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INTEGRATING ARTIFICIAL INTELLIGENCE INTO LIFE CYCLE ASSESSMENT IN THE BUILDING INDUSTRY: A BIBLIOMETRIC AND CRITICAL REVIEW

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Abstract: Increasing environmental impacts of buildings necessitate robust sustainability assessment tools, positioning Life Cycle Assessment (LCA) as a central methodology for evaluating environmental performance. Artificial Intelligence (AI) offers strategic potential to enhance the accuracy, efficiency, and automation of LCA processes. This study critically reviews AI-integrated LCA research in the construction sector. A bibliometric analysis of 883 publications from Web of Science and Scopus was conducted, alongside a systematic review of 18 articles explicitly integrating AI into LCA workflows. Findings show Machine Learning (ML) and Artificial Neural Networks (ANN) are predominantly used to predict energy consumption and carbon emissions. However, AI-LCA integration remains fragmented due to unstructured data, lack of standardized protocols, low interoperability, and restricted access to high-quality datasets. Current literature primarily focuses on operational energy use, largely neglecting embodied impacts and broader sustainability indicators. Future research should prioritize AI frameworks incorporating standardized data schemas, real-time monitoring, and case-based validation. Integrating AI into LCA offers transformative potential for data-driven, transparent, and adaptable sustainability strategies in construction.

Keywords: Buildings, Life cycle assessments, Artificial intelligence, Bibliometric analysis, Systematic analysis

Yapay Zekânın Yapı Sektöründe Yaşam Döngüsü Değerlendirmesine Entegrasyonu: Bibliyometrik ve Eleştirel Bir İnceleme

Öz: Binaların çevresel etkilerindeki artış, sürdürülebilirlik değerlendirme araçlarının kapsam ve güvenilirliğine yönelik ihtiyacı belirginleştirmiş; bu bağlamda Yaşam Döngüsü Değerlendirmesi (LCA), çevresel performansın nicel analizinde merkezi bir konuma yerleşmiştir. Yapay zekâ (YZ), LCA süreçlerinin doğruluğunu, verimliliğini ve otomasyon potansiyelini artırmada stratejik bir araç olarak öne çıkmaktadır. Bu çalışma, inşaat sektöründe YZ entegreli LCA araştırmalarına yönelik güncel ve eleştirel bir inceleme sunmaktadır. Çalışmada, Web of Science ve Scopus veri tabanlarından elde edilen 883 yayının bibliyometrik analizi ile YZ tekniklerinin LCA iş akışlarına açıkça entegre edildiği, metodolojik şeffaflığa sahip 18 seçilmiş makalenin sistematik değerlendirmesi yürütülmüştür. Bulgular, makine öğrenmesi ve yapay sinir ağlarının enerji tüketimi ve karbon emisyonu tahminlerinde yaygın kullanıldığını göstermektedir. Ancak YZ-LCA entegrasyonu; yapısal olmayan veriler, standart protokol eksikliği, düşük araç uyumluluğu ve kaliteli veriye kısıtlı erişim nedeniyle henüz bütüncül bir yapıya ulaşamamıştır. Mevcut literatür çoğunlukla operasyonel enerjiye odaklanıp, gömülü etkileri ve geniş sürdürülebilirlik göstergelerini ihmal etmektedir. Gelecek araştırmalar standart veri şemaları, gerçek zamanlı izleme ve vaka temelli doğrulamalar içeren YZ çerçevelerine öncelik vermelidir. Bu entegrasyon, yapı sektöründe veriye dayalı, şeffaf ve uyarlanabilir sürdürülebilirlik stratejileri için dönüştürücü potansiyel taşımaktadır.

Anahtar Kelimeler: Yapılar, Yaşam döngüsü değerlendirmesi, Yapay zeka, Bibliyometrik analiz, Sistematik analiz

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1. INTRODUCTION

The construction industry is a major contributor to global environmental challenges, particularly in terms of resource consumption and greenhouse gas emissions (Change, 2022; UNEP, 2020). As buildings are responsible for over one-third of global energy-related carbon dioxide emissions, their environmental performance has become a focal point for sustainability efforts (IEA, 2022). According to OPEC's World Oil Outlook 2025, global primary energy demand is projected to rise by approximately 23 % by 2050, increasing from about 308 million barrels of oil equivalent per day (boe/d) in 2024 to nearly 378 mboe/d, with oil demand expected to reach around 123 million barrels per day by 2050 (Opec, 2025). Furthermore, the construction sector alone accounts for approximately one-third of the greenhouse gas emissions driving climate change (Yılmaz & Seyis, 2021).

The implementation of Life Cycle Assessment (LCA) methods in the built environment has gained significant traction in recent decades (Yardimci&Kurucay, 2024). The International Organization for Standardization (ISO) published the first LCA standard in 1997, establishing a four-phase structure: goal and scope definition, life cycle inventory (LCI) analysis, life cycle impact assessment (LCIA), and interpretation (ISO, 1997; ISO 14040; ISO 14044). Since then, LCA has become a globally recognized methodology, providing a structured framework for quantifying environmental impacts across different stages of a product's life cycle (Hou et al., 2015; Yardımcı et. al., 2024). Scientific interest in LCA has grown rapidly since the 1990s, with a continuous increase in both academic publications and practical applications (Ligozat et al., 2022). Despite this progress, traditional LCA processes remain labor-intensive and time-consuming, requiring extensive data and domain expertise. In this context, artificial intelligence (AI) has emerged as a transformative technology with the potential to streamline LCA practices, automate data handling, and enhance predictive accuracy. AI encompasses a broad spectrum of computational methods that simulate human intelligence, including machine learning (ML), deep learning, and neural networks (Karadag&Gür, 2025). Subfields such as ML and artificial neural networks (ANNs) are particularly relevant to LCA due to their ability to detect nonlinear patterns, predict environmental performance, and optimize material selections based on large, complex datasets.

