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REVIEW ARTICLE

Explainable and interpretable artificial intelligence for embodied carbon assessment and decarbonization of building materials: A PRISMA-based systematic and bibliometric review

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Abstract

Embodied carbon (EC) in building materials poses a significant challenge to decarbonizing the construction industry, necessitating data-driven methods for transparent and informed decisions. This study systematically reviews the use of artificial intelligence (AI) and explainable AI (XAI) in assessing EC and promoting low-carbon building materials. A PRISMA 2020–based review and bibliometric analysis of Scopus publications from 2015 to June 2026 explored trends, geographic distribution, research themes, AI/XAI methods, and their applications in EC assessment and material decarbonization. Research has notably increased in 2023, highlighting AI's growing role in life cycle assessments and material decarbonization. Machine learning methods such as neural networks, random forests, support vector machines, gradient boosting, and deep learning are increasingly used for EC prediction, material performance evaluation, and optimization. However, XAI applications are limited, with more focus on prediction accuracy than model transferability. Key XAI techniques include Shapley Additive exPlanations, partial dependence plots, sensitivity analysis, and feature importance analysis. The review identifies limitations such as regional data gaps, limited model explainability, limited database integration, and limited empirical validation. A conceptual framework is proposed combining localized life cycle data, AI prediction, XAI interpretation, optimization, and decision support. The review concludes that XAI can enhance transparency and aid low-carbon material decisions, though further validation across laboratories, manufacturing, and regions is needed for practical implementation.

Keywords: Embodied carbon; Building materials; Explainable artificial intelligence; Artificial intelligence; Decarbonization; Machine learning; Life cycle assessment

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1. Introduction

One of the most important global problems of the 21st century is climate change, which is mostly caused by rising greenhouse gas (GHG) emissions from human activity. The building and construction industry uses around one-third of the world's

energy resources and contributes to the world's energy-related carbon emissions.[1,2] Decarbonization initiatives have traditionally concentrated on reducing operational carbon related to building operation, lighting, cooling, and heating. However, the proportional influence of embodied carbon (EC) is increasing as building energy efficiency improves, making it a crucial objective for reaching net-zero carbon goals.[1,3] Due to their energy-concentrated extraction, transportation, construction, maintenance, and end-of-life processes, materials such as aluminum, glass, cement, steel, and bricks account for a substantial quantity of EC.[4,5] The entire GHG emissions linked to a construction material or product throughout the course of its life cycle, from the stage of extraction of the raw materials to disposal or recycling, are referred to as EC.[6]

Life cycle assessment (LCA), a standard approach that evaluates environmental consequences across many stages of a life cycle, is commonly used to measure EC. By identifying carbon hotspots and assessing substitute materials and design approaches, LCA-based EC aids in decision-making.[7] Additionally, carbon footprint assessment techniques are becoming important tools for assessing and comparing the environmental impacts of building materials and construction systems, helping guide decarbonization efforts across the built environment.[4,8] Artificial intelligence (AI) has been a game-changing technology in the construction industry in recent years, allowing for sustainability optimization, data-driven decision-making, and predictive analytics.[9,10] The use of machine learning (ML) approaches to forecast building carbon emissions, systematize LCA procedures, estimate emissions that are associated with materials, and optimize the selection of low-carbon materials has grown.[11] Artificial neural networks (ANN), random forest (RF), support vector machines (SVM), gradient boosting machines, and deep learning algorithms are examples of AI-based models that have shown excellent prediction accuracy in sustainability analysis and carbon assessment.[12-14] Moreover, AI has also made it easier to develop low-carbon concrete mixes, material substitution techniques, and carbon-resourceful building strategies, all of which support the construction industry's broader decarbonization goals. Many innovative AI models function as "black boxes," generating outputs without clearly explaining how they make decisions, despite their predictive power. For practitioners, policymakers, and stakeholders who need reliable and accountable decision-support systems, especially in applications linked to sustainability, this lack of transparency poses serious problems.[15] By offering interpretable insights into model behavior and predictions through methods such as Shapley Additive exPlanations (SHAP), local interpretable model-agnostic explanations (LIME), feature importance analysis, and rule-based explanations, explainable artificial intelligence (XAI) has emerged as a solution to this problem.[16] XAI has the potential to enhance sustainable material selection and carbon-reduction methods in the construction industry while improving confidence, transparency, accountability, and the regulatory acceptability of AI-driven choices.[17,18]

Research combining explainable and interpretable AI with EC assessment and building material decarbonization remains fragmented, even though many studies have examined EC assessment, AI-based carbon prediction, and sustainable building materials separately.[19,20] Reviews that are now available mostly focus on AI applications for carbon prediction or XAI in energy-efficient buildings, paying little attention to XAI methods for decarbonization decision-making across building life cycles, material selection, and EC estimation. Thus, the aim of this study is to conduct a systematic and bibliometric examination to review XAI and interpretable AI uses in building materials decarbonization and EC assessment from 2015 to 2026 using the Scopus database. Previous studies have investigated AI and deep learning applications in smart buildings as well as the role of explainability in low-carbon urban systems.[19,20] Nevertheless, no study has thoroughly synthesized the evolution of EC assessment for low-carbon materials, from traditional LCA to AI-based prediction and, ultimately, explainable decision support. As a result, the role of explainability in reliable carbon decision-making remains theoretically unclear. This study presents five unique academic contributions compared with earlier reviews. The main objectives are to (i) analyze publication trends, countries, citations, keyword co-occurrence, most significant journals, and research themes; (ii) identify AI and XAI techniques applied to EC assessment and decarbonizing building materials; (iii) examine the importance of XAI in decarbonizing building materials in practice; and (iv) suggest a future research framework for integrating XAI into EC management and low-carbon building material decision-making. By providing a wide-ranging understanding of AI/XAI methods adoption, supporting decarbonization, and making better decisions on material selection while adopting these methods by professionals, researchers, and stakeholders, the study answers the following questions: Q1: What AI models and XAI techniques are adopted in EC assessment and decarbonization of building materials? Q2: How has XAI research on EC in building materials changed over time? Q3: How has decarbonization affected building materials using XAI in practice? Q4: What framework can direct future research and practices?

2. Methodology

2.1. Design

The review combined systematic review and bibliometric analysis to identify and map studies on XAI for EC assessment and building materials decarbonization. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, which provide an open framework for identifying, screening, evaluating, and reporting relevant research, were adhered to in this review.[21] While bibliometric analysis statistically investigated publication trends, influential authors, and research networks and maps, the systematic review provided a thorough qualitative synthesis of the study issues.[22,23] Selection of a database, data retrieval, data screening process, systematic results, and bibliometric analysis are all part of the methods carried out.

2.2. Selection of database

Data retrieval was conducted using the Scopus database as the main source of literature. This database was chosen because it has broad coverage of peer-reviewed literature in the fields of engineering, environmental science, construction, and AI.[24] It is well known for its extensive citation indexing and bibliometric features, which make it useful for locating significant works, authors, and research trends. Its standard metadata makes it easier to have reliable network analysis and bibliometric mapping.[25,26]

2.3. Search strategy

A structured search string that combines keywords related to XAI, ML, EC, LCA, and building materials such as concrete, cement, bricks, and glass was developed using Boolean operators (OR, AND) to facilitate the retrieval of relevant studies. The first step of the search string comprises "Explainable Artificial Intelligence" OR "Interpretable Machine Learning" AND "Embodied Carbon" OR "Carbon Emission" OR "Decarbonization" AND "Building Materials" OR "Concrete" OR "Cement." However, a limited number of documents were displayed as the results, which is not encouraging or suitable for the study. To increase the number of documents to a reasonable number that is perfectly adequate for the analysis, the second search was focused on "Explainable AI" OR "Artificial Intelligence" OR "Machine Learning" AND "Building materials" OR "Concrete" OR "Cement" OR "Bricks" OR "and" AND "Embodied Carbon" OR "Carbon Emissions" OR "Decarbonization." The results from the database were exported in CSV format for analysis. The search strategy aimed to capture the overlap between AI, XAI, EC, decarbonization, and building materials. However, terminology in this field varies, and relevant studies may use alternative terms such as carbon binders, supplementary cementitious materials, life cycle inventory (LCI), EC databases, carbon monitoring, environmental product declarations (EPDs), carbon optimization, and sustainable material selection without explicitly using the main search terms. Therefore, the retrieved dataset represents literature found through the specified search strategy, not the entire research work on AI-enabled building material decarbonization.

2.4. Inclusion and exclusion criteria

The inclusion criteria focused on studies that are based on AI and XAI application methods or techniques indexed in Scopus for EC assessment or decarbonization in building materials; publications must be from 2015 to June 2026, be journal articles or review papers, and be published in English. The exclusion criteria removed studies that were not construction- or building-related, lacked AI-related methods, or were conference abstracts, notes, or non-English articles. The screening process is represented in a PRISMA flow diagram involving identification to show the name of the database and record of retrieved data; removal of duplicate studies; title and abstract screening; full-text assessment; and selection of the final study, as guided by PRISMA 2020. Bibliometric analysis used Microsoft Excel for data arrangement, descriptive statistics, and trend analysis, and VOSviewer (version 1.6.20) for mapping and visualizing networks.

2.5. Screening process

The initial Scopus search identified 375 records. Before detailed screening, 105 records were excluded based on predefined criteria: 41 were outside the selected subject areas, and 64 did not meet document type requirements. The remaining 270 records were screened for full-text assessment. After applying the inclusion and exclusion criteria (13 non-English exclusions), 257 studies were included in the final review and bibliometric analysis. The process follows the PRISMA 2020 guidelines[21], as presented in Figure 1.

