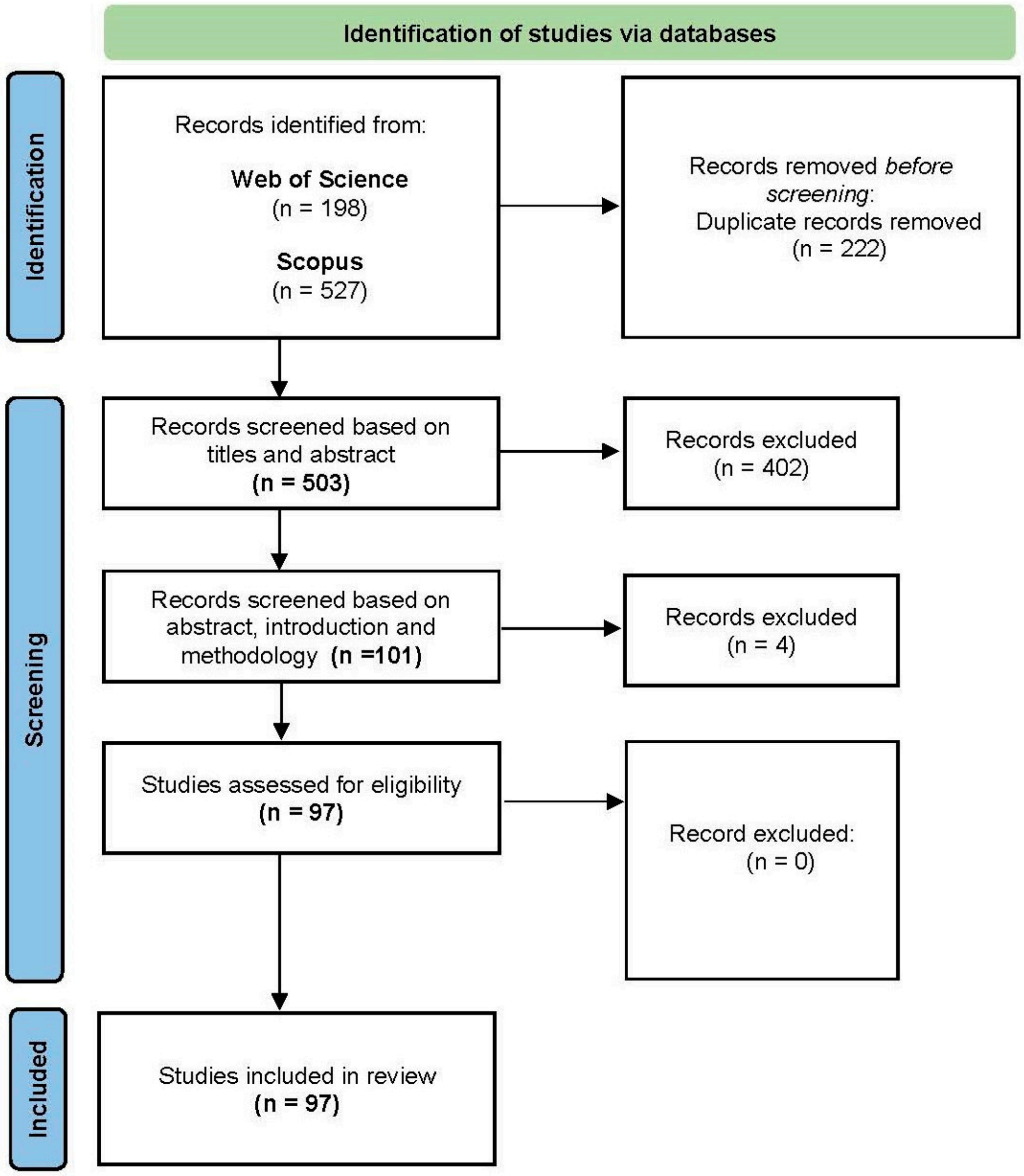

Figure 1. PRISMA selection flowchart of identified literature.

