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Towards built environment Decarbonisation: A review of the role of Artificial intelligence in improving energy and Materials' circularity performance

Bankole Awuzie [a,b], Alfred Ngowi [c,*], Douglas Aghimien [d,e]

[a] Department of Construction Management and Quantity Surveying, University of Johannesburg, Johannesburg, South Africa
[b] Faculty of Environmental Sciences, KO Mbadiwe University, Ogboko, Nigeria
[c] Office of the Deputy Vice-Chancellor: Research, Innovation and Engagement, Central University of Technology (CUT), Bloemfontein, South Africa
[d] School of Art, Design and Architecture, Faculty of Arts, Design and Humanities, De Mont University, Leicester, United Kingdom
[e] SARChi in Sustainable Construction Management and Leadership in the Built Environment, Faculty of Engineering and the Built Environment, University of Johannesburg, Johannesburg, South Africa

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ABSTRACT

Mitigating climate change challenges in the built environment through the decarbonisation of energy and construction materials remains a pressing challenge. The circular economy (CE) has been identified as a critical pathway to achieving this objective. CE promotes the efficient use of resources, extending their lifecycle and minimising their environmental impact using a plethora of methods. The link between CE and decarbonisation becomes evident when the intertwined relationship between materials, energy, and the environment is considered. By reducing waste and ensuring the continuous use of materials and energy resources, CE significantly lowers carbon emissions. This approach is inherently aligned with the overarching goals of the decarbonisation agenda. The emergence of digital technologies such as artificial intelligence (AI) has continued to transform how the built environment activities are conducted and improved. However, the utility of AI models in engendering the actualisation of the decarbonisation agenda through improved circular economy performance within the built environment context remains under-researched. This study addresses this knowledge-practice gap, using a scientometric and scoping analysis of relevant peer-reviewed and grey literature. Findings from the scientometric analysis revealed AI has been explored separately in circular economy and decarbonisation. Yet, studies exploring AI in relation to the circularity performance of the built environment for improved decarbonisation remain scant. The narrative review from the scoping analysis further revealed the usefulness of AI in driving optimal decarbonisation and levels through improved circularity performance of materials and energy across various economic sectors, including the built environment for optimal decision making which in turn, encourages responsible producer and consumer behaviour for improved CE performance.

1. Introduction

The construction industry remains critical to the sustenance of contemporary society as it is responsible for delivering critical economic and social infrastructure in what is termed the built environment [1–3]. The built environment is an outcome of the various endeavours executed by the construction industry. It comprises residential, commercial, and industrial buildings and social and economic infrastructure like schools, roads, bridges, refineries, ports, airports, etc. The potential for such infrastructure to enhance national productivity, competitiveness, and citizens' health and well-being has been established [4,5]. Accordingly, the availability of adequate infrastructure stock or otherwise has been used to delineate between developed and developing countries [6]. Therefore, the drive for continuous infrastructure development and upgrade remains pivotal across various countries. However, the construction industry's reputation for posting debilitating impacts that negate society's sustainability aspirations persists [7,8]. The industry consists of several anthropogenic activities which have continued to undermine the sustainability performance of projects therein [9,10]. The tendency of these activities to outweigh the expected benefits

* Corresponding author.
E-mail addresses: ngowiab@gmail.com (A. Ngowi), aghimiendouglas@gmail.com, douglas.aghimien@dmu.ac.uk (D. Aghimien).

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accruing from the delivery of infrastructure resonates in extant literature. In an apparent recognition of this paradox, stakeholders have stepped up advocacy for a drastic reduction in the incidence of these anthropogenic activities towards improved sustainability performance.

