sustainability

Systematic Review

AI-Powered Advanced Technologies for a Sustainable Built Environment: A Systematic Review on Emerging Challenges

Muhammad Ehtsham [1], Giuliana Parisi [2], Flavia Pedone [3], Federico Rossi [4], Marta Zincani [1], Eleonora Congiu [5,*] and Chiara Marchionni [1,*]

[1] Department of Civil, Construction-Architectural and Environmental Engineering (DICEAA), University of L'Aquila (UNIVAQ), 67100 L'Aquila, Italy; muhammad.ehtsham@graduate.univaq.it (M.E.); marta.zincani@graduate.univaq.it (M.Z.)
[2] Department of Civil Engineering and Architecture (DICAR), University of Catania (UNICT), 95125 Catania, Italy; giuliana.parisi@phd.unict.it
[3] Department of Astronautical, Electrical and Energy Engineering (DIAEE), Sapienza University of Rome (UNIROMA1), 00184 Roma, Italy; flavia.pedone@uniroma1.it
[4] Department of Civil, Environmental and Architectural Engineering (DICEA), University of Padua (UNIPD), 35131 Padova, Italy; federico.rossi.7@studenti.unipd.it
[5] Department of Civil, Environmental Engineering and Architecture (DICAAR), University of Cagliari (UNICA), 09123 Cagliari, Italy
* Correspondence: eleonora.congiu@unica.it (E.C.); chiara.marchionni@univaq.it (C.M.)

Abstract

The integration of digital technologies with Artificial Intelligence could serve as a strategic approach to achieving the goals set by the European Union, mainly concerning sustainability, carbon emission reduction, and digitalization in the construction sector. In this regard, this paper aims to examine the major trends in the application of AI integrated with digital technologies to boost the environmental sustainability of the built environment throughout its life cycle. A systematic literature review was conducted, in accordance with the PRISMA guidelines, inspecting the Scopus database from 2015 to 2025. After having applied specific exclusion and inclusion criteria, 102 studies have been examined to identify key trends and transformative innovations enhancing sustainable approaches for the built environment. The results have been systematized based on the phases of the building life cycle which are impacted most by AI-powered digital technologies, and on sustainability areas that are attracting the greatest attention. The main research gaps are identified in the limited exploration of renovation and end-of-life phases of the life cycle, in the lack of technologies interoperability, in data complexity and quality issues, in a lack of cost-effective solutions, and in limited regulation and standardization.

Keywords: sustainability; artificial intelligence; built environment; digital technologies; BIM; IoT; digital twin; machine learning; optimization techniques

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1. Introduction

Improving sustainability in the built environment (BE) is a crucial issue in the challenges of climate change and global warming. The building sector, in fact, is still responsible for 32% of global energy consumption, and contributes to 34% of global carbon dioxide (CO_2) emissions. Therefore [1], the construction of new buildings as well as the renovation and management of the BE should be in line with the Sustainable Development Goals (SDGs) of Agenda 2030 [2] and the European Green Deal [3], also to mitigate climate changes and to provide design solutions to environmental adaptation [4].

The growing energy footprint of the construction sector requires the adoption of effective strategies to reduce resource consumption. Over the next 30–40 years, this challenge will involve both developed and developing countries, with a particular focus on energy efficiency and the decarbonization of buildings [5]. To achieve sustainability goals, the BE has to integrate eco-friendly and resource-efficient practices throughout its life cycle, which represents the entire time span from the initial conception of a building project to its demolition. Specifically, this research considers the production phase, the design phase, the construction phase, the operation and maintenance phase, the renovation phase, and the end-of-life phase. This concept, adopted in the field of environmental assessment and sustainability, is fundamental to reduce AECO environmental impact, promote circular economy (CE) and energy efficiency, minimize waste, and use sustainable materials.

In this context, recent progress in Artificial Intelligence (AI) can further enhance the use of advanced technologies to improve sustainability throughout the entire BE assets life cycle. In fact, AI can be a strategic lever for optimizing performance, energy efficiency, and resource management as it encompasses algorithms and systems enabling complex tasks that used to require human intelligence such as learning, reasoning, and problem solving, assisting in improving decision making and developing perception, association, planning, machine learning (ML), and deep learning (DL) [6,7]. The use of such intelligent computational techniques is revolutionizing the AECO (Architecture, Engineering, Construction, and Operations) sector, enabling designers to analyze, predict, and optimize the energy, environmental, and operational performance of buildings, supporting data-driven decisions to reduce the environmental impact of the sector and improve resource efficiency [8]. When applied to the BE, AI usually acts in synergy with enabling technologies such as the Internet of Things (IoT) and Digital Twins (DT), forming an intelligent ecosystem capable of analyzing real-time data and predicting future behaviors through dynamic simulations. The role of AI in enhancing digital technologies is widely recognized in the scientific literature, and several authors examined the diffusion of such advanced technologies in different fields of sustainability. Shaamala et al. [9] investigated the use of AI-driven tools for green infrastructure optimization, providing a comprehensive systematic review on the matter by also providing a new framework of AI-driven optimization for tackling climate change. Mehaffy [10] studied how Artificial Neural Networks (ANN), Bayesian Networks, and other advanced computational techniques may strongly boost urban design decision support tools to achieve a reduction in GHG emissions, taking into account the limitations of various models due to the dynamic nature of the analyzed phenomena. Yevu et al. [11] studied the relationships between digital technologies and sustainability for supply chain and procurement processes with the support of blockchain smart contracts and, all in all, they underlined that they are not well connected. Çetin et al. [12] identified in AI, big data and analytics, BIM, digital platforms/marketplaces, DTs, and IoT some digital technologies that may facilitate the transition towards a CE in the BE sector. This review provides relevant insights on the subject, but, as explicitly declared by the authors, the study is affected by a fundamental limitation related to the fact that it only analyzed papers concerning CE, thus potentially neglecting other relevant sustainability fields which are taking advantage of such cutting-edge digital technologies. Adewale et al. [13] highlight AI capability to improve sustainability in AECO by the optimization of energy efficiency, maintenance predictions, enhanced waste management and recycling, and minimized carbon footprint. They identify ML, robotics, DTs, and IoT as particularly promising AI technologies, but only analyze the three primary phases of the life cycle: design, construction, and operations. Elmousalami et al. [14] examine the impactful influence of AI in fostering construction automation, enhancing sustainability, and boosting operational efficiency, but focus especially on the construction management phase, emphasizing advancements in IoT, DTs, and big data analytics for real-time monitoring of construction sites, CO_2 reduction, and structural health assessment. Also, El Hafiane et al. [15], examining the integration of lean construction CE to improve sustainability and reduce environmental impacts, identify the strategic role of advanced digital tools such as AI, DTs, IoT, and BCT. However, this systematic review is limited to 18 peer-reviewed articles.

Notwithstanding that AI-powered advanced digital technologies are attracting increasing interest from both the scientific and the professional communities, significant barriers, due to still unsolved interoperability and cybersecurity issues, social acceptance barriers, and a lack of awareness of actual benefits, still slow down a potential wider adoption. In this context, this systematic literature review aims to specifically investigate the existing research about the dissemination status of AI in the field of digital technologies, pursuing two main objectives: firstly, underlining how much the integration of AI with other advanced digital technologies is increasingly supporting all phases of the building life cycle; secondly, investigating how AI-enhanced digital technologies are boosting environmental sustainability of the BE.

In the next Section 2, the paper presents the proposed research methodology based on the PRISMA 2020 protocol (Supplementary Materials). In Section 3, the results are described, with the identification of the main digital technologies enhanced by AI. In Section 4 the discussion underlines the main gaps and future challenges related to the impact of AI-boosted technologies on each building life cycle phase and on the identified sustainability areas.

2. Materials and Methods

The research identifies, in an effective integration of advanced digital technologies with AI, a solid possibility to boost sustainability in all life cycle phases of the BE, and identifies, in the systematic literature review based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyzes) protocol, the most rigorous method to retrieve a reliable data source to investigate the state of the art of the considered subject. The purpose of the proposed approach is to ensure clarity, reproducibility, and rigor across the analysis process in relation to the examined literature.

The methodology adopted for the study was structured into three main sequential macro-phases:

- The initial phase led to the identification of the key digital technologies enhanced by AI which are effectively contributing to fostering sustainability in the BE.
- In the second phase, an accurate analysis of the literature concerning the identified technologies with a specific focus on the actual contribution to sustainability of AI integration across the various phases of the building life cycle was carried out.
- In the third phase, the results were systematically categorized by all building life cycle phases and relevant sustainability areas of application. The resultant clustering process offers insights on building life cycle phases and sustainability categories which are most significantly impacted by AI-powered digital technologies.

In Figure 1, all sequential steps of the proposed approach based on the PRISMA protocol are reported, providing the total number of the preliminarily identified papers throughout the Scopus database, the numbers of papers progressively screened against specific inclusion and eligibility criteria, and the final number of papers definitely included in the review.

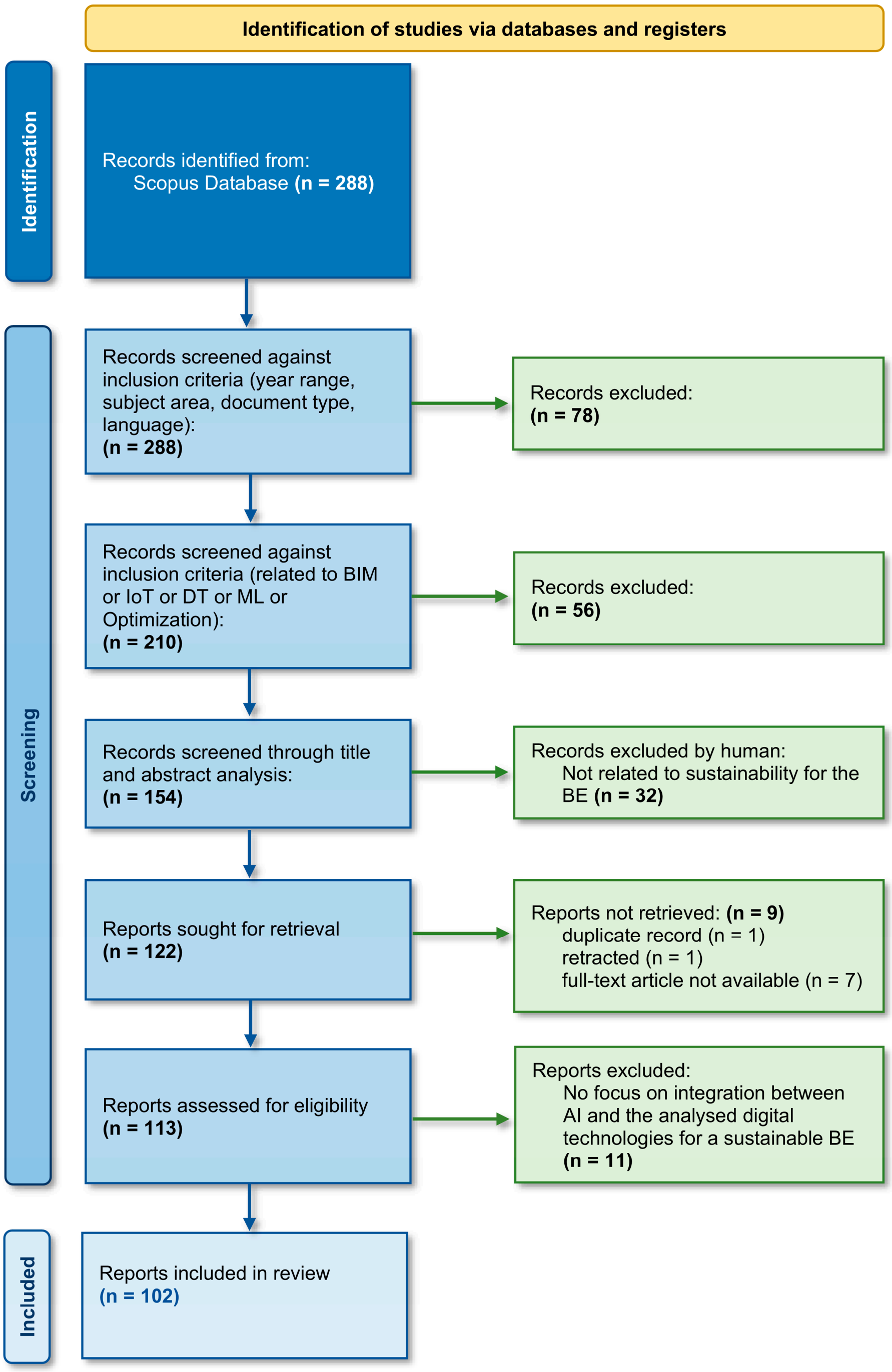

Figure 1. PRISMA flowchart elaborated by the authors.

2.1. Database Selection and Search Strategy

The first methodological phase involved macroscopic research using a general search string. Scopus was selected as the reference database, while advanced search strings were used to query the database by "Title, Abstract and Keywords". More specifically, the first articles were selected querying the database on February 2025 through the following search string: ("Sustainability" OR "Sustainable development" OR "Ecological environment" OR "Energy Efficiency" OR "Green Technolog*" OR "Carbon Footprint" OR "Smart Building*" OR "Green Building*" OR "Sustainable Building*" OR "Circular Economy") AND ("AI" OR "Artificial intelligence") AND ("Construction" OR "Building*" OR "Built Environment") AND ("Digitalization" OR "Digitalisation" OR "Digitization" OR "Digitisation" OR "Digital Tool*" OR "Digital Technolog*" OR "Digital Innovation").

It is worth noting that the search string above is composed of four main clusters of keywords: one concerned sustainability and decarbonization, the second referred to AI, the third one related to the BE, and the last one concerned digital tools and technologies. The aforementioned keyword groups are linked to each other with the operator "AND" to make the research more specific, whereas the operator "OR" is used to include, in each cluster, different acronyms and declensions of the same term or other related topics. This advanced search strategy allowed for an automated collection of a comprehensive catalogue of papers addressing the investigated subject.