2.6. Bibliometric analysis

The bibliometric analysis was performed using Microsoft Excel and VOSviewer version 1.6.20. Co-authorship, keyword co-occurrence, citation, and country collaboration networks were visualized. Descriptive statistical analysis, including publication trends, citation counts, and journal productivity, was performed using Excel. The identification of new topics, research hotspots, and intellectual structures within the study was performed using combined methods.[27,28] Bibliometric mapping included keyword co-occurrence, authors' collaboration,

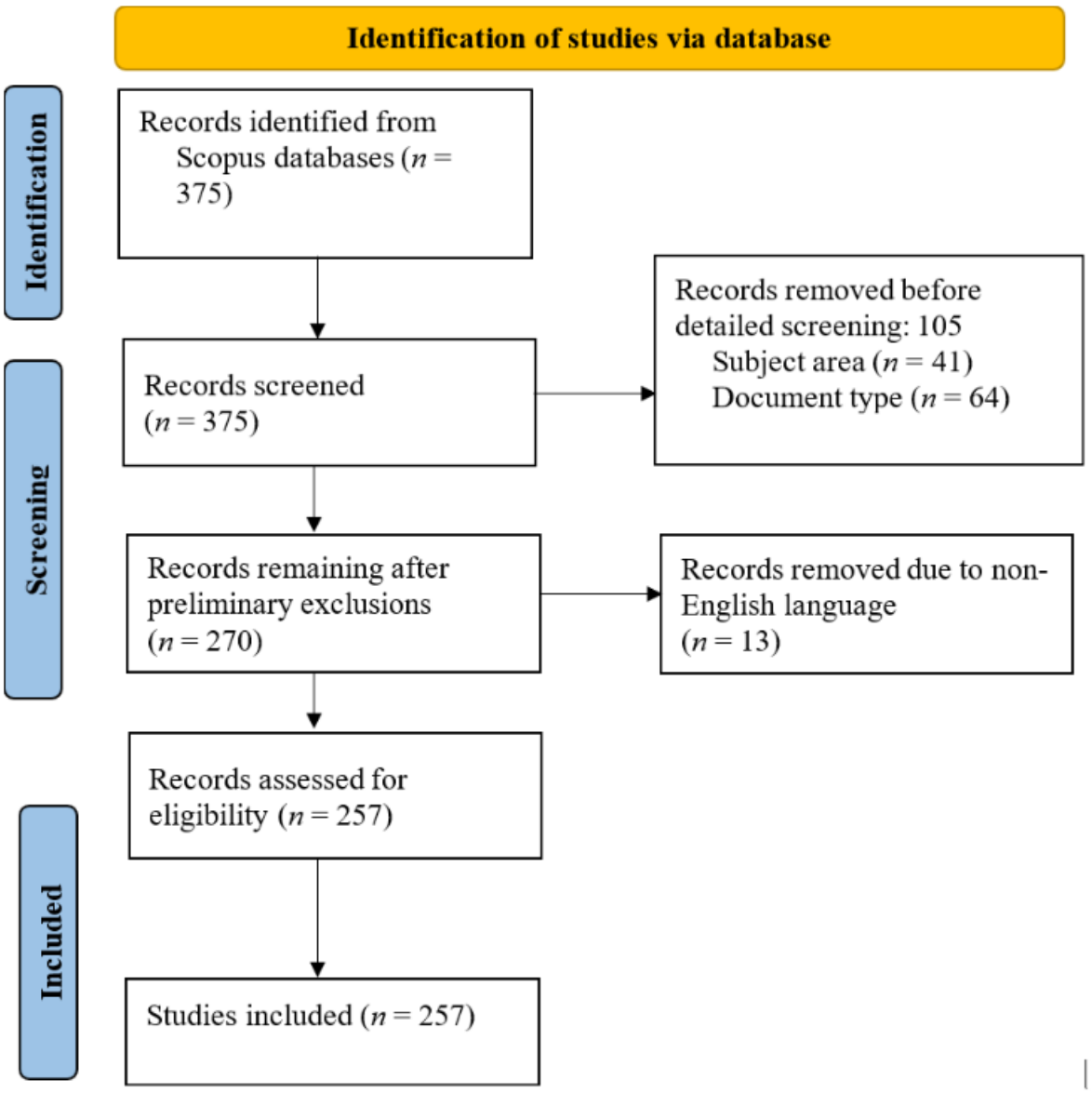


Figure 1. PRISMA 2020 flow diagram for the XAI selection process
Abbreviations: PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses; XAI: Explainable artificial intelligence.

country collaboration, bibliographic coupling, and overlay map. Descriptive statistics included publication trends by year, most influential or productive journals, top countries, and most-cited papers.

3. Results

3.1. Scientific publication trend

Research publications on AI-based EC assessment and sustainable building materials have increased significantly, as shown by the annual publication trend (Figure 2). No records matching the search criteria were identified for 2015–2017. This does not mean no relevant research existed; it means no Scopus-indexed publications met the specific search terms and criteria. The absence likely reflects the emerging nature of this research intersection and search limitations. Therefore, 2015–2017 is regarded as a period with no identified records under this procedure, not a definitive absence of research. Publication began in 2018 with one paper and had no publications in 2019. Between 2020 and 2022, publication activity was fewer than 10 publications per year. Notably, publications increased dramatically from 27 in 2023 to 41 in 2024, peaking at 94

in 2025. Although 75 publications were identified for 2026, compared with 94 in 2025, this does not indicate declining research. The 2026 data reflect publications indexed up to the retrieval date of June 16, 2026, plus early online publications. Thus, 2026 is treated as partial and is not directly compared with the full year for trend analysis. This rapid development suggests growing worldwide interest in using AI methods to address sustainability problems in the construction industry. The trend also reflects the need for data-driven strategies to support the selection of low-carbon materials and environmental decision-making, as well as increased awareness of carbon reduction goals.

3.2. Most influential journals

The analysis identified where researchers focused their discussion and the journals that shape the evolving field. Figure 3 shows the most influential journals for the specified year range in the study. The most productive journals began publishing in 2020, with *Construction and Building Materials* leading with 16 documents. This journal started with one paper in 2021 and steadily increased to five in 2024, suggesting accelerated adoption of AI-driven methods for sustainable building materials. Because concrete, steel, and wood account for a significant share of life-cycle emissions, the journal's focus underscores the decisive role building materials play in reducing emissions. The result demonstrates that decarbonization initiatives are mostly focused on building materials rather than more comprehensive construction systems.

The *Journal of Building Engineering* ranked second (16 total documents). This journal shows no publications before 2023, while activity remained steady and increased until 2026 (five papers). This indicates that AI-based carbon assessment studies are moving beyond academic demonstration toward practical application in real-world construction developments. *Journal of Cleaner Production* ranked third, with 14 publications. Its activity increased substantially in 2023 (four papers), with lower output in 2025 and 2026 (two papers each year). The journal ranks among the foremost sustainability publications, and its recognition as a highly productive source explains the growing emphasis on EC assessment within broader frameworks of environmental management, net-zero transitions, production sustainability, and the circular

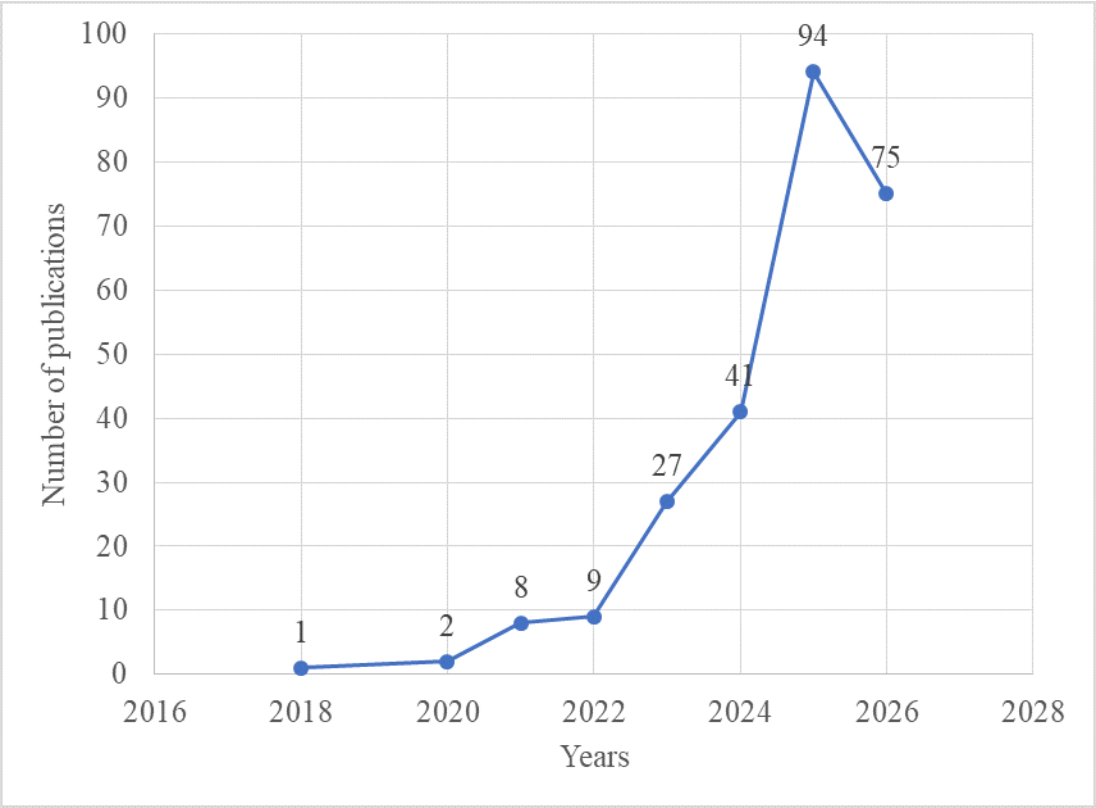


Figure 2. Annual publications (2015–2026)