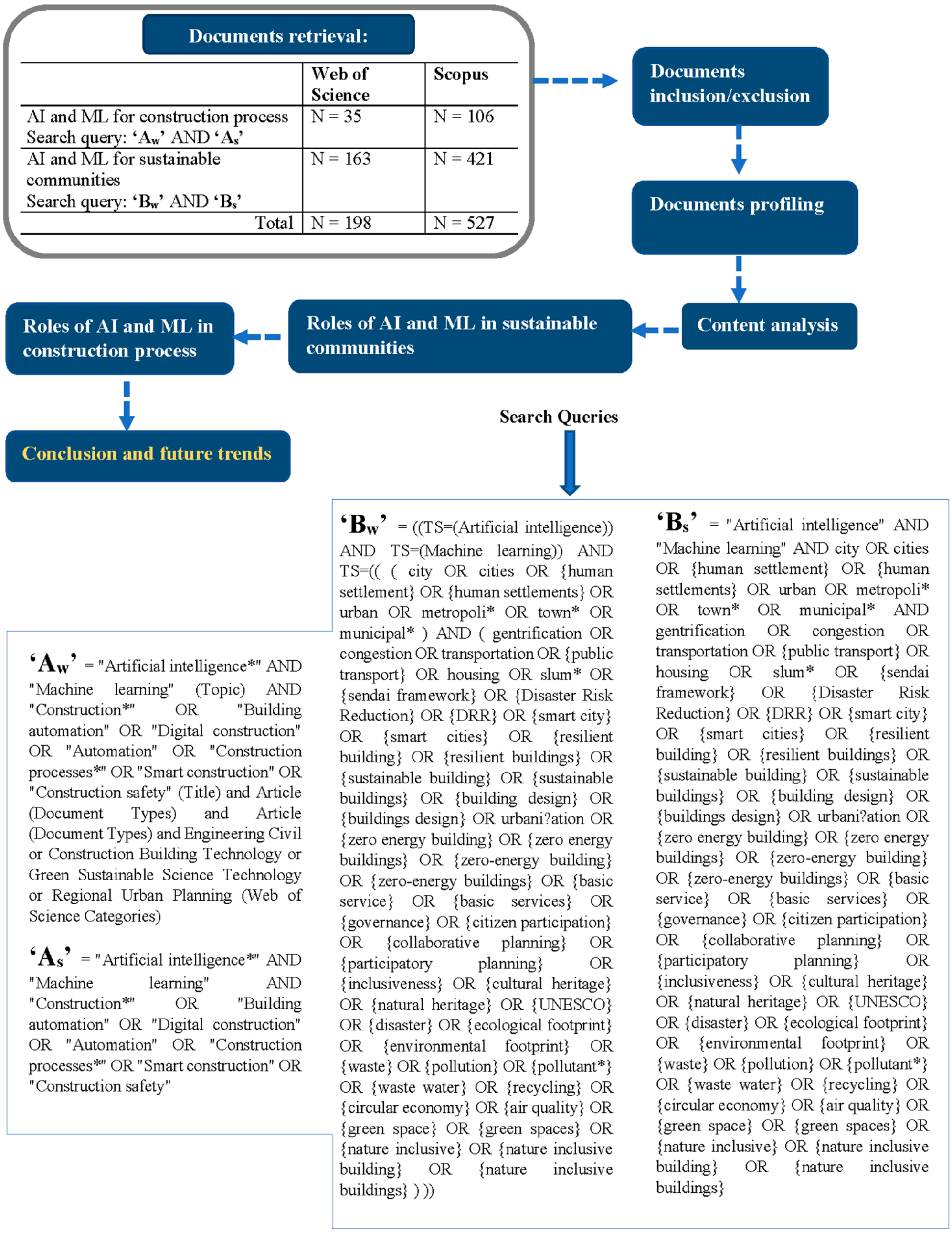

Figure 2. Research flowchart with search queries.

Profile of Publications

A total of 725 journal articles were retrieved from the databases, of which 222 duplicate articles were removed. Next, the unique 503 articles were inspected based on their titles and abstract. Based on the PRISMA standard, non-relevant articles were then removed. The present study included a total of 97 articles based on their relevance to the aim and research questions the study seeks to answer. Figure 3 outlines the included articles in this study per the year of publication and publishers. About 63% (61) of the included publications were published between 2021 and 2023, indicating an increase in research interest and applications of AI and ML in the built environment in recent years. Also, Table A1 shows the sources of the included articles.

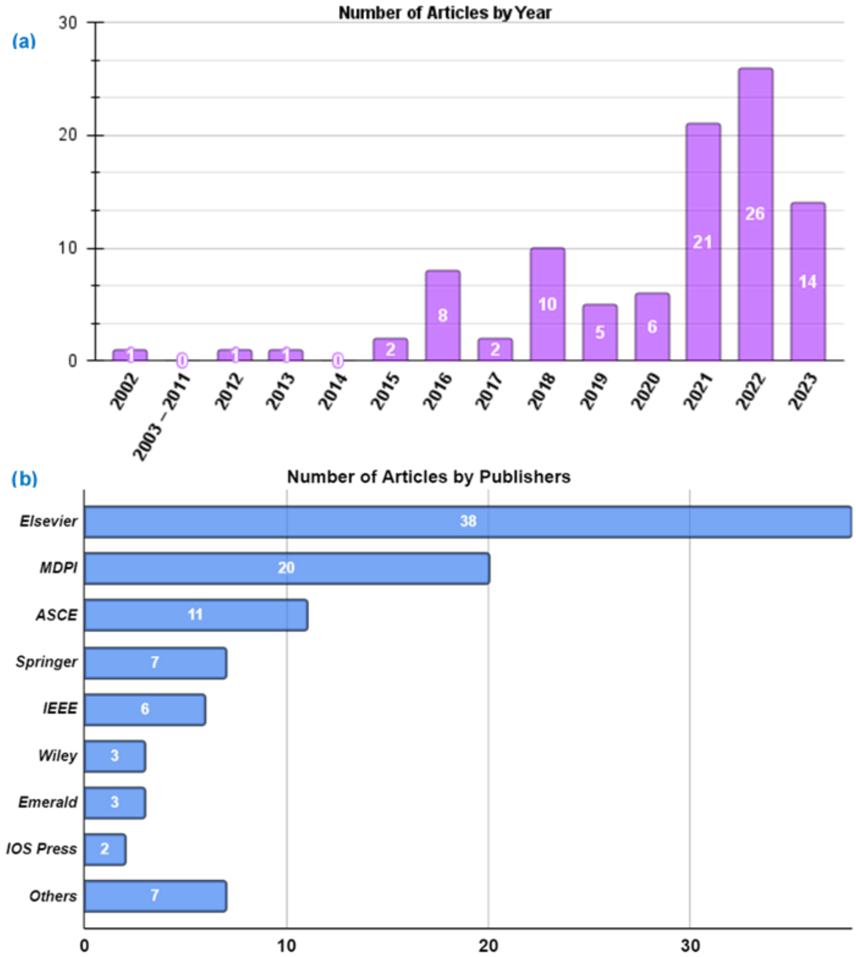

Figure 3. (**a**) Number of articles by year; (**b**) Number of articles by publishers.

Most of the featured publications were published by Elsevier, MDPI, ASCE, Springer, and IEEE. Aside from Wiley, Emerald, and IOS Press, which published eight articles included in this study, seven articles from seven additional publishers were also included.

Furthermore, keywords retrieved from the article titles indicated that the frequently used keyword is "energy", "air quality", and "construction safety". Also, the common authors' keywords are "machine learning", "artificial intelligence", and "deep learning" as shown in Figures 4 and 5. The articles included in the study stem from different educational institutions across the globe. The countries were based on the authors' institutions. Figure 6 shows that the United States and China have the largest publications in the research corpus.