Recent comprehensive reviews have further consolidated the growing body of knowledge on the integration of artificial intelligence into Life Cycle Assessment (LCA). For example, Popowicz et al. (2025) provided an extensive analysis of digital technologies for LCA, proposing an integrated combination framework that encompasses data acquisition, processing, and application phases across multiple sectors, including the built environment. Their study emphasized the potential of combining BIM, IoT, and AI-driven analytics to enhance the accuracy and efficiency of LCA workflows. Similarly, Neupane et al. (2025) conducted an analytical review of machine learning algorithms in LCA studies, highlighting methodological advances in supervised, unsupervised, and reinforcement learning, as well as the challenges associated with data heterogeneity, interoperability, and model validation. While the present research focuses specifically on bibliometric and critical analysis of AI–LCA integration in the building industry, the insights from these broader reviews provide valuable context and underline the novelty of narrowing the scope to construction-related applications.

This study addresses a critical research gap by evaluating how AI techniques have been applied to LCA in the construction industry and by identifying current limitations and future research opportunities. While recent studies suggest a growing interest in integrating AI into LCA workflows, there has been limited synthesis of this interdisciplinary field. This review is thus timely and essential, as it explores the state-of-the-art developments, underlying methodologies, and implementation challenges at a time when both LCA and AI are undergoing rapid evolution.

To accomplish this, the review adopts a two-tiered methodology: first, a bibliometric analysis of 883 articles was conducted to map the research landscape and identify key trends. Based on predefined inclusion criteria, a systematic review was then carried out on 18 influential studies integrating AI and LCA. Bibliometric analysis provides a structured, data-driven method for mapping research trends and scholarly networks. It is defined as the application of quantitative methods to the study of bibliographic data (Hawkins, 1978). As Żarczyńska and De Bellis (2012) note, bibliometrics allows for the identification of core authors, institutions, and topics across disciplines. In the context of LCA research, Moutik et al. (2023) demonstrated its utility in highlighting emerging clusters and methodological patterns over time.

By combining quantitative and qualitative approaches, this study aims to critically examine how AI is reshaping the application of LCA in the building industry. Furthermore, it outlines the technical, practical, and institutional challenges that must be addressed for AI-supported LCA to achieve greater reliability and scalability.

2. MATERIAL AND METHOD

This research conducted a bibliometric analysis of studies on building life cycle assessment (LCA), followed by a systematic review of publications integrating artificial intelligence (AI). The bibliometric analysis was carried out using the Bibliometrix package in R, a programming language widely used for statistical analysis and visualization (Aria & Cucurullo, 2017). To ensure the breadth and accuracy of the analysis, two major citation databases were utilized: Web of Science (WoS) Core Collection and Scopus, both recognized for their comprehensive indexing of high-quality scientific publications (Qian, 2014; Zhu & Liu, 2020; Moutik et al., 2023).

We conducted a topic search using the keywords: “BIM”, “building information modelling”, “digital twin”, “artificial intelligence”, “machine learning”, “deep learning”, “automated”, and “optimisation”, in combination with “LCA” and “life cycle assessment”. This search was performed in the title, abstract, keywords, and author keywords sections. The search yielded 5235 records from WoS and 7863 records from Scopus.

To focus the scope specifically on the building industry, records were filtered by selecting subject areas such as architecture, environment, engineering, materials, construction, and buildings. This yielded 2632 records from WoS and 3169 from Scopus. After removing off-topic records (e.g., unrelated to buildings or infrastructure), 1284 records remained from WoS and 1114 from Scopus. Duplicates within each database were removed (WoS: 602 valid; Scopus: 491 valid).

The valid datasets from WoS and Scopus were merged, and 210 duplicates between the databases were removed. This led to a final dataset of 883 unique records specifically focused on LCA applications in the construction sector. Studies not related to building projects or architecture/construction engineering contexts (e.g., automotive, agriculture, etc.) were excluded.

From the final dataset obtained through bibliometric filtering, a total of 18 studies were systematically selected in accordance with predefined inclusion and exclusion criteria. The inclusion criteria required that studies demonstrate a direct application of artificial intelligence methods within the context of Life Cycle Assessment (LCA), maintain a clear focus on the building sector—particularly in architecture, construction, or material-related applications—and present a transparent and methodologically sound research design. On the other hand, studies were excluded if they contained only superficial mentions of AI without methodological integration, focused on sectors unrelated to the built environment, or lacked access to full-text content necessary for critical evaluation. This selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guideline to ensure methodological rigor and transparency. Only studies published up to the end of 2024 were considered for inclusion, in line with the data collection timeline. The detailed progression of identification, screening, eligibility, and final inclusion is presented in Table 1.

Table 1. Flows chart of this research.

Stage	Process Description	Output (n)
Identification	Comprehensive search conducted in Web of Science and Scopus databases using combinations of "LCA", "BIM", "AI", and related digital technologies. Searches were applied to title, abstract, and keywords.	WoS: 5,235 Scopus: 7,863
Screening	Filtering by relevant research areas: architecture, engineering, environment, construction, building, and materials. Exclusion of non-building sectors and unrelated domains.	WoS: 2,632 Scopus: 3,169
Eligibility	Manual review of title and abstract for relevance to LCA in building context. Duplicate records removed within each database.	WoS: 602 Scopus: 491
Integration	Combined eligible records from both databases. Duplicates between WoS and Scopus eliminated. Final sample determined.	Total unique studies: 883
Inclusion	Of 883 relevant studies, 18 were selected for systematic review based on four criteria: a clear LCA methodology, direct AI application, building sector focus, and methodological transparency.	Final studies analysed: 18

3. BIBLIOMETRIC ANALYSIS

The studies chosen for bibliometric analysis were analysed based on years, publication source, publication location, authors' publication numbers, most cited studies, most relevant words and most trending word groups.

3.1. Years of Publications

Figure 1 illustrates the annual distribution of publications related to the integration of artificial intelligence (AI) in life cycle assessment (LCA) within the construction sector. From 1999 to 2010, the number of publications remained minimal, never exceeding 8 articles in any given year. However, a significant upward trend began after 2013, with notable acceleration starting in 2017. The number of publications nearly doubled from 63 in 2017 to 104 in 2019, peaking at 150 in 2021.