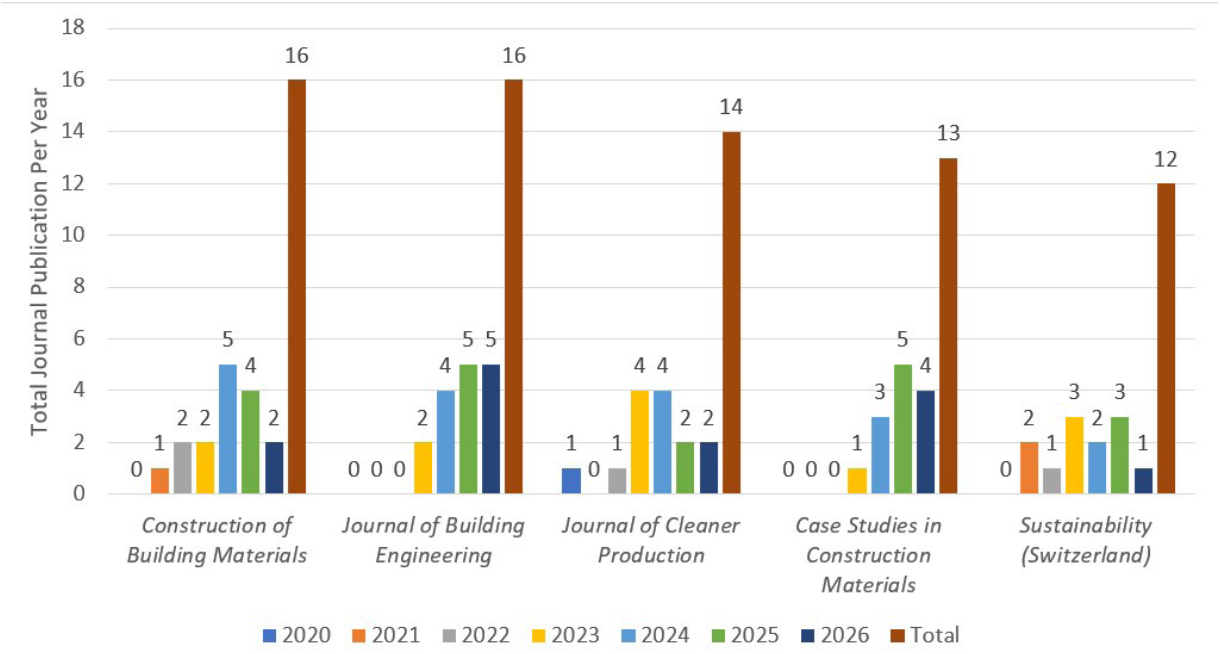


Figure 3. Most influential journals

economy. This shows that EC assessment is increasingly recognized within the broader contexts of production sustainability, environmental management, net-zero transitions, and the circular economy. Thus, it provides a stronger foundation for a sustainable orientation for XAI in carbon assessment.

Case Studies in Construction Materials published 13 papers. Publication activity began in 2023 (one paper) and continued through 2026 (four papers). This journal is known as a materials practical-applications-focused journal, and adding it to this study supports efforts to validate AI models through practical application in construction projects rather than academic datasets. It helps build stakeholder trust, bridge practical implementation and academic research, demonstrate model transparency in practice, and show how explainable predictions affect material decisions. This shows that the field is moving toward practical deployment of explainable carbon assessment tools.

Sustainability (Switzerland) ranked fifth, with 12 papers. Publications were relatively consistent from 2021 (one paper) and remained at 1–3 per year throughout the study period. *Sustainability* is an interdisciplinary journal to which researchers from management, engineering, and environmental science are attracted. This contribution to top-cited journals suggests that EC assessment is a constraint on sustainable governance and is no longer regarded exclusively as a construction challenge. The examination of publications such as decision-making systems, policy implications, carbon reduction strategies, and Sustainable Development Goals is in alignment with XAI because policy acceptance and stakeholder confidence are determined through transparent models. This interdisciplinary circulation indicates that EC assessment and decarbonization need collaboration across numerous research fields.

3.3. Top productive countries

Figure 4 presents the publication contributions of the top 10 countries in the reviewed research area. China was the most productive country, with 109 publications. India ranked second with 33 publications, followed by the United Kingdom (27 publications), the United States (25 papers), and Saudi Arabia (23 papers). Australia contributed 20 papers, and South Korea and Pakistan each published 11. Canada and Germany completed the contribution chart with 10 and 8 publications, respectively. The results show a high concentration of research effort in Asia, especially in China and India, consistent with the growing focus on carbon-reduction innovation, AI, and sustainable construction. The predominance of Asian countries suggests a global shift toward research in areas where infrastructure and urbanization are rapidly developing.

Notably, only Germany and the United Kingdom were in the top 10 among the European nations, and no South American or African nation was listed among

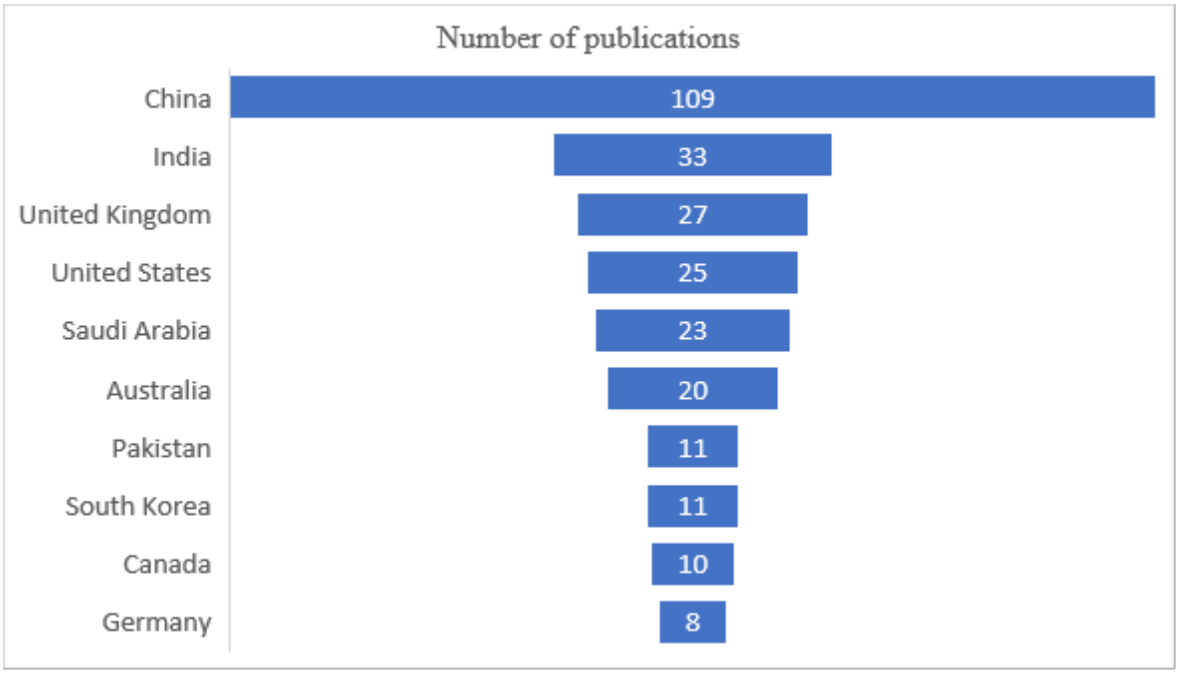


Figure 4. Top 10 productive countries by number of publications

the top 10. This regional disparity emphasizes the need for more research on AI-enabled EC assessment and decarbonization in underrepresented areas, including South America and Africa.

3.4. Most-cited papers

Twenty significant research studies that show how AI, ML, deep learning, and optimization algorithms are increasingly being used in decarbonization strategies, EC assessment, and sustainable building materials are shown in Table 1.[29–48] These papers cover 2018–2025 and show that optimization frameworks for carbon awareness have replaced performance-prediction methods. With almost 70% of papers focusing on concrete, it remains the most popular material. This is expected, as concrete production, especially cement, is a major contributor to the world's GHG emissions.[30] The results show that the most widely used AI method is ML, followed by deep learning models and hybrid optimization methods. Beyond strength prediction, research focuses on EC assessment, life cycle implications, cost optimization, waste minimization, and circular economy goals.

Recent research shows a shift toward multi-objective optimization that considers mechanical performance along with economic and environmental factors.[35,42] Generally, the studies show that AI is being used more often to address three significant sustainability issues in the construction industry: quantification and reduction of EC using optimization and prediction models[37,42]; creation of low-carbon building materials, including concrete generated from industrial waste, recycled aggregate concrete, and geopolymer concrete[29,36,39]; and promoting and practicing circular economy, such as material reusability, reduction of waste, and life cycle management. Despite these developments, most research still prioritizes prediction accuracy over transparency. Few studies use interpretability strategies such as XAI techniques, future significance assessment, or sensitivity analysis.

3.5 Network mapping analysis

3.5.1. Co-authorship country analysis

Figure 5 shows the co-authorship country network, demonstrating global collaboration in research on XAI, EC assessment, and building materials decarbonization. Node size represents the publication output of each country, whereas line thickness indicates the strength of collaboration between countries. China had the largest node and an extensive collaboration network involving Australia, India, Saudi Arabia, and Hong Kong, indicating its prominent role in research on machine learning methods for building materials, sustainable construction, and EC prediction. India also showed a strong position as a link between Asian and European countries. India, Germany, Italy, Canada, and China were found to have strong

Table 1. Top 20 most-cited papers

Rank	Title	Reference	Journal	Number of citations
1	"Machine-learning methods for estimating compressive strength of high-performance alkali-activated concrete"	29	*Engineering Applications of Artificial Intelligence*	172
2	"Embodied carbon analysis and benchmarking emissions of high and ultra-high-strength concrete using machine learning algorithms"	30	*Journal of Cleaner Production*	147
3	"Estimating construction waste generation in the Greater Bay Area, China, using machine learning"	31	*Waste Management*	136
4	"Optimization design for alkali-activated slag-fly ash geopolymer concrete based on artificial intelligence considering compressive strength, cost, and carbon emission"	32	*Journal of Building Engineering*	135
5	"Mixture optimization for environmental, economic, and mechanical objectives in silica fume concrete: A novel framework based on machine learning"	33	*Resources, Conservation and Recycling*	128
6	"A machine learning-assisted numerical predictor for compressive strength of geopolymer concrete based on experimental data and sensitivity analysis"	34	*Applied Sciences*	108
7	"Developing a data-driven surrogate model for holistic performance-based assessment of mid-rise RC frame buildings"	35	*Engineering Structures*	101
8	"Compressive strength prediction of sustainable concrete incorporating rice husk ash using hybrid machine learning algorithms"	36	*Case Studies in Construction Materials*	99
9	"Prospective on energy-related carbon emissions peak integrating optimized intelligent algorithms with dry process technique application for China's cement industry"	37	*Energy*	80
10	"Artificial intelligence and carbon emissions inequality: Evidence from industrial robot application"	38	*Journal of Cleaner Production*	79
11	"Modelling the compressive strength of geopolymer recycled aggregate concrete using ensemble machine learning"	39	*Advances in Engineering Software*	74
12	"A digital life cycle management framework for sustainable smart manufacturing in energy intensive industries"	40	*Journal of Cleaner Production*	70
13	"Virtual mix design: Prediction of compressive strength of concrete with industrial wastes using deep data augmentation"	41	*Construction and Building Materials*	68
14	"Hybrid machine learning and multi-objective optimization for intelligent design of green and low-carbon concrete"	42	*Sustainable Materials and Technologies*	68
15	"Optimizing concrete mix design for cost and carbon reduction using machine learning"	43	*Journal of Human, Earth and Future*	65
16	"Reuse of steel in the construction industry: challenges and opportunities"	44	*International Journal of Steel Structures*	65
17	"Intelligent mix design of recycled brick aggregate concrete based on swarm intelligence"	45	*Journal of Building Engineering*	64
18	"Machine-learning-based comprehensive properties prediction and mixture design optimization of ultra-high-performance concrete"	46	*Sustainability*	63
19	"Design of concrete incorporating microencapsulated phase change materials for clean energy: A ternary machine learning approach"	47	*Engineering Applications of Artificial Intelligence*	62
20	"Efficient creep prediction of recycled aggregate concrete via machine learning algorithms"	48	*Construction and Building Materials*	59

collaborative links. Another significant collaboration cluster emerged between the United States and the United Kingdom, underscoring their continued importance in LCA, sustainable construction, and AI-enabled decision-support research. As research output in carbon-neutral development and sustainable construction increased, Saudi Arabia became another research hub linking researchers from Asia, the Middle East, and Africa. AI-enabled EC assessment models have advanced, driven by China's significant activity in AI, digital construction technologies, and sustainable construction. However, the transferability and generalizability of these models raise concerns about this regional concentration.