The second phase aimed to investigate more specifically the literature on Industry 5.0 digital technologies, which was outlined as central to the research scope. In this phase, the original search string was expanded and adapted to include specific keywords for each digital technology under investigation (shown in Figure 2): BIM, IoT, DT, ML and DL, and Optimization techniques. For each identified technology, a thematic filtering process was conducted to identify suitable articles.

2.2. Eligibility Criteria for Documents Inclusion/Exclusion

In the first phase, the proposed approach led to the preliminary identification of 288 publications. Following the initial search, a series of exclusion criteria were applied through Scopus search filtering based on year range of 2015–2025, subject areas, types of documents, and English language. These specific exclusion criteria (resumed in Table 1) lowered the publication count to 210 articles (Figure 1).

Table 1. Eligibility criteria.

Criteria	Inclusion	Exclusion
Time range	Papers published in the last decade (2015–2025)	Papers published before 2015
Subject area	Engineering; Energy; Environmental sciences; Social sciences; Computer sciences	Papers concerning subject areas different from engineering, energy, environmental, social and computer sciences
Article type	Article; Conference paper; Review; Book Chapter; Editorial	Article types different from journal article, conference paper, review, book chapter, and editorial
Language	Papers written in English	Papers written in languages different from English
Relevance to specific technologies integrated with AI	Papers concerning BIM, IoT, DT, ML/DL, or Optimization techniques boosted by AI	Papers not regarding the integration of AI with BIM, IoT, DT, ML/DL, or Optimization techniques
Relevance to sustainability of the BE	Papers that address sustainability issues related to the BE	Papers not specifically concerning sustainability of the BE
Full-text availability	Full text available	Full text not available

Another 56 papers were then excluded by integrating the original search string, through the "AND" operator, with additional strings (Figure 2), which referred to the specific digital technologies under investigation (BIM, IoT, DT, ML and DL, and Optimization techniques). The remaining 154 papers were then screened by analyzing titles and abstracts in order to promptly exclude studies not concerning sustainability of the BE for irrelevance. In the end, papers were sought for retrieval before the full-text screening, thus detecting one duplicate record and one retracted paper to exclude. Additionally, the full texts of seven papers turned out not to be available. The final full-text screening aimed at more thoroughly assessing papers' relevance as compared to the investigated topic in order to only include studies specifically focusing on the integration of AI with the considered digital technologies to boost sustainability in the BE.

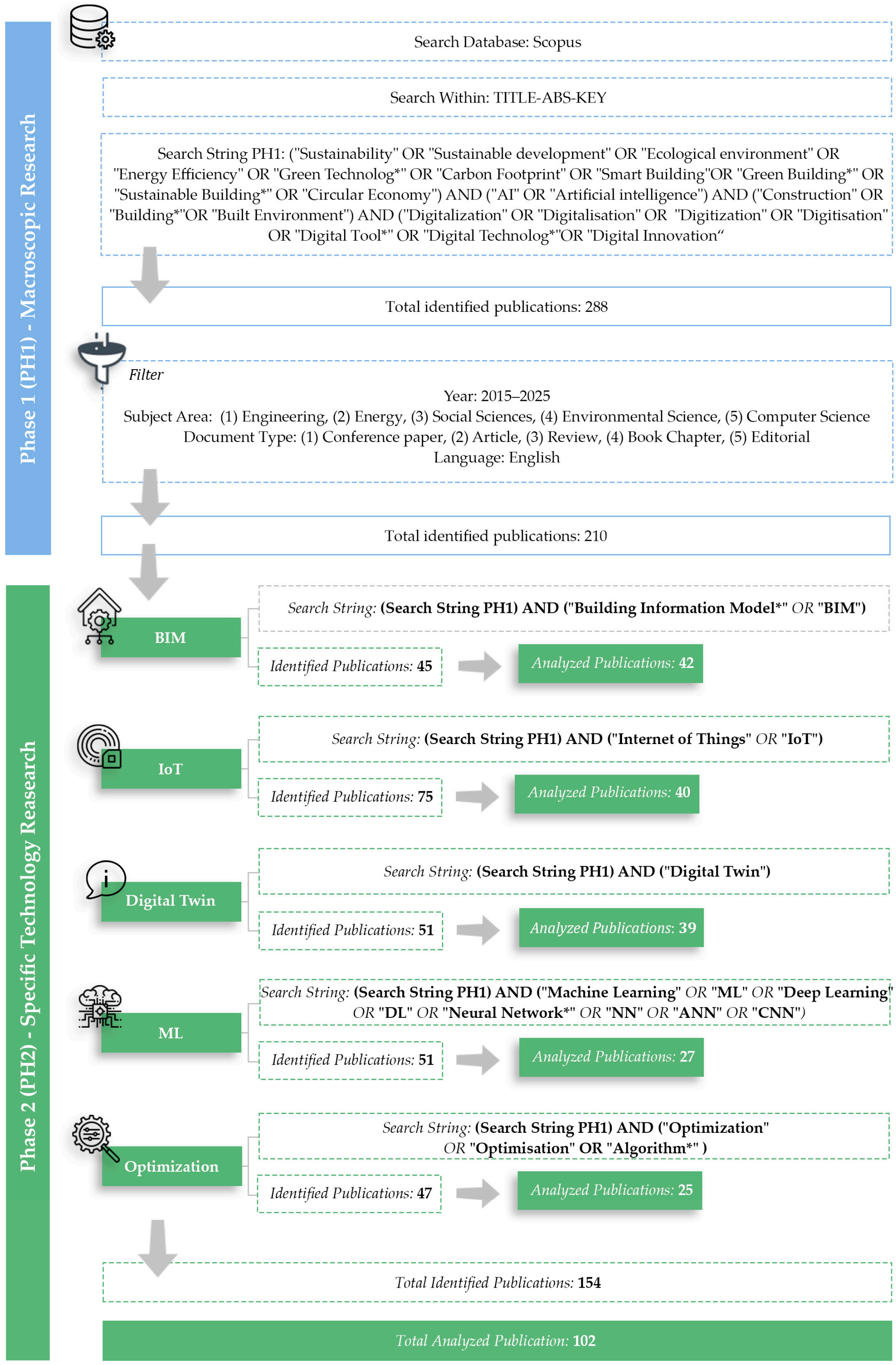

Figure 2. Detailed search and filtering criteria (the asterisk * replace one or more characters in a word, helping to find word variations).

Then, each article underwent a full-text analysis to assess whether it was suitable for the intended purpose of the systematic review and to facilitate specific categorization under the respective digital technological groups.

In several cases, the analyzed articles addressed more than one digital technology, resulting in overlaps. After accounting for these overlaps and the aggregation of results, the total number of full-text articles analyzed was 102, as highlighted in Figure 3. To enhance reliability and minimize the risk of bias, the 102 articles were independently read in full at least by two authors and then categorized first based on main digital technologies involved and their relationship with AI, then based on the impacted building life cycle phase(s) and sustainability field(s) of application. Any doubts that arose during the categorization process were resolved through discussion among all authors through specific brainstorming. Additionally, to ensure the inclusion of high-quality studies, a systematic quality assessment was conducted based on the following criteria: (1) clarity of research objectives, (2) clear definition of research questions, (3) transparency of data sources, (4) methodological rigor, and (5) relevance of findings regarding AI integrations with advanced digital technologies to enhance sustainability of the BE. For each study, each criterion was assessed through a 5 point scoring scale (1 = inadequate, 5 = excellent). It is worth underlining that the fifth criterion related to relevance of findings within the investigated topic definitely played the role of main discriminating factor, leading to the exclusion of all papers with a score lower than 3 (3 = adequate) for relevance. When the two authors designated to assess the considered full text disagreed, at least a third author was involved in the brainstorming to overcome the impasse.

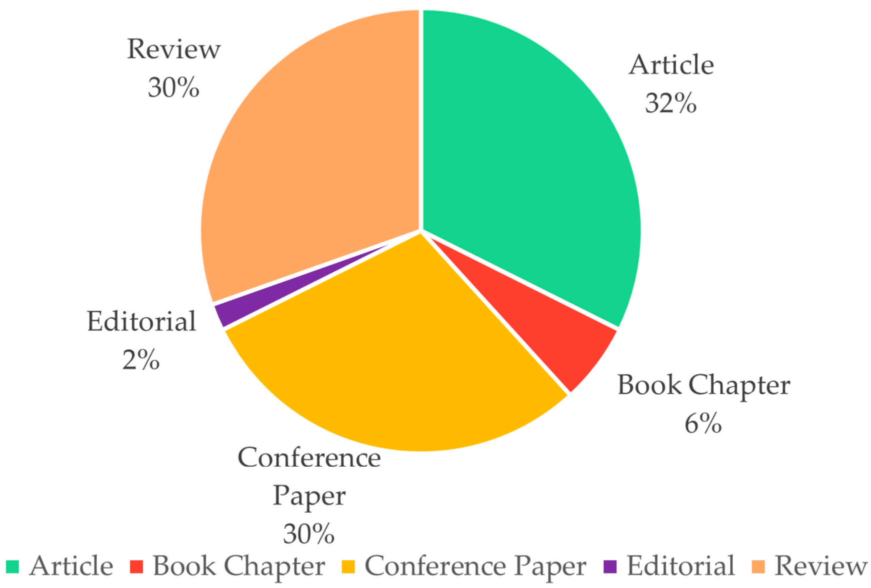

Figure 3. Documents by type.

2.3. Synthesis Methods for Results Summary

As a synthesis method to support data collection and systematization, authors arranged a tabular structure in a shared Excel spreadsheet to underline the main survey categories of each article and automatically summarize results. More specifically, each article group referring to a single technology under investigation was analyzed in-depth to assess which building life cycle phases and which sustainability areas of application were actually impacted. In this regard, note that results synthesis per technology are provided reporting radar graphs summarizing the numbers of studies impacting each building life cycle phase, along with tables reviewing key findings and gaps per phase. Synthesis results on sustainability categories are instead tabulated in the final Discussion.

It is worth noting that all 102 papers definitely included in the analysis have been considered in the synthesis results. Figure 3 shows that most of the 102 analyzed manuscripts resulted in being equitably categorized in the amount of almost 30% as journal articles, reviews, and conference papers, whereas only a neglectable percentage of papers were classified as book chapters and editorials.

3. Results

The review revealed an increasing interest in the use of AI to support digital technologies to increase sustainability in the different phases of the life of buildings. In this regard, the co-occurrence network in Figure 4, which referred to the 102 analyzed papers, provides an intuitive representation of the increasingly strict correlation between the investigated topics (AI, digital technologies and sustainability issues referred to the BE) by displaying the relationship between keywords characterized by at least 10 occurrences in the analyzed literature.

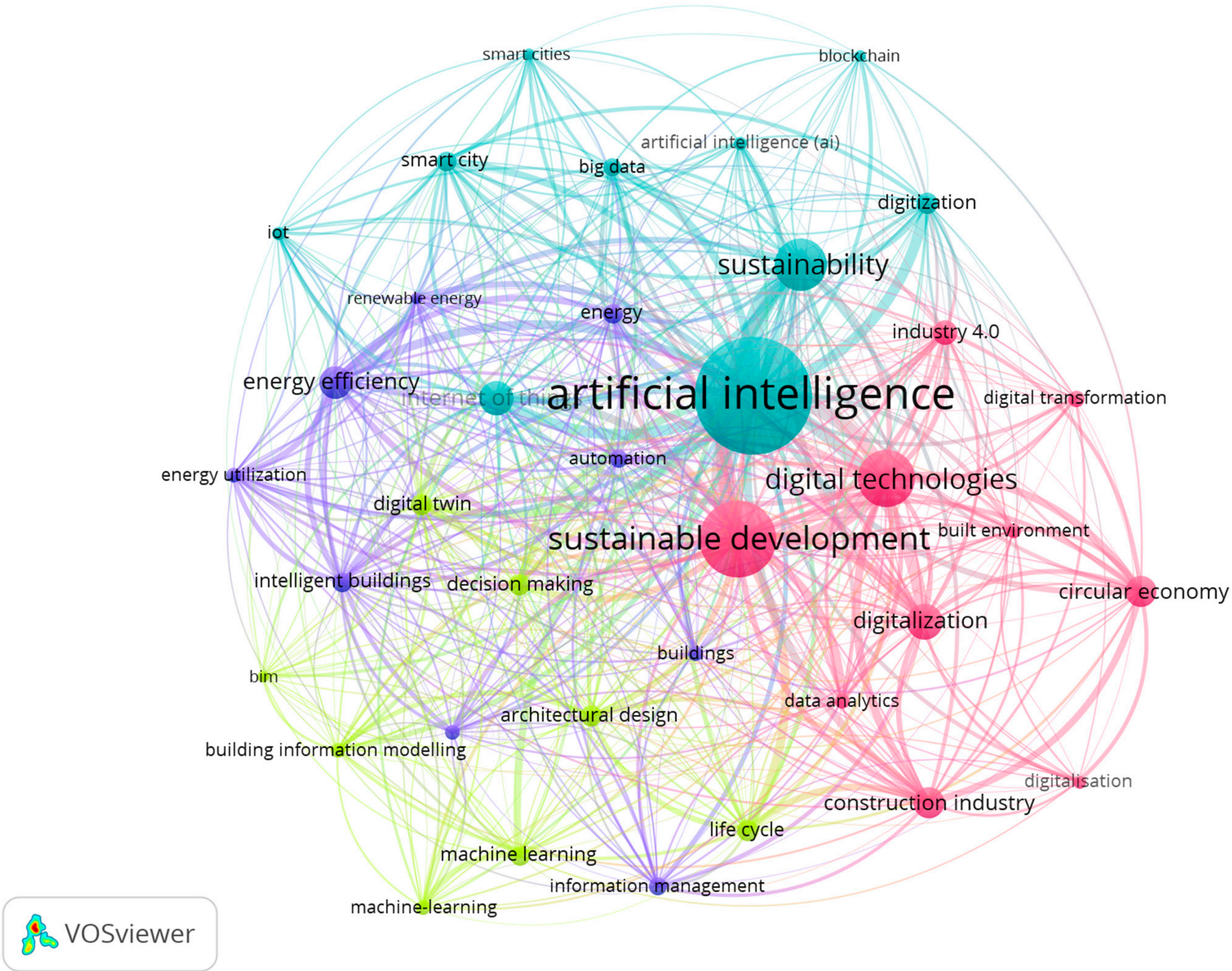

Figure 4. Co-occurrence network referred to the whole analyzed database (keywords characterized by at least 10 occurrences are shown).

