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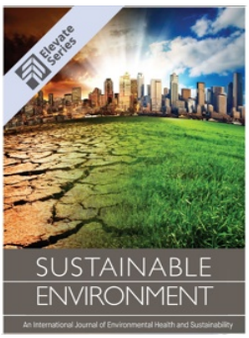

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Critical review of using artificial intelligence for environmental, social and governance (ESG) assessment in construction

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ABSTRACT

The rise in the use of artificial intelligence (AI) in every facet of life is associated with some benefits and constraints, especially in non-information technology-related fields. This study evaluates the current landscape of artificial intelligence (AI) techniques, drivers and barriers to environmental, social and governance (ESG) assessments within construction project management (PM). The study adopted a systematic literature review approach. It involved formulating research questions, identifying search keywords, collecting and screening the articles and thoroughly examining the literature to determine the emerging AI techniques, critical drivers and barriers to AI adoption for ESG assessment and proposing future research avenues. Using Scopus, 129 related papers were selected for the review. ESG assessment in construction PM has significantly relied on machine learning techniques, with environmental and governance areas being the primary focus. Some emerging techniques include deep learning for image recognition and natural language processing for text analysis. The top three drivers for adopting AI for ESG assessment are the reduction in human errors in ESG assessment, improved efficiency in ESG assessment and efficient data management. The top three barriers are a lack of critical ESG data/information, inadequate AI construction expertise and the high cost of maintaining AI systems. The findings of this research will inform project professionals and policymakers about the innovative and reliable AI technologies they can utilise in projects to achieve more sustainable outcomes. Overall, the study presents a collection of observations, propositions and pathways for future efforts that examine the contribution of AI-driven PM research to ESG issues.

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Artificial intelligence; construction industry; construction management; environmental, social and governance; systematic literature review; project management.

1. Introduction

Environmental, social and governance (ESG) assessment has emerged as a vital aspect of project evaluation, with stakeholders increasingly recognising its importance in promoting sustainable development practices (Boadi et al., 2026a; Friede et al., 2015; Sadiq & Khalfan, 2025; WBCFSD, 2019). These three facets (environmental, social and governance) are fundamental to a firm's long-term strategy and facilitate responsible and sustainable project services (Işık et al., 2026). Consideration of ESG allows interested parties to evaluate a project's potential impacts on the environment, society and governance, including issues like climate change, resource depletion, human rights, community engagement, corruption and board independence (WBG, 2017). According to Podrecca et al. (2022), ESG assessment enables project investors to mitigate risks, identify opportunities and align their portfolios with sustainable development goals. By considering ESG factors in construction projects, investors and other stakeholders are better informed about project outcomes, including return on investment, value for money and benefits to society that will ultimately promote responsible and sustainable initiatives (Boadi et al., 2026b).

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Sustainability assessment has evolved to integrate ESG factors, which are essential for internalizing risks caused by external factors like climate change. The Environmental pillar focuses on quantifying impacts such as embodied carbon emissions, energy consumption and pollution. Advanced tools such as Building Information Modelling (BIM) and IoT enable real-time monitoring and life-cycle assessments (LCA), which are identified to help optimise resource use and reduce ecological footprints (Shehadeh and Alshboul, 2024, 2025). The Social dimension addresses the human dimension, including safety, user comfort and community impacts. Digital extensions such as 'Social ADE' are proposed to link physical asset data with service-user perceptions, ensuring that infrastructure functions as a competent sociotechnical system (Zarei and Nik-Bakht, 2024). The governance dimension provides a framework for regulatory compliance, institutional transparency and accountability. Technologies such as blockchain are increasingly vital for creating traceable records of sustainability data, thereby preventing the falsification of emission reports and supporting credible policy implementation (Yoon & Aurangzeb, 2026). Research demonstrates that Artificial Intelligence (AI) enhances ESG assessment by automating data collection through IoT and BIM, providing precise predictions for carbon emissions and energy usage. For instance, Machine Learning (ML) models have been used to optimise material selection and quantify complex socio-environmental risks in construction projects (Kissi et al., 2025). Furthermore, Explainable AI (XAI) ensures governance transparency by identifying the specific factors influencing sustainability outcomes (Amro et al., 2026).

Artificial intelligence techniques used in construction project management (PM) have gained significant traction in recent years (Kissi et al., 2025). Project professionals use them to augment their managerial processes, including decision-making, performance evaluation, resource allocation and employee selection (Karki & Hadikusumo, 2023; Ottaviani et al., 2024; Razi & Ansari, 2024; Wang et al., 2024). AI applications are also used to enhance PM tasks, and techniques such as machine learning and neural networks assist in risk assessment, task scheduling and cost estimation (Darko et al., 2023; De Marco et al., 2024; Narbaev et al., 2024). The research has revealed a positive relationship between AI adoption in an organisation and its effectiveness in delivering projects more successfully (Kozhakhmetova et al., 2024; Nenni et al., 2024; Shang et al., 2023). Past studies have explored how integrating AI within the PM field supports various project assessments throughout the project lifecycle.

Recent studies highlight the potential of AI in ESG assessments in projects. For instance, some research has investigated the use of machine learning algorithms to predict environmental impacts (He et al., 2023; Maceika et al., 2024), while others have examined AI-driven methods for analysing social risks and community engagement (Malek & Bhatt, 2024). Also, adopting AI for ESG assessments in PM can significantly contribute to achieving the United Nations' Sustainable Development Goals (SDGs). By facilitating efficient and data-driven evaluations of ESG factors, AI algorithms could assist project managers and stakeholders in identifying potential impacts more accurately, allowing for informed decisions that minimise adverse effects while maximising positive contributions to the SDGs (Işık et al., 2024a). For instance, AI-driven assessments can enhance the understanding of climate change mitigation strategies (SDG 13), promote inclusive and sustainable cities (SDG 11) and improve governance evaluations, thereby fostering accountable institutions (SDG 16) (Alshboul et al., 2025; Amade & Nwakanma, 2021; Solana-González et al., 2021; Zhang et al., 2023). AI algorithms can analyse vast amounts of data, enabling project managers to identify trends, patterns and correlations that might otherwise go unnoticed. For instance, Lipianina-Honcharenko et al. (2024) illustrated how AI-driven predictive analytics can assist with crisis demand forecasting, facilitating swift market adjustments and strategic inventory management, which allows for proactive mitigation strategies contributing to SDG 9: Industry, innovation and infrastructure.