Most AI models were developed using datasets from specific local manufacturing processes, material compositions, building codes, and environmental factors. Therefore, when applied in areas with different material compositions, suppliers, weather conditions, transportation distances, energy mixes, and construction measures, models trained using Chinese datasets may not achieve comparable prediction accuracy. This limitation is especially critical for developing nations, such as many African countries, where there are significant differences in local material compositions, weather conditions, and available datasets. To improve the robustness and global applicability of AI-enabled EC assessment systems, future research should prioritize developing region-specific datasets, validating cross-country models, developing transfer-learning models, and combining international databases.

3.5.2. Co-citation authorship network analysis

Figure 6 presents the author collaboration network. It maps the relationships among authors and how often they are collectively cited or linked through publications. The network shows several interconnected clusters that reflect the intellectual framework of studies on sustainable building materials and AI-driven EC assessment. Author influence is shown in node size, while the occurrence of co-citation networks is indicated by link strength. The most significant authors were Shafighfard (2024), Kashem (2024), and Zaker Esteghamati (2021); these authors held

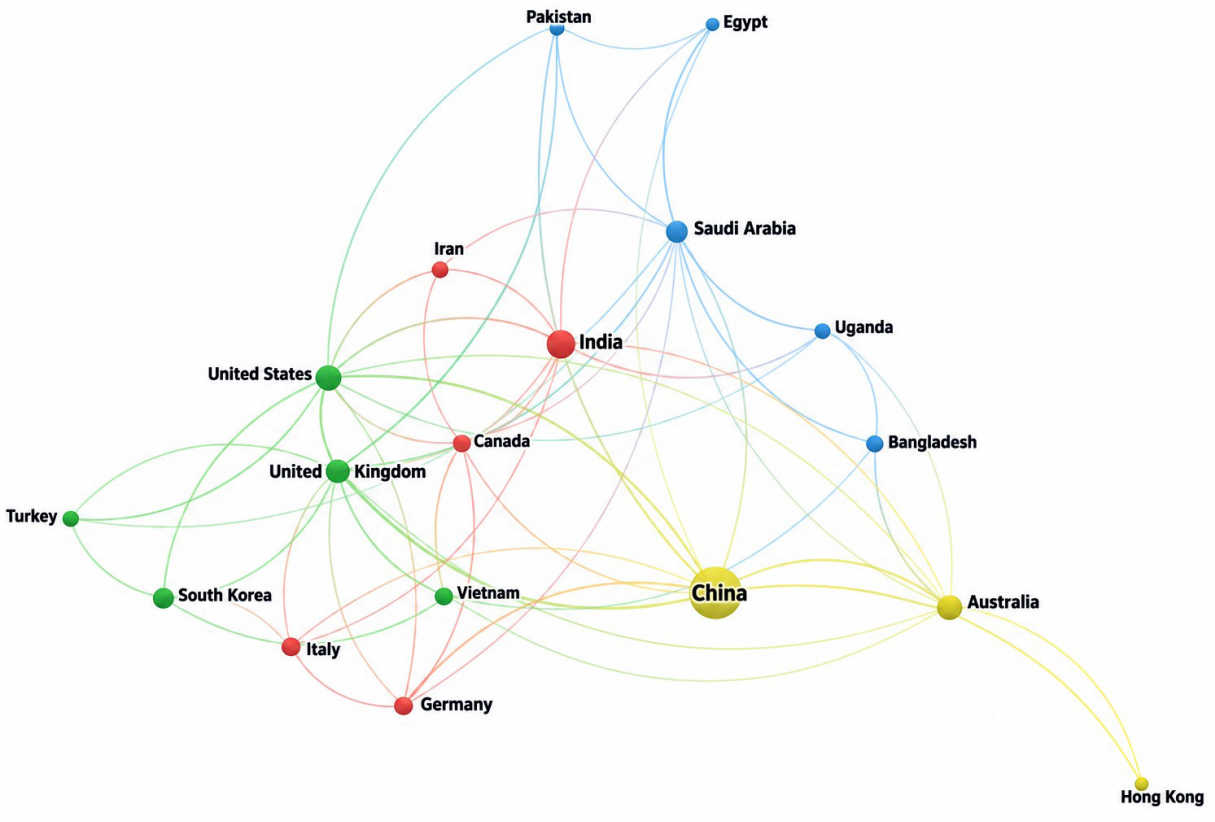


Figure 5. Co-authorship country network

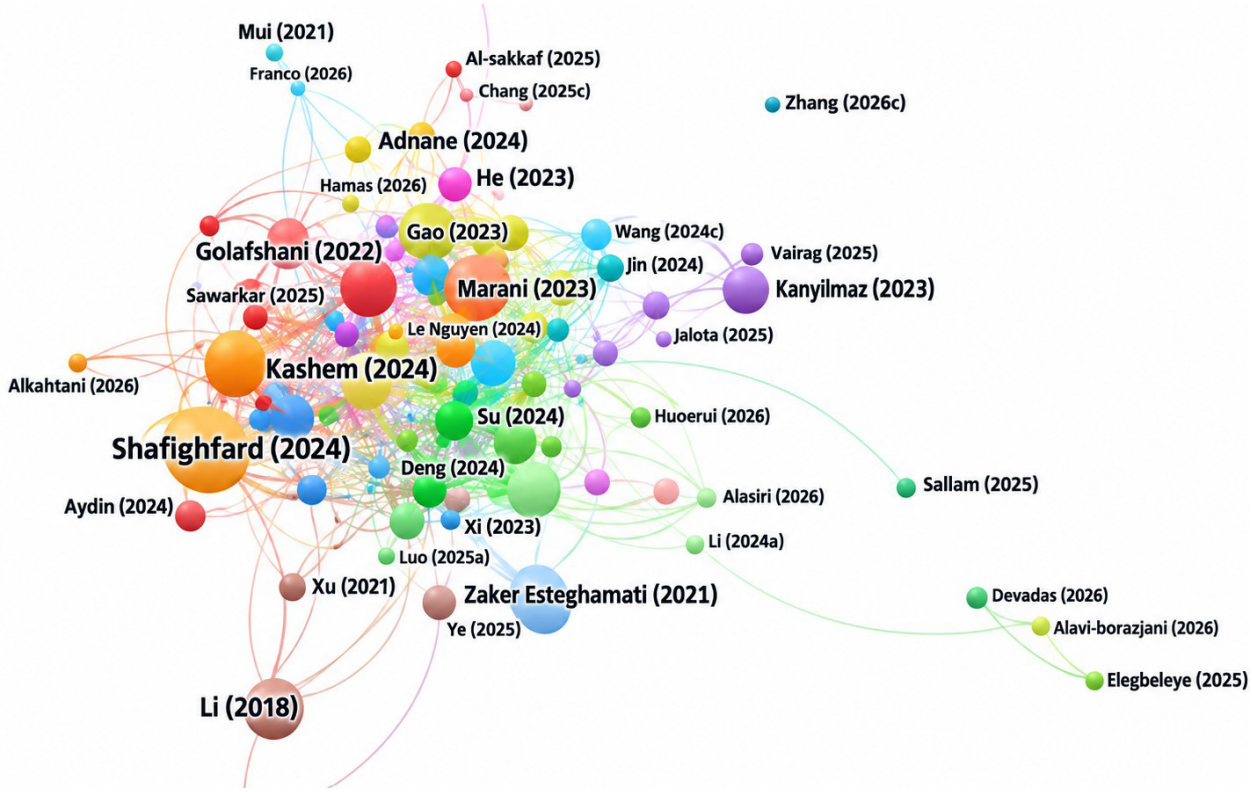


Figure 6. Co-citation authorship network

prominent positions in the network and showed close relationships with other authors. Several clusters indicate that the area covers a wide range of research topics, such as sustainable concrete optimization, XAI applications, ML-based carbon prediction, and LCA. Additionally, several supporting authors were identified, suggesting a new research focus area that could become important in subsequent studies. Overall, the close links between clusters indicate a developed and cooperative research environment with growing multidisciplinary integration.

3.5.3. Keywords co-occurrence analysis

The keyword co-occurrence network is shown in Figure 7. The network shows that the most common research topic in the literature on EC assessment and building materials decarbonization is ML. ML, compressive strength, carbon emissions, sustainable development, and LCA have the strongest relationships, suggesting that AI methods are mostly used to forecast material performance while promoting sustainability goals. A number of theme groups surfaced; keywords including ML, neural networks, SVMs, gradient boosting, and prediction are encompassed in the first cluster, which concentrates on model prediction. The second cluster links carbon emissions, carbon footprint, EC, and LCA, emphasizing environmental and sustainability evaluation. The third cluster focuses on circular economy techniques, including recycling, demolition waste, recycled aggregates, and construction waste management. Low-carbon binders, such as fly ash, slag, geopolymers, and rice husk ash, are the focus of another cluster. Lastly, a growing interest in net-zero construction pathways is specified by an emerging cluster that includes carbon capture, carbon sequestration, and zero-carbon concepts. The growth of XAI techniques in sustainable construction studies is further revealed by the appearance of expressions such as "uncertainty analysis," "Shapley," "decision-making," and "sensitivity analysis." However, explainability remains underdeveloped in relation to traditional ML methods, indicating a significant research gap and potential for further study.