Moreover, the preliminary general results summarized in Figure 5 prove that the interest for the topic is quite recent and is growing rapidly, as the number of papers published in 2024 in the field is double compared to the previous year. Additionally, the subject is mainly investigated in the United Kingdom, Europe, China, India, Australia, and the United States.

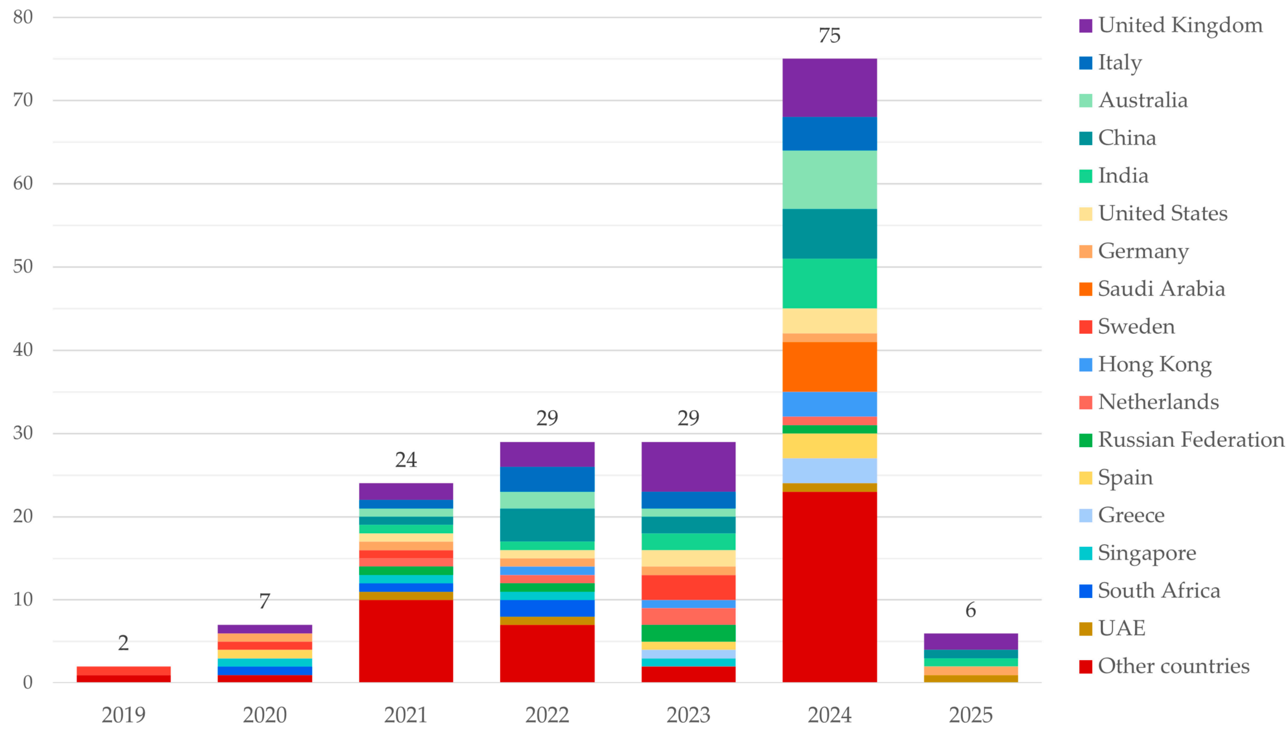

Figure 5. Documents by country per year.

After an initial synthesis process, the 102 selected articles were first divided into five groups, identifying the digital technologies that are powered the most by AI to improve sustainability. More specifically, the following advanced digital technologies turned out to be the most promising in the investigated field:

- BIM is a key methodology of Industry 5.0 applied to the AECO sector, enhancing the digital transition by improving stakeholder coordination, reducing errors, and enhancing information management throughout the building life cycle [16].
- IoT refers to an extensive network of interconnected sensors and devices capable of autonomously collecting and exchanging data in real time [17]. It therefore represents a fundamental element for the synergic relationship between different technologies such as AI, DT, and ML.
- DT technology provides a digital replica of physical assets, systems, or processes synchronized at a specified frequency and fidelity through a bidirectional connection between the real world and the virtual environment [18]. DTs gather and process IoT data from the physical world to enable real-time monitoring, simulations, optimizations, and data-driven decision making.
- ML and DL focus on enabling machines to learn from data and make decisions without being explicitly programmed [19]. ML techniques rely on algorithms that improve their performance over time through exposure to data, thus progressively enhancing their capabilities by learning from accumulated data [20]. DL is a specialized branch of ML, and hence a subset of AI that employs ANNs with multiple layers to model complex and high-level abstractions in data [21].
- Optimization techniques refer to a wide range of methods and algorithms aimed at identifying the best solution for a given problem, which maximize or minimize a single- or multiple-objective function. To achieve this goal, optimization algorithms play a key role by transforming data into concrete results through advanced computational processes [22]. Thus, optimization methods allow for the evaluation of

multiple potential solutions to identify those best suited based on a balance between performance, costs, and other constraints [23].

3.1. Research Findings in Cutting-Edge Digital Technologies Powered with AI for a Sustainable BE

According to the proposed methodological approach, a more in-depth literature analysis concerning each of the aforementioned digital technologies enhanced by AI in effective integrated applications to boost sustainability in the BE has been carried out. Therefore, the following sections of the present study will be devoted to illustrating the main research findings that emerged from each technology literature review, underlining the contribution to every phase of the BE life cycle.

3.1.1. BIM-AI Integrations

The interoperability between BIM authoring tools and simulation software enables the advanced evaluation of a building's sustainability impact [24]. However, BIM-based models may generate large volumes of heterogeneous data that are difficult to analyze due to limited interoperability among software. In this context, AI provides an enabling tool, leveraging multiple techniques such as ML, data analysis, natural language processing, and computer vision, to process information from BIM-based models [25]. The integration between AI and BIM presents new opportunities to enhance sustainability assessment, promoting the SDGs of the 2030 Agenda, particularly SDG 7, 9, 11, and 12 [26].

One of the most relevant sustainability areas relates to CE, which can be effectively supported through the latest cutting-edge digital technologies. Rodrigo et al. [27] categorized these technologies into advanced systems and approaches for sustainable construction and underlined that the AI-BIM integration stood out in optimizing CE strategies. Moreover, the synergy between BIM and AI for optimizing CO_2 emissions was also investigated both at an urban scale and at a building scale. As far as the urban scale is concerned, Li et al. [28] argued that AI, with predictive models, can effectively support data processing and analysis from BIM environments to predict urban CO_2 emissions with high accuracy, achieving error margins around 5%. At the building scale, Płoszaj-Mazurek et al. [29] developed a web application, available on GitHub (https://github.com/, accessed on 22 June 2025), to support designers in reaching low-carbon buildings by combining AI, Large Language Model (LLM), and BIM. The method allows users to upload an IFC (Industry Foundation Classes) model, which may be processed to generate a bill of quantities (BoQ) and materials definition, and receive AI-based suggestions for lower-impact alternatives. The workflow offers element specification both in 3D and BoQ view, total carbon footprint calculation, and integrates through API to an AI agent, ChatGPT LLM gpt-3.5-turbo-instruct model, to receive recommendations, further guiding environmentally optimized design decisions. Net Zero goals depended on the proper management and circulation of material-related information, with Material Passports (MPs) serving as key tools for this purpose. BIM turned out to be the most studied technology for digitalization related to MPs due to its data management capabilities, while AI was recognized as valuable for analyzing and cross-referencing BIM data [30].

The AI-BIM integration may also help reduce the environmental impacts of the AEC industry, enabling the minimization of waste and the optimization of material recycling starting from the early design phase [7].

Considering the design phase, BIM may provide digital models for resource evaluation, whereas AI makes material selection and construction methods more efficient. Intelligent material databases integrated into the BIM model may effectively support the monitoring of material flows and the estimation of construction waste, with algorithms and AI techniques like ANNs and Ant Colony Optimization (ACO) offering innovative waste prediction methods [16,31]. As far as the end-of-life phase is concerned, AI may support optimized demolition and material recovery, while BIM may track and facilitate material reuse [32]. Additionally, BIM enables data storage for MPs, which AI can harness to predict reusable and recyclable material quantities from demolitions [33]. Such circular virtuous practices require the implementation of waste classification systems using digital images, DL models for assessing economic reusability, and automated algorithms to improve waste management accuracy. Moreover, neural networks were developed to estimate reusable materials and waste based on national demolition data [12,34,35].

On the whole, AI techniques integrated with BIM for sustainability purposes often include computer vision to recognize waste composition, DL for predicting waste quantities, and automating sorting, as well as visual programming language, like Dynamo, and genetic algorithms for optimal material selection and construction cost reduction [26,36]. All these applications facilitated higher protocol LEED scores of the building stock by reducing construction waste and improving material recovery, reuse, and recycling [31].

The integration of BIM and AI may also provide an effective strategy to improve energy efficiency in the AEC sector by optimizing energy management throughout the building life cycle. AI-supported management, monitoring, and optimization of projects, including infrastructure projects, thus contributes to the overall efficiency improvement [37]. The synergy between AI and BIM has proven helpful in identifying potential gaps in projects by extracting data from BIM models and simulation software, as well as in processing data from BIM models and simulation tools to optimize building energy and thermal performance [16]. In a data extraction-based process, ensured through open BIM frameworks and standardized formats like IFC, an effective AI-BIM integration may facilitate efficient data flow, reduce time and costs, and improve the accuracy of energy analysis [38]. The authors of this study observed that the integration of BIM and AI for energy-efficient buildings requires the development of advanced data schemes to deal with interoperability issues. Open formats such as IFC and gbXML (Green Building XML) enable efficient information transfer and compatibility improvement among BIM, AI, and other digital tools. Additional strategies include the use of open BIM frameworks and the adoption of standardized file schemas that allow direct integration with energy modeling tools. Among the AI-BIM integrated energy simulation methods, the so-called BO-LGBM (Bayesian Optimization Light Gradient Boosting Machine) model, combining optimization algorithms with a SHAP (SHapley Additive exPlanations)-based explanatory method, may enable the prediction of building energy performance [26].

At the urban scale, Industry 5.0 integrated with AI-based predictive analysis based on BIM data has proven effective in identifying suitable areas for renewable energy systems and predicting different efficient energy use scenarios, while AI technologies like the fuzzy analytic hierarchy process and Augmented Reality or Virtual Reality (VR) are often applied to design sustainable smart cities, particularly in developing countries. At the building level, AI-BIM integration focuses on two main algorithmic approaches: generative design (GD) algorithms linked to energy simulation for optimizing ZEBs [39] and ML models using BIM data to predict occupancy and energy consumption influenced by occupant behavior [40]. Implementing such advanced digital technologies could lead to a 30–50% improvement in the construction sector energy intensity by 2040 [41].

The integration of BIM and AI may also support quality control processes for sustainability optimization, which focus on verifying the technical and performance characteristics of the executed works by comparing them with the standards established during the design phase [42]. Several authors identified BIM as a valuable methodology for the digital representation of building information, while AI techniques are commonly used for data processing and scenario simulation, as well as for continuous monitoring and predictive maintenance, enabling proactive risk management [43]. Some authors [32,41] underline that AI-BIM integration was also relevant in post-disaster monitoring and planning, while also combined with tools like GIS to support strategic decision making and predictive analysis. An example of this application was found in the workflow proposed by Khan et al. [44], which aimed to predict and simulate the failure of an air handling unit using fire alarm and maintenance data processed through ML techniques.

The integration of BIM and AI in project management may enable the automation of decision-making and improve sustainability regulatory compliance. To address the challenge of adapting traditional environmental regulations to digital tools, Izbash et al. [45] proposed converting them into machine-readable formats using structured databases, semantic annotations, and application programming interfaces. Several studies focus on analyzing the transformative potential of BIM in construction project delivery [46], highlighting how its integration with AI may innovate traditional project management practices. The outcomes achievable through AI-BIM integration in project management were tested in real-world applications such as the "ENEL HQVRM" project, which used data-driven approaches to enhance construction and operational management while promoting sustainability [16].

To sum up, Figure 6 and, in more detail, Table 2 bring the impact of BIM-AI integrations for the BE sustainability on each building life cycle phase to light by underlining both key findings and unaddressed challenges. On the whole, the design and O&M phases turned out to benefit the most from this combo whereas, the production, the renovation, and the end-of-life phases resulted in being less impacted.

Table 2. BIM and AI: papers by building life cycle phase.

Building Life Cycle Phase	References	Key Findings	Gaps
Production Phase	-	-	-
Design Phase	[6,7,12,16,26–39,41,42,45–61]	• Assessment resources and environmental impacts in the design stage.	• Most studies focus on the initial design and do not include iterative revisions throughout the life cycle.
		• AI enhances efficiency in material selection and construction methods integrating ML and 3D applications. • Support design of ZEBs.	• Limited attention to the automated verification of environmental standards in the design phase. • Lack of standards for integration with energy simulation software.
Construction Phase	[6,7,16,34,39,41,42,45–47,49,57,58,60,62]	• Waste prediction and reduction through ANNs and ACO. • Improvement of LEED scores through optimized material selection strategies and waste management. • Support to automatic classification of construction waste.	• Limited adoption of AI-BIM tools directly on construction sites. • Lack of established methods to transfer data from BIM models to physical site management. • Challenges in scaling AI solutions for complex or large-scale projects.