With the increasing interest in using AI techniques in PM, there is still a need for research to understand how these AI methods can be effectively utilised to enhance sustainability practices (Razi & Ansari, 2024; Wang et al., 2024). Limited research has systematically reviewed AI applications for ESG assessments. Past studies often focused on isolated aspects of ESG assessments or overlooked AI in such assessments. This study advances the integration of ESG assessment within construction by synthesizing the application of artificial intelligence through the lenses of systems thinking and sustainability theory. While existing research acknowledges AI's role in augmenting managerial processes (Kissi et al., 2025; Kozhakhmetova et al., 2024), these works failed to establish the barriers to AI adoption. Theoretically, this current study integrates a system thinking approach to establish specific barriers to AI adoption within the context of ESG. Because ESG assessment has become crucial for achieving net-zero ambitions and sustainability

practices in construction, it is essential to evaluate and identify existing trends in AI applications for ESG assessment in construction. Practically, this study provides project professionals with answers on how AI can improve the social dimension of infrastructure projects. This study uniquely integrates descriptive analysis, content analysis and develops a matrix of data sources and AI techniques for ESG assessment. Additionally, the study classifies AI techniques and algorithms that support construction-related ESG assessment. Against this background, this study aims to review the existing AI applications used for ESG assessment in the field. It seeks to enhance the communication of sustainability practices and contribute to a deeper understanding of more efficient AI-driven approaches for holistic ESG assessments, enabling more sustainable project management in the future. For this, the research puts forward the following questions:

1. What AI techniques and algorithms are available for ESG assessment in PM?
2. What tasks does AI perform in ESG assessment?
3. What are the drivers of and barriers to adopting AI in ESG assessment? What directions for future studies do they indicate?

The contributions of this study are two-fold. First, the study analyses the existing AI techniques and algorithms for ESG assessments in construction projects. It classifies them by tasks performed and across the three areas (environmental, social and governance). This will provide a solid foundation for future studies on the application of AI for ESG assessments in projects. Second, the research identifies the drivers of and barriers to the adoption of AI in PM. Project professionals and policymakers in the field can promote the drivers and address the barriers to facilitate the adoption of AI for ESG assessments in future projects. Such findings will also inform practitioners about the innovative and reliable technologies that can be employed in projects to achieve more sustainable outcomes.

2. Methodology

The study adopted a systematic literature review that followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. This approach demonstrates an unbiased and scientifically valid exploration of the research questions (Page et al., 2021). Similar studies in the field established the appropriateness of using this approach to examine emerging research topics (Naz et al., 2022). The methodology involved formulating research questions, identifying search keywords, collecting and screening the articles and examining the literature to determine the drivers and barriers to AI adoption for ESG assessment, and proposing future research avenues.

2.1. Literature search and screening

This study utilised only the Scopus database to search and collect academic literature related to the research scope. This database is selected as it covers most of the publications within the field of construction and project management (Boadi et al., 2026b). Therefore, it was considered prudent to use Scopus for the search. The search terms represented the three research domains (AI, ESG and PM). AI was represented by terms such as artificial intelligence, machine learning, natural language processing, computer vision, deep learning and neural networks. ESG was represented by terms such as sustainable, sustainability, environmental, social and governance. PM was represented by terms such as project approach, project management and construction project. The search was conducted in October and November 2024. Literature was searched using combinations of these keywords; for instance, the 'OR' was used for the terms within each dimension and 'AND' for combining the two dimensions. An asterisk at the end of a search keyword was used to cover a broad range of results. Using the word builders the following search terms were used; TITLE-ABS-KEY ('Artificial intelligence' OR 'machine learning' OR 'natural language processing' OR 'computer vision' OR 'deep learning' OR 'neural networks' OR 'Algorithm') AND TITLE-ABS-KEY ('Environmental, Social and Governance' OR 'ESG*' OR 'social sustainability' OR 'Corporate Social Responsibility' OR 'Environmental Sustainability' OR 'Governance Sustainability') AND TITLE-ABS-KEY ('project approach' OR 'project management' OR 'Construction*' OR 'construction project').

The search in Scopus returned 549 records (Figure 1). Papers not meeting the inclusion criteria, such as non-English books, conference papers, notes, data papers, retracted works, book chapters, short surveys and duplicates, were excluded from the study. To ensure methodological rigour, the study selected peer-reviewed articles published in journals with an impact factor above 1.70 (Denicol et al., 2020). This screening resulted in 212 articles. Next, based on abstract and full-text readings, the study retained 129 articles for the final review.

2.2. Literature analysis

The review employed a rigorous data analysis to ensure accurate and comprehensive extraction of relevant information from the selected articles. The authors read all 129 articles to ensure a thorough understanding of the issue and to extract pertinent information accurately. The review elements included specific AI techniques and models, data source, the tasks they perform in ESG assessment and their distribution across the three pillars (environmental, social and governance). All this information was analysed thematically using the content analysis technique (Braun & Clarke, 2008). The frequency of each review element's occurrence was determined by the number of articles in which it appeared, reflecting the prevalence of specific AI techniques, models and their tasks within the PM literature.