This growth trend can be attributed to several contextual factors. First, global climate commitments (the Paris Agreement and the SDGs agenda etc.) have strengthened the role of life cycle thinking in policy and industry, increasing attention to LCA tools across disciplines (UNEP Life Cycle Initiative, 2017). Second, the rising availability and maturity of AI techniques has encouraged their use for optimization, automation, and predictive modelling within LCA workflows, a direction consistently highlighted by recent analytical reviews (Neupane et al., 2025). The sharp increase visible around 2020–2021 also plausibly reflects post COVID digitalisation dynamics that prioritised data driven methods when field work was constrained (Amankwah-Amoah et. al., 2021; Elrefaey et. al., 2022). A slight dip in counts for 2022 is commonly observed in bibliometric series and may reflect indexing and publication lags rather than a structural decline.

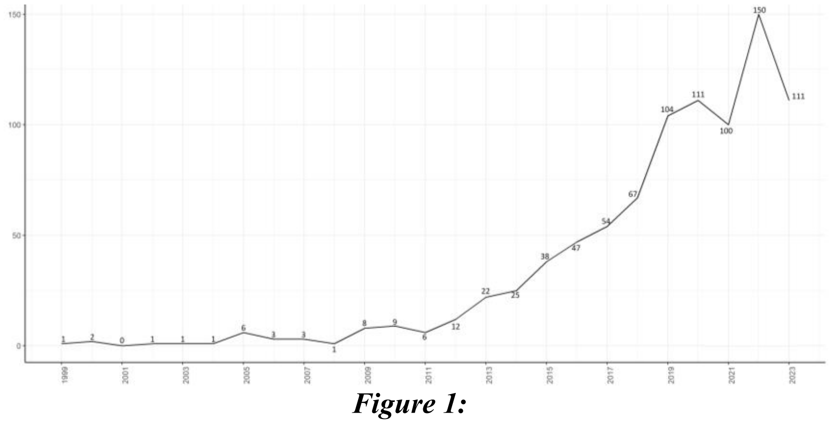

Figure 1:
Distribution of the number of scientific studies by annually.

3.2. Publication Source

The bibliometric analysis revealed that Sustainability, Journal of Cleaner Production, and Energy and Buildings were the most prolific sources in the field of AI-integrated LCA research in the building industry, as shown in Figure 2. These journals were followed by Building and Environment, Journal of Building Engineering, and Automation in Construction.

This distribution highlights a concentration of research at the intersection of sustainability, digital construction, and environmental performance assessment. Sustainability, the most dominant source with 85 publications, offers an open-access, interdisciplinary platform that has increasingly attracted research on AI-based modeling and lifecycle methodologies. Journal of Cleaner Production and Energy and Buildings follow with 53 and 49 publications respectively, both focusing on environmental optimization and data-driven solutions in the construction sector.

As illustrated in Figure 2, this cluster of high-impact journals indicates a preference for venues that emphasize interdisciplinary frameworks, practical application of AI in built environment contexts, and strong alignment with climate policy and sustainable development goals. Their editorial openness to emerging technologies and their hybrid or open-access publication models may also explain their prominence in the field.

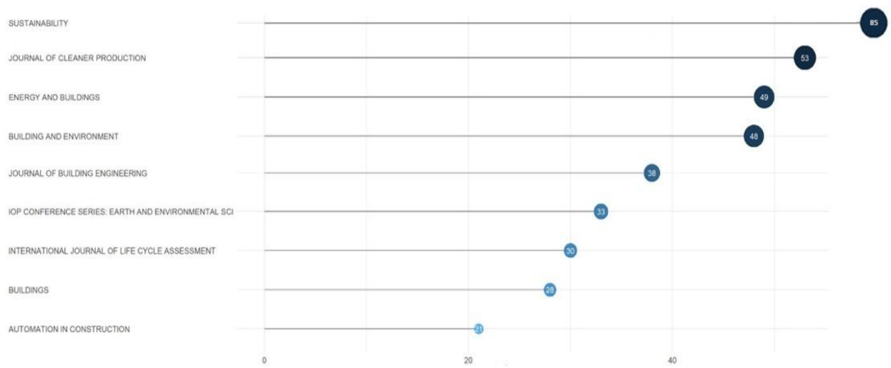

Figure 2:
The number of studies according to the journals

3.3. Location of Publications

Figure 3 presents the geographical distribution of scientific publications in the field of AI-integrated LCA. The leading contributors are China (194 publications) and the United States (176 publications), followed by Spain (124), Italy (121), Germany and the United Kingdom (93 each), Australia (80), Canada (78), Portugal (68), and South Korea (61). The prominence of China and the United States aligns with their large construction markets and sustained research investment in digital and low-carbon transitions, while European output benefits from policy frameworks such as the European Green Deal that explicitly embed LCA in product and building regulations (Long et al., 2025; Fu et al., 2023; Sala et al., 2023). The USA also demonstrates strong academic leadership in AI applications, supported by high levels of private sector investment and interdisciplinary research institutions. This global distribution indicates that technological infrastructure, environmental policy, and national research priorities strongly influence publication productivity in the AI-LCA domain (Bonoli et al., 2021; Islam, 2025). The notable gap in contributions from regions such as Africa and South America underscores the need for broader research inclusivity and capacity-building efforts in emerging economies (Prabhakar, 2025).