Other commonly used keywords derived from article titles include "project management," "Real estate price estimation," "Waste management," "Construction management," "Load prediction," and "Accident prediction" (Figure 4). Other top keywords used by the authors include "Smart cities", "Smart city", "Support vector machine", "Artificial neural network", "Smart buildings", and "Neural network", among others (Figure 5).

According to Figure 6, the number of the included article(s) per country shows that Egypt and Morocco are the two African countries having notable research papers (six and three, respectively) included in this study. Angola, Ecuador, Iraq, Ireland, Japan, Kazakhstan, Mexico, Pakistan, Poland, Russia, Sweden, and Thailand are among the "others" countries with only one representative article in the research. More so, Asia and Europe have the largest number of publications included in the study, while the most productive authors are Kerim Koc and Asli Pelin Gurgun, with five publications each, as shown in Figure 7.

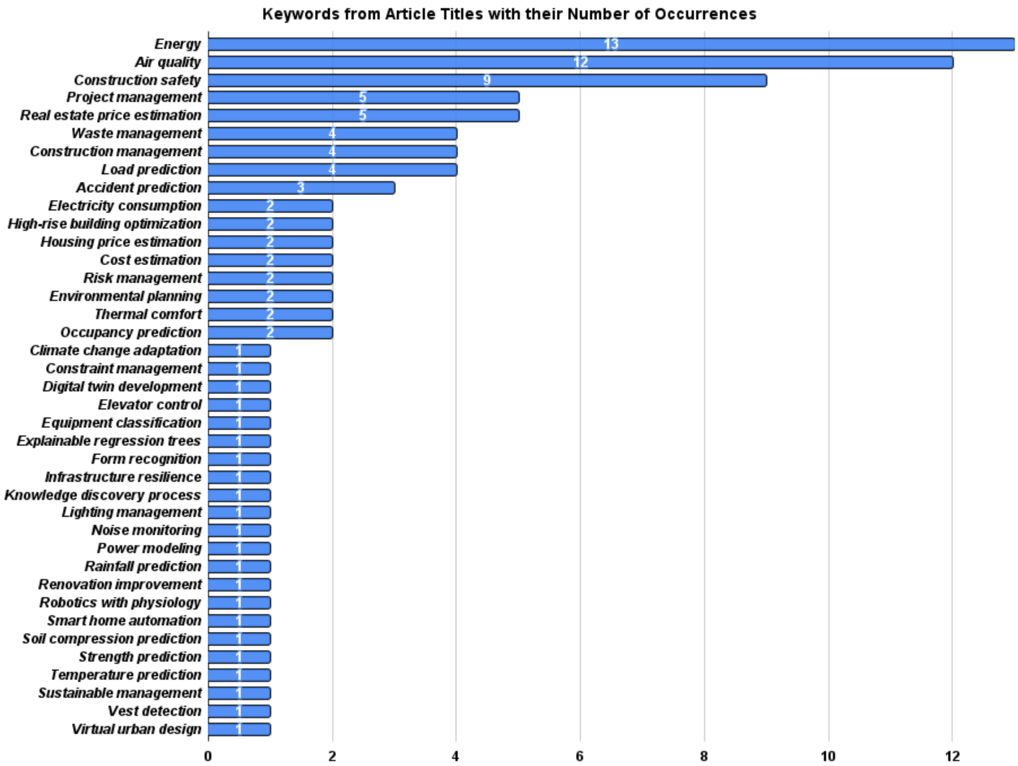

Figure 4. Keywords from article titles.

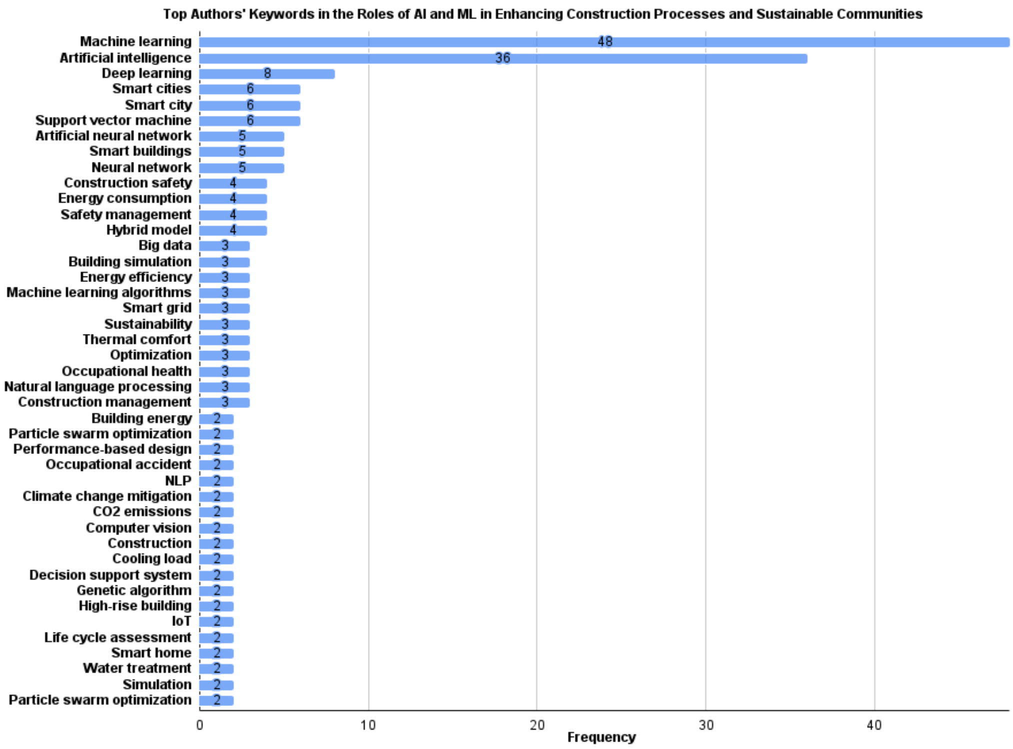

Figure 5. Most frequent authors' keywords.