An area where the increasing incidence of these anthropogenic activities has been felt is the heightening carbon footprint of the built environment and its associated construction processes. The increasing levels of carbon and other greenhouse gas (GHG) emissions have been linked to rising temperatures, thereby resulting in climate change [11,12]. Locke et al. [13] refer to climate change as a shift in temperature and weather patterns over a long duration. The negative impact of climate change has been widely documented in extant literature. These impacts range from incessant flooding, desertification, famine, drying up of water bodies, irregular seasons, etc [14,15]. The worrisome nature of the escalating levels of GHG emissions globally and the impact thereof on societal advancement and well-being has placed the challenge on the front burner of global economic developmental discourse. The United Nations (UN) has since picked the gauntlet to initiate and drive global partnerships towards managing carbon footprint, among other challenges. The annual convocation of the Conference of the Parties (COP) is one of the platforms through which the UN has sought to adumbrate issues relating to climate change whilst also trying to gain consensus as it pertains to potential solutions. The last episode of this gathering (COP28) was held in the United Arab Emirates in 2023. The sustainable development goals (SDGs), especially SDG 13, also consider the impact of climate change and the attendant panacea for tackling its incidence.

The construction industry and the built environment have continued to draw attention from protagonists of the carbon neutrality initiative for obvious reasons. According to Locke et al. [13], the built environment plays a vital role in combating climate change and adapting to its effects, as it involves a multiplicity of climate-related factors like energy, water, materials, human welfare, biodiversity, and transportation. Also, the scholars traced 40 % of the entirety of GHG emissions to the construction industry and over 36 % of total global end-use energy utilisation to the buildings and the built environment [16–18]. This is indicative of the magnitude of the construction industry's contributions as platforms for carbon and GHG emissions. The industry's performance vis-à-vis its contribution to the increasing global carbon footprint has been attributed to the materials used [9,10], and attendant operational requirements like ventilation and illumination [13] and other built environment features. Also, scholars have adopted a whole-life cycle perspective when trying to unravel the industry's contribution towards carbon emissions [17,19]. It is expected that this would engender a comprehensive understanding of the energy dissipated in the extraction of raw materials and the industrial processes involved with the production of the construction materials as well as the transportation to the site and eventual installation on construction sites. Justifying this stance, especially regarding energy, Röck et al. [19] enthused that energy was a vital component for manufacturing construction products, the construction of new buildings and the retrofitting process. Furthermore, the authors identified activities like transportation of materials and installation, dismantling, and disposal of buildings and materials as consuming significant amounts of energy [19]. This viewpoint was corroborated by Locke et al. [13] and Tam et al. [17], who highlighted the significant contribution of energy to every facet of human activity, a fact that positions it as a major cause of global warming and climate change. From the foregoing, it is obvious that the energy consumption potential of the built environment transcends all the stages of the built asset's lifecycle, extending beyond the construction and operations (use) phases to the end of life or decommissioning phase.

As part of its transformative journey towards reducing its carbon emission quota, the construction industry has introduced various innovative strategies. These strategies include lean construction/production, sustainable construction, smart construction (construction digitalisation and automation), and circular economy (CE), among others. These strategies are being adopted in varying degrees across the globe with a focus on the eventual decarbonisation of the construction process and the built environment. Whereas some of these strategies have experienced significant adoption, some are still nascent. However, most, if not all, of them have been described as having the potential to contribute towards the actualisation of society's decarbonisation agenda. Recently, the adoption of CE principles in the construction industry and the subsequent improvement in the industry's circularity performance have been observed as posting significant contributions towards the decarbonisation of the built environment. Impliedly, the adoption of CE principles in the delivery and subsequent management of the built environment would culminate in less use of materials and energy, thereby supporting the decarbonisation agenda. Scholars have advocated for the adoption of digitalisation towards optimising CE implementation for effective decarbonisation due to their inherent qualities [20–24]. However, despite the potential contributions of digital technologies such as Artificial Intelligence (AI) to facilitate improved circularity performance of construction materials and energy and extension, a paucity of literature articulating the application of these technologies towards achieving effective decarbonisation of the built environment through improved material and energy circularity performance has been observed.

Existing studies have focused on the use of AI in either enhancing circularity performance of materials during the construction process [25–27]; decarbonization of the building sector [28], improving environmental sustainability through effective energy management [29], avoiding energy shortages during decarbonization of national economies [30], articulating effective circular economy policies for enabling sustainable