3.6. Artificial intelligence methods and prediction

The reviewed studies show that the most common AI methods used in EC and sustainable building materials research are ANN, gradient boosting (extreme gradient boosting [XGBoost]), RF, decision tree (DT), deep learning, and SVM, as presented in Table 2.

Compressive strength, EC, and geopolymer

Table 2. AI method application in embodied carbon (EC) assessment

S/N	AI method	Application in the study	Prediction	Sources
1	ANN	Geopolymer concrete, concrete, material optimization, and sustainable design mix	Durability, EC, compressive strength, relationship of cost performance	30,32,34
2	Random forest	Prediction of sustainable concrete, EC modeling, and recycled aggregate concrete	Carbon emissions, strength properties, and environmental predictors	49-51
3	SVM	Nonlinear modeling of material behavior and performance	Carbon properties, strength, and sustainability pointers	34,52
4	XGBoost/Gradient boosting	Sustainable material optimization, high-accuracy prediction	Carbon emissions, EC, and design mix optimization	50,53,54
5	Deep learning	Recycled concrete	Material performance and sustainability outcomes	41,47
6	LightGBM/CatBoost	An ensemble learning method	Carbon evaluation and performance of sustainable concrete	55
7	Decision tree	Predicts interpretability and decision support	Carbon decisions, material selection, and sustainability assessment	49-51

Abbreviations: AI: Artificial intelligence; ANN: Artificial neural network; SVM: Support vector machine.

performance were the main outcomes predicted using ANN models.[32,36,56] The most popular ensemble learning techniques, RF and XGBoost, were also included because of their high predictive accuracy and ability to identify key factors influencing carbon emissions and sustainability outcomes.[55,57,58] While DT-based models enabled comprehensible sustainable decision-making, deep learning was mostly used for recycled aggregate concrete and complex materials datasets.[57,59] AI adoption transitioning beyond descriptive models was assessed by combining the examined studies into a research maturity context based on application emphasis, explainability, and adoption readiness, as shown in Table 3.

Table 3. Research maturity and limitations of AI Application in EC assessment

AI type	Models	Application	Maturity	Limitation	Sources
Prediction	ANN, RF, SVM, XGBoost	Estimation of EC	High	Black-box behavior and inadequate interpretability	30,34,58,60
Optimization	NSGA-II, GA, PSO	Mix design optimization	Medium–High	Limited explainability of optimization choices	32,33,57,61
Explainability	SHAP, PDP, Feature importance	Interpretation	Medium	Mostly post-training interpretation with inadequate engineering validation	51,54,62
Decision Support	Hybrid AI-XAI	Material selection	Low	Few practical applications and limited real-world distribution	51,59

Abbreviations: AI: Artificial intelligence; ANN: Artificial neural network; EC: Embodied carbon; GA: Genetic algorithm; NSGA-II: Nondominated sorting genetic algorithm II; PDP: Partial dependence plot; PSO: Particle swarm optimization; RF: Random forest; SHAP: Shapley Additive exPlanations; SVM: Support vector machine; XAI: Explainable artificial intelligence; XGBoost: Extreme gradient boosting.

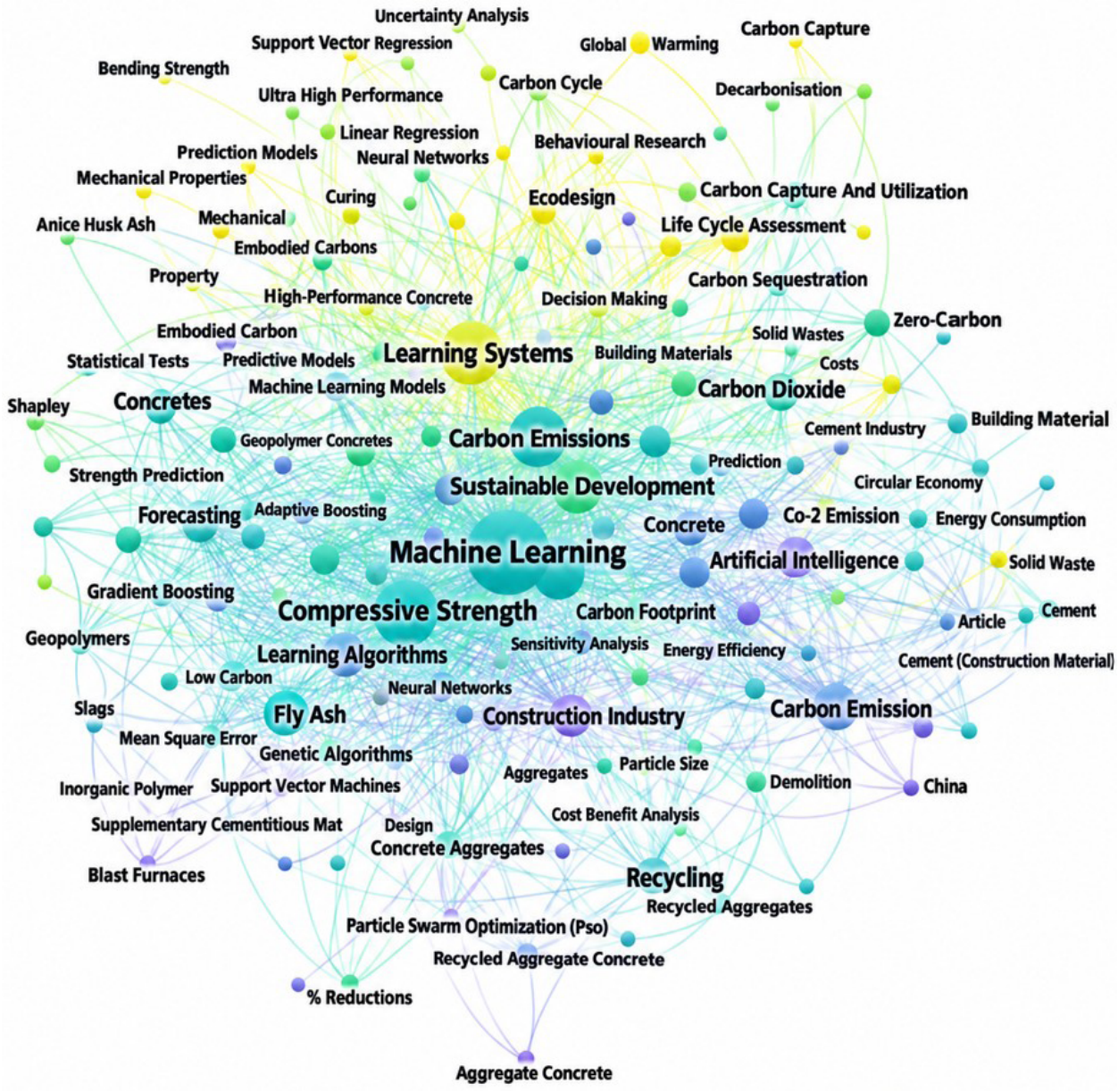


Figure 7. Keywords co-occurrence network

The findings show that ANN, RF, SVM, and XGBoost are the most popular models for quantifying EC, assessing life cycle performance, simulating sustainable concrete mixtures, and predicting compressive strength. Their strong predictive accuracy and ability to handle complex nonlinear interactions are shown in their general distribution.[30,52,58] However, most of these models remain black-box methods, limiting transparency and reducing stakeholder trust in AI-generated recommendations. Optimization research has advanced to a medium-to-high degree.[32,33] The combination of multi-objective optimization methods such as genetic algorithms, NSGA-II, and particle swarm optimization with ML helps concrete compositions minimize EC while maintaining cost-effectiveness and structural performance.[32,33,57,61] Although the optimization process itself often lacks transparency, these methods evidently show an evolution from basic prediction toward carbon-aware design optimization. The application of XAI methods remains at an early stage of adoption. The most popular methods for analyzing model behavior and determining significant factors influencing EC are SHAP, partial dependence plots (PDP), and feature importance

analysis. Recent studies show that SHAP and other XAI methods help interpret ML predictions, improve assurance in sustainable materials optimization, and identify important design variables.[51,54,62] However, these methods are not intrinsically interpretable modeling approaches; rather, they are primarily post-training interpretations used after model training. Lastly, few studies have combined LCA, AI prediction, XAI interpretation, and sustainable goals into a unified framework to support real-world material selection and regulatory decision-making. This suggests the field is still moving from model development to reliable and ready-to-use AI solutions for low-carbon construction. The maturity assessment shows that explainability and decision-support integration are still struggling, despite significant maturity in prediction and optimization research. This serves as a basis for the next section's in-depth analysis of evidence-based XAI techniques.[51,59]

3.7. Explainable artificial intelligence techniques

Table 4 summarizes the different XAI techniques and their applications identified in the reviewed literature. SHAP, feature importance analysis, sensitivity analysis, partial dependence-based visualization, and explainable decision support frameworks were specifically documented in the chosen research. SHAP was the most popular technique, especially in research on geopolymer concrete, waste-glass concrete, and nano-modified concrete. The results show that carbons are influenced by binder composition, waste-glass content, and durability parameters.[51] The contributions of variables affecting the performance of construction sustainability were explained using SHAP.[55] Similarly, SHAP also explained EC, strength of model predictions, and workability.[56] In order to determine the factors most strongly affecting EC and material performance, ML studies often used feature importance analysis.[36,57,58] These studies present ranked procedures for identifying the most significant mix-design parameters, the strength of dominant predictors, and building-material variables based on their contribution to EC prediction. Explainable ML was used to demonstrate how material strength and sustainability goals are influenced by nano-silica content[55], and how waste-glass incorporation is affected using comparative analysis of feature-effect visualizations and PDP.[51] Sensitivity analysis was used to assess the effects of binder composition and predictor content[32], the effects of rice husk ash and mix factors[36], and EC and prediction performance.[56] In contrast, LIME and other advanced explainable techniques such as rule-based explanations and permutation importance were only briefly mentioned in the literature, suggesting areas for further research.