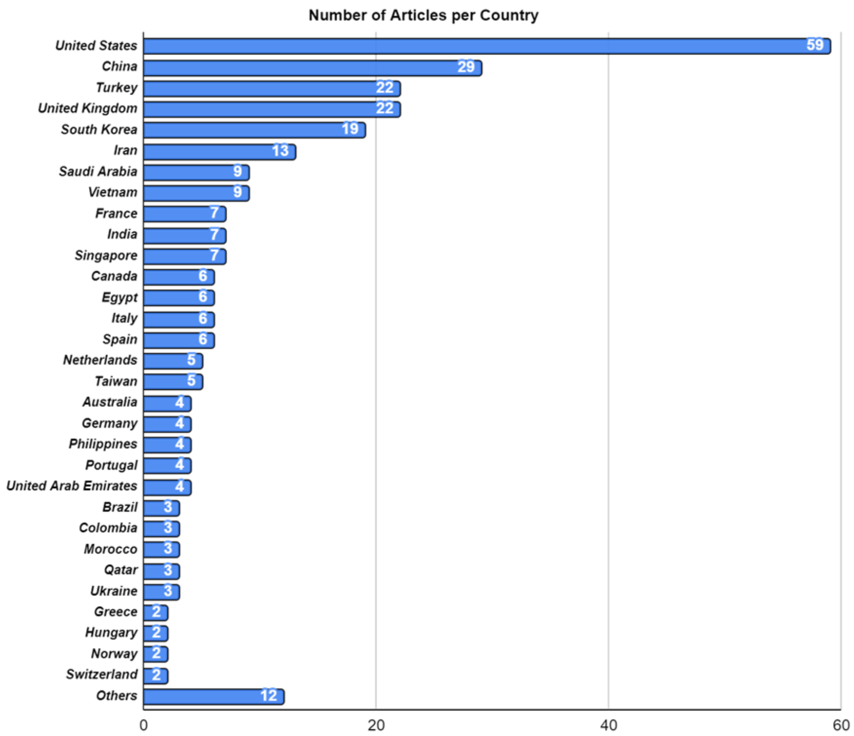

Figure 6. Article source per country.

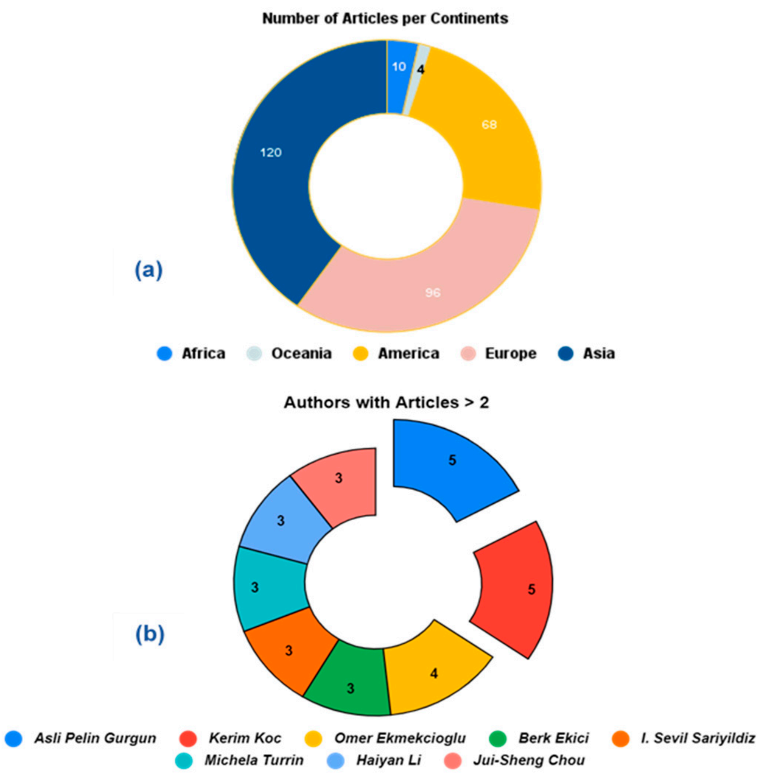

Figure 7. (**a**) Articles distribution per continent (**b**) Authors with more than two articles.

The authors' institutions determined the number of countries and continents. Furthermore, most of the articles had several authors. As shown in Figure 7a, most of the authors representing various institutions are from Asia, Europe, and America. Africa and Oceania have the least representative institutions per continent.

3. Roles of AI and ML in Sustainable Communities

3.1. Indoor Environment

3.1.1. Energy Management

Ref. [38] employed AI to turn the Europoint Towers in Rotterdam into self-sufficient buildings by taking into account energy use and food production (lettuce crops). The study looked into optimizing high-rise buildings for self-sufficiency in food production and energy usage based on daylight availability. Unlike the majority of AI models now used in energy forecasting, which is traditional and deterministic, 'transformer,' a novel deep learning paradigm, leverages the idea of self-attention [39]. The study developed a transformer-based model to predict the energy consumption of a real-world university library and compare it to a baseline model. Ref. [40] delved into pilot systems and prototypes that demonstrate how AI may aid in the process of achieving energy sustainability in smart cities. The study investigated smart metering and non-intrusive load monitoring (NILM) to establish a case for the latter's utility in profiling electric appliance power usage. Using ML approaches, Ref. [41] investigated the energy consumption trends of residential assessment units. Ref. [42] focused on creating an energy management approach that combined photovoltaics and storage systems, using a multi-story building with a high density of families as the major case study to provide data that allows feasibility forecasting. Ref. [43] aimed to reduce the computation required to determine the energy consumption of various combinations by identifying suitable training samples, computing their energy consumption with EnergyPlus, and estimating the rest of the data's energy consumption with ML techniques.