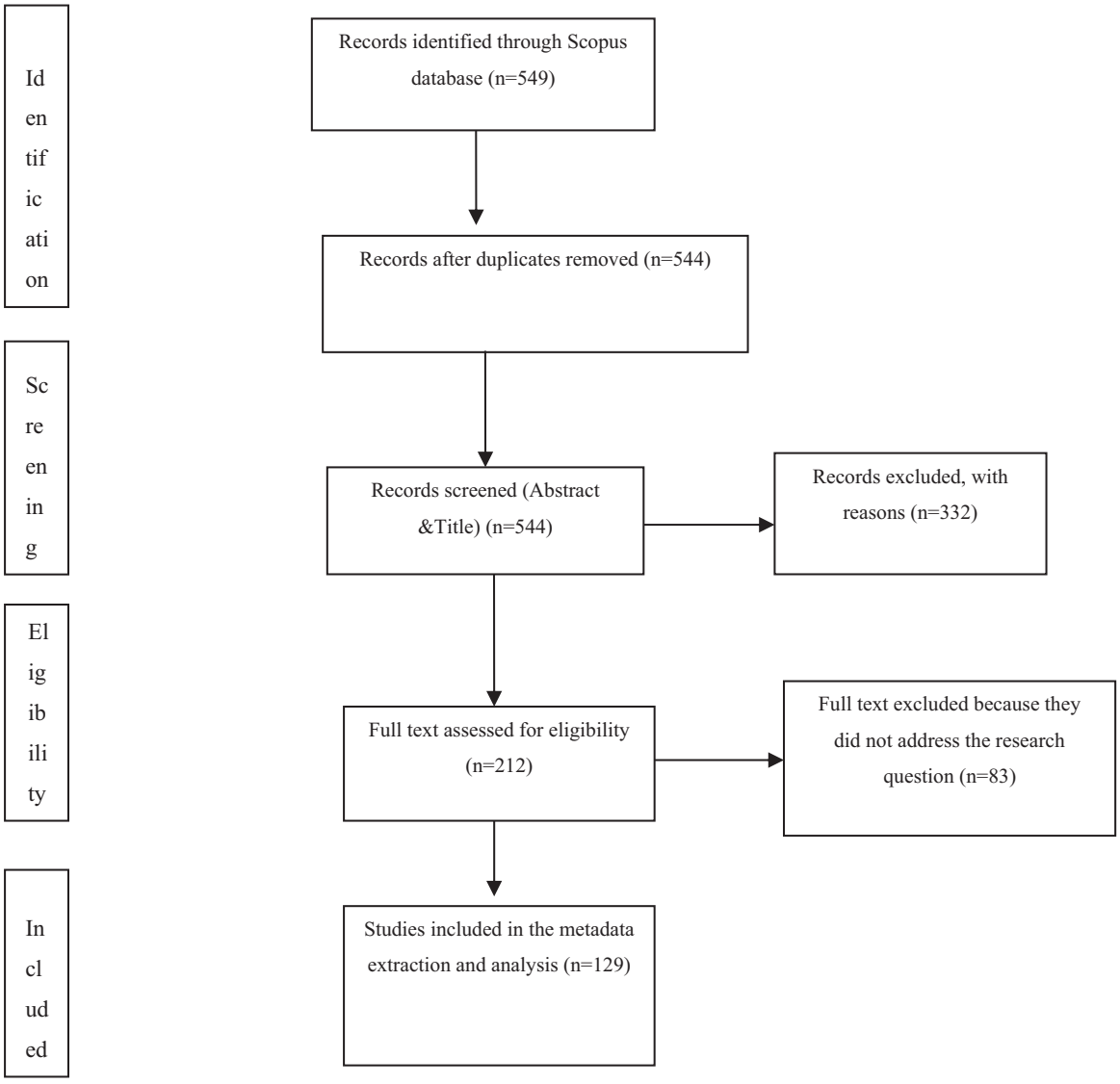

Figure 1. PRISMA flow chart.

3. Results and discussions

Having described the systematic literature review approach, the results and discussion section presents analysis, synthesis and discussion of findings. The next section presents the dominant AI techniques identified.

3.1. Dominant AI techniques and tasks performed for ESG assessment

Table 1 presents the distribution of studies on applying various AI techniques derived from the selected studies. As indicated earlier, the AI techniques were derived from the papers through a thorough review of the selected papers. Results show that the most widely used AI technique for ESG assessment is machine learning (ML), followed by neural networks (NN), generative AI, heuristics, fuzzy logic, natural language processing (NLP), deep learning (DL) and computer vision.

ML methods are significantly more prevalent in assessing ESG factors. Notably, predictive models like ML-based regression trees have gained significant attention for their effectiveness in forecasting project outcomes based on historical data. A review by Taboada et al. (2023) established that ML is considerably useful in managing construction and IT projects, providing promising forecasting and decision-making capabilities. It is further demonstrated that some unsupervised learning methods, such as clustering algorithms employed by project managers, are used to group similar projects or identify patterns in large datasets that connect project characteristics with ESG performance outcomes (Du, 2021).

Another prominent technique is NN, which is particularly effective in managing non-linear relationships between variables relevant to sustainability metrics within PM contexts (Jain et al., 2024). Encouragingly, within rapid development, Wen et al. (2024) have used the backpropagation NN to construct an opportunistic behaviour recognition model to detect the level of opportunistic behaviour risk for project governance. Generative AI methods were used to synthesise, automate and monitor data collected from various stakeholders. Examples include feedback collected from project stakeholders and project reports to identify ESG issues (Chai et al., 2024). This technique was frequently used to automate periodic reporting of project expenses and respond to suppliers and customers upon their request. NLP techniques were employed for the sentiment analysis of stakeholder feedback concerning ESG initiatives in PM practices. For instance,

Table 1. Dominant AI techniques used for ESG assessment.