Table 2. *Cont.*

Building Life Cycle Phase	References	Key Findings	Gaps
Renovation Phase	[12,16]	• Support of post-event monitoring and intervention planning with GIS integration. • Support predictive maintenance through AI-based façade mapping.	• Few applications on existing or historical buildings. • Limited availability of updated BIM data for the existing building stock.
Operation and Maintenance Phase	[6,7,16,28,33,35,37,39–47,56,57,61–63]	• Prediction of failures and intervention planning through sensors and systems. • Facilitation of continuous monitoring, predictive maintenance, and proactive risk management. • Some predictive models (e.g., BO-LGBM) offer reliable energy performance.	• Real-time data is rarely used in BIM to enable continuous feedback loops. • Lack of frameworks for the dynamic representation of operating conditions within the BIM environment. • Need for further study on occupancy prediction to enhance operational efficiency.
End-of-Life Phase	[16,33,61]	• Optimization of demolition and material recovery through the analysis of BIM-based information. • BIM enables the archiving of data for Material Passports, useful for estimating reusable and recyclable quantities. • Estimation of recoverable materials based on national demolition data.	• Need for the development of AI-BIM interfaces capable of guiding strategic disassembly decisions. • Simulation tools for the end-of-life phase are not yet commonly integrated into BIM environments. • Limited standardization of data for post-use environmental assessment.

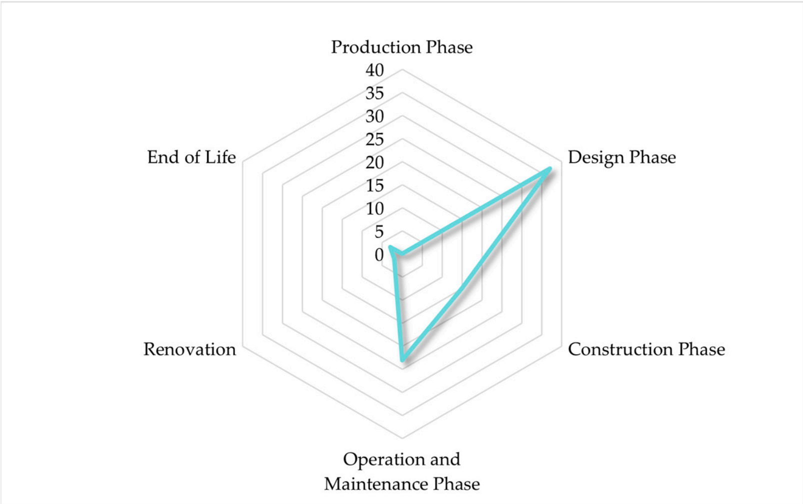

Figure 6. Papers on BIM-AI integrations by building life cycle phase.

3.1.2. IoT-AI Integrations

The construction industry utilizes IoT in numerous ways, spanning from managing projects to assessing work quality.

Additionally, as the field advances, increasing benefits and value-added services would be seen arising [7,62].

As highlighted in the literature, IoT applications in construction span a broad spectrum, from project management and progress tracking to quality assurance and compliance monitoring. Furthermore, as the technology keeps on advancing, it is expected to deliver an expanding range of benefits and value-added services to the sector [64], as the role of the digital technologies associated with the IoT has been widely discussed due to their potential to solve big sustainability challenges, enable Industry 4.0, improve social wellbeing, and counteract the effects of climate change [65,66].

IoT is implemented potentially through each phase of the building life cycle, even though most of the applications are for the operation and maintenance of the BE, as clearly shown in Figure 7. During this phase, IoT can be connected to building systems and devices to optimize building control and monitoring, which may improve user comfort and save energy consumption.

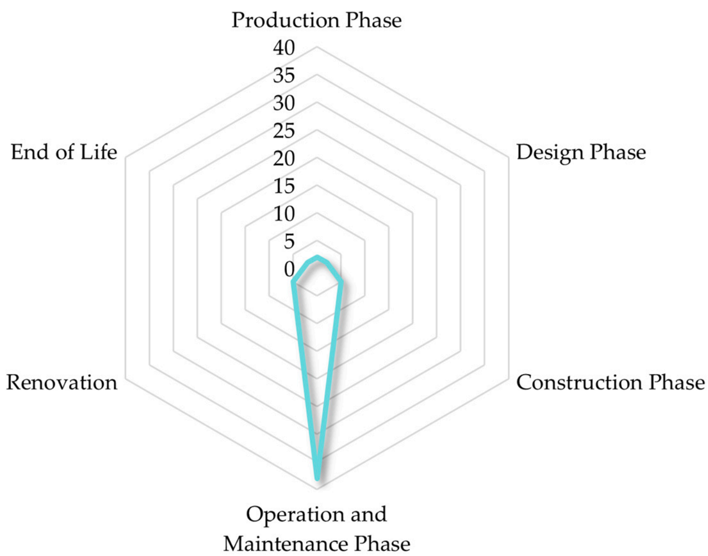

Figure 7. Papers on IoT-AI integrations by building life cycle phase.

Asif et al. [41] estimated that IoT may reduce up to 35% of energy consumption through a coordinated digital building system, an energy management system that uses big data analytics and IoT to monitor and control the energy consumption of building systems and appliances. Digital technologies such as IoT may result in a 30–50% enhancement in energy efficiency for space heating, water heating, lighting, and cooking by 2040 [41]. IoT also offers significant potential to enhance operational efficiency by reducing labor costs, minimizing delays associated with rework, and optimizing material usage through the automation and integration of key processes [41]. In this regard, IoT also plays a key role in the communication and coordination between the many stakeholders involved, hence creating collaboration and cooperation for a healthy conductive environment with openness among all [67].

One of the main applications of IoT in the AEC sector is related to energy management and efficiency. Introducing digitalization in building energy systems has lately enhanced energy efficiency and sustainability, thanks to the important role that digital technologies such as IoT and AI took on in the process, offering promising solutions to optimize energy use, enhancing facility governance, and fostering resilient infrastructure [6,62,68]. Their application to passive building principles, renewable energy integrations, and energy control strategies made a big contribution to optimizing building energy management and enabling sustainable communities [69]. It has emerged from the literature that their application may lead to a significant reduction in energy costs and consumptions through predictive control systems integrating AI and ML, such as the implementation of flexible energy governance through demand–response strategies. Moreover, more efficient building management is enabled by real data monitoring for fault detection and the implementation of self-recovery to power failures [70]. Real-time monitoring allows dynamic remote control and, additionally, the integration with AI and cyber–physical systems enables consumption optimization, predictive maintenance, resilience, and flexibility in facing emergencies.

Examples of how digital technologies can facilitate the recovery of energy systems are the early warning systems triggered by monitored networks and the smart automated technologies that enable autonomous recovery mechanisms supported by IoT through data-driven real-time automated diagnosis, isolation of faulty components, and power re-distribution [55]. Building environmental sensors and smart actuators can detect parameters such as temperature, humidity, lighting, and occupancy [6], allowing for an automated regulation of heating, ventilation, air conditioning (HVAC), and lighting systems based on actual needs. Through IoTs, almost everything can be effectively automated in smart buildings, from waste management to energy usage, by collecting and monitoring power consumption patterns and enabling energy flexibility by adjusting their behavior [71]. Aiming to support sustainability and energy efficiency, IoT is also applied to photovoltaic systems to address issues such as PV module overheating, faults, and dust accumulation, hindering their efficiency [72]. Home Energy Management Systems (HEMS) have lately gained significant attention from both researchers and industrial engineers. The implementation of IoT-based HEMS can lead to significant energy savings and a reduction in GHG emissions [73].

Sassanelli et al. [71] underline that IoT facilitates advanced monitoring and the control of energy consumption in buildings, as well as energy use optimization and the minimization of inefficiencies. These techniques are viewed as a convergence of the smart grid and smart home: they enable communication with users, home devices, on-site generation sources, storage units, and grid operators, facilitating agile decision-making [40] and enabling a more intelligent and efficient energy management [73]. This kind of digitalized process may create effective opportunities for the bidirectional integration of the electrical grid with buildings.

The application of IoT helps smart cities to be flexible and resilient to specific needs, with smart waste management, smart lightening, smart parking, traffic control and management, and environmental monitoring. They all support sustainability, efficiency, and overall life quality actions [74], reducing CO_2 emissions and energy consumption without compromising consumers' comfort requirements [70].

IoT sensors also enable the continuous real-time monitoring of environmental conditions and equipment performance on construction sites. IoT can be used to monitor workers' safety through a system of sensors: it was reported in an IBM (International Business Machine corporation) study that its integration can result in 22–29% cost savings [41]. This allows for the early detection of potential issues, prevention of equipment failures, and overall optimization of construction processes.

Notable applications involve automated monitoring to supervise and track construction productivity, using digital technologies combining IoT and AI to improve process efficiency, analyzing existing process flows, and eliminating waste, ultimately improving overall construction productivity [65].

IoT can also contribute to improving the quality of construction work by monitoring material properties, workmanship, and structural performance, and can verify compliance with industry standards and design specifications, ensuring higher quality outcomes. Additionally, real-time monitoring and the deployment of IoT-enabled alerts and data-driven insights may also play a pivotal role in mitigating risks and maintaining a secure working environment by identifying and signaling potential hazards promptly, thereby contributing to improved worker safety [64].

Looking at sustainability in the construction site, IoT can support CE principles by tracking construction materials throughout their life cycle, facilitating reuse, recycling, and recovery. Trubina et al. [33] highlighted that digital MPs can be created using IoT-generated data integrated with BIM to optimize material recovery and minimize waste, promoting a more sustainable construction industry.

Additionally, IoT-based data collection and performance analysis may enable the identification of areas for improvement and the implementation of corrective actions to enhance overall construction quality. By analyzing data collected from sensors, AI-driven predictions can estimate when maintenance is required for a building or its systems, thus preventing unexpected failures and reducing repair costs.

Predictive maintenance enhances the longevity and efficiency of building infrastructure by enabling proactive rather than reactive maintenance strategies [43].

The prevalent adoption of IoT-AI integrations to enhance sustainability in the O&M phase with respect to all other phases of the BE life cycle clearly emerges from Figure 7 as well as from the data reported in Table 3. In particular, the main still unaddressed challenges are underlined in gaps, including the high costs of implementation and maintenance, persistent concerns over data security and privacy, and the lack of standardized protocols to ensure interoperability among devices and systems. All these currently slow down the full realization of its potential benefits in terms of efficiency, sustainability, and overall building performance, in all its lifecycle phases.

Table 3. IoT and AI: papers by building life cycle phase.

Building Life Cycle Phase	References	Key Findings	Gaps
Production Phase	[33,75]	• Support of sustainability and circularity through smart product–service systems, reducing production costs and environmental impact.	• Limited large-scale adoption of IoT for material tracking and production management, and lack of data standardization.
Design Phase	[33,35]	• Optimization of building design, simulating performance and reducing resource consumption. • Support of environmental control and space use, enhancing life cycle performance.	• Data integration complexity impedes consistent linkage between real-time IoT data and digital models. • Underdeveloped predictive capabilities for proactive, circular-oriented design.

Table 3. *Cont.*

Building Life Cycle Phase	References	Key Findings	Gaps
Construction Phase	[33,41,49,62,67]	• Improvement of supply chain visibility and logistics through real-time tracking of components. • Safety on-site is enhanced via automated hazard detection and alerts. • Resource tracking and predictive maintenance optimize equipment use and lifespan.	• Limited large-scale implementation of IoT in construction practices. • Persistent cybersecurity, interoperability, and workforce skill gaps. • Lack of integrated IoT–DT frameworks for fully autonomous and customized construction management.
Renovation Phase	[43,67,76–78]	• Digital technologies can enable data-driven prioritization of energy retrofits, also in heritage buildings. • Structural health monitoring supports intelligent maintenance and long-term preservation.	• Lack of historical data for existing buildings limits retrofit potential. • High implementation costs and modeling complexity hinder broad adoption.
Operation and Maintenance Phase	[6,7,12,17,32–35,40,41,43–46,55,62,64,65,67–74,76–87]	• Improvement of environmental performance: IoT systems (e.g., smart meters, HVAC controls) enable real-time energy monitoring and optimization. • Support of predictive maintenance, reducing downtime and repair costs. • Occupancy tracking enhances space use and occupant comfort through dynamic resource allocation.	• Unreliable connectivity and data flow in large-scale IoT implementations. • Cybersecurity, interoperability, and workforce readiness. • Data security and privacy concerns due to extensive operational data collection. • User behavior is not fully integrated, limiting energy efficiency despite smart systems.
End-of-Life Phase	[33,76]	• Enable digital and physical tracking of materials for reuse and recycling. • Improvement of material availability transparency for circular reuse.	• Data governance and uncertainty limit material tracking and reuse. • Limited large-scale practical implementation of IoT in deconstruction beyond pilot projects.

3.1.3. DT-AI Integrations

The pivotal role of DT in optimizing the use of energy and resources while contributing to implementing CO_2 mitigation strategies for the construction sector is increasingly being recognized [88]. DTs are fed real-time data from IoT devices concerning energy consumption, environmental parameters, occupancy, and equipment performance. This enables continuous monitoring, analysis, and optimization, and allows DTs to provide accurate, comprehensive, and dynamic information about the performance of the BE, a necessary requirement for improving sustainability, efficiency, and occupant comfort [46].

The use of DT technology can promote sustainable practices across the entire life cycle of BE assets, optimizing resource use, shortening timelines, and increasing both efficiency and accuracy [7].

GD, in which AI algorithms automatically generate, evaluate, and optimize a wide range of design options based on user-defined criteria constraints, is highly effective for energy efficient design approaches [39]. DTs that integrate generative AI simulation models, particularly those based on evolutionary algorithms, can enhance building performance and user experience. Analyzing data about building usage and environmental parameters, they can identify patterns and trends to inform the design process by predicting building efficiency, comfort, and safety [89].

DTs and AI can also be used to engage stakeholders in the early design stages and to encourage them to adopt sustainable practices. Liu et al. [90] developed a low-cost digital platform that integrates AI, DT, and VR technologies to provide project sustainability assessment through real-time cost analysis and sustainability indicators. This tool allows stakeholders to evaluate design alternatives considering both financial and environmental factors, thus enabling informed decision-making in interior design.

AI-powered DTs can also be leveraged to improve sustainability throughout the construction phase. DTs streamline construction management, increasing productivity and reducing redundancies through automated data collection and knowledge extraction. Lean construction goals of waste reduction and process optimization can be achieved through real-time monitoring and feedback loops enabled by DTs [6]. By gathering, structuring, and delivering effective information, DTs can enhance stakeholders' collaboration and improve transparency, traceability, and efficiency in construction, thus supporting CE approaches [7].