Based on the experts' competence, ref. [44] attempted to analyse the electrical energy usage in Mashhad, Iran, using ML methods to offer dynamic solutions for encouraging residents' interest in renewable energy generation. Ref. [45] used machine learning interpretability approaches to predict whether a room is occupied or unoccupied, resulting in energy savings in buildings. Ref. [46] developed an AI-based framework for addressing various scientific issues in green buildings, such as providing clean energy, developing a smart and sustainable biogas production control system, and integrating solid waste management with the Sustainable Development Goals (SDGs). The AI techniques used were Random Tree (RT), Random Forest (RF), artificial neural network, and Adaptive-Network-based Fuzzy Inference System (ANFIS). Ref. [13] provided a bottom-up strategy for creating heat load analysis and forecasting utilizing ML techniques such as support vector machines, feed-forward neural networks, multiple linear regression, and regression trees. [47] unveiled a new simulation environment created by combining CitySim, a building energy simulator, and TensorFlow, a powerful ML library capable of developing building energy scenarios in which ML algorithms are applied to the major problems and opportunities that modern cities face. Ref. [48] developed a novel ensemble model based on actual data to estimate energy consumption in residential buildings.

The ensemble model combines two supervised learning machines—least squares support vector regression and the radial basis function neural network—and incorporates symbiotic organism search to automatically discover its best tuning parameters. The study by [49] developed a technique for estimating domestic energy demand that included statistical data matching, ML, and household/population synthesis. Through the combination of data-driven methodologies with physics-based model ML algorithms, ref. [50] created a hybrid model to handle the problem of residential electricity consumption forecasting. Using an AI model, ref. [10] forecasted residential building energy use and greenhouse gas emissions. Ref. [51] addressed the need to develop methods for accurately modelling and characterizing building energy consumption in cities by proposing a novel data-driven urban energy Simulation (DUE-S) framework that integrates a network-based ML algorithm with engineering simulations to better understand how buildings consume energy across multiple temporal and spatial scales in a city.

3.1.2. Thermal Comfort, Power, and Cooling

Ref. [52] built an automated platform that offers data on home power consumption in each Taiwanese city. To anticipate future domestic electricity consumption, ML was employed. Furthermore, to improve the accuracy of the top machine learner, a nature-inspired optimization strategy was used, resulting in an even superior hybrid ensemble model. The suggested approach in [53] is a hybrid of artificial neural networks and stochastic fractal search (SFS-ANNs) designed to handle the problem of early cooling demand prediction in buildings. To forecast indoor temperature more correctly and effectively, Ref. [54] presented a hybrid model based on feature selection approaches such as feature significance and support vector regression (SVR). Ref. [7] created a recurrent neural network (RNN) model with a one-hour resolution to produce medium-to-long-term predictions of power consumption profiles in commercial and residential buildings. Ref [9] employed ML to bridge the gap between controlled building factors and thermal comfort. The study demonstrated that neural networks are good ML approaches for simulating comfort levels.

3.1.3. Circulation and Automation

The study [55] takes advantage of the image collecting and processing system's knowledge of passenger group sizes and waiting durations. The objective was to create a decision engine that could govern the elevator's movements while increasing user satisfaction. Ref. [56] investigated edge AI-enabled technology and suggested a fully featured IoT and edge computing-based cohesive system for smart home automation.

3.2. Outdoor Environment

3.2.1. Pollution—Air, Noise, and Waste

- Air pollution

Ref. [57]'s study on AI-based air quality early warning systems is expected to play a vital role in its future accuracy and usefulness. Ref. [58] suggested an improved ML strategy for predicting urban ambient particulate matter ($PM_{2.5}$) concentrations that combines cascade and PCA algorithms to reduce data dimensionality and investigate nonlinear relationships across variables. Ref. [59] proposed a novel algorithm based on cloud model granulation (CMG) for air quality forecasting. Ref. [60] developed a system that monitors and forecasts urban air pollution by using ML algorithms to construct credible forecasting models for various air pollutant concentrations. Ref. [61] suggested a network that predicts future air quality, resulting in cutting-edge performance in urban air quality prediction. Ref. [62] presented an ML technique based on six years of meteorological and pollutant data analysis to forecast $PM_{2.5}$ concentrations from wind (speed and direction) and precipitation levels. Ref. [63] presented a cost-effective and efficient air quality modelling framework that incorporates various elements while utilizing cutting-edge AI-based approaches.

Using environmental monitoring data and meteorological observations, Ref. [64] developed an ML-based strategy for reliably predicting the air quality index. Ref. [65] created a regression model of daily air quality forecast using the SVM approach at the local scale in the Gijón metropolitan region of Northern Spain. Ref. [66] investigated a new technique of daily air pollution prediction based on observed carbon mono oxide (CO) concentrations utilizing a combination of Support Vector Machine (SVM) as a predictor and Partial Least Square (PLS) as a data selection tool.

- Waste

Ref. [2] created a rule-based ML model to assess the influence of city and nation variables on the disposal of waste. The findings identified municipal government, employment, and technical research as key factors influencing sustainable waste management. To choose waste-to-energy plants, Ref. [67] created and used a hybrid framework that included the analytical hierarchy method with ML approaches. Ref. [68] offered an investigation of three AI-related models as tools for forecasting the development of urban solid waste in the city of Bogota to learn the behaviour of such types of waste.

- Noise

Renaud [14] investigated the capacity of Gradient Boosting and Deep Learning to produce long-term noise level forecasts using noise data gathered in a suburb of an English metropolis and then offered a strategy for identifying noise level anomalies based on predictions.