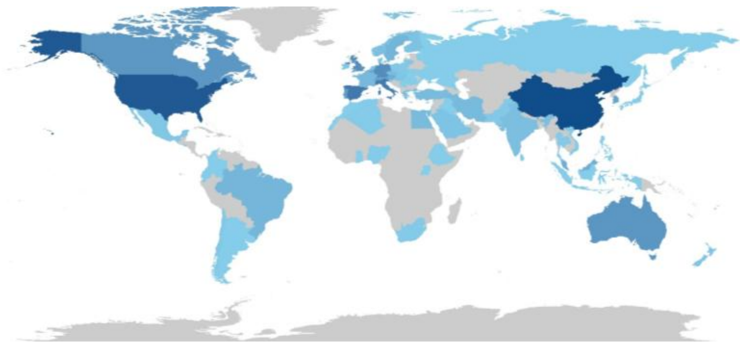

Figure 3:
The country distribution of the studies

3.4. Number of Publications by Author

The bibliometric analysis identified several leading authors who have significantly contributed to the literature on the integration of artificial intelligence (AI) and life cycle assessment (LCA) in the building sector. As shown in Table 2, Alexander Passer leads with 20 publications, followed closely by Guillame Habert and Alexander Hollberg with 19 each. Other prolific contributors include Carmen Llatas (2009–2022), Bernardette Soust-Verdaguer (2014–2023), and Karen Allacker (2010–2024), among others. A common thread among these authors is their deep engagement with sustainability metrics, digital construction strategies, and AI-supported life cycle modeling. For example, Passer and Hollberg have worked extensively on parametric LCA tools and BIM-integrated environmental assessments. Habert and Röck (2012–2024) are frequently cited for their contributions to embodied carbon quantification and optimization frameworks using machine learning algorithms. Many of these researchers are affiliated with prominent European institutions such as TU Graz, ETH Zurich, and KU Leuven, which are known for their interdisciplinary research environments and strong policy-driven sustainability agendas. Notably, the fractional publication scores indicate not only quantity but also the level of author contribution. The high fractional scores of researchers such as Habert (5.012) and Hollberg (4.276) suggest primary authorship or leadership roles in collaborative projects, reinforcing their intellectual impact on the field. The presence of authors from geographically diverse institutions—including Australia, Portugal, and Hong Kong—also points to the growing global reach of AI-LCA research, though contributions remain concentrated within a relatively small academic network.

Table 2. The number of studies of the authors

No	Author	Number of Articles	Fraction
1	Alexander Passer	20	3,764
2	Guillame Habert	19	5,012
3	Alexander Hollberg	19	4,276
4	Carmen Llatas	17	3,933
5	Bernardette Soust-Verdaguer	12	2,992
6	Costa A	11	2,983
7	Karen Allacker	10	2,3374
8	Martin Röck	10	1,677
9	José Dinis Silvestre	10	2,4
10	Syed Shujaa Safdar Gardezi	9	2,733
11	Amin Hammad	9	3,033
12	Werner Lang	9	1,936
13	Ruben Santos	9	2,45
14	Vivian Wy Tam	9	2,066
15	Xiaoyi Chen	8	1,775

3.5. Most Cited Publications

Table 3 presents the top 15 most cited publications related to LCA in the building sector. These publications have received widespread recognition and reflect significant milestones in the development of LCA methodologies, BIM integration, and AI-assisted environmental assessments. Among these, six are comprehensive literature reviews, and nine are applied case studies, indicating a balanced interest in both theoretical frameworks and practical implementations. The most cited study is the foundational work on the ecoinvent database by Frischknecht et al. (2005), with 676 citations, underscoring its central role as a standardized data source for life cycle inventories. The second most cited paper by Basbagill et al. (2013) focuses on early-stage LCA integration in building design, reflecting growing interest in shifting sustainability considerations upstream in the design process. It is noteworthy that 13 out of 15 studies were published after 2016, revealing the recent surge of scholarly attention in the field. This trend correlates with the increasing availability of computational tools such as BIM and AI, which have enabled more sophisticated environmental assessments. Prominent themes among the most cited works include BIM-based environmental visualization (Röck et al., 2018), BIM–LCA integration frameworks (Najjar et al., 2017; Santos et al., 2019), and early-stage optimization of embodied impacts (Shadram et al., 2016; Meex et al., 2018).

Overall, this citation landscape highlights the transition of LCA from a back-end evaluation tool to a front-loaded design decision-support system, especially in combination with AI and BIM technologies.

Table 3. The number of citation

No	Cititation	Name	Author
1	676	The ecoinvent Database: Overview and Methodological Framework (7 pp)	Frischknecht et. al., (2005)
2	444	Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts	Basbagill et. al., (2013)
3	313	Building Information Modeling (BIM) for green buildings: A critical review and future directions	Lu et. al., (2017)
4	293	Critical review of bim-based LCA method to buildings	Soust-Verdaguer et. al. (2017)
5	254	Calculation of a building's life cycle carbon emissions based on Ecotect and building information modeling	Peng (2016)
6	250	Life cycle analysis in the construction sector: Guiding the optimization of conventional Italian buildings	Asdrubali et. al., (2013)
7	207	A mixed review of the adoption of Building Information Modelling (BIM) for sustainability	Chong et. al., (2017)
8	182	LCA and BIM: Visualization of environmental potentials in building construction at early design stages	Röck et. al., (2018)
9	180	Bibliometric analysis and review of Building Information Modelling literature published between 2005 and 2015	Santos et. al., (2017)
10	174	Life cycle energy efficiency in building structures: A review of current developments and future outlooks based on BIM capabilities	Eleftheriadis et. al., (2017)
11	157	Integration of BIM and LCA: Evaluating the environmental impacts of building materials at an early stage of designing a typical office building	Najjar et. al., (2017)
12	152	Integration of LCA and LCC analysis within a BIM-based environment	Santos et. al., (2019)
13	147	An integrated BIM-based framework for minimizing embodied energy during building design	Shadram et. al., (2016)
14	146	Requirements for applying LCA-based environmental impact assessment tools in the early stages of building design	Meex et. al., (2018)
15	146	Green building assessment tool (GBAT) for integrated BIM-based design decisions	Ilhan & Yaman, (2016)

3.6. The Most Relevant Words

Figure 4 illustrates the most frequently occurring terms in the analyzed studies based on titles, keywords, and abstracts. The top keywords include “architectural design” (310 occurrences), “life cycle” (304), “environmental impact” (158), “sustainable development” (145), and “building information modelling” (136). These results reflect the thematic orientation of the field, where environmental assessment, digital modelling tools (particularly BIM), and sustainability strategies dominate scholarly discourse. The prominence of terms like “life cycle assessment (LCA)” and “environmental impact” confirms the methodological core of the studies. Meanwhile, “architectural design” and “construction” point to practical applications in the built environment, suggesting that AI-enhanced LCA research is tightly linked with real-world design decision-making. Terms such as “optimization”, “decision making”, “ecodesign”, and “energy utilization” further highlight a shift toward predictive modeling and early-stage integration of LCA in building processes. The presence of “information theory” and “life cycle analysis” also suggests a growing interest in formalizing data structures and improving interoperability in digital design ecosystems. Overall, the dominance of both technical (e.g., BIM, energy) and strategic (e.g., decision making, sustainability) keywords indicates that the integration of AI in LCA is not only about automation but also about enabling intelligent, data-driven decisions in sustainable architecture.