The adoption of DT technology for the construction phase, combined with the use of AI algorithms and IoT devices, allows real-time monitoring, enabling an optimized use of energy, water, and building materials. Additionally, this integration may lead to more accurate resource planning and inventory management, preventing overproduction, minimizing material waste, and ultimately reducing environmental impact and contributing to long-term environmental sustainability [62]. Salem et al. [49] propose a framework for construction project management that leverages DT, AI, and computer-aided engineering to tackle budget, time schedule, safety, and environmental impact. Comparing IoT data related to site activity progress with the plans stored in its database, the DT can forecast scenarios to make decisions or, in complex situations, to inform decision-makers.

During the operation phase, the combined use of AI, DT, and IoT can contribute substantially to creating a more sustainable, efficient, and resilient BE, enabling the development of smart buildings that dynamically adjust to real-time changes to reduce energy use, minimize CO_2 emissions, and improve occupant comfort and safety [6]. Through real-time monitoring of energy use and comfort parameters, predictive analysis, and systems optimization, DTs combined with AI and, in particular, ML significantly advance zero-energy building goals [39]. The combined use of DT, BIM, and AI technologies is increasingly valued for their ability to improve occupant thermal comfort and energy efficiency in buildings [91].

The integration of IoT, optimization algorithms, and ML techniques within a DT allows the system to perform historical and real-time data analysis to forecast future trends, identify inefficiencies, and propose strategies to improve energy management and reduce the carbon footprint [6,88].

AI and DTs for building energy systems enable real-time energy use visualization, fault detection, simulation, prediction, and simultaneous optimization of a range of objectives such as energy efficiency, cost savings, environmental impact reduction, and performance monitoring and control [92]. Energy efficiency can also be enhanced by AI and DTs through the optimization of space management, reducing energy usage and CO_2 while improving user satisfaction [40].

AI-integrated DTs enable predictive maintenance, contributing significantly to sustainability. Leveraging ML algorithms to analyze high volumes of data, DTs can simulate diverse operational scenarios to foresee equipment failures and performance degradation. This enhances building operations control and facilitates proactive maintenance scheduling, preventing operational disruptions, extending infrastructures life, achieving cost savings, and improving sustainability [6,40,41,88].

DT technology is also crucial for historic buildings preservation. Serving as the central hub for IoT, AI, and H-BIM (Heritage BIM), DT enables real-time monitoring and simulations, generating insights for informed decision-making in risk management and conservation strategies. Enhancing the resilience of heritage structures and boosting occupant wellness, DTs and AI can foster sustainability and contribute to the realization of the SDGs [43]. Ni et al. [77] created a DT that utilizes IoT, cloud computing, and ML to ensure the sustainable maintenance of historic structures, harmonizing energy efficiency, occupant comfort, and conservation of BE. Jiménez Rios et al. [93] underscore the advantages that Industry 5.0 brings to conservation, such as strengthened resilience, real-time monitoring, and community involvement in the decision process. They recognize AI and DT as enabling technologies with the greatest potential for built cultural heritage preservation.

DT-enabled energy management systems can leverage AI and IoT technologies to optimize energy use, increase system efficiency, and improve operational effectiveness. Dulaimi et al. [81] presented a United Arab Emirates case study on developing a smart energy hub that relies on DT to successfully implement energy efficiency improvements through AI and real-time data. Testasecca et al. [94] explored three European case studies on DTs for energy system optimization to enhance efficiency and reduce environmental impact. They emphasize that DTs can support the integration of renewable energy sources, enhance grid automation, and improve grid stability. In BIPV systems, the combined use of DTs and AR/VR enables the forecasting of PV panel performance, facilitates a more comprehensive analysis of unforeseen and unpredictable events, and allows for the visualization of preventive strategies to ensure panel longevity [72].

At the urban scale, DTs and AI are essential also for the development of sustainable smart cities. DT-AI integration enables data-driven and simulation-based urban planning, real-time monitoring, and predictive maintenance of building assets and infrastructure, thus supporting CO_2 reduction, the optimized use of resources, waste minimization, and asset life extension [6,44]. Li et al. [28] emphasize the significant interdependence between Net-Zero Carbon Cities and DTs, highlighting the role played by this technology in building a solid network that allows for real-time monitoring and data-driven decision making. Concurrently, the integration of AI models enables the accurate forecasting of future trends in CO_2 emissions and potential scenarios, using historical, real-time, and simulated data.

AI-powered DTs can also enhance critical infrastructure's climate resilience through real-time asset assessment, informed decision-making, adaptive strategies, and proactive early warnings that prevent severe performance degradation [55].

As expected, Figure 8 and Table 4 show that, analogously to what emerged for the IoT, the integration of DTs with AI for sustainability purposes has currently impacted mainly the O&M phase within the BE life cycle, whereas the production, the renovation, and the end-of-life phases present the greatest unexploited potential.

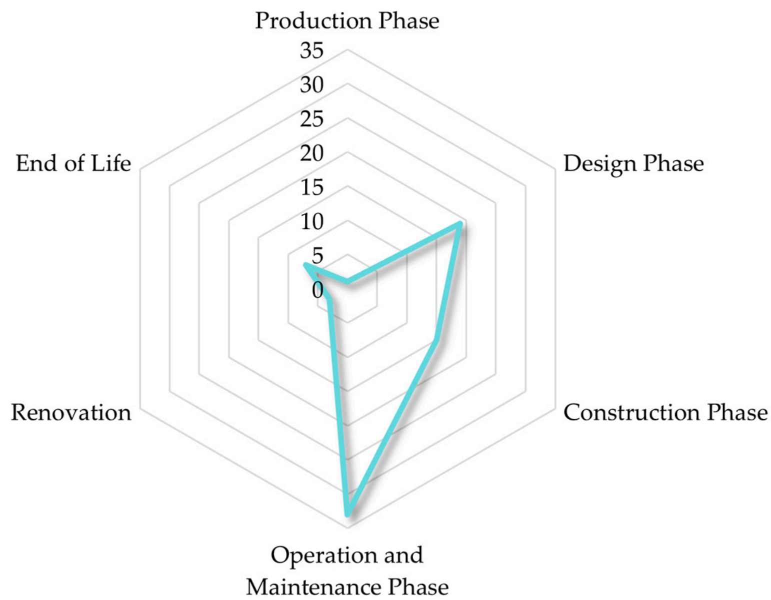

Figure 8. Papers on DT-AI integrations by building life cycle phase.

Table 4. DT and AI: papers by building life cycle phase.

Building Life Cycle Phase	References	Key Findings	Gaps
Production Phase	[95]	• Predictive analytics aimed at optimizing control decisions for manufacturing operations.	• Research related to offsite construction involving digital technologies is still limited.
Design Phase	[6,12,28,35,41,45,46,49,50,54,56,57,82,88–90,93,96,97]	• Automatic generation and assessment of design options for enhanced building performance and user experience. • Inform the design process by analyzing building usage and environmental data to predict building efficiency, comfort, and safety. • Enable informed decision-making by providing project sustainability assessment through real-time cost analysis and sustainability indicators.	• Current studies mainly focus on the use of parametric design tools that require expertise. • Studies on DTs for building energy consumption are quite limited and generally produced at a theoretical level. • Research should focus more on sustainable design principles and real-time decision-making tools.

Table 4. *Cont.*

Building Life Cycle Phase	References	Key Findings	Gaps
Construction Phase	[6,7,12,41,45,46,49,54,56, 57,62,88,93,95,96]	• Increase stakeholders' collaboration and improve transparency, traceability, and efficiency in construction, supporting CE. • Optimization of resource use, prevention of overproduction, reduction in material waste, and environmental impact. • Analysis of IoT data from construction sites to tackle budget, time schedule, safety, and environmental impact, and automate decision-making.	• Trust concerns associated with reducing human involvement in construction sites management. • Resistance to change, project complexity, high initial investments, absence of standardization. • Need for a paradigm shift for stakeholders to move away from document-based processes towards data-driven management and monitoring.
Renovation Phase	[12,88,98]	• Help construction teams to better analyze recycling needs to achieve material savings. • Identification of optimal energy-saving solutions for renovation projects.	• Lack of DT applications for renovation phase and limited number of papers exploring this field. • Applications for energy saving and emission reduction are still limited.
Operation and Maintenance Phase	[6,7,12,28,35,39–41,43–46,54–57,62,72,77,81,82, 84,86,88,91–94,96–100]	• Development of smart buildings that dynamically adjust to real-time changes to minimize CO_2 emissions and improve occupant comfort and safety. • Real-time energy use optimization, fault detection, simulation, prediction, and environmental impact reduction. • Simulation of operational scenarios to foresee equipment failures and performance degradation, enabling predictive maintenance.	• Data security and privacy: The collection and integration of large amounts of data in real time can increase vulnerability to cyber-attacks. • DT's reliance on power supply makes them vulnerable to disruptions. • . • Need for further research on real-time control and building system optimization to achieve actual energy savings.
End-of-Life Phase	[12,46,54,56,88,93,101]	• Increase recyclability of construction materials and products, turning construction waste into valuable resources and cutting the environmental footprint of the sector. • DTs and MPs can enable reuse at the building's demolition phase.	• Lack of sufficient information about materials and substances at the end-of-use phase hinders the reuse and recycling of resources in buildings. • Interoperability and data sharing can be challenging.

3.1.4. Machine Learning (ML)/Deep Learning (DL) and AI Integrations

ML and DL are playing a pivotal role in the transformation of the BE to align with modern, sustainable, and environment-friendly practices. Over the past decades, these technologies have been introduced and exploited in various related applications and processes, including safety at construction sites [102], photovoltaic optimization [103], building energy consumption management [104,105], and solutions to architectural [106,107] and supply chain challenges [108]. The applications of ML and DL techniques in the BE have shown great promise and a future in enhancing sustainability and operational efficiency throughout the building stages. Studies have revealed that reinforcement learning and ANNs are effective in optimizing energy consumption and adapting building systems in real time.

Within ML, reinforcement learning (RL) is distinguished by its ability to learn optimal strategies without the need for an explicit model of the environment. Recent studies [109] demonstrate how advanced methodologies, including multiagent RL and proximal policy optimization, can improve energy efficiency and autonomous power flow management in smart buildings and microgrids, overcoming the limitations of traditional approaches and fostering a transition to decentralized and adaptive systems. The framework proposed by Hernández Moral et al. [97] integrates building management systems with ML and DL techniques to perform sensor data prediction, which is used as a comparison to identify malfunctions. In a study by Um-e-Habiba et al. [110], RL was employed for dynamic decision-making in smart buildings, enabling systems to continuously learn and improve energy efficiency by adjusting the environmental conditions and building occupant behaviors.

The application of AI-driven tools, especially DL for fault detection and predictive maintenance, has proven effective in identifying system errors and preventing costly failures in electrical power grids [111], as well as in heating, ventilation, and air conditioning systems in buildings [112].

In the context of offsite and modular construction, techniques like Convolutional Neural Networks (CNNs) and ANNs have shown significant promise in enhancing productivity, safety, and resource optimization. These AI models improve real-time monitoring, fault identification, and intelligent decision-making, which not only optimize resource usage but also contribute to sustainability by enabling predictive maintenance and reducing carbon footprints. Models like CNNs and ANNs specifically improved cost estimation and safety assessment. The AI-driven assessments reduce human errors and optimize resources more efficiently [113].

Kozin et al. [98] employed ANN models integrated with financial DTs for efficient marine property management. The work focused on developing a decision-making framework for managing marine infrastructure property complexes, ensuring economic viability and public efficiency. The authors investigated ANN models for decision-making support and set evaluation criteria for the maritime property complex efficacy by defining it as an infrastructure property. The proposed digital framework depicted appropriate results in improving infrastructure development and resource distribution efficiency by enabling real-time data processing and optimization.

In architectural design, ML and LLMs contribute to Life Cycle Assessment (LCA) by optimizing material selection and minimizing carbon footprints [29]. Furthermore, ML and DL models can enhance data-driven decision-making, improving energy efficiency and reducing the environmental impact of buildings [114].

Studies highlight the transformative role of these technologies in driving sustainability and efficiency across diverse sectors. For instance, Tseng et al. [115] proposed a data-driven circular supply chain framework that integrates ML, AI, and big data analytics to identify key attributes and trends influencing its implementation, emphasizing resource recovery and reverse supply chain practices.

The combination of AI, UAVs, and robotics in building-integrated photovoltaics (BIPV) was exploited by Singh et al. [72]: this research employs AI, UAV-based monitoring, robotics, DTs, fog computing, and 6G-assisted IoT for optimizing BIPV performance, fault detection, and real-time analytics. The study revealed that these technologies can assist in the better management and operation of the BIPVs. Specifically, the complex topics addressed include, but are not limited to, temperature rise in PV modules, fault diagnosis, and dust or debris accumulation on module surfaces. All the aforementioned challenges can reduce the efficiency of BIPVs. Results revealed that cooling PV modules can increase electrical conversion efficiency by 7–8% compared to those without cooling. Digitalized BIPV architecture proved successful through the incorporation of real-time monitoring and intelligent analytics to enhance system performance.

The study by Malik et al. [116] underscores the advantages of digital transformation through ML and DL, emphasizing the increase in automation and efficiency in various engineering domains, such as manufacturing, healthcare, and construction. Moreover, the research by Manzoor et al. [117] studied the integration of AI and ML in civil engineering projects, contributing to resource optimization and sustainability in construction: the study revealed that the use of AI has led to improvements in construction efficiency, reduced resource consumption, and better project outcomes.

Collectively, these studies illustrate the broad applicability and growing impact of AI and ML in advancing sustainability and operational efficiency, though challenges such as data security, high costs, and industry-specific integration hurdles remain significant barriers to widespread adoption [41,115,116].

AI models, when utilized for property and resource management, have demonstrated competitive performance. However, Kozin et al. [98] highlights the necessity of employing financial DTs and AI to modernize property regulation processes. Leveraging large language models and diverse data sources can ensure the adaptability, inclusiveness, and real-world effectiveness of AI-driven solutions. This will pave the way for wider adoption and maximized sustainability outcomes in the BE.