3.2.2. Real Estate and Prices

Ref. [69] offered an overview of ML approaches for forecasting property values. Ref. [70] provided an experiment on estimating real estate prices using seven ML approaches and five years of historical data on real estate transactions in major French cities. A unique ML approach was presented in [71] to address the complexity of real estate modelling. The study investigated the possibility of call detail data for forecasting real estate prices using AI. Ref. [72] used ML approaches to forecast house prices in two Italian cities. Ref. [73] developed an innovative and complete model for calculating the price of new houses during the design or early construction phase by combining a deep belief-restricted Boltzmann machine with a unique non-mating genetic algorithm. Ref. [11] employed location-based services APIs as an urban data source to assess the attractiveness of a residential area for users looking for long-term rental apartments by developing a machine learning model to forecast days on the market. As a research approach, ML algorithms were employed in the study [74] to construct a house price forecast model.

3.2.3. Infrastructure Development

Sousa et al. [75] combined semantic modeling and data-driven AI methodologies to deliver autonomous assessments for the operation of a public street lighting network to maximize energy usage while maintaining light quality patterns. To optimize the waste management process, ref. [76] presented an AI-based Hybridized Intelligent Framework (AIHIF) for automated recycling. The system introduced using ML and graph theory will maximize waste collection within a limited distance. Ref. [77] suggested an ML-based technique that could be utilized to extract elements of regional architectures and assess architectural forms in the process of urban redevelopment. Ref. [78] offered a novel AI-based technique for an urban-scale application that quantifies both subjective and objective human-scale streetscape perceived quality. Ref. [79] used ML algorithms to create models to aid in quick decision-making for optimal resource allocation in the aftermath of disruption and to assist investment decisions for the structural reconfiguration of urban systems.

Ref. [80] created a unique hybrid AI model that predicted building destruction in South Korean redevelopment zones by combining standalone algorithms with architectural and engineering technologies. Ref. [20] demonstrated how the multi-zone optimization (MUZO) methodology developed in the first phase of their research project could improve the overall performance of a high-rise building in crowded metropolitan neighbourhoods. Ref. [81] explored the various challenges in the formulation and execution of overall country-specific urban planning by combining big data technology and ML to build a virtual design model of urban planning and develop the functional structure of the model based on actual demands. Ref. [82] presented the MUZO methodology that supports decision-making for high-rise buildings per floor levels and performance aspects.

3.2.4. Life Cycle Assessment and Rainfall Prediction

Koyamparambath et al. [83] explored AI techniques to forecast the environmental performance of a product or service per life cycle assessment (LCA). The data is processed using natural language processing (NLP), which is then taught to the random forest method, an ensemble tree-based machine learning approach. Ref. [84] combined fuzzy cognitive maps with a metaheuristics-based rainfall prediction system (FCMM-RPS). The FCMM-RPS approach aims to predict rainfall in an automated and efficient manner.

3.2.5. Other Applications

Bui et al. [85] offered an ML approach to replace traditional testing for determining the coefficient of soil compression. The novel method combines the Multi-Layer Perceptron Neural Network (MLP Neural Nets) with Particle Swarm Optimization (PSO). Using AI/ML approaches, ref. [86] focused on environmental injustice. Ref. [87] investigated a metamodel-based method that included simulated data gathering and data-driven approaches for forecasting and optimizing heating and cooling loads in three different climates in Morocco.

4. Roles of AI and ML in Construction Processes

The roles of AI and ML are discussed in this section. The roles are discussed per the classification of the construction phases, namely preconstruction, construction, and post-construction phases. The detailed discussions follow next.

4.1. Pre-Construction Phase

4.1.1. Risk and Cost Estimation

Ref. [88] used ML to predict contractor risk and support decision-making at each project step, based on data gathered during the project development stages. Ref. [19] introduced the XGBoost model as an input selector and predictor to improve cost estimation accuracy. Ref. [18] described two main modules, Critical Risk Check (CRC) and Term Frequency Analysis (TFA), that were developed as a digital contract risk analysis tool for contractors by merging AI and text-mining techniques. Ref. [16] proposed an ML technique to create leading indicators that identify building sites based on their safety risk. Cost overrun difficulties in construction projects can be addressed by focusing on cost overrun risk relationships throughout the risk assessment process [89]. Ref. [90] sought to improve the efficacy of risk management (RM) in construction projects by building a knowledge-based RM tool using case-based reasoning.

4.1.2. Other Applications

Rashidi et al. [91] compared the efficacy of various ML approaches for detecting three typical construction materials: concrete, red brick, and oriented strand board (OSB). Using ML approaches, ref. [92] offered a model for estimating carbon footprint at an early design stage. Ref. [93] developed an ensemble approach to improve building cooling and heating load prediction. Using AI-based technologies, the study [94] aimed to answer the problem of determining the professional adaptive capacities of construction management employees. Ref. [95] aimed to identify the features of competent project managers using expert opinion and to evaluate their competence level using a questionnaire survey to create a prediction model using a supervised ML methodology.

4.2. Construction Phase

4.2.1. Safety Management

The study [6] centred on the application of AI to develop a better hybrid model for narrating construction accidents, which included the Gated Recurrent Unit (GRU) and Symbiotic Organisms Search (SOS). Ref. [96] evaluated the identification of safety vests using colour information in construction-site photos. The study employed six different types of ML algorithms to classify safety vest pixels based on colour models of safety vests created from data sets. Ref. [97] presented a less expensive accident-avoidance method that detects the presence of mobile equipment using auditory signals. The study addressed the issue by enhancing the auditory situational awareness of construction workers exposed to loud noises using a unique sound detection model that employs AI to detect the sound of collision hazards hidden in a plethora of ambient noises. The study was divided into three phases:

1. gathering audio data from construction equipment;

2. constructing a novel audio-based ML model for the automated identification of collision hazards; and
3. performing field trials to assess the system's efficiency and latency.