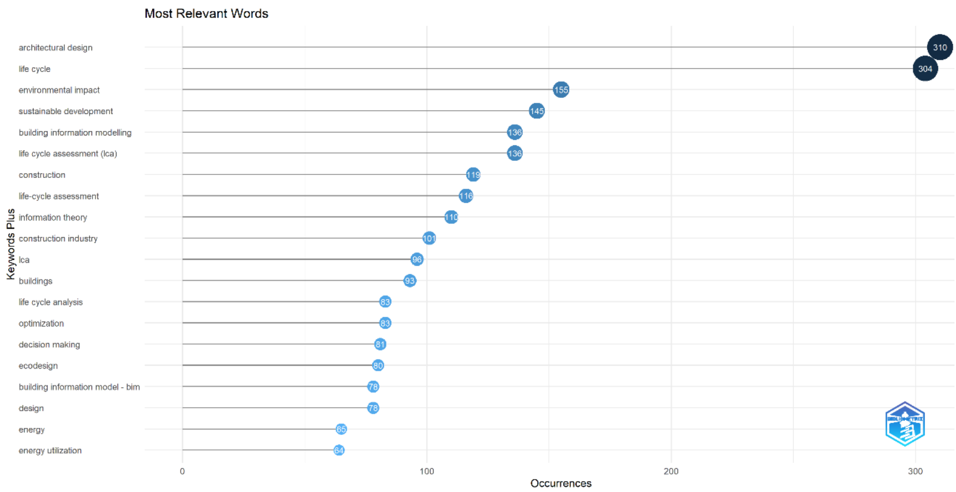

Figure 4:
The most relevant words

3.7. The Most Frequencies Words

Figure 5 shows the temporal distribution and intensity of key terms used in AI-integrated LCA studies over the past decade. Terms such as “BIM”, “life cycle”, “building information modelling”, “LCA”, and “sustainability” reached their peak frequencies in 2020 and 2021, marking a period of intense scholarly focus on these foundational concepts.

The persistence of these terms into subsequent years reflects their continued relevance in both theoretical and applied research. Their high frequency also suggests that researchers increasingly rely on these frameworks for conducting environmental assessments and informing early-stage design decisions. In more recent years, “machine learning” and “climate change” have gained prominence, particularly in 2022, signaling a thematic shift toward predictive analytics, automated environmental modeling, and climate-resilient design strategies. These emerging terms suggest a growing awareness of the potential of AI not just for optimization, but for holistic environmental forecasting in the building sector. The timeline also reveals the maturation of certain topics (e.g., “energy efficiency”, “carbon emissions”) and the emergence of new ones (e.g., “decision support”, “modelling”, “design optimization”), pointing to a diversification in methodological approaches and application areas. This evolution aligns with global sustainability goals and the increasing urgency of climate adaptation in architecture and construction.

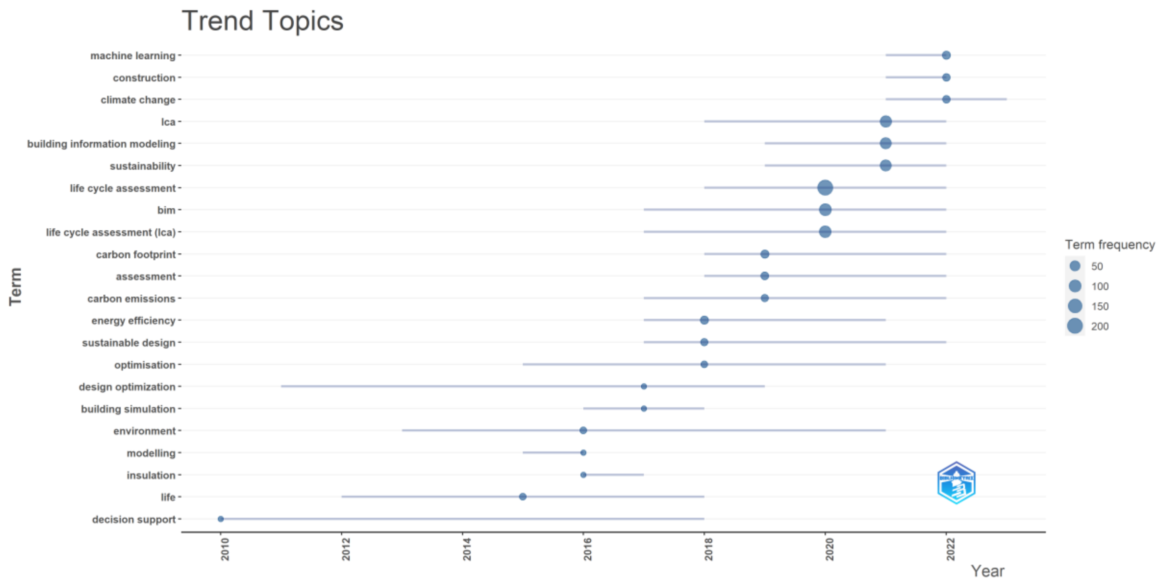

Figure 5:
Most frequencies words

4. SYSTEMATIC LITERATURE REVIEW

Building on the bibliometric filtering described above, the final set of 18 studies was systematically included in the qualitative synthesis. These studies were selected because they demonstrated the explicit integration of artificial intelligence (AI) methods within Life Cycle Assessment (LCA) workflows in the building sector, in line with the inclusion criteria defined in the methodology section. In particular, the selected publications focus on architecture, construction, or material-related applications, and report their methods with sufficient transparency to allow for comparison across cases. Studies that referred to AI only superficially, targeted non-construction sectors, or lacked methodological rigor were excluded. This procedure followed the PRISMA guideline for systematic reviews to ensure methodological rigor and reproducibility (Page et al., 2021). To manage the heterogeneity within the dataset, the studies were coded according to the primary AI technique applied to the LCA task. This yielded four analytical categories: (i) automated systems, (ii) machine learning methods (excluding ANN), (iii) artificial neural networks (ANN), and (iv) other AI studies. Where multiple methods were applied, classification was based on the dominant approach used for model development and validation.