To sum up, Figure 9 and Table 5 clearly show that ML/DL-based technologies enhanced by AI are prevalently supporting the building life cycle O&M phase, whereas the production, the renovation, and the end-of-life phases still face the greatest barriers to a wider adoption.

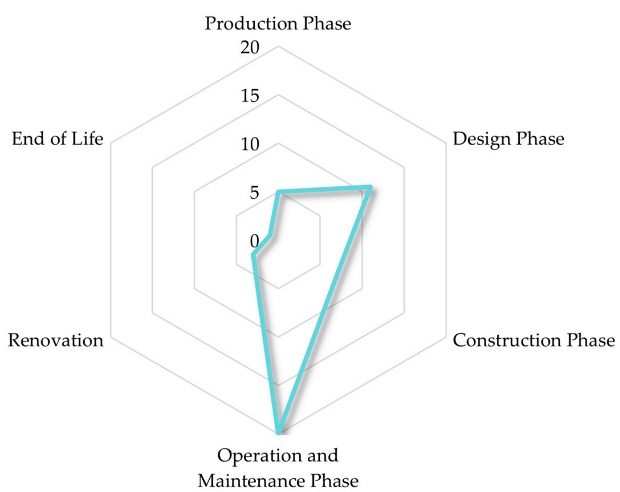

Figure 9. Papers on ML/DL-AI integrations by building life cycle phase.

Table 5. ML/DL and AI: papers by building life cycle phase.

Building Life Cycle Phase	References	Key Findings	Gaps
Production Phase	[113,117–120]	• Support on automation, simulation, and optimization of offsite and modular construction processes. • Optimization of performance and sustainability of prefabrication offsite through CNN and ANN models. • Assistance for decision makers and managers in fast decisions regarding material selection and component production.	• Lack of integrated and standardized frameworks for embedding AI-based tools in early-stage production. • Minimal practical implementations of ML and DL models in raw material processing, and sustainable materials. • Data interoperability and real-time integration challenges persist in digital manufacturing and offsite platforms.
Design Phase	[5,29,91,117–119,121]	• Support of data-driven decision-making to improve energy efficiency, comfort, and performance. • Help in design optimization by analyzing large simulation outputs and assisting in the selection for high performance. • Reduction in design iteration time, support of multi-objective optimization.	• Lack of labeled high-resolution design-phase datasets limits the training and validation of ML and DL models. • Lack of studies focusing on multi-objective optimization simultaneously considering energy, cost, and comfort. • Scalability and computational cost of DL models.
Construction Phase	[27,41,62,113,114,117,119,122,123]	• Improvement of accuracy and efficiency in monitoring, fault detection, and resource optimization. • Integration of ML with BIM and IoT enhances data-driven decision-making in the construction phases. • Enhancement of prediction performance with limited datasets through transfer learning and hybrid models.	• Insufficient research on real-time ML and DL deployment on construction sites. • Lack of multi-modal data fusion techniques combining visual, sensor, and textual data for holistic analysis. • Need for standardized datasets and benchmarks for training and validating ML and DL models.
Renovation Phase	[77,98,114]	• Support of scalable data collection, storage, and ML model training, facilitating deployment across multiple buildings. • Improvement of anomaly detection, occupancy prediction, and energy consumption.	• Need for integration of highly heterogeneous data sources. • Need for further research to scale DL solutions across diverse building types, historic contexts, and geographic regions.

Table 5. *Cont.*

Building Life Cycle Phase	References	Key Findings	Gaps
Operation and Maintenance Phase	[5,40,41,62,72,77, 82,86,91,92,97,98, 110,113,114,116–118,124]	• Improvement of real-time building energy management by optimizing HVAC, lighting and fault detection, achieving up to 20–30% energy savings. • Improvement of defect detection and quality control, reducing errors by 25%. • Improvement of energy use optimization through AI-powered occupant behavior modeling. • Assistance in better management and operation of BIPVs and grid integration of renewables.	• Lack of robust, transferable AI models that perform well across different building types, climates, geographic locations, and operational conditions. • Hesitation among the senior decision makers to application. • Insufficient practical application due to data availability, model accuracy, and integration with existing workflows. • Underexplored AI applications in logistics, maintenance, and long-term system resilience phases.
End-of-Life Phase	[114]	• Improvement data management by integrating heterogeneous sources (material logs, demolition data, structural records). • Promotion of circularity by improving material tracking and reuse.	• Need for designing complex pipelines for unstructured data, managing inconsistencies caused by data heterogeneity. • High computational costs for metadata processing; reliance on domain expertise.

3.1.5. Optimization Techniques and AI Integrations

Due to the complexity of building design, the integration of AI and ML models enables the automation of the optimization process across various domains, including energy and structural analysis [125]. In this context, the construction materials industry is crucial for sustainability, especially given the extensive use of concrete. Haist et al. [126] proposed the use of composite cement with three or more components, but highlighted the lack of a digital and holistic system for quality control and monitoring during production. Based on this, the methodology proposes a digital control system based on computer vision and AI, aimed at continuously monitoring the rheological properties of concrete during the mixing phase, allowing for real-time adjustments to increase the safety of the manufactured elements and to enable the use of recycled materials in the production of the composite. During cement production, electricity consumption surpasses thermal energy use, but the high level of automation in the cement industry enables continuous performance monitoring. Some studies [127] have suggested methods to shift electricity consumption to periods of lower economic demand, integrating various components into a simulation model to accurately predict their impact on production and costs. In line with this approach, the model integrates optimization algorithms and AI techniques, such as CNN and LSTM, to predict in real time the workability of self-compacting concrete based on video sequences of the mixing process. This integration enables a reduction in material waste, processing time, and production costs. Additionally, Coenen et al. [128] estimate that recycled cement production, using cement paste derived from concrete waste, consumes 30% less energy compared to clinker production. In addition, automation and advanced process control systems are essential for optimizing electricity use in cement production. Predictive modeling and optimization algorithms enable model predictive control technologies to optimize process parameters, improving energy efficiency and increasing production, resulting in cost savings and contributions to SDGs [75].

The need for integrating materials from building demolition into production processes is increasing, promoting material reuse. In this context, Rodonò et al. [120] developed an AI-supported methodology for designing raw earth components. The adoption of ANNs allows for analyzing various solutions in terms of thermal and acoustic performance, enabling multi-criteria optimization.

AI-driven optimization improves the functionality, efficiency, and sustainability of the BE from the earliest stages of design. AI can overcome traditional GD methods, which generate solutions with small, meaningless variations, due to its ability to handle and analyze large amounts of data. Integrating AI with GD optimizes architectural and urban solutions according to environmental and human factors. However, shifting from automation to goal-oriented optimization requires a structured communication framework between algorithms and professionals. In this framework, AI acts as an intelligent assistant, not as a substitute [48].

Currently, design is primarily cost-driven, often at the expense of energy efficiency. Multi-objective optimization has thus emerged as a key tool to balance sustainability, materials, costs, and CO_2 emissions. AI algorithms such as Swarm Intelligence, Simulated Annealing, ANNs, and Bayesian Optimization have been studied in the literature [129].

In building performance simulations, AI integration shows promising results. Among the most widely adopted AI algorithms in energy modeling and performance-based design are ANNs, support vector machines, and decision trees, which may complement or enhance traditional simulation methods. However, a clear framework for integrating these tools into the design process is still lacking [118]. Several frameworks are emerging in the AEC sector. For instance, Geraldi & Ghisi [130] propose a seven-stage model that uses post-analysis detection to train a neural network in order to accurately predict building performance, while Dong et al. [131] propose intelligent automation focused on lighting and energy performance.

In structural design, Mathern et al. [121] propose an innovative AI-driven approach that integrates Set-Based Design, LCA, and multi-criteria decision analysis for structural optimization. AI-enhanced Set-Based Design facilitates the generation and evaluation of various design options, eliminating non-compliant solutions and proposing more feasible alternatives.

LCA and multi-criteria methodologies analyze projects based on environmental, economic, and social criteria, improving transparency and facilitating complex decisions. Additionally, AI leverages historical data to optimize design choices, enhancing efficiency and sustainability throughout the entire building life cycle. Wu and Maalek [36] propose a decision-support methodology for interventions in old buildings. The aim is to identify the best intervention between renovation, demolition, and deconstruction with reconstruction, comparing costs, energy consumption, and CO_2 emissions.

In the context of optimizing the relationship between function and cost of buildings is value engineering. Khan et al. [61] highlight how its automation by AI, BIM, and ML systems can lead to the exploration of multiple design layouts, material optimization selection, and cost–benefit analyzes to assess the actual impact of the decisions triggered by value engineering. In addition, the extension of this to the entire life cycle of a construction enables the optimization of operation, maintenance, and end-of-life costs through the integration of sensor data with BIM platforms. The adoption of ML and DL enables the development of data-driven and predictive approaches for intelligent energy control that include load prediction, fault detection and diagnosis, and occupancy prediction-based solutions [132,133].

With a view to improving energy utilization, smart energy systems emerge, given by an integrated set of smart electricity, heat, and gas grids, interfaced with storage technologies [134]. In fact, Javed et al. [79] propose a methodology of demand–response optimization within smart energy systems with local clouds, formed by thermostats and smart sockets and devices installed inside homes. The optimization algorithm is integrated into the home energy management system, which interfaces with a system to predict optimal setpoints for the climate control of individual rooms. At the same time, the study by Zhou et al. [92] highlights how the digitization of the energy sector and the integration of AI are being applied to optimize the sizing and performance of plant systems, such as heat pumps and recovery systems, photovoltaic systems, and energy storage solutions. These optimization techniques encompass GA and multi-objective optimization approaches.

In air-source heat pumps, ref. [135] proposed a hybrid Hooke–Jeeves particle swarm algorithm to optimize the operation of the machine under different climatic conditions.

In conclusion, taking stock of the analyzed literature concerning combined uses of optimization techniques with AI, the design and the O&M phases of the BE life cycle turned out to be the most supported, whereas, once again, the production, renovation, and end-of-life phases show the greatest gaps (see Figure 10 and Table 6).

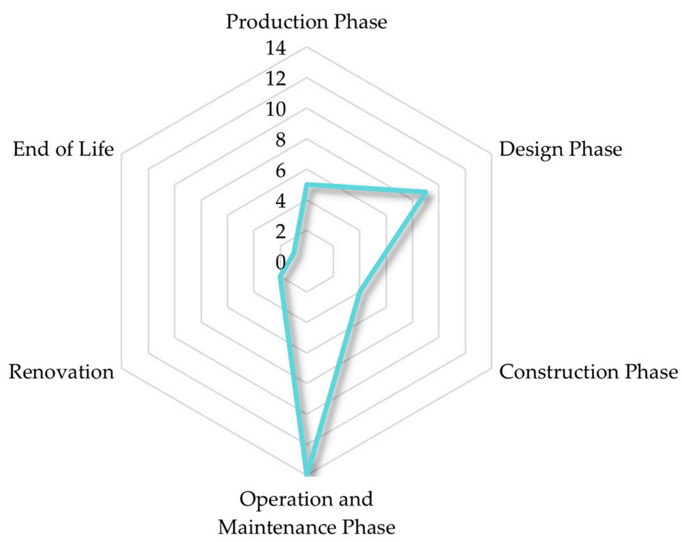

Figure 10. Papers on Optimization-AI integrations by building life cycle phase.

Table 6. Optimization and AI: papers by building life cycle phase.

Building Life Cycle Phase	References	Key Findings	Gaps
Production Phase	[61,75,118,120,126]	• AI enables real-time monitoring of concrete rheology to reduce waste. • Predictive algorithms shift energy use to off-peak hours in cement plants. • AI helps optimize composite materials using recycled inputs.	• Lack of integrated digital control systems for quality monitoring. • Limited adoption of AI-driven LCA tools in material production. • Insufficient datasets on recycled material performance in production.

Table 6. *Cont.*

Building Life Cycle Phase	References	Key Findings	Gaps
Design Phase	[6,29,46,48,61,89,118,121,129]	• AI enhances GD with data-driven environmental analysis. • Multi-objective optimization balances cost, emissions, and performance. • ANN and SVM improve building energy modeling accuracy.	• No standardized framework for integrating AI into design workflows. • Limited collaboration between AI models and human designers. • AI models often lack transparency and explainability for professionals.
Construction Phase	[46,61,62,136]	• AI supports structural optimization using LCA and MCDA. • Set-Based Design with AI filters unsustainable options early. • AI enables material and layout optimization through value engineering.	• Scarce real-time AI applications on construction sites. • Data fragmentation hinders AI performance during construction. • Lack of automation in integrating AI outputs with BIM execution plans.
Renovation Phase	[36,61]	• Support of decision-making between renovation and redevelopment based on life cycle sustainability. • GA optimize lightweight and sustainable reconstructions. • Multi-objective optimization identifies solutions that balance cost, performance, and sustainability criteria.	• Limited AI datasets for old or heritage buildings. • Poor integration of structural and energy models in renovation scenarios. • Most studies lack empirical validation through real renovation projects.
Operation and Maintenance Phase	[5,6,46,61,62,73,79,91,92,97,109,137]	• Improvement of HVAC control and reduction in energy use. • Increase in predictive maintenance through sensor-based performance forecasting. • Multi-objective optimization can balance comfort, cost, and emissions in real time.	• Fragmented sensor data limits model accuracy. • Few models integrate real-time optimization into daily BMS operations. • Lack of long-term validation of AI models in real-world operations.
End-of-Life Phase	[61]	• Support of selective deconstruction and material reuse. • Multi-objective optimization balances cost, reuse value, and environmental impact. • Integration with BIM enhances demolition/deconstruction planning.	• Lack of standardized data on reuse potential and deconstruction. • Data fragmentation prevents integrated, holistic optimization. • Limited case studies on AI-driven end-of-life optimization.

4. Discussion

The analysis of the main research results that emerged from the literature review led to the identification of the phases of the building life cycle which are most impacted by AI-powered digital technologies. The conducted research allowed us to identify the digital technologies that contribute the most to every phase of the building life cycle by also detecting the main sustainability fields of application that turned out to have benefitted more from digital technologies enhanced by AI integration. More specifically, the following sustainability application areas were detected:

- Circular economy;
- Building energy performance optimization;
- Construction site management optimization;
- Asset management optimization;
- Sustainable heritage preservation;
- Smart cities and urban resilience management;
- Smart grids and renewable energy production.