AI technique	Tasks performed in the ESG assessment	Frequency of 129 (%)	Key references
Machine learning	Classification, clustering, dimensionality reduction, object detection, object recognition, prediction, regression, risk analysis	43 (33.3%)	Yaakobi et al. (2019) Lipianina-Honcharenko et al. (2024) Deepa et al. (2023)
Neural networks	Anomaly detection, classification, object detection, object recognition, pattern mining, prediction, real-time monitoring, regression, risk analysis, rule-based classification	25 (19.4%)	Shao et al. (2018) Lu et al. (2023) Liu and Ran (2020) Han and Wang (2021)
Generative AI	Anomaly detection, automation, classification, real-time monitoring, regression	15 (11.6%)	Hamid et al. (2020) Mishra et al. (2023) Naz et al. (2022) Jang et al. (2021)
Heuristics	Classification, clustering, recommendation, regression, risk analysis, rule-based classification	15 (11.6%)	Kanyilmaz et al. (2022) Eirgash and Toğan (2024) Akbari et al. (2018)
Fuzzy approach	Classification, emotion modelling, frequent pattern mining, regression, risk analysis, sentiment analysis	11 (8.5%)	Hussain and Hussain (2023) Amade and Nwakanma (2021) Sahu et al. (2018)
Natural language processing	Classification, natural language generation, sentiment analysis, topic modelling	9 (7.0%)	Wu et al. (2022) Morales-Ramirez et al. (2019) Yaakobi et al. (2019)
Deep learning	Anomaly detection, automation, object recognition, object segmentation, prediction, regression, risk analysis	8 (6.2%)	Liu et al. (2024) Wang et al. (2024) Zhao (2024)
Computer vision	Object detection	3 (2.3%)	Xiao et al. (2024) Chau et al. (2024)

Zhang et al. (2018) purport that using data from public opinion on water conservation projects and employing NLP techniques, namely sentiment analysis and topic modelling, provided real-time monitoring of public opinion and improved the level of public participation.

3.2. Data sources for using AI in ESG assessment

The data sources for employing AI in ESG assessments were examined, as displayed in Table 2. The table also lists the number of articles that utilised these sources. However, only the key references are included in the last column of the table. As shown in Table 2, the most prevalent data sources included project data, mentioned in 42 examined articles out of 129 (32.6% of the articles), multiple sources (29, 22.5%) and literature reviews or case studies (18, 14.0%). Experimental and environmental data accounted for 13.2% of all articles; these data sources provide context-specific insights, such as environmental impact assessments (Maceika et al., 2024). Digital media data (15, 11.6%) significantly contributes to AI in ESG assessment. Data from office activities, schedules and user interactions demonstrate the importance of practical experience and user insights in understanding AI's application in ESG assessment (Tambe, 2008). Expert opinions and interviews (8, 6.2%), though less frequent, offer valuable perspectives from practitioners, such as those gathered through Delphi surveys (Wang et al., 2024) or interview-based studies (Bang & Andersen, 2022).

Also, the combination of multiple sources allows for a comprehensive understanding of AI's adoption, benefits, barriers and best practices in PM, as seen in studies combining expert opinions with literature reviews or case studies (Chang & Liang, 2023; Karki & Hadikusumo, 2023; Wuni, 2024). These data sources present a robust representation of AI's integration into construction PM and balanced insights from academic and practical perspectives.

3.3. AI techniques, their algorithms and application areas in ESG assessment

Table 3 presents the AI techniques identified, their algorithms and the sustainability areas to which they have been applied in ESG assessment. Exploring these sustainability areas is crucial for understanding the key domains within ESG where AI has been predominantly employed. Consequently, the figures in the table indicate the number of articles associated with these sustainability areas. This insight will guide future research and practices regarding which AI technologies and their algorithms are suitable for specific sustainability pillars of ESG assessment.

ML algorithms are found to be widely utilised for ESG evaluation. This technique involves learning from diverse data sources, including digital media from construction sites, expert opinions and project data or records automatically related to a task and performance measure. For instance, a study by Jain et al. (2024) used expert survey data and applied ML techniques to develop a framework for contractor selection and order allocation. This framework minimises time and cost overruns by considering diverse criteria for contractor selection. Also, using multiple sources of datasets, Karki and Hadikusumo (2023) used ML techniques to identify the characteristics of competent project managers. ML algorithms can identify patterns and relationships in data that facilitate accurate predictions regarding ESG risks. The table also lists unsupervised learning techniques, such as association rule mining, which is used for requirement elicitation during project initiation phases, and supervised learning methods, like random forests, utilised for predicting project success probabilities.

NN also relies on project data and records and multiple data sources for its investigations. All these AI techniques handle vast amounts of data and interconnected information. This technique gains knowledge through a learning process. Therefore, modelling is based on biological NN structures, processing methods and learning abilities (Balusamy et al., 2021). NN techniques primarily integrate deep and ML methods for their application investigation. According to Han and Wang (2021), artificial neural network algorithms such as backpropagation NN, convolutional NN, long short-term memory and hybrid versions are proven to be a beneficial capacity to predict water quality effectively to monitor water indicators leading to increased sustainability standards.

Generative AI techniques represent a category of DL designed to generate various data modalities, including text, images, audio and videos, similarly to how humans do (Aggarwal et al., 2021). Therefore,

Table 2. A matrix of data sources and AI techniques in ESG assessment.