Ref. [98] aimed to forecast occupational accident outcomes using ML approaches combined with various resampling procedures based on national data. Baker et al. [99] verified the prior study's NLP and ML strategy by demonstrating that qualities still have excellent predictive power when the safety outcomes are external and independent. Ref. [100] aimed to create a nationwide data-driven safety management system based on accident outcome prediction, which can help anatomize fatality precursors and hence reduce fatal accidents on construction sites. Ref. [101] created a thorough framework for predicting construction employees' post-accident impairment status. Ref. [102] used ML models to forecast injury kinds and then developed safety measures in construction. Ref. [103] aimed to enhance construction safety management by using discrete wavelet transform (DWT) and other ML approaches to estimate the frequency of occupational accidents using time series data. Ref. [17] developed a scenario-based automated pre-processing algorithm that identifies the best scenario for forecasting the severity of construction accidents.

4.2.2. Planning, Scheduling, and Construction Equipment

Ref. [104] used text-clustering approaches and neural network language models to cluster construction activity names. The research revealed ways to pre-process activity names from building schedules for subsequent AI-based quantitative analysis. To determine class membership among major construction equipment categories, ML techniques such as k-nearest neighbours and support vector machines are used [105]. Using point cloud data, the study developed a new principle axis descriptor for construction-equipment classification. Following an NLP-based multi-stage ranking formulation, Ref. [106] offered the first attempt to automate tying look-ahead planning tasks to master-schedule activities. To improve the practicability of package-based constraint management (PCM) knowledge bases [107] addressed the identified incompleteness issue in previous similar studies.

4.2.3. Construction Management, Human Resources, and Conflict Resolution

The study [15] looked at the process of knowledge discovery in databases to uncover the reasons for construction delays. Ref. [108] suggested an ontology-based, multilabel text classification (TC) technique for categorizing environmental regulation phrases in construction to facilitate automated compliance checks. Ref. [109] introduced a support vector machine (SVM) learning strategy for automated progress monitoring for construction projects, which tracks, analyses, and displays the as-built status of buildings under development. Per [110], the opportunity to automate monitoring for construction management processes using AI facilitated the development of an automated construction management system aimed at improving management and remote monitoring of substation construction.

Naumets and Lu [4] presented a situation in which AI algorithms were used to anticipate project labour hours based on prebid estimate data. Ref. [1] employed ML techniques using empirical data to forecast the occurrence of conflicts in the construction process. Ref. [111] presented a unique way for creating and testing a low-cost, ubiquitous construction worker activity detection system capable of identifying a variety of behaviours common on construction sites. By combining generative adversarial networks, autoencoder, ML, and robot adaption approaches, Ref. [112] offered a unique physiological computing system that enables the collaborative robot to efficiently assess construction workers' psychological states and manage its performance.

4.3. Post-Construction Phase

Lu et al. [8] emphasized using AI-enabled digital twins in facility management. Ref. [113] highlighted the potentials, restrictions, and possible solutions of employing ML/AI techniques at the design stage of deep renovation building projects using As-Built BIM models as input to enhance decision-making toward the adoption of energy-saving measures. The compressive strength of alkali-activated construction demolition waste geopolymers (CDWG) was predicted by [114] using random forest (RF), gradient boosting (GB), and extreme gradient boosting (XGB). Cakir and Akbulut [12] aimed to assist building managers in predicting the heat experience of occupants under specified conditions. The study created and tested a deep neural network (DNN) for accurately forecasting temperature sensations independent of building characteristics.

5. Conclusions

5.1. Overview of Current Applications of AI and ML

AI and ML technologies play crucial roles in creating sustainable communities, both in indoor and outdoor environments. In the indoor environment, they contribute to energy management by optimizing energy usage, identifying inefficiencies, and suggesting improvements to reduce consumption. This helps to minimize the environmental impact associated with energy generation. Similarly, AI and ML technologies help address pollution concerns. They can monitor air quality, noise levels, and waste management systems to promptly detect and mitigate pollution sources. This information can be used to develop effective strategies for reducing pollution and improving the overall environmental quality of the community.

Furthermore, AI and ML technologies have significant roles in various stages of the construction process, from pre-construction to post-construction phases. These technologies enhance efficiency, safety, and sustainability throughout the construction lifecycle. Through the SR, this study attempts to evaluate the roles of AI and ML in optimizing construction processes and developing more sustainable communities. The review aims to identify not only the roles of AI and ML in facilitating the development of sustainable communities and construction processes but also future research trends and practical applications of AI and ML in the built environment. Figures 8 and 9 outline the present roles and applications of AI and ML technologies in enabling sustainable communities and construction processes, as presented in this study.