In this regard, Figure 11 summarizes the results of the clustering process conducted on the 102 analyzed papers in a recap matrix where the numbers of papers per technology that impacted on each building life cycle phase (grouped by column) and on each identified sustainability category (grouped by row) are reported. For a better understanding, it is essential to specify that most of the papers involve more than a single technology, and often affect multiple sustainability areas and building life cycle phases. As far as the building life cycle is concerned, it is worth noting that the investigated literature suggests that all technologies except for BIM impact on all phases of the life cycle. BIM, which most supports the design phase, turned out not to be adopted in support of the production phase. In regard to the identified sustainability fields of application, BIM and optimization techniques came out not to support all sustainability areas. More specifically, it emerged that BIM provides the greatest support to CE practices, whereas it has been unused so far for smart cities and smart grid applications, likely because BIM is currently more convenient to use at the building scale than the urban scale. IoT, DTs, ML/DL, and optimization techniques came out instead to contribute most to asset management optimization, which may benefit more from the use of dynamic real-time data and predictive models.

Production Phase	BIM	IoT	DT	ML	Optimization
Circular Economy		2		2	4
Building Energy Performance Optimization			1	2	1
Construction Site Management Optimization			1	4	
Asset Management Optimization		1		2	
Sustainable Heritage Preservation					
Smart Cities and Urban Resilience Management					
Smart Grids and Renewable Energy Production					
Papers by phase per technology	0	2	1	5	5

Design Phase	BIM	IoT	DT	ML	Optimization
Circular Economy	21	2	8	4	6
Building Energy Performance Optimization	7		9	5	4
Construction Site Management Optimization	6		8	4	2
Asset Management Optimization	5	2	8	5	2
Sustainable Heritage Preservation			2		
Smart Cities and Urban Resilience Management			3	1	1
Smart Grids and Renewable Energy Production			1	1	1
Papers by phase per technology	37	2	19	11	9

Construction Phase	BIM	IoT	DT	ML	Optimization
Circular Economy	2	3	7	2	2
Building Energy Performance Optimization	5	2	7	2	1
Construction Site Management Optimization	6	4	9	6	3
Asset Management Optimization	4	4	6	4	2
Sustainable Heritage Preservation			2		
Smart Cities and Urban Resilience Management		1	2		1
Smart Grids and Renewable Energy Production			1		1
Papers by phase per technology	15	5	15	7	4

Operation and Maintenance Phase	BIM	IoT	DT	ML	Optimization
Circular Economy	8	21	8	1	4
Building Energy Performance Optimization	8	20	10	11	6
Construction Site Management Optimization	6	4	8	5	2
Asset Management Optimization	5	36	23	17	12
Sustainable Heritage Preservation	1	2	4	1	
Smart Cities and Urban Resilience Management		15	8	6	2
Smart Grids and Renewable Energy Production		4	5	5	2
Papers by phase per technology	23	38	33	20	14

Renovation Phase	BIM	IoT	DT	ML	Optimization
Circular Economy	1	2	2		2
Building Energy Performance Optimization	1	3	1	2	
Construction Site Management Optimization	1	1	1		
Asset Management Optimization		5	2	3	
Sustainable Heritage Preservation		2		1	
Smart Cities and Urban Resilience Management				1	
Smart Grids and Renewable Energy Production				1	
Papers by phase per technology	2	5	3	3	2

End of Life	BIM	IoT	DT	ML	Optimization
Circular Economy	1	2	5		1
Building Energy Performance Optimization	1		2	1	
Construction Site Management Optimization	2		2		
Asset Management Optimization		2	2	1	
Sustainable Heritage Preservation			1		
Smart Cities and Urban Resilience Management			1	1	
Smart Grids and Renewable Energy Production			1	1	
Papers by phase per technology	3	2	7	1	1

Papers by category per technology	BIM	IoT	DT	ML	Optimization
Circular Economy	21	22	10	7	12
Building Energy Performance Optimization	10	20	13	12	8
Construction Site Management Optimization	7	5	10	9	4
Asset Management Optimization	8	36	23	17	12
Sustainable Heritage Preservation	1	2	4	1	0
Smart Cities and Urban Resilience Management	0	15	8	6	2
Smart Grids and Renewable Energy Production	0	4	5	5	2

BIM IoT DT ML Optimization

Figure 11. Resulting matrix summarizing the number of papers per technology that impact on each building life cycle phase and on the identified sustainability fields of application.

To sum it up, Figure 12 shows that 70% of the 102 papers impacted on the operation and maintenance phase, followed by 50% which contributed to the design phase. On the other hand, the least investigated building life cycle phases are the renovation (10%) and the end-of-life phases (16%), thus revealing a crucial gap in the field.

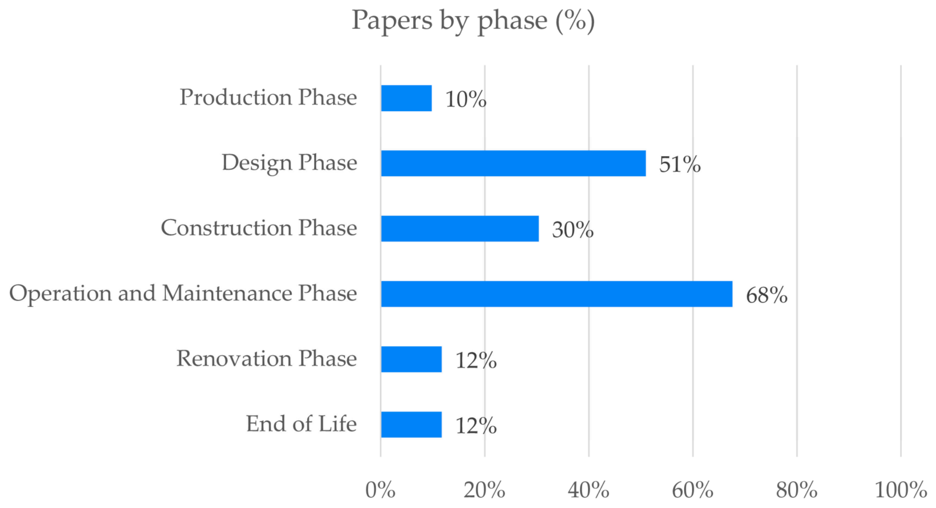

Figure 12. Percentages of the 102 analyzed papers that impacted on each building life cycle phase.

With regard to sustainability areas that are attracting the greatest attention, asset management, CE in general, and building energy performance optimization came out to be the fields of application enhanced the most by such advanced digital technologies integrated with AI (Figure 13). Conversely, the field of sustainable heritage preservation remains the least explored, together with smart grids and renewable energy production, which therefore must be considered as still unaddressed challenges.

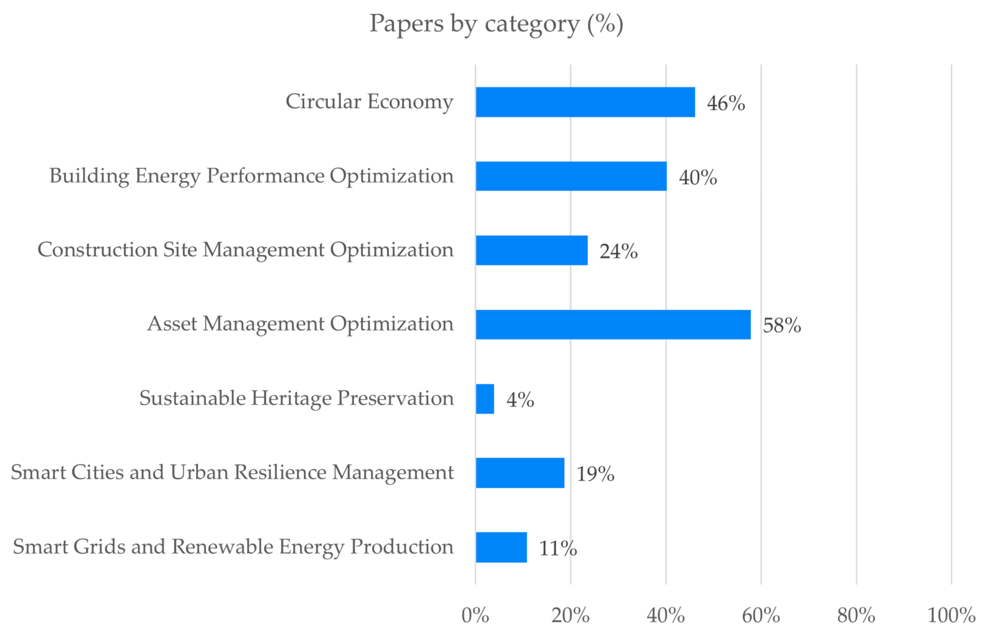

Figure 13. Percentages of the 102 analyzed papers that impacted on each sustainability category.

Getting more to the bottom of the literature analysis concerning each technology, the integration of BIM and AI turned out to be a strategic opportunity to enhance environmental sustainability in the construction sector by improving energy efficiency, resource management, and the quality of design decisions. The combined use of AI techniques, such as ML, GA, and ANN, with BIM models enables advanced simulations, GD, and predictive analyzes, yielding benefits not only at the building scale, but also in urban and educational contexts through the use of immersive technologies like AR/VR. Real projects demonstrate how this synergy contributes to reducing emissions and construction waste, while supporting the achievement of several SDGs, such as SDGs 7, 11, and 12. The present research unexpectedly led to no articles specifically supporting the production phase of the BE life cycle and no studies focused on integrating BIM and AI in the off-site construction phase. However, some studies concerning BIM-AI integrations enhancing generative design in industrialized construction, which were not included in the 102 analyzed papers, are worth mentioning. It should be remembered that these articles are not part of the main research findings because they did not meet the search criteria herein adopted to conduct the systematic review. By way of example, Alvarez et al. [138] propose an integrated workflow based on BIM and AI to support industrialized construction and prefabrication by correlating BIM element data with ERP (Enterprise Resource Planning)-managed material databases. Focusing on pipes and fittings, the authors apply rule-based NLP (Natural Language Processing) algorithms, executed on Revit via Dynamo and Python (https://www.python.org/about/ accessed on 22 June 2025), to automate the classification and information assignment of BIM components, thus enhancing the prefabrication processes. Gao et al. [139] also suggest a BIM and AI-powered approach for parametric generative design in industrialized construction. Their workflow processes BIM data through encoding, cleaning, and standardization, and then uses AI, including LLMs and evolutionary algorithms, to facilitate quick prototyping as well as multi-objective optimization. The approach optimizes structural integrity, cost efficiency, and other design criteria, offering a systematic pathway to optimized design solutions.

The IoT technology came out to be the one most used to provide the data streams required to effectively implement and keep updated DTs, while ML and AI may analyze IoT-supplied data to predict future behaviors, optimize the real-time performance of buildings, and automate decision-making processes, making the integration of such technologies a powerful combination for enhancing efficiency and innovation, especially in sustainability matters [6].

DT technology, by relying heavily on IoT data, can also effectively enhance sustainability throughout the life cycle of BE assets [7]. The integration of AI algorithms within DT platforms allows the processing of the collected data into insights, identifying patterns and forecasting future behavior to optimize energy management, building performance, and overall resource utilization [6]. Additionally, AI-integrated DTs can facilitate policymakers in developing Net-Zero CO_2 emission strategies and enhance public knowledge of carbon footprints and climate change impacts [130].

The applications of ML and DL techniques in the BE have shown great promise and a future in enhancing sustainability and operational efficiency throughout the building stages. AI models turned out to be able to enhance real-time monitoring, fault identification, and intelligent decision-making, thus not only optimizing resource usage but also contributing to sustainability by enabling predictive maintenance and reducing carbon footprints.

AI-driven optimization may improve the functionality, efficiency, and sustainability of the BE from the earliest stages of design. AI can overcome traditional generative design methods, which generate solutions with small, meaningless variations, due to its ability to handle and analyze large amounts of data. Integrating AI with GD optimizes architectural and urban solutions according to environmental and human factors. However, shifting from automation to goal-oriented optimization requires a structured communication framework between algorithms and professionals. In this framework, AI acts as an intelligent assistant, not as a substitute [48].

To conclude, although AI-integrated digital technologies present considerable advantages, widespread adoption is hampered by several challenges. Firstly, it can be argued that one of the main obstacles for the implementation of digital technologies is related to the lack of interoperability among the sources that generate data and the heterogeneity of information from building digitization [140]. To overcome these barriers, Xu et al. [137] propose a framework based on the "Brick semantic model" in the field of building energy management. By way of example, in the context of energy management, difficulties in information exchange between BIM, "Brick semantic model" and optimization environments often generate information loss and limit the application of AI-based optimization strategies [137].

Optimization algorithms are often complex to manage and govern, which limits their integration into traditional design and construction management workflows [129]. At present, several AI-based commercial applications are emerging to support sustainability optimization in the BE. While some of these tools are designed to be interoperable with BIM, their full integration into conventional design and management workflows remains limited, and their practical implementation is still evolving. Importantly, none of the studies analyzed in this systematic review reported the use of such AI-driven applications.

Representative examples include Integrated Environmental Solutions (IES) parametric tools, Autodesk Forma, Stellis AI, MetWaves, and Finch, though their implementation in practice is still evolving. IES offers a comprehensive suite for building performance simulation. AI and ML functionalities are currently under development and are primarily applied within digital twin frameworks for operational management, enabling predictive analytics and optimization during the building life cycle [141]. Autodesk Forma [142] is a cloud-based platform that combines BIM with AI-driven generative design to optimize building and urban-scale configurations, considering daylight, energy performance, wind, and microclimate. Stellis AI [143] provides the AI-Driven Resource and Waste Optimization module, employing predictive analytics and AI-based optimization to reduce material consumption and construction waste within a BIM workflow. MetWaves [144] offers the AI-Driven Material Optimization module, enabling data-driven selection of construction materials to improve efficiency, reduce costs, and enhance sustainability. Finally, Finch [145] is a Revit-integrated generative design tool that applies AI and optimization algorithms to automatically generate and evaluate spatial layouts according to criteria such as space efficiency, orientation, and environmental performance.