Data sources	Computer vision	Deep learning	Fuzzy approach	Generative AI	Heuristics	Machine learning	Natural language processing	Neural networks	Frequency of 129 (%)	Example sources	Key references
Project data and records	1	3	1	4	7	15	1	10	42 (32.6%)	Contractor records, BIM data, IoT sensor data, accident cases, historical records, design briefs, site characteristics	Jain et al. (2024) Poh et al. (2018) Kanyilmaz et al. (2022)
Multiple sources	1	3	4	4	1	6	6	4	29 (22.5%)	Combination of one or more sources of data	Ershadi and Ashtiyani (2019) Morales-Ramirez et al. (2019) Hakimi et al. (2024)
Literature reviews and case reviews	0	0	2	5	2	6	0	3	18 (14.0%)	Literature review, case study	Lu and Antwi-Afari (2024) Kiani (2024)
Experimental and environmental data	2	0	3	0	4	4	1	3	17 (13.2%)	Concrete mixtures, environmental impact assessment, policy document	Kumar et al. (2024) Nessari et al. (2024) Pallaske (2024)
Digital media and user interaction	2	4	0	1	1	3	1	3	15 (11.6%)	Office activities, schedules and user interactions, video feeds, text, images, videos, audio, sensors and other digital sources	Aljawder and Al-Karaghouli (2024) Tambe (2008) Serrano (2022) Su et al. (2021)
Expert opinions and interviews	0	0	1	1	0	4	1	1	8 (6.2%)	Expert interviews, questionnaire survey, Delphi surveys	Maceika et al. (2024) Wang et al. (2024)

Table 3. AI techniques, algorithms and areas they are used for in ESG assessment.

AI techniques	Algorithms/methods	Environmental	Social	Governance	General sustainability
Machine learning	Support vector machines, random forest, AdaBoost, k-nearest neighbours, gradient boosting regression, repertory grid technique, naïve Bayes, sequential minimal optimisation, logistic regression, Kstar, J48, random forest	22	1	16	4
Neural networks	Backpropagation neural networks, Bayesian neural networks, backpropagation algorithm, feedforward neural networks or multilayer perceptron, recurrent neural networks, long short-term memory	13	–	11	1
Generative AI	Smart contract algorithms, self-organising map, simulated annealing, generative adversarial network	2	2	11	
Heuristics	Genetic algorithms, opposition-based learning, tournament selection, mutation and crossover, analytic hierarchy process, technique for order of preference by similarity to ideal solution, support vector machines, minimum spanning tree, maximum critical path, spatial perception models	11	1	2	1
Fuzzy approach	Fuzzy inference system, weighted sum method, fuzzy multi-criteria decision-making	5	2	1	3
Natural language processing	Named entity recognition, dependency parsing, latent semantic analysis, latent Dirichlet allocation, text classification algorithms, Word2Vec or GloVe, ontological modelling	4	1	4	
Deep learning	Recurrent neural networks, probabilistic deep learning algorithms, deep Q-learning and multi-objective optimisation	7	–	1	–
Computer vision	You only look once (YOLOv5 and YOLOv8), convolutional neural networks	1	–	1	–

the technique generates synthetic data, including artificial images or scenarios, that can be used to simulate risks and evaluate project performance. It employs generative adversarial networks and advanced algorithms like stable diffusion and transformer-based algorithms, providing more accurate and diverse outputs of the trained data. An application of this technique is observed in construction management. In a review of generative adversarial networks in the construction industry, Chai et al. (2024) showed that generative adversarial networks are predominant in design generation, image quality enhancement, data management and safety improvement within the construction realm.

Heuristic approaches have proven to be a vital and evolving AI technique considering economic, social and environmental feasibility to create optimal sustainability solutions (Ismaeil and Sobaih, 2023). Heuristic approaches, also grounded in cognitive science algorithms within AI, enable systems to generate approximate solutions to problems. In this context, heuristics support decision-making in ESG assessments to find approximations, particularly when managing complex and dynamic systems like those in PM. Heuristic search techniques rely on genetic algorithms, a natural mechanism for determining approximate solutions. Kanyilmaz et al. (2022) demonstrated this by using this algorithm to analyse a wide range of safe, economical and low-CO_2 options for the conceptual design of buildings. Findings from the study indicated that the algorithm produced a feasible solution in a short computational time, which an engineer would typically struggle to evaluate within a traditional conceptual design process. Also, using the heuristic approach for the installation of a geothermal heat pump and thermal photovoltaic systems as dual renewable systems to achieve net-zero energy, Ismaeil and Sobaih (2023) have demonstrated how this technique provided a practical approach for achieving a net-zero energy residential building.

Next, fuzzy set theory paved the way for fuzzy approaches and has been recognised in data mining for addressing challenges associated with collecting extensive natural data. Fuzzy approaches are notable for their exhaustiveness and structurally modelling connections between complex issues (Amade & Nwakanma, 2021). They used a fuzzy approach to manage uncertainty and imprecision in ESG assessments, particularly when dealing with complex and dynamic systems. This technique is employed in projects requiring the evaluation of multiple variables and their interactions. Wuni (2024) used a fuzzy approach to assess additional sustainability requirements in construction projects that introduce new layers of complexity, challenges and risks. Utilising a multicriteria framework and mathematical formulation of the fuzzy synthetic evaluation approach, the study quantified the overall risk level of a project. It provided decision support to project teams to enhance risk management for sustainable construction. Fuzzy approaches are demonstrated to assist in project decision-making, particularly in designing a decision support system for the construction sector.

Another field of AI that helped computers understand human speech and text as understood by humans was NLP (Balusamy et al., 2021). NLP analyses text-based data, such as project reports or stakeholder feedback, interpreting the natural language that humans understand. Projects requiring the evaluation of ESG performance based on stakeholder engagement and involving the opinions of interested parties necessitate natural language understanding and generation to inform decision-making. In predicting the environmental impacts of construction products, Koyamparambath et al. (2022) have utilised NLP to predict the environmental performance of a product or service to assist life cycle assessment practitioners and verifiers. This study uses data from the environmental product declaration products obtained from websites regulated by stakeholder policies to establish the ability to predict environmental performance with defined variability using NLP.