A comparative analysis of the main XAI techniques identified in the examined literature is shown in Table 5. The analysis shows that SHAP has become the most widespread explainability technique; it quantifies the influence of each input variable and explains both the local and global behavior of ML model predictions. SHAP has been used in recent research to increase stakeholder confidence in ML results, identify important material properties, and explain EC prediction models.[51,59] Additionally, model outcomes' and predictor variables'

Table 4. XAI techniques adopted in EC assessment

S/N	XAI technique	Use	Sources
1	SHAP	Explains how each feature contributes to model predictions	51,62
2	LIME	Defines individual local predictions	59
3	Feature importance analysis	Classification of most significant predictors	36,49,50
4	PDP	Predictors and results relationship visualization	51,54
5	Decision tree visualization	Offers interpretable decision pathways	49,50
6	Sensitivity analysis	Deals effectively with input variation based on outputs	30,34,63
7	Permutation importance	Measures importance by creating variables	Not clearly identified
8	Rule-based explanations	Produces human-readable decision rules (explainable framework)	51,59

Abbreviations: EC: Embodied carbon; LIME: Local interpretable model-agnostic explanations; PDP: Partial dependence plot; SHAP: Shapley Additive exPlanations; XAI: Explainable artificial intelligence.

connections are being visualized using PDP. PDP allows researchers to understand how variations in factors such as the percentage of recycled aggregate, water-to-cement ratio, cement content, and other cementitious materials affect EC prediction or concrete performance. However, when predictor variables are extremely correlated, PDP's interpretation becomes less trustworthy because it implies independence among variables. Thus, to obtain more reliable and robust interpretations, research suggests combining PDP with SHAP.[51,59] LIME was mentioned only infrequently in the examined literature compared with SHAP and PDP. All abbreviations are compiled in Table A1, a glossary of terms or AI/XAI methods.

Although LIME can be used with almost any ML model and provides local explanations for specific predictions, its use in EC assessment and sustainable construction remains limited. This implies that research on XAI in the construction industry is still in its early stages and needs more extensive validation using actual engineering datasets. Feature importance analysis remains the simplest, fastest, and most efficient XAI technique. Researchers used this method for ranking and classifying the most significant factors influencing model predictions of EC. However, this method alone cannot describe how variables interact or explain the rationale behind a prediction. To create more transparent and reliable AI models, new research increasingly suggests combining feature importance analysis with SHAP, PDP, and sensitivity analysis.[51] Generally, the examined literature shows that although explainability techniques are increasingly used in EC prediction research, their use is mostly applied after the model is trained rather than integrated into the construction model. Future research should concentrate on creating hybrid AI–XAI frameworks that combine LCA, prediction, optimization, and explainability into unified decision-support systems. This is to support sustainable material selection and EC reduction throughout the construction life cycle.

3.8. Importance of XAI in decarbonizing building materials

According to the reviewed studies, XAI offers three main advantages:

(i) Determination of the properties of carbon-driven materials: The material factors that have the highest effect on EC emissions can be determined using XAI techniques. XAI can assess the effects of variables such as cement content, binder quantity, aggregate type, supplementary cementitious material replacement levels, and processing needs on carbon results

Table 5. Comparative analysis of the main XAI techniques applied in EC

XAI techniques	Purpose	Strength	Weakness	Future research
SHAP	Explains both local and global content of model predictions	It is highly interpretable and explains how each feature contributes to predictions	It is complex, and computations are expensive, especially for large datasets.	There is a need for extensive validation across different building materials to improve timely decision-support systems
PDP	Demonstrates how individual variables affect predictions	It enhances global interpretation while visualizing future effects	It assumes feature independence that can lead to wrong interpretations when there are connected variables	There should be a combination of models to enhance reliability and robustness
LIME	Explains local model predictions	It is simple and flexible to use with any ML model	Unbalanced explanations as a result of limited implementation	More adoption and research are needed
Feature importance analysis	Classification of significant variables based on their contribution to model performance	It is easy, fast, and efficient for computing and interpretation	Lack of variable interactions and relationships	Detailed explanation while integrated with other models (SHAP, PDP, and sensitivity analysis)

Abbreviations: EC: Embodied carbon; LIME: Local interpretable model-agnostic explanations; ML: Machine learning; PDP: Partial dependence plot; SHAP: Shapley Additive exPlanations; XAI: Explainable artificial intelligence.

using techniques such as SHAP, feature analysis, and sensitivity analysis. XAI helps practitioners identify which design factors influence emissions and, therefore, need prioritization when optimizing materials.[51,56,58] This transparency increases trust in AI model predictions and helps focus on decarbonization strategies.

(ii) Explaining AI suggestions for low-carbon replacements: XAI's ability to explain an ML model's recommendation for a specific low-carbon material or design mix is one of its main features. Techniques such as SHAP provide measurable and visual explanations of how variables affect predictions, as shown in the study. For example, higher waste-glass content and lower cement usage can enhance carbon-credit significance and sustainability performance.[51] Similarly, the process of how XAI models support the usage of ground granulated blast-furnace slag (GGBFS) and fly ash in geopolymer concrete was also demonstrated.[56] XAI turns AI from a black-box prediction model into a transparent decision-making system that practitioners can rely on by offering clear explanations.

(iii) Carbon, cost, and strength trade-off: A number of studies adopted AI with multi-objective optimization frameworks in creating a balance between structural performance (strength), economic viability (cost), and a sustainable environment (decarbonization). Optimization of nano-silica-modified concrete using explainable ML was evaluated.[32] Optimization of geopolymer concrete by concurrently taking cost, strength, and carbon into consideration using AI was also investigated.[55] XAI frameworks may assess trade-offs between sustainability and economic goals in reinforced concrete structures.[59] By balancing carbon, cost, and strength, XAI helps practitioners understand decisions about material selection. The reviewed literature shows increasing use of AI-based models for alternative and low-carbon building materials, such as geopolymer concrete, slag and fly-ash-based binders, and concrete with agricultural or industrial waste. These studies highlight how a data-driven model can identify links between material composition and performance. However, results depend heavily on the specific experimental data, material properties, and regional conditions of each study. Thus, claims of carbon reduction should not be universally applied without further LCA and independent experimental or field validation.

Based on the duration, research growth, and studies included in the review, Table 6 outlines three broad periods of research emphasis in the development of AI applications for EC assessment and sustainable building materials. These three phases are proposed based on the temporal distribution of the reviewed literature. These periods are employed as an analytical framework for evaluating prevailing themes in the literature. Explainability, prediction, and optimization intersect throughout, and the adoption of future research does not mean that earlier methods are no longer employed. Phase 1 focused on prediction research (2018–2020); this involved the use of ML models to predict material and structural performance, including EC and associated environmental impacts, which characterized the earliest defined period.

A major focus during this time was whether AI models could learn correlations between material composition, structural performance, and environmental outcomes. As a result, the literature shows a preliminary shift from traditional analytical methods to data-driven prediction. Accurate prediction was, however, typically more significant than integrated optimization or model interpretability.[30,34,37] Phase 2 focuses on optimization and multi-objective support (2021–2023); in addition to prediction, this stage shows a growing emphasis on optimization. Considering

Table 6. Historical research emphases in AI/XAI applications for EC assessment

Phase	Duration	Research characteristics
Phase 1	2018–2020	Integration of LCA and the development of AI prediction applications
Phase 2	2021–2023	Expansion of AI-driven concrete mixture optimization using multi-objective optimization models that take EC, cost, durability, and strength into account
Phase 3	2024–2026	An AI-based decision-support system that integrates XAI and interpretable ML to manage EC and sustainable construction emergence

Abbreviations: AI: Artificial intelligence; EC: Embodied carbon; LCA: Life cycle assessment; ML: Machine learning; XAI: Explainable artificial intelligence.

engineering, economic, and environmental performance, the reviewed studies increasingly integrated ML with optimization models and multi-objective techniques. Applications included combined optimization, carbon reduction, structural performance, and cost-related goals.[32,33,41,48,52] Phase 3 deals with integrated decision support and explainability (2024–2026). Explainability, interpretability, and integrated decision support have received comparatively more focus in the most recent years. In addition to ML and optimization techniques, recent research has increasingly considered methods such as SHAP, PDP, feature importance analysis, and sensitivity analysis. This trend highlights growing interest in understanding the reasons behind specific predictions and how model outputs can support transparent material and design choices. However, explainability should be seen as an additional focus rather than a complete replacement for prior AI methods, as prediction and optimization remain significant components of recent studies.[32,33,41,48,52] These three phases are technological stages that are subject to change. The borders are analytical and represent the dominant research areas found in the material that was collected. Prediction, optimization, and explainability are closely related, and some studies may use techniques from diverse phases or periods. Therefore, the proposed framework for analyzing shifts in research concentration should follow a clear technological maturity procedure.

4. Discussion

4.1. Evolution process (LCA–AI–XAI)

The review findings emphasized that research has broadly shifted from traditional life cycle–based evaluation to data-driven prediction, optimization, and, more recently, to explainability-oriented decision support. This development should not be seen as AI and then XAI replacing LCA in a linear approach. Instead, the data show that these methods are becoming more integrated: optimization supports alternative selection, AI provides predictive and computational capabilities, LCA continues to provide environmental assessment principles, and XAI adds interpretability to model outputs. This systematic procedure makes it possible to identify carbon hotspots across the extraction, manufacturing, transportation, construction, maintenance, and end-of-life phases, making it essential for sustainable construction design. However, as construction projects have become more data-intensive, traditional LCA has encountered problems with large data requirements, time-consuming computational processes, and limited capacity to analyze complex nonlinear interactions among several factors. These limitations have prompted the integration of AI methods that can process big datasets and produce fast and highly accurate predictions.

The expanding use of AI for EC assessment and sustainable material selection is reflected in the bibliometric analysis, which shows a significant rise in research activity after 2023. Growing international commitments to carbon neutrality, advancements in digital construction technology, increased accessibility to public databases, and the rapid development of ML models all align with this trend. This review shows that AI applications have progressed beyond basic material-property prediction to include concrete mixture optimization, LCA emissions, recycled-material utilization, waste reduction, and multi-objective decision-making that concurrently considers structural performance, environmental impact, and economic feasibility. The review also identified ANN, RF, SVM, XGBoost, DT, and deep learning as the most popular predictive models because they can capture complex nonlinear relationships between material composition and sustainability performance. Recent research increasingly seeks optimal combinations of cement alternative materials, recycled aggregate, additional cementitious materials, and other design variables that can reduce carbon and cost while maintaining structural performance rather than predicting EC.