The lack of interoperability between BIM environments and simulation software hinders the efficient analysis of complex, heterogeneous data, limiting the real-world impact of BIM-AI integration. Also, DTs in construction involve a vast volume of heterogeneous data, and pose significant challenges related to data quality [88], scalability [94], and integration [6]. Technical limits also include connectivity and interoperability [100], data security [55], privacy protection [41], and governance [72], representing current research gaps that need to be further investigated.

In the context of sustainable building design, digital technologies like IoT, BIM, and AI can optimize energy use and improve sustainability; but there are drawbacks as well, like high upfront costs and a shortage of qualified workers [41]. In fact, a further hurdle is posed by cost factors of DT [41,62], and future research should be conducted focusing on developing cost-effective DTs solutions [88]. According to Regona et al. [119], key barriers to AI adoption in construction include cost-effectiveness, equitable access to AI-driven solutions, weak AI technological training of human resources, and data integration and security issues. Additionally, legal and ethical concerns, such as intellectual property rights, liability, cybersecurity, and employment impact, need to be addressed to ensure responsible AI implementation.

Many researchers also suggest focusing on creating awareness and knowledge about new technologies and their benefits, considering also social and psychological aspects influencing adoption, incentives and public governance [40]. Successful DT implementation in construction relies on stakeholder acceptance and understanding. The low level of technical expertise [72] and the need for continuous staff training and upskilling [41,62] are, therefore, major challenges. Moreover, there are trust concerns related to automated decision-making [55] and reduced human oversight [49]. Researchers also pointed out social acceptance barriers mostly related to a lack of cognitive elements, people's perception of too futuristic products and failure to understand the benefits, prices still considered too high, complexity, and difficulty of the interactions.

Another challenge that needs to be overcome is the lack of standardization, a major gap widely acknowledged by scholars [6,46,49,55,81,88]. Future research should focus on standardizations and compatibility between devices, smart analysis for real-time energy consumption information, and the analysis of the interaction between energy consumption, wellness, and health [78]. Finally, limited integration of CO_2 assessments, the difficulty of adapting AI to dynamic site conditions, and the reliance on specific AI models like CNN and ANN, which may overshadow other potentially effective techniques and models [113], remain challenges.

In the end, Table 7 underlines both the main key findings and the still unaddressed challenges that emerged from the proposed literature analysis related to each sustainability category assumed as relevant for the BE impacted by AI-enhanced Industry 5.0 technologies.

Table 7. Papers by sustainability fields of application.

Sustainability Application Areas	Key Findings/AI Contribution	Challenges
Circular economy	• AI supports reuse and recycling of materials by processing data stored in BIM, particularly through MPs, enabling circular decision-making.	⇒ Poor interoperability between material databases and BIM tools, and no standardized data structures for reusable or recyclable materials.
	• AI-powered IoT enables real-time tracking of building materials, facilitating circularity across the construction life cycle.	⇒ Lack of data governance and standardization limits the interoperability of systems and full traceability of materials.
	• AI empowers DT to structure facilitating the monitoring and management of circular flows of resources and enabling reuse.	⇒ Low number of users on both demand and supply sides limits the effectiveness for circular material flows.
	• Subdomains of AI, ML, and DL enable efficient material flow tracking and waste stream optimization.	⇒ Lack of legislation and standardized, quality data and explainable models for life cycle material reuse decisions.
	• AI facilitates recycling and material reuse through LCA-driven optimization and demolition decision-making.	⇒ Limited accuracy and applicability of AI models due to the absence of standardized data on reused components
Building energy performance optimization	• BIM-AI integration enables automated energy simulations and predictive models that offer accurate energy performance evaluations during design and operation.	⇒ Lack of interoperability between BIM models and energy simulation software limits seamless integration in the design workflow.

Table 7. *Cont.*

Sustainability Application Areas	Key Findings/AI Contribution	Challenges
Building energy performance optimization	• IoT integrated with AI algorithms enable predictive control of HVAC systems, improving energy efficiency and enhancing occupant comfort. • AI and DTs identify inefficient areas, simulating scenarios to propose strategies for energy use optimization and CO_2 emissions reduction, predicting their impact on building efficiency, comfort, and safety. • ML and DL optimize HVAC, lighting, and other energy uses in buildings by learning occupant patterns and building dynamics. • Optimization algorithms (MPC, RL, ANN) balance comfort, improve HVAC control, and reduce energy consumption.	⇒ Integration of user behavior and occupancy dynamics into AI models remains limited, reducing the accuracy of energy optimization strategies. ⇒ Need for further research on developing a reference architecture to integrate AI-based simulation models with DTs for smart building design. ⇒ Poor generalization across varying building types, regions, and climates due to heterogeneity in operational data. ⇒ Inadequate integration with BMS platforms, and fragmented data limit real-time deployment.
Construction site management optimization	• AI and BIM are combined to predict construction waste, optimize on-site logistics, and classify waste automatically. • IoT-enabled AI enhances real-time safety monitoring and logistics coordination, reducing delays and optimizing resources. • AI enables DTs to automate data collection and knowledge extraction from real-time IoT data, providing an up-to-date view of resource status, optimizing energy, water and building material usage. • ML and DL models improve and assist decision makers in defect detection, safety monitoring, and resource scheduling. • AI helps with material flow optimization, resource allocation, and task scheduling to cut down on emissions.	⇒ Limited on-site adoption of these integrated systems, and gap between digital BIM models and real-time site operations persists. ⇒ Fragmented data systems and lack of end-to-end integration prevent holistic, AI-driven site management and automation. ⇒ Project complexity, lack of standardization, cost, and trust issues hinder the implementation of DTs for construction site management. ⇒ Underexplored real-time deployment and challenges in integration with diverse site conditions. ⇒ Limited data availability.
Asset management optimization	• BIM and AI integration supports predictive maintenance by analyzing real-time data from sensors and operating systems, improving building performance.	⇒ Lack of frameworks for continuously updating the BIM model with dynamic operational data hinders truly intelligent facility management.

Table 7. *Cont.*

Sustainability Application Areas	Key Findings/AI Contribution	Challenges
Asset management optimization	• AI-powered predictive maintenance, enabled by IoT sensors, extends the lifespan of building systems and infrastructure, reducing emissions, downtime, and costs. • AI-integrated DTs allow instant monitoring of energy usage and comfort data, enabling resource efficiency improvement, predictive maintenance, fault detection, and risk management. • ML/DL models predict maintenance needs and extend building lifespan through predictive analytics. • AI-driven predictive maintenance and life cycle optimization lower costs and increase energy efficiency.	⇒ Scalability and interoperability issues across diverse assets and systems hinder widespread adoption of smart asset management solutions. ⇒ Increasing complexity of DT data, driven by its growing heterogeneity and volume, presents challenges in collection, fusion, and storage, and in ensuring data quality and security. ⇒ Data silos, high model uncertainty, and limited interpretability hinder confidence and applicability. ⇒ Problems with BIM, IoT, and AI model interoperability lower the dependability of optimization results.
Sustainable heritage preservation	• AI integrated with BIM can support the mapping of historical façades and predictive maintenance. • AI and IoT support real-time monitoring of environmental conditions, informing maintenance and adaptive conservation. • AI enables DTs to perform real-time monitoring and simulations, generating insights for informed decision-making in risk management and conservation strategies, increasing the durability and balancing energy efficiency and occupant well-being. • ML/DL assist in anomaly detection, structural monitoring, and optimized retrofitting of historic buildings.	⇒ Lack of application to historical buildings due to the absence of updated digital models and AI training datasets. ⇒ Lack of historical baseline data and high digitalization costs limit AI-driven preservation strategies for many older structures. ⇒ Handling large volumes of data, software interoperability, lack of guidelines, and absence of suitable databases for DT development and validation. Need for further research on specific AI models for autonomous control for energy efficiency optimization. ⇒ Scarcity of domain-specific models and datasets, and challenges in adapting models to varying contexts.
Smart cities and urban resilience management	• IoT and AI facilitate data-driven urban management, enabling smart mobility, air quality control, and risks prediction for resilient city planning. • AI empowers DTs to adapt in real-time to changing conditions and to anticipate critical infrastructure needs, enabling predictive maintenance, extending asset life.	⇒ Fragmented governance and insufficient cross-sector data integration impede system-wide resilience and coordinated AI deployment. ⇒ Lack of practical applications of AI-enhanced DTs for smart city carbon emission prediction and reduction.

Table 7. *Cont.*

Sustainability Application Areas	Key Findings/AI Contribution	Challenges
Smart cities and urban resilience management	• ML/DL assist in analyzing urban data for climate resilience and disaster response. • AI supports urban planning and energy use forecasting for more resilient and adaptive systems.	⇒ High computational demands; difficulties in making different city systems and devices work together. ⇒ Data privacy, infrastructure gaps, and governance issues hinder large-scale AI deployment in cities.
Smart grids and renewable energy production	• AI-enabled IoT platforms improve forecasting and real-time balancing of renewable energy supply and demand, enhancing grid flexibility. • AI enables DTs to enhance smart grids through advanced monitoring, optimization, and predictive analytics, advancing grid automation, boosting its reliability, and contributing to integrating RES. • ML and DL improve solar and wind energy forecasting, demand response, and grid stability. • Optimization algorithms improve load balancing, demand response, and integration of RES.	⇒ Limited grid infrastructure readiness and cybersecurity concerns challenge the secure and scalable integration of AI-IoT systems in energy networks. ⇒ Effective data collection and storage, seamless and secure physical–digital interaction and communication, and model accuracy and calibration are primary challenges for DTs applications in energy systems. ⇒ Model robustness under extreme weather, and privacy and security concerns of data in grid operations. ⇒ Variability in RES complicates predictive accuracy and control.

5. Conclusions

The proposed systematic review provides an exhaustive big picture of the most relevant academic literature produced in the latest decade on such an actual matter as the dissemination of AI-enhanced digital technologies to boost sustainability in the AECO sector. A total of 102 articles published between 2015 and 2025 were analyzed through a systematic literature review based on PRISMA protocol. The preliminary results (summarized in the histogram in Figure 5) prove that interest in the topic is quite recent, and it is growing rapidly over time. Additionally, it emerged that the subject is mainly investigated in the United Kingdom, Europe, China, India, Australia, and the United States. Wide geographic areas, such as South and Central America or African countries except for South Africa, seem to be left behind in the AI-driven digital transition of the AECO sector, likely because of the great deal of effort in terms of economic and technical resources required to afford such a digital revolution. Such geographic differences are also related to evident digital infrastructure disparities as many economies, particularly in developing regions, lack access to high-speed broadband, reliable electricity, and modern telecommunication networks, which limit their participation in the global digital economy [146].

The results identify seven main sustainability areas improved by technologies, such as BIM, IoT, DT, ML and DL, and optimization techniques boosted by AI integration. Most of the analyzed articles focus on asset management optimization and promotion on CE principles, especially in the operation and maintenance phase. AI-powered BIM and DTs have proven especially useful in the design phase, enhancing efficiency in material selection and enabling informed decision-making by providing project sustainability assessment through real-time cost analysis and sustainability indicators. Additionally, BIM and DTs enhanced by AI integration also proved to effectively support the operation and maintenance phases, facilitating continuous monitoring, predictive maintenance, and real-time energy use optimization. As expected, IoT technology combined with AI turned out to be particularly beneficial to the operation phase. In particular, it may enhance building environmental performance through real-time energy monitoring and optimization, predictive maintenance, and occupancy tracking to optimize space use and indoor comfort dynamically. ML and DL also mostly support the operation and maintenance phases, enhancing defect detection and quality control, as well as real-time building energy management. Even though optimization techniques also mainly support the operational phase, they have also proven useful in the production phase of the building life cycle, contributing to reducing waste and optimizing the use of recycled materials.

The study underlines that key challenges still remain, including the difficulty with adapting regulatory frameworks into machine-readable formats, the complexity of data management, and the high level of technical expertise required, which hinder large-scale adoption. Finally, investment in public datasets and adaptive algorithms will be essential to fully unlock the potential of this integration. While these technologies are promising, their adoption is hindered by technical complexities and regulatory obstacles. Current optimization methods of AI struggle to consider economic, environmental, social, and technological values in an integrated way throughout the building life cycle. Interdisciplinary tools and innovative analyses are needed to bridge the gaps in knowledge, data, models, and objectives in assessing overall sustainability [61].

Future developments should focus on scaling applications to the urban level, digitizing regulations, automating sustainability compliance verification, and enhancing interoperability.

In conclusion, this study is also affected by some limitations which must be acknowledged. First, only papers written in English were included in the analysis. Second, the study was limited only to specific digital technologies integrated with AI, so the contribution of other technologies should be further investigated. Finally, only the Scopus database was investigated: further research is therefore also needed to extend the field of investigation to include additional databases.

Considering how rapidly the investigated matter is evolving and attracting increasing interest from the academic community, this literature analysis will need to be kept up-to-date regularly, as potential innovations and new research directions still unpublished may be underrepresented.

The results of the study provide insight for researchers and practitioners, offering a systematic overview of actual challenges and advancements in AI-powered technologies to improve environmental sustainability in BE.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su17178005/s1, PRISMA 2020 Checklist. Reference [147] are cited in the Supplementary Materials.

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Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant Colony Optimization
AEC	Architecture, Engineering and Construction
AECO	Architecture, Engineering, Construction, and Operations
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BCT	Blockchain Technology
BE	Built Environment
BIM	Building Information Modeling
BIPV	Building Integrated Photovoltaic systems
CNN	Convolutional Neural Networks
DNN	Deep Neural Networks
EMS	Energy Management System
ERP	Enterprise Resource Planning
GD	Generative Design
GIS	Geographic Information System
HEMS	Home Energy Management System
IES	Integrated Environmental Solutions
LEED	Leadership in Energy and Environmental Design
ML	Machine Learning
MPs	Material Passports
O&M	Operation and Maintenance
PV	Photovoltaic
SDGs	Sustainable Development Goals

SES	Smart Energy Systems
VPL	Visual Programming Languages
VR	Virtual Reality
ZEBs	Zero-Energy Buildings

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