The DL technique applications relied on complex data sets, using information such as sensor data from construction sites, satellite images of project locations and various interconnected sources. Unlike ML, DL has algorithms inspired by NN in the human brain. It possesses more advanced learning capabilities than ML (Janiesch et al., 2021). In ESG assessment, Zhao (2024) has used an ultrasonic rebound enhancement approach to enhance concrete damage detection using DL techniques. The findings suggest that DL algorithms, such as the genetic particle swarm optimisation algorithm (GA-PSO) and the backpropagation neural network, establish the GA-PSO-backpropagation long-term concrete ultrasonic rebound comprehensive strength. In a similar vein, Wang et al. (2024) developed a novel DL framework that captures the shape information of objects with additional attribute features at a construction site to identify construction activities under different environmental conditions accurately. This technique is a critical tool that provides rich information for activity identification.

Computer vision was used to analyse visual data, such as images and videos, to extract relevant information about environmental impacts (e.g. deforestation, pollution). This technique supports tasks like image recognition, detection, segmentation and tracking of objects. In sustainability assessment, Xiao et al. (2024) explored how a computer vision technique can be used for worker detection at a construction site, monitoring performance and feasibility analysis to ensure sustainable practices. The study found that this edge computing solution tackles data security, installation complexity and time delay challenges in computer vision-based construction site monitoring. Also, Chau et al. (2024) have used computer vision for sustainable marine ecosystem resource management. Within the marine sector, the study demonstrated how the YOLOv8 computer vision object detection algorithm achieved 85.2% and an accuracy of 87.7% for oyster detection. The results of this study comprehensively assess oyster population sizes within specific reef areas to ensure sustainable oyster restoration PM.

3.4. Drivers of AI adoption for ESG assessment

Several key drivers motivate construction organizations to integrate AI into their ESG assessment frameworks. Effective adoption of AI for ESG assessment in projects enhances overall PM efficiency, improves decision-making, supports proper risk management and promotes sustainable project practices. Based on a critical analysis of the literature, seven drivers were identified. Table 4 presents these drivers that motivate organisations to adopt AI for ESG assessment.

The primary driver is reducing human error in ESG assessment (68 of 129 articles). Using AI, project teams handle complex and uncertain environments through real-time monitoring (Wen et al., 2024). By analysing projects' historical data and identifying patterns, AI can predict risks more accurately and support proactive mitigation strategies without human interference, reducing human-generated errors (Poh et al., 2018; Su et al., 2021). Moreover, AI-driven real-time monitoring allows for early detection of anomalies and potential issues, enabling quicker responses and reducing project delays or disruptions (Su et al., 2021).

The improved efficiency in ESG assessment (58 of 129 articles) is the second most addressed driver in the literature, while proper data management (47 of 129 articles) is the third. The increasing availability of data and advanced analytics tools also drives AI adoption in ESG assessment. As organisations generate and collect vast amounts of project-related data, there is a growing need to leverage sophisticated analytical techniques to extract insights and make data-driven decisions (Kanyilmaz et al., 2022). A study by Choi et al. (2021) indicated that plant projects generate massive amounts of data throughout their life cycle, and adopting AI techniques is a growing demand in engineering PM to handle complexities associated with

Table 4. Identified drivers of AI adoption for ESG assessment.

Drivers	Description	Key references	Frequency of 129 (%)
Reduced human error	Ability to handle complex and uncertain environments through real-time monitoring without humans	Poh et al. (2018) Eghbali-Zarch et al. (2022) Bang and Andersen (2022) Wen et al. (2024)	68 (52.7%)
Improved efficiency in ESG assessment	AI adoption for ESG assessment provides better service by learning from data	Tambe (2008) Deepa et al. (2023) Aljawder and Al-Karaghouli (2024)	58 (45.0%)
Data management	Ability to process large volumes of data efficiently with enhanced data security	Poh et al. (2018) Xiao et al. (2024) Wu et al. (2022) Eirgash and Toğan (2024) Deepa et al. (2023)	47 (36.4%)
Meeting policy and regulation	Provides enhanced decision-making capabilities for policy formulation and alignment with stringent regulations	Deepa et al. (2023) Eghbali-Zarch et al. (2022) Tran and Nguyen (2024) Liu et al. (2024)	45 (34.9%)
Enhanced estimation of ESG ratings	Improved estimation and forecasting based on organisational learning and social cohesion	Taboada et al. (2023) Eghbali-Zarch et al. (2022) Bang and Andersen (2022) Dvir et al. (2006)	41 (31.8%)
Expedite decision making	Enhances decision-making capabilities by leveraging domain-specific knowledge. The speed it takes to capture and utilise expert knowledge systematically	Chashyn et al. (2024) Shao et al. (2024) Kanyilmaz et al. (2022)	35 (27.1%)
Sustainability	Provides a sustainable process to meet management needs	Aljawder and Al-Karaghouli (2024) Xiao et al. (2024) Hussain and Hussain (2023) Mishra et al. (2023)	33 (25.6%)

generated project data. AI provides the tools needed to transform raw data into actionable intelligence, helping with ESG assessment and proper data management for competitive advantage.

Policy and regulation, which align strategically with organisational objectives and industry trends, are other key drivers for AI adoption for ESG assessment. Organisations recognise the importance of staying ahead by embracing cutting-edge technologies like AI while aligning these innovations with their broader business goals, industry standards and transformation strategies (Tran & Nguyen, 2024). Ershadi and Ashtiyani (2019) purport that an economy's increasing growth necessitates considerable investment in infrastructure. AI adoption is seen as an excellent investment where regulators and organisations prioritise, and meeting regulations is seen as the significant determinant for its adoption for ESG assessment. By integrating AI for ESG assessment, organisations can advance their culture of innovation, meet policy and regulation, improve sustainability practices and better position themselves to capitalise on emerging opportunities. This driver was studied in 45 articles in the literature.