Table 4 lists the 18 studies included in the review, together with their authors, publication sources, and topics. As shown, five studies fall under automated, six under machine learning, four under artificial neural networks and three under other AI studies.

Table 4. AI studies selected for the systematic literature review

Authors	Name of Journal	Name of Publications	Topic
Li et. al. (2016)	Habitat international	Development of an automated estimator of life-cycle carbon emissions for residential buildings: A case study in Nanjing, China.	Automated systems
Yung & Wang (2014)	International Journal of Advanced Robotic Systems	A 6D CAD model for the automatic assessment of building sustainability	Automated systems
Serrano-Baena et. al. (2023)	Energy and Buildings	Optimising LCA in complex buildings with MLCAQ: a BIM-based methodology for automated multi-criteria materials selection.	Automated systems
Mohammed (2023)	Journal of Architectural Engineering	Process Map for Accessing Automatization of Life Cycle Assessment Utilizing Building Information Modeling.	Automated systems
Růžička et. al. (2022)	Sustainability	BIM and automation in complex building assessment	Automated systems
Ji et. al. (2021)	Building and Environment	Building life-span prediction for life cycle assessment and life cycle cost using machine learning: A big data approach	Machine Learning
D'Amico et. al. (2019).	Structures	Machine learning for sustainable structures: a call for data	Machine Learning
Venkatraj et. al. (2023)	Energy and Buildings	Toward the application of a machine learning framework for building life cycle energy assessment.	Machine Learning
Toosi et. al. (2022)	Building and Environment	A novel LCSA-Machine learning based optimization model for sustainable building design-A case study of energy storage systems.	Machine Learning
Farahzadi & Kioumarsi (2022)	Journal of Cleaner Production	Application of machine learning initiatives and intelligent perspectives for CO2 emissions reduction in construction	Machine Learning
Ghoroghi et. al. (2022)	The International Journal of Life Cycle Assessment	Advances in application of machine learning to life cycle assessment: a literature review	Machine Learning
D'Amico et. al. (2019)	Journal of Cleaner Production	Artificial Neural Networks to assess energy and environmental performance of buildings: An Italian case study.	Artifical Neural Networks
Yan et. al. (2023)	Journal of Building Engineering	A real-time operational carbon emission prediction method for the early design stage of residential units based on a convolutional neural network: A case study in Beijing, China.	Artifical Neural Networks
Savino & Tondolo (2021)	Frontiers of Structural and Civil Engineering	Automated classification of civil structure defects based on convolutional neural network	Artifical Neural Networks
Ahmed et. al. (2022)	Sustainability	Artificial neural networks for sustainable development of the construction industry	Artifical Neural Networks
Yu et. al. (2021)	Environmental Impact Assessment Review	Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence	Other AI Studies
Ligozat et. al. (2022)	Sustainability	Unraveling the hidden environmental impacts of AI solutions for environment life cycle assessment of AI solutions.	Other AI Studies
Koyamparambath et. al. (2022)	Sustainability	Implementing artificial intelligence techniques to predict environmental impacts: Case of construction products.	Other AI Studies

4.1. Automated Systems

This group includes five studies (Li et al., 2016; Yung & Wang, 2014; Serrano-Baena et al., 2023; Mohammed, 2023; Růžička et al., 2021) that focus on the development of automated systems to streamline LCA implementation in the building sector. These systems generally aim to reduce user dependency by integrating predefined workflows, BIM models, and rule-based evaluation techniques to generate environmental performance outputs with minimal manual input.

For example, Li et al. (2016) developed the CEERB (Carbon Emission Estimator for Residential Buildings), an automated LCA tool built specifically to overcome the lack of national carbon emission databases in China. The tool relies on standardized methodologies and extensive coefficient libraries and was tested using a reinforced concrete masonry building in Nanjing. Similarly, Yung and Wang (2014) proposed a 6D BIM model by integrating scheduling (4D), cost (5D), and sustainability (6D) dimensions into a CAD-based system. Their model enables automated sustainability assessments that cover economic, environmental, and social criteria for design alternatives.

More recent studies, such as Serrano-Baena et al. (2023), introduced MLCAQ, a BIM-integrated methodology supporting automated multi-criteria material selection. This system was validated on a high-rise case study and proved capable of calculating embodied carbon, energy use, waste generation, and cost differences between conventional and circular material choices. Mohammed (2023) focused on creating a process map for BIM-LCA integration, validated through surveys and Analytical Hierarchy Process (AHP), emphasizing improvements in LCA accuracy and scope. Furthermore, Růžička et al. (2021) concentrated on evaluating BIM-based data models for complex building quality assessments in the Czech context, using SBToolCZ and proposing conditions for automating evaluations.

Despite their promise, these systems primarily rely on static rules and predefined data structures, limiting flexibility in handling diverse design contexts or region-specific variables. Most of the tools do not incorporate adaptive learning or context-specific recalibration, which restricts their responsiveness to project-specific complexities. Furthermore, reliance on fixed databases (e.g., Ecoinvent) without dynamic updating mechanisms may reduce the long-term validity of impact calculations. Nevertheless, this category excels in ease of use, integration with commercial BIM tools, and early-stage design applicability, which are crucial for practical adoption. Future efforts should aim to hybridize automation with intelligent systems—such as machine learning—to enhance system adaptability and provide more context-sensitive, scalable LCA solutions.

4.2. Machine Learning

Machine learning (ML) is a subset of artificial intelligence that enables computer systems to automatically learn and improve from experience without being explicitly programmed. In the context of the built environment, ML is increasingly used to identify patterns in large datasets, develop predictive models, and support optimization tasks across various sustainability domain (Gür &Karadag, 2024).