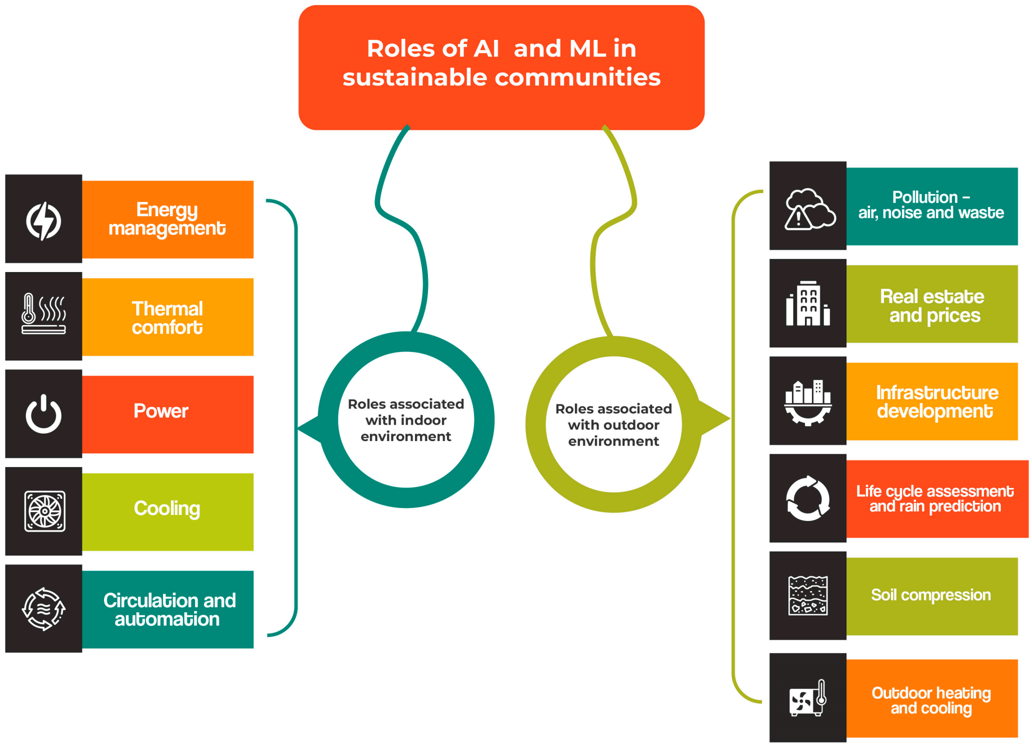

Figure 8. AI and ML applications in enhancing sustainable communities.

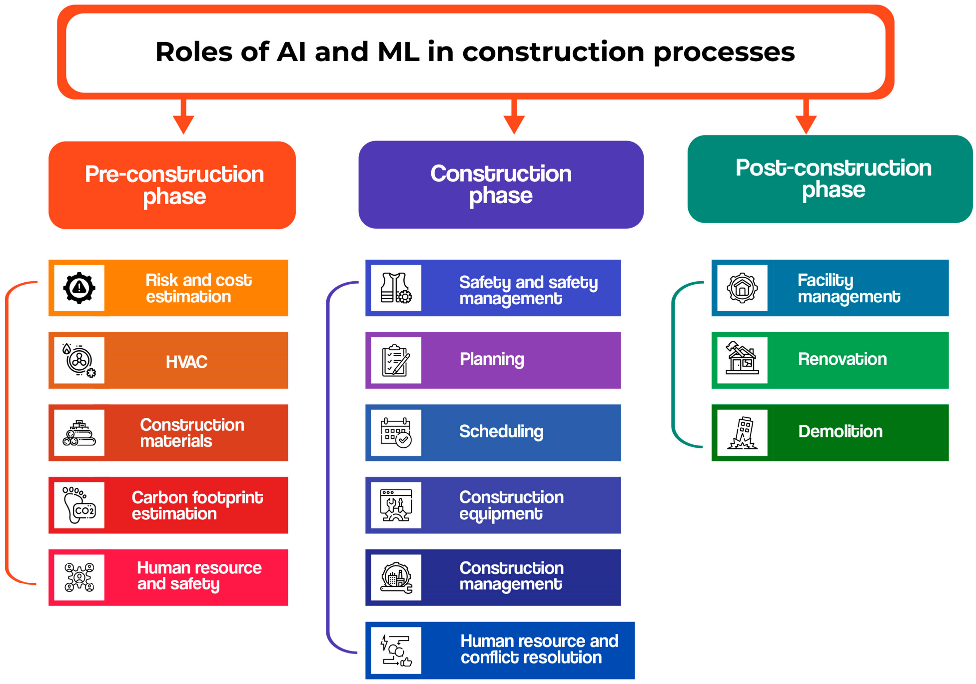

Figure 9. Roles of AI and ML in construction processes.

The roles of AI and ML in the construction of sustainable communities that have been recognized are centred on both indoor and outdoor environments. The former includes applications such as energy management, thermal comfort, electricity, cooling, circulation, and automation, whereas the latter includes applications in reducing pollution, estimation of real estate prices, and LCA, among others. Similarly, the applications of AI and ML technologies in construction processes have been highlighted at all stages, namely pre-construction, construction, and post-construction.

5.2. Study's Contribution to Practices and Future Direction

This study's relevance spans practice and research in the AEC domain. As a result of the study's emphasis on the critical roles of AI and ML technologies in both indoor and outdoor environments, as well as at all stages of construction processes, valuable insights for construction professionals facilitating informed decisions regarding the implementation of these technologies for sustainable development abound. Similarly, as technology plays an increasingly crucial role in the built environment, it is critical to harness its power for the benefit of society and the environment. The study adds to the developing field of sustainable development by highlighting the key applications of AI and ML in sustainable construction and giving a roadmap for future research and development in this area.

The study's main shortcoming is the lack of a detailed depiction of AI and ML techniques. However, the findings emphasize that AI and ML technologies play a vital role in advancing global efforts toward a sustainable and environmentally friendly built environment. AI and ML technologies are critical in sustainable construction, notably in energy management. Furthermore, by monitoring and detecting pollution sources in real time, these technologies help in tackling environmental concerns such as pollution. Finally, the future trends of AI and ML in construction processes and sustainable communities revolve around enhanced automation, optimization, and decision-making capabilities. These technologies will continue to revolutionize the construction industry, driving efficiency, safety, and sustainability in the built environment.

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Appendix A

Table A1. Sources of included articles.

Source	Number
Automation in Construction	9
Sustainability	7
Energies	6
Journal of Construction Engineering and Management	6
IEEE Access	5
Journal of Computing in Civil Engineering	4
Energy	3
Expert Systems with Applications	3
Sustainable Cities and Society	3
Applied Energy	2
Energy and Buildings	2
Journal of Building Engineering	2
KSCE Journal of Civil Engineering	2
Solar Energy	2
Others	41
Total	97

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