Also, AI's ability to learn from data enhances predictive analytics and the estimation of ESG ratings, leading to more accurate assessments, which were studied in 41 articles (Aljawder & Al-Karaghouli, 2024; Deepa et al., 2023; Tambe, 2008). The following driver concerns how AI expedites decision-making, collaboration and communication among project parties (investigated in 35 studies). According to Tran and Nguyen (2024), facilitating a shared digital environment that promotes precision, efficiency and improved collaboration across the project lifecycle using AI techniques refines PM methodologies. It addresses complex challenges in the design, execution and maintenance phases of a project. The data suggest that AI provides a centralised platform for ESG data sharing and analysis enables better coordination and expedited decision-making (Tran & Nguyen, 2024). AI-driven chatbots and virtual assistants can facilitate more efficient communication and information exchange with ESG data project teams (Lipianina-Honcharenko et al., 2024).

3.5. Barriers to AI adoption for ESG assessment

A diverse array of informational, technological and economic barriers hinders the adoption of AI for ESG assessments. While the previous section highlighted the drivers, AI adoption for ESG assessments faces challenges. Six barriers were identified as drawbacks of AI for ESG assessment. Table 5 presents these main barriers.

Informational barriers, such as those related to the lack of critical data or information for AI applications in ESG assessment. AI techniques require a significant amount of data to predict outcomes accurately. However, most construction organisations, particularly the small and medium-sized ones, usually do not have accurate data on ESG issues and practices that could help to conduct a thorough ESG assessment properly. The lack of ESG data, therefore, hinders the practical application of AI for ESG assessment.

Technological barriers pose another set of challenges to AI adoption. According to Jaiswal et al. (2024), incorporating Industry 4.0 in the construction PM sector is challenged with skill deficiencies, affecting adoption. The scarcity of skilled professionals capable of implementing, maintaining and effectively employing AI tools for ESG assessment remains a critical issue. Additionally, the insufficiency of technological infrastructure is believed to limit the adoption of AI for ESG assessment. AI techniques rely on massive datasets to make decisions; the datasets used in the experimental evaluation, taken from various sources within the project, mostly require high-level technological infrastructure to process (Morales-Ramirez et al., 2019).

Economic factors also play a substantial role in delaying the integration of AI. A study by Chashyn et al. (2024) addressing the limitations of current digital simulations suggests that cost is a critical determinant in digitally maintaining and managing historical dwellings at construction project sites. The high costs associated with implementing, maintaining and updating AI systems can be excessive for organisations. Initial investments in hardware, software and data collection, as well as ongoing expenses related to system updates and data management, make it burdensome to adopt AI techniques for ESG assessment (Wu et al., 2022). Also, projects are primarily associated with overruns in cost; therefore, it is difficult to put some of its resources into innovative technologies like AI, which is termed budgetary limitations (Jaiswal et al., 2024).

The strategic alignment of AI with organisational objectives is an institutional barrier that needs to be addressed. Many organisations lack a clear roadmap or strategy for integrating AI for ESG assessment; this

Table 5. Identified barriers to AI adoption for ESG assessment.

Barriers	Description	Key references	Frequency of 129 (%)
Informational	There is a need for extensive experimentation to understand AI tools' capabilities. Threat to job security	Wen et al. (2024) Iftekhar and Pannell (2022) Kumar et al. (2024)	56 (43.4%)
Technological	The complexity of model training and the lack of AI talents. Insufficient technological infrastructure within organisations	Al-Tabtabai & Alex, (1998) Al-Tabtabai et al., (1999) Buah et al. (2020) Kumar et al. (2024) Ju et al. (2023)	43 (33.3%)
Economic	High costs associated with data quality, availability, budgetary limitations and implementing AI tools	Deepa et al. (2023) Wu et al. (2022)	40 (31.0%)
Institutional	Institutional barriers due to existing systems and processes. Complexity in integrating AI tools with existing systems and organisational strategy. Lack of leadership commitment	Maceika et al. (2024) Karki and Hadikusumo (2023) Zhao (2024) Jaiswal et al. (2024)	38 (29.5%)
Political and cultural	Resistance to adopting new technologies. Threat to job security	Tran and Nguyen (2024) Shen and Li (2023) Maceika et al. (2024) Wang et al. (2024) Zhang et al. (2024)	35 (27.1%)
Legal	Data security concerns. Privacy concerns related to data usage. Legal barriers to AI adoption or implementation	Tambe, 2008 Xiao et al. (2024) Jung et al. (2022a) Jung et al. (2022b)	28 (21.7%)

hinders effective implementation and limits the potential benefits of these technologies (Tambe, 2008). Without proper alignment with business goals, AI projects may demonstrate meaningful returns on investment when they are well-crafted around the strategic goals of the institution adopting them. However, it has been shown that organisational unwillingness can also slow down the adoption of AI. Established practices and resistance to change within organisations can make introducing new technologies like AI challenging, even when their potential benefits are evident (Shen & Li, 2023). Taking opportunities to use these techniques requires strong leadership support, clear communication about the advantages of AI and careful planning to ensure minimal disruption during implementation.

Another critical barrier is an organisation's political and cultural landscape, making it challenging to embrace AI. Political and cultural influences significantly hinder the adoption and investment in AI techniques for ESG assessment, particularly due to investment risks. Adopting technology without substantial official support from key actors makes this task daunting. Consequently, actors view it as a threat to job security. The social perspective of some individuals involved is that AI adoption introduces uncertainties related to job loss, issues surrounding stakeholders' acceptance and imbalances among interested parties. Social norms and cultural resistance contribute considerably to this barrier, with stakeholders expressing concerns about job displacement due to automation. Furthermore, limited awareness and understanding of AI's potential benefits and the resistance to adopting new technologies hinder its adoption for ESG assessment (Zhang et al., 2024).

Lastly, legal considerations related to ethics pose a significant barrier to AI adoption for ESG assessments. Concerns regarding data privacy, algorithmic bias, transparency and accountability have arisen as AI becomes more prevalent in decision-making processes (Tambe, 2008; Wang et al., 2024). Ensuring that AI models are fair, unbiased and explainable is crucial to building trust among stakeholders and gaining acceptance for these tools for ESG assessment (Boadi et al., 2025). Issues about data usage, security and other legal barriers may not encourage the use of AI for ESG assessment.