This section presents studies that incorporate machine learning (ML) techniques into Life Cycle Assessment (LCA) frameworks. The selected articles were grouped into three categories: prediction-oriented studies, integration with life cycle-based methodologies, and general contributions to sustainability goals.

Ji et al. (2021) developed predictive models using both deep learning and conventional ML algorithms to estimate the lifespan of buildings. Their dataset included over 1.8 million construction and demolition records in South Korea. The deep learning model outperformed traditional methods, achieving a coefficient of variation between 0.932 and 0.955. This study illustrates the potential of deep learning for long-term planning and resource allocation in the building sector. However, the findings are limited to the South Korean context and require testing in diverse geographic regions to assess generalizability. Venkatraj et al. (2023) proposed a machine learning framework for early-stage prediction of energy consumption—embodied and operational—across multiple building typologies. Their model, tested on a case study, achieved high accuracy with minimal input data. While promising, the study is primarily focused on energy performance, without extending its application to other LCA impact categories such as carbon footprint or material depletion.

Toosi et al. (2022) introduced a novel framework integrating ML within a broader Life Cycle Sustainability Assessment (LCSA) framework. This approach combines LCA, Life Cycle Costing (LCC), and Social Life Cycle Assessment (S-LCA) to evaluate new design alternatives and retrofit scenarios. The integration of ML in the optimization process supports dynamic, data-driven decisions. This work exemplifies a shift from mono-criterion LCA models to holistic multi-dimensional sustainability evaluations. Farahzadi and Kioumarsi (2022) reviewed 78 studies addressing the role of ML and AI technologies in reducing CO_2 emissions during the construction phase. They categorized contributions under sustainable design, energy optimization, and decision-making platforms. Despite the breadth of this review, a lack of case-specific validation was noted, limiting the practical implications of many AI-supported tools.

D'Amico et al. (2019) underscored the potential of AI tools, particularly ML and neural networks, to improve building sustainability. Their short communication highlighted the lack of harmonized international datasets as a major constraint, which continues to limit the broader applicability of ML models in environmental assessments. This early work set the stage for subsequent research by advocating data transparency and interoperability. Ghoroghi et al. (2022) offered a critical perspective on the use of ML in LCA, emphasizing the importance of dynamic data and scenario-based optimization. Their review suggests that ML methods can enhance the accuracy and responsiveness of LCA tools, especially in uncertain design environments. However, the article also warns against overfitting and over-reliance on small datasets, pointing to the need for standardized benchmarking methods in LCA-ML studies.

A chronological review of the selected studies indicates a clear trend: While early works (pre-2020) focused on conceptual frameworks and theoretical feasibility, recent studies (post-2021) increasingly emphasize practical implementation, model validation, and integration into design workflows. The field is evolving from proof-of-concept studies to applied, multi-criteria decision-making systems, highlighting the growing maturity of ML in LCA-based construction analysis.

4.3. Artificial Neural Networks (ANN)

Artificial Artificial Neural Networks (ANNs) have increasingly been employed in LCA-related studies to model complex, nonlinear relationships within the building sector, especially when conventional models fall short in predictive accuracy (D'Amico et al., 2019; Yan et al., 2023). One notable example is the study by D'Amico et al. (2019), where ANNs were used to assess both energy and environmental performance of buildings. Their Italian case study demonstrated the model's ability to process large datasets and uncover patterns that traditional methods might overlook, highlighting ANNs as a viable decision-support tool in early design stages. However, the authors acknowledged that the availability and quality of training data are critical for ensuring robustness, suggesting that country-specific databases need further development. Similarly, Yan et al. (2023) proposed a real-time carbon emission prediction method based on Convolutional Neural Networks (CNNs), aimed at early-stage residential building design. Their case study from Beijing demonstrated that CNNs can effectively process spatial and temporal data simultaneously, offering superior performance over traditional LCA estimation methods. Yet, the study also emphasized the necessity of integrating these models with practical design workflows to ensure usability by non-technical stakeholders. Savino and Tondolo (2021) focused on automated classification of civil structure defects using CNNs, indicating that such networks can contribute not only to LCA assessments but also to ongoing structural health monitoring. While their study does not directly involve life cycle modelling, the outcomes suggest that ANN-driven defect recognition could be integrated with predictive maintenance modules in future LCA tools. Ahmed et al. (2022) explored how ANNs can support the sustainable development of the construction sector. Their model, based on regional construction practices, allowed the assessment of environmental impacts with minimal manual input. However, consistent with the findings of other ANN-based studies (D'Amico et al., 2019; Yan et al., 2023; Savino & Tondolo, 2021; Ahmed et al., 2022), they highlighted that the lack of standardized datasets and interoperability between ANN platforms and BIM/LCA tools remains a major barrier. In summary, ANN-based studies show significant promise in improving the granularity and adaptability of LCA analyses. They excel particularly in situations involving complex, multivariable datasets. Nonetheless, a key limitation across all reviewed studies in this category (D'Amico et al., 2019; Yan et al., 2023; Savino & Tondolo, 2021; Ahmed et al., 2022) is the absence of methodological standardization and clearly defined integration pathways into mainstream design and assessment platforms. To enhance their effectiveness, future work should focus on developing harmonized workflows that connect ANN outputs directly with environmental databases and LCA software tools.

4.4. Other AI Studies

Yu et al. (2021) proposed an AI-supported environmental planning framework based on the 4R principles (Reduce, Reuse, Recycle, Recover). Their study emphasizes the use of structured logic and intelligent decision-making algorithms to prioritize sustainable material flows and waste minimization strategies. Although the approach is conceptual and lacks a fully implemented prototype, it highlights how AI can enhance sustainability planning beyond quantitative LCA. Ligozat et al. (2022) shifted the perspective by applying LCA directly to AI solutions themselves. Their work assesses the hidden environmental impacts of developing and deploying AI tools, such as the carbon footprint of training large models or data center operations. This reflective application of LCA methodology is critical in light of the growing scale of AI usage in architecture and engineering, as it encourages more responsible development of digital tools. Koyamparambath et al. (2022) proposed a predictive framework that applies AI techniques to estimate environmental impacts of construction products. Their model integrates LCA databases with pattern recognition algorithms to rapidly assess material-level impacts at early design stages. The study demonstrates potential for enhancing preliminary environmental decision-making, but also acknowledges challenges related to data generalizability and uncertainty propagation.