The review identifies a notable disparity between model transparency and prediction accuracy despite these technological advancements. The majority of AI models continue to be black-box systems that make highly accurate predictions without clarifying how factors affect the results of decisions. Although these models perform well statistically, their limited interpretability reduces stakeholder confidence and limits practical application in construction practice. While material selection decisions affect durability, life cycle performance, structural safety, regulatory compliance, and cost, clients, certification bodies, professionals, and regulatory agencies demand transparent data to support their choices. As a result, explainability should be a basic requirement for reliable AI-enabled EC assessment rather than an optional advancement. The field is progressing toward transparent decision-support systems that promote sustainable construction practices, as shown by the growing use of SHAP, PDP, feature analysis, and sensitivity analysis. China had the highest publication output in the reviewed Scopus-indexed dataset, showing high research activity in this area. However, publication volume alone does not indicate research maturity, quality, or impact, as it does not account for citation influence, methodological rigor, data quality, validation, reproducibility, model transferability, or practical implementation. The geographic concentration of publications highlights current research hubs and

the importance of assessing whether models built on region-specific data can apply to construction systems with different materials, energy sources, environments, transport distances, and regulations.

4.2. Limitations to adopting AI and XAI

Despite the fact that AI has greatly improved EC prediction and optimization, a number of limitations still prevent its widespread usage in the construction industry. The main challenge is that many advanced ML models are not yet transparent. The demand for construction decisions is greatly influenced by practical explanations, long-term building performance, structural performance, economic feasibility, and environmental impact, unlike other industries where prediction accuracy alone may suffice. Therefore, professionals and stakeholders need decision-support systems that can explain why specific material compositions or design options are recommended rather than just showing prediction outcomes. The review also shows that, beyond incorporating design models, existing explainability techniques are mainly used after model development, and these techniques—SHAP, PDP, feature importance analysis, and sensitivity analysis—explain only predictions after model training. These techniques do not fully meet the need for interpretable AI systems that can support construction decisions throughout the decision-making process, despite increased model transparency. Therefore, future research should focus on immediate incorporation of explainability into prediction and optimization frameworks.

The availability and quality of data present another limitation. For training and validation, AI models rely significantly on dependable and large datasets. However, the quality and standardization of EPDs differ significantly, and EC datasets remain inconsistent across nations. Limited LCI data, uneven reporting procedures, and missing variables all limit model generalization across various building environments and reduce prediction reliability. Hence, improving data quality through comprehensive EC databases and consistent reporting frameworks is crucial for improving AI performance. Another limitation identified by the review is geographical inconsistency. The geographical distribution reveals a concentration of research in the English-language Scopus-indexed literature reviewed. China leads in publication output, followed by India, the United Kingdom, the United States, and Saudi Arabia.

Australia, South Korea, Pakistan, Canada, and Germany also rank among the top 10 most productive countries. This pattern highlights significant research activity in Asia, especially in China and India, along with contributions from North America, Europe, the Middle East, and Oceania. However, no countries from Africa or South America were among the top 10, and European representation was limited to the United Kingdom and Germany. These results should be viewed considering the English-language limitation in the search strategy, which may have reduced representation of research published in national or regional languages, particularly from non-English-speaking European countries such as Germany, France, and Scandinavian nations. This raises concerns about the transferability of current prediction models and shows a significant application of AI-enabled sustainable construction. Material compositions and properties, manufacturing processes, modes of transportation, and weather conditions vary across countries. As a result, AI models trained on datasets from one region or country may not produce equally reliable predictions elsewhere. External dataset validation, regional standardization, and increased international collaboration in data sharing will be necessary to overcome this challenge.

4.3. Practical implications and research gaps

The reviewed studies highlight that AI and XAI methods have potential for supporting EC assessment, material selection, combination optimization, and sustainable construction decisions. Explainability techniques such as SHAP, PDP, feature importance, and sensitivity analysis can identify key factors influencing model predictions. However, applying these techniques directly in engineering depends on data quality, geographic relevance, representativeness, and independent validation in laboratory, manufacturing, and project settings. Regarding regionalization and transferability, AI and EC research emphasizes the need for region-specific validation instead of assuming models developed in one context are universally applicable. Localized datasets should at least include material type and composition, life cycle stage, energy source, electricity mix, production technology, transport distance and mode, recycled or alternative content, EC factors, geographical location, and data quality, as presented in Table 7. These variables can standardize regional LCI and AI datasets. A model trained in one region should be tested on independent data from other regions, and if performance drops, transfer learning or model adaptation can integrate local data while preserving knowledge from the original dataset.

The systematic review highlights a number of important research gaps that should guide the development of XAI for EC assessment. First, relatively few studies in sustainable construction research specifically address explainability, despite the rapid expansion of AI applications. Transparency, accountability, uncertainty quantification,

and user trust are given far less consideration than prediction accuracy in model evaluation. This disparity limits practical adoption because construction decisions necessitate not only accurate predictions but also comprehensible explanations. Second, supporting evidence for XAI techniques remains limited. SHAP has emerged as the most popular technique because it offers both local and global explanations of model behavior, while PDP, sensitivity analysis, and feature importance analysis are also commonly used in current research. However, in EC research, methods such as LIME, permutation importance, rule-based explanations, uncertainty-aware explainability, and naturally interpretable ML remain largely unexplored. Extending these techniques would provide resourcefulness for various construction applications and enhance comprehension of model behavior.

Table 7. Proposed standardized variables for regional EC datasets

Category of data	Variables
Material identification	Type, grade, composition
Material quantity	kg, kg/m^3, tonnes
Carbon factor	kg CO_2e/kg, kg CO_2e/m^3, kg CO_2e/t
Life cycle stage	A1–A5, B, C
Production	Technology, process
Energy	Electricity, fuel, energy intensity
Electricity	Regional grid emission factor
Transportation	Distance, transport mode, vehicle or load
Alternative materials content	Alternative or recycled percentage
Geographical location	Country, region
Source	EPD, LCI, database, manufacturer, supplier
Data quality	Indicator/ Data quality score
Global Warming Potential (GWP) methods	GWP100 method
Validation	Lab, field, or independent dataset

Abbreviations: EC: Embodied carbon; EPD: Environmental product declaration; LCI: Life cycle inventory.

A prominent geographic disparity in research production is also revealed in the review. China has a substantial national commitment to AI-enabled sustainable construction and EC reduction, as evidenced by its dominance in publication output and international collaboration, raising concerns about model generalizability. The majority of current AI models are developed utilizing locally produced datasets that reflect specific building materials, production techniques, environmental factors, and legal frameworks. Applying these models directly in developing countries may reduce prediction reliability because locally accessible materials may have different physical, structural, and environmental properties. For Africa and other developing countries that are rapidly urbanizing and need to increase sustainable construction, this finding is vital. Developing a complete LCI, localized standard prediction models, and region-based EC datasets must become a research aim. Robustness would be increased, and prediction bias related to regional datasets would be reduced by validating AI models across various geographical regions. Additionally, combined global databases may provide more illustrative training data to support international applications of AI systems.

The literature suggests that XAI can enhance transparency by identifying the variables that most affect EC predictions, helping engineers balance environmental, structural, cost, and durability considerations. Thus, these are potential uses, not proven engineering implementations. This review did not include laboratory tests, plant measurements, or field trials, so the practical effectiveness of XAI recommendations remains unverified. Three evidence phases were identified in the literature: (i) model-based evidence, where AI or XAI predicts, explains, or optimizes EC and material performance; (ii) experimentally supported evidence, where models are developed or validated with laboratory-generated data; and (iii) engineering implementation evidence, involving real-world manufacturing, construction, or use. Most evidence falls within the first two phases, with limited proof of sustained plant or project-scale application. This distinction is crucial for understanding the practical impact of XAI on decarbonizing building materials.

4.4. Future direction for XAI in sustainable construction

The synthesis suggests that future studies should focus on integrated, empirically validated decision-support systems rather than isolated developments in prediction accuracy. These systems could openly reflect uncertainty and regional variation while integrating LCA, AI prediction, optimization, and explainability. However, independent datasets, laboratory tests, production data, and project-level case studies must be used for validation

as engineering implementation progresses. Therefore, future studies should assess model interpretability, external validation, uncertainty, transferability, and practical decision performance in addition to predicting accuracy. Future frameworks should incorporate LCA, prediction, optimization, and explainability into combined decision-support stages rather than treating them as distinct study areas. Professionals should be able to concurrently assess EC, structural performance, economic viability, life cycle implications, and sustainable goals using XAI, which also provides clear explanations for every decision and choice. To expand the application of these models across various geographical areas, future AI models should also include adaptive learning, transfer learning, uncertainty analysis, and continual model updates. These techniques would improve model transferability and reduce regional prediction bias by enabling effective adaptation of current models using local datasets without necessitating a full redevelopment. Establishing shared EC databases, consistent reporting standards, and validating AI models across construction environments will require international collaboration between researchers, professionals, government agencies, and regulatory bodies. Finally, the shift from traditional LCA to AI and XAI reflects a change in sustainable construction decisions, not just a technological development. Future outcomes will rely on developing transparent, reliable, and globally adaptable decision-support systems that can accelerate the shift to low-carbon and sustainable construction, along with increasingly accurate prediction models.

4.5 Recommended conceptual framework

The study proposed a conceptual framework that consists of six stages (Figure 8). The first stage is data acquisition on building materials from databases, LCI, EPDs, construction companies, material suppliers, and carbon data to produce a dataset. Data acquisition involves cleaning, normalization, feature selection, and integration of variables. These variables form a high-quality dataset for model development for predictive modeling of EC, building-material performance, material combinations, sustainable outcomes, and optimization. XAI techniques are introduced to explain model outputs and identify critical carbon emitters. Model output explanations lead to decisions that balance carbon, cost, performance, strength, and durability, strengthening sustainable material selection for engineers, professionals, and policymakers and enabling feedback on recommended materials, project performance, and model adoption. This framework is a conceptual synthesis that was developed from the literature review. It is meant to show how decision-support procedures, AI predictions, XAI, and LCI data could be combined for EC management. The framework is not developed as an implementation model that has been verified by experimentation. Therefore, practical implementation requires that its components be empirically tested using material records, laboratory measurements, production data, and project-level proof.