4. Directions for future research

Despite the promising results and growing interest in using AI to address ESG issues in construction projects, several questions remain. The optimistic perspective on integrating AI offers substantial potential for improving ESG assessments, which could foster more sustainable PM practices for businesses. Amid the current surge in AI, attention is necessary to mitigate the drawbacks associated with its implementation and leverage the benefits highlighted in this study. The following are promising research questions that can be addressed in future studies.

First, there is a growing interest in ML applications for project risk analysis. In analysing the dominant AI techniques and tasks they perform, ML algorithms were noted as effective for classification, clustering and prediction tasks. Given that any project is unique, risk and uncertainty related to ESG aspects of projects will remain an important area of research in future. Also, research into how explainable AI, hybrid models and benchmarking datasets can support ESG assessment will be an interesting future research area.

Second, using real data and expert opinion to validate ESG assessments in practice. The findings from the analysis of data sources revealed that the use of real project data is prevalent in the literature. However, most project data concern financial and accounting information, such as costs, stakeholders and risks, which organisations do not share due to their internal policies. This may limit the practical validation of the investigated ESG issues. Also, human expertise will remain crucial in designing practical implications of ESG assessments in PM. Due to the rise of generative AI (e.g. ChatGPT), which can generate project reports and communications instantly and effectively, reliance on expert opinions and interviews to inductively derive insights into the project's unique characteristics will be an important aspect of future research methodologies.

Third, more research on AI applications for social impact assessment. The study findings highlighted notable gaps in using AI tools for social impact assessments in PM. Most existing studies concentrate on assessing the environmental and governance pillars, while the social pillar—a vital component for project success—remains overlooked. Therefore, leveraging AI methods for social impact assessment offers a distinct advantage for future research.

Fourth, research into identified drivers of and barriers to adopting AI for improved ESG assessment is needed. The seven drivers and six barriers were identified based on the current review of the academic literature. More empirical research using case studies will be necessary to examine the benefits of individual drivers and the impact of individual barriers to adopting AI tools for ESG project analysis across different countries and contexts.

Overall, the findings facilitate the pinpointing of gaps in current research and suggest innovative research directions for AI utilisation in ESG assessment. Unlike other investigative efforts, this systematic review delivers more comprehensive insights to policymakers in this field, enhancing informed decision-making and optimising AI integration for ESG evaluations. The results emphasise using AI techniques such as ML algorithms for data analysis, NLP for textual insights and DL methods for automated image analysis, which could aid in developing ESG assessment frameworks for ongoing, completed and prospective projects.

5. Conclusion

In summary, the study examined the progression of knowledge related to adopting AI for ESG evaluation in projects. Based on the systematic literature review of 129 articles, the research examined the diverse techniques, algorithms and tasks AI executed for ESG assessments. This review demonstrated that the current practice has not fully leveraged AI capabilities to enhance ESG assessments, suggesting a need for deeper investigation into diverse AI applications in this field. Furthermore, the study uncovered a notable gap in research on using AI to assess social impacts within ESG evaluations, as most studies predominantly focus on environmental and governance facets.

Moreover, the review highlights the drivers and barriers to AI adoption in this area, providing insights for the future implementation of AI technologies in ESG assessments. On one side, drivers such as reduced human error, improved efficiency in ESG assessment and better data management promote AI adoption for ESG assessments in organisations. On the other hand, multiple barriers, such as political and cultural factors, the technical intricacies of AI integration and insufficient information on the capabilities of AI tools, prevent or slow down AI adoption. The study makes two major contributions: Theoretical and policy. Theoretically, the research maps AI algorithms against the three ESG pillars, thereby extending knowledge of AI-driven project management through the lens of sustainability theory. The findings provide insights for policymakers to develop targeted interventions that address the institutional and legal barriers identified in the review.

From the findings of this study, it is recommended that local firms must prioritise overcoming technological and informational barriers by investing in specialised AI construction expertise and robust digital infrastructure. Thus, firms should align AI adoption with their strategic business goals, moving beyond isolated implementations towards a clear institutional roadmap for ESG assessment. Policymakers should focus on addressing barriers such as the high cost of maintaining AI systems while incentivising reductions in human error in ESG evaluations. Policymakers can further facilitate adoption by enacting mandatory disclosure requirements and standardised reporting, which is foundational for corporate transparency.

Also, investors can leverage machine learning to predict environmental impacts more accurately and align their capital allocation with global standards. Auditors can base their findings on this study to shift from subjective project evaluations to rigorous, data-driven assessments. It is established that NLP algorithms allow for the automated analysis of vast textual data such as project reports and stakeholder feedback to detect governance risks. Project managers can use these algorithms to help handle and support their projects.

Finally, an analysis of the current research landscape reveals gaps that should be addressed in future research. Overall, the study establishes a collection of observations, propositions and pathways for future efforts examining the contribution of AI-driven PM research to ESG issues.

Progress in AI technologies and innovation is essential, and AI can serve as a dynamic instrument for ESG assessment in projects. These findings are intended to equip academics, practitioners and policymakers with viable AI techniques, related tasks, data sources, drivers and barriers that can be considered for effective ESG evaluations.

Author contributions

CRediT: **Robert Osei-Kyei:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Software, Supervision, Validation; **Timur Narbaev:** Conceptualization, Data curation, Funding acquisition, Supervision; **Caleb Boadi:** Formal analysis, Investigation, Methodology, Writing – original draft; **Filippo Maria Ottaviani:** Data curation, Formal analysis, Funding acquisition, Writing – review & editing.

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Data availability statement

The data that support the findings of this study are available in this article and in the supplementary material.

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