These studies collectively illustrate that the role of AI in LCA is not limited to traditional model training but is expanding toward more diverse and interdisciplinary applications. They encourage rethinking the boundaries of LCA by incorporating AI in both reflective and predictive capacities. However, the practical deployment of such systems often requires improved interoperability with existing LCA databases and decision-making platforms. As these alternative approaches mature, future research should prioritize validation through real-world implementation and comparative performance benchmarking.

5. DISCUSSIONS

The results of the bibliometric analysis revealed that while the integration of AI technologies into LCA studies began in the late 1990s, a significant rise in publication volume occurred after 2012. This trend coincides with growing global attention to sustainability, digital design tools, and environmental regulations. The dominance of countries like China and the USA can be attributed to their high-volume construction sectors, extensive digitalisation initiatives, and national research investments in sustainable development. However, this concentration also reveals a research gap in developing countries, where both digital infrastructure and LCA datasets are still limited.

The systematic review shows that machine learning and artificial neural networks dominate AI applications in LCA. These methods are particularly effective in predicting energy consumption, estimating embodied carbon, and optimising material selection. Their popularity stems from their adaptability to non-linear, high-dimensional data typical of construction projects. However, these approaches are still mostly limited to predictive models. Few studies achieve full integration of AI throughout the entire LCA workflow, such as scenario generation, impact assessment, and feedback loops for design iteration.

The technical challenge of integrating AI into LCA workflows lies primarily in data quality, interoperability, and standardisation. Most studies rely on case-specific or region-specific datasets, leading to limited generalisability. There is a clear need for open-access, structured, and standardised LCA datasets to improve the reliability of AI models. Moreover, current AI-supported LCA tools often lack explainability, making them difficult to adopt in regulatory or practical decision-making contexts.

Another major finding is the disciplinary gap in how AI is framed within LCA. While machine learning and neural networks are frequently applied, other AI domains such as expert systems, natural language processing (e.g., for EPD parsing), and reinforcement learning remain underexplored. Furthermore, the application of AI is often limited to energy-related dimensions of LCA, while other critical impact categories—such as water usage, land transformation, or toxicity—are rarely addressed. This shows a methodological imbalance that must be rectified in future research.

Finally, the reviewed studies indicate that AI-assisted LCA processes are still in their infancy in terms of implementation. Many tools remain at the conceptual or pilot project level, with little evidence of wide-scale industry adoption. Institutional inertia, lack of legal mandates, and the absence of training programs for practitioners act as significant barriers. These challenges and patterns observed in this study align closely with recent high-level reviews in the field, providing an important point of comparison for interpreting the present findings. Popowicz et al. (2025) identified similar barriers, noting that while digital technologies—including AI, BIM, and IoT—have considerable potential to streamline LCA workflows, their integration is hampered by fragmented data sources, insufficient interoperability, and the absence of standardised protocols. They proposed an integrated combination framework aimed at addressing these challenges through coordinated data acquisition, processing, and application strategies. Likewise, Neupane et al. (2025) emphasised that the dominance of machine learning and neural network approaches in LCA is accompanied by significant methodological constraints, including dataset heterogeneity, limited model validation, and a lack of explainable AI methods. Their review also underscored the underutilisation of emerging AI domains—such as reinforcement learning and natural language processing—for advancing automation in LCA tasks. The alignment between these broader findings and the results of the present study reinforces the urgency of addressing interoperability, dataset standardisation, and methodological diversification to accelerate the adoption of AI-supported LCA in the construction sector.

6. CONCLUSION

This study critically examined the current landscape of artificial intelligence applications in life cycle assessment within the construction industry, employing a dual-layered approach that combines bibliometric analysis and systematic literature review. The results reveal that although scholarly interest in AI-integrated LCA has accelerated in recent years—particularly since 2012—the field is still in an early phase of practical implementation. The review demonstrates that most studies focus on machine learning and artificial neural networks due to their ability to handle complex, multidimensional data, especially for energy prediction and carbon estimation tasks. However, the integration of AI into LCA remains largely confined to predictive modelling, with minimal exploration of scenario-based design feedback, automated interpretation of impact categories, or dynamic multi-objective optimisation. This limited scope underscores the need for broader and deeper methodological expansion. Moreover, the success of AI models in environmental assessment is closely linked to the availability, accuracy, and interoperability of datasets. Current implementations are heavily dependent on case-specific or localised data, which restricts their scalability and reproducibility. The lack of standardised datasets and frameworks also contributes to the difficulty in validating AI-supported LCA tools across diverse contexts. Another important observation is the predominance of energy-related metrics in AI-assisted LCA applications. While this focus reflects global priorities around energy efficiency and emissions, it leaves other crucial impact categories—such as water consumption, biodiversity, human toxicity, and resource depletion—relatively unexplored. This thematic imbalance suggests a future research need to expand the environmental dimensions covered by AI. Despite these limitations, the reviewed studies indicate a growing awareness of the benefits of integrating AI into LCA. From automating carbon estimation and materials selection to supporting early-stage design decisions, the contributions are diverse and promising. Nonetheless, widespread industry adoption remains limited, hindered by a lack of regulatory frameworks, technical standardisation, and user-friendly software integration. In conclusion, AI has the potential to fundamentally transform how environmental impacts are assessed and managed in the building sector. Realising this potential will require not only technological innovation but also institutional support, cross-disciplinary collaboration, and a shared commitment to data transparency. Advancing this integration is essential for enabling more responsive, accurate, and sustainable decision-making in the construction industry.

DECLARATION OF COMPETING INTEREST

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

AUTHOR CONTRIBUTIONS

Yiğit Yardımcı undertook the literature review, data collection, execution of the bibliometric and systematic analysis processes, and writing of the original draft. Yasemin Erbil contributed to the conceptualization and methodological design of the study, critical evaluation of the findings, and supervision of the research process.

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