4.6. Limitations of the study

The study acknowledged some limitations: The review relied exclusively on Scopus databases, which means that some relevant studies might have been missed since other databases such as Google Scholar, ScienceDirect, Web of Science, and IEEE Xplore were not included. The study was limited to English-language studies, where some valuable studies in other languages might have been excluded. Metadata depth and quality, on which bibliometric findings depend, are limited within Scopus. Much of the reviewed literature lacks public datasets, which may hinder external validation; the focus of the study is on EC, while other environmental impacts were not examined. As XAI research is an emerging area, some recent growth in the literature may not be fully represented. The proposed conceptual framework requires empirical validation through practical case studies. Limiting the review to English-language publications may have excluded important studies published in other languages, especially from countries where research on sustainable construction, AI, and EC is circulated through regional or national journals. Likewise, depending solely on Scopus as the bibliographic database might have led to the omission of relevant works indexed elsewhere. To ensure broader geographical and language representation, future reviews should incorporate multilingual research and multiple databases such as Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar, and also utilize regional databases to broaden searches and reduce bias from database-specific selection. The review should be read in light of the understanding that the available information is primarily based on literature, in addition to database and search-strategy limitations. The practical efficiency of the XAI techniques identified in the literature cannot be empirically validated because the current study did not independently generate laboratory, manufacturing, or field data. Additionally, 2026 is an incomplete observation period because the analysis is based on publication and indexing dates. The suggested research emphasis periods are analytically categorized rather than defined by objective stages of technological maturity. Lastly, publication productivity is treated as a measure of research effort, not research maturity. These limitations emphasize the necessity of more empirical research using standardized regional LCI datasets, independent validation, uncertainty

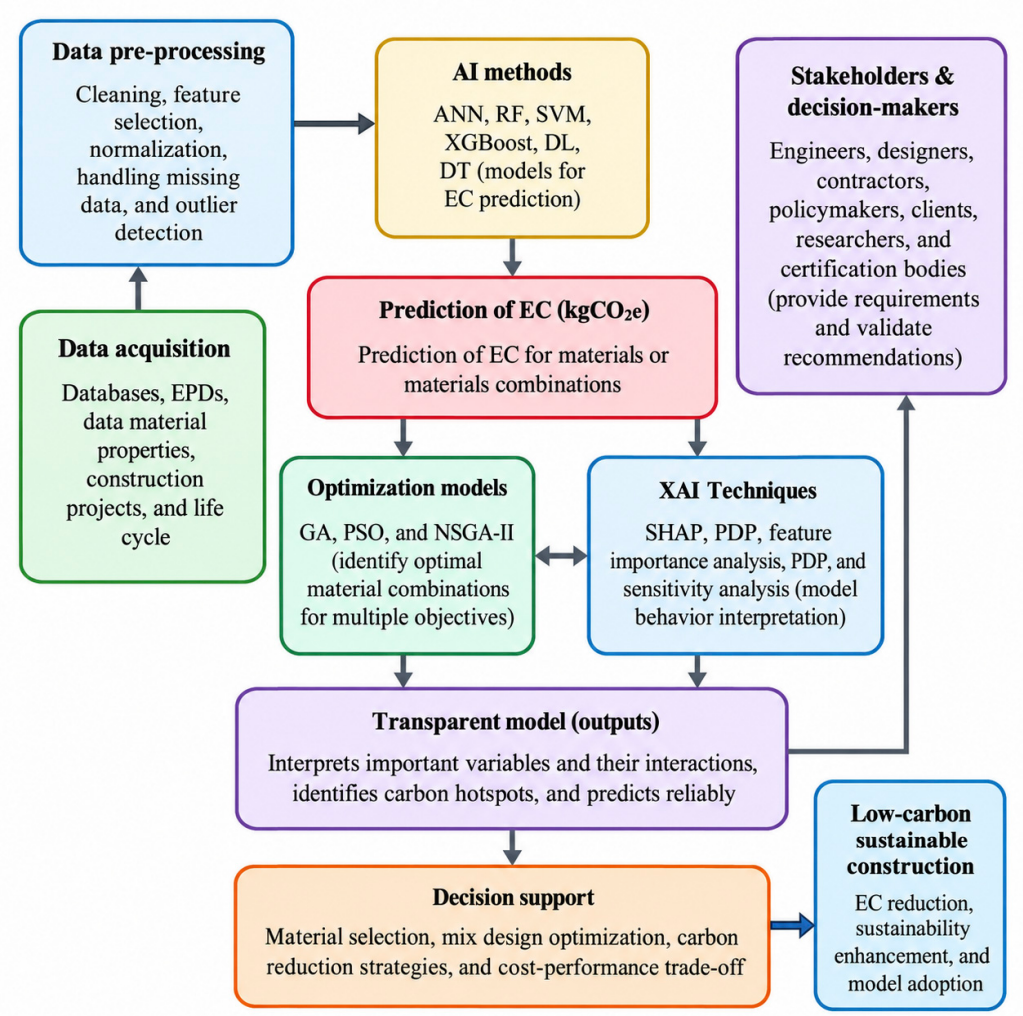


Figure 8. XAI decision-making framework
Note: The conceptual framework was developed from a methodological synthesis of the literature and requires empirical validation before practical application.
Abbreviations: AI: Artificial intelligence; ANN: Artificial neural network; DL: Deep learning; DT: Decision tree; EC: Embodied carbon; EPD: Environmental product declaration; GA: Genetic algorithm; NSGA-II: Nondominated sorting genetic algorithm II; PDP: Partial dependence plot; PSO: Particle swarm optimization; RF: Random forest; SHAP: Shapley Additive exPlanations; SVM: Support vector machine; XAI: Explainable artificial intelligence; XGBoost: Extreme gradient boosting.

analysis, laboratory testing, and practical construction applications.

5. Conclusion

The development of XAI and AI for EC assessment is thoroughly summarized in this review. The bibliometric analysis shows a sharp rise in research activity over the last ten years, reflecting growing global interest in digital technologies to reduce construction and building-material-related carbon emissions. The review shows that research on EC assessment and building-material decarbonization increasingly integrates LCA, AI, optimization, and explainability. The data highlight a change in research focus from mostly prediction-oriented applications to optimization and, more recently, to integrated decision support and model interpretability. However, this does not necessarily reflect a linear path toward technological maturity. The actual use of XAI still depends on dataset quality, regional representativeness, external validation, and engineering implementation evidence. The results show that ML models achieve strong predictive performance for EC prediction and building-material optimization, especially ANN, RF, SVM, deep learning,

DT, and XGBoost. The ability of AI to identify material combinations that reduce carbon while maintaining structural and economic performance is further demonstrated using optimization models such as particle swarm optimization and genetic algorithm. However, the review shows that model interpretability has not advanced as predictive models have. The majority of current research still uses black-box models, limiting transparency, trust, and practical application in construction practice. The study further identifies that the main XAI techniques currently used for EC prediction are SHAP, sensitivity analysis, PDP, and feature importance analysis. These techniques enhance understanding of model behavior and facilitate transparent and reliable construction decision-making by identifying the factors that most significantly affect prediction outcomes. When XAI technique usage is compared with AI, the rate of usage is relatively low, indicating substantial future research.

A number of important research gaps were identified. The geographical concentration of existing research, with China accounting for the majority of publications, raises concerns about the transferability of AI models to areas with distinct building materials, climates, manufacturing processes, and regulatory frameworks. Furthermore, the generalizability of existing AI systems is still constrained by inconsistent EC databases, lack of specific regional LCI data, and inadequate external model validation. More international collaboration, standard EC databases, and the validation of AI models in construction are necessary to address these limitations. Finally, this study shows that establishing transparent, reliable, and internationally adaptable AI-driven decision-support systems is more important for the future of EC assessment than simply increasing prediction accuracy. By integrating XAI with LCA, optimization strategies, digital construction technology, and regional databases, professionals and stakeholders can make better, evidence-based decisions that hasten the shift to low-carbon and sustainable construction. This study creates a basis for future studies that are intended to develop explainable and reliable AI frameworks that can help the construction industry achieve its global sustainable goals. Therefore, rather than experimental proof of the efficiency of particular XAI procedures or low-carbon materials, the findings present a literature-based research framework. Future studies should use cross-regional datasets, production data, laboratory tests, and field data to evaluate XAI-enabled decision-support techniques. The reliability of the relationship identified using AI models across various material compositions, manufacturing systems, and geographic locations would be ascertained with the use of such validation.

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The authors declare they have no competing interests.

Author contributions

Conceptualization: All authors
Formal analysis: Funmilayo C. Jayeola
Investigation: Funmilayo C. Jayeola
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Writing – review & editing: Funmilayo C. Jayeola

Availability of data

The bibliographic dataset for this study was sourced from the Scopus database. Processed data and bibliometric analysis results can be obtained from the corresponding author upon reasonable request.

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Appendix

Table A1. Glossary of terms for AI/XAI methods

Terminology	Abbreviation	Explanation
Artificial intelligence	AI	A vast domain encompassing computational techniques that execute functions necessitating abilities such as reasoning, learning, predictions, and decision-making
Machine learning	ML	A subset of AI where models learn patterns from data to generate predictions or make decisions
Artificial neural network	ANN	A framework composed of interlinked computational elements capable of predicting complex nonlinear relationships between inputs and outputs
Random forest	RF	A collective ML method (ensemble learning) that integrates several decision trees to enhance predictive accuracy and reduce overfitting
Support vector machine	SVM	A supervised learning technique that determines an ideal decision boundary and is capable of modeling nonlinear relationships through kernel functions
Gradient boosting machine	GBM	A collective learning method that incrementally constructs predictive models, where each subsequent model rectifies the inaccuracies of its predecessors
Extreme gradient boosting	XGBoost	A refined gradient-boosting model frequently employed for predicting with organized datasets
Deep learning	DL	A category of ML methods utilizing multilayer neural networks that can predict complex patterns from extensive or high-dimensional datasets
Decision tree	DT	A model utilizing a tree structure that predicts an outcome by employing a series of decision criteria on input variables
Explainable artificial intelligence	XAI	Methods that assist users in comprehending and explaining the mechanisms by which AI models generate predictions or decisions
Shapley Additive exPlanations	SHAP	A method in XAI that assesses the impact of specific input features on a model's prediction
Local interpretable model-agnostic explanations	LIME	An XAI technique that offers a comprehensive representation of a model concerning a specific prediction
Partial dependence plot	PDP	A graphical method illustrating the impact of alterations in one or more input variables on model predictions, while averaging the effects of other variables
Feature importance analysis	–	A technique for ranking input variables based on how important or contributing they are to model predictions
Sensitivity analysis	–	A method that investigates how model outputs are affected by changes in input variables
Permutation importance	–	A feature-importance technique that assesses how changing a feature at random affects model performance
Explainable decision support	–	Predictive suggestions are combined with explanations so that users can comprehend the reasoning behind the recommendations in this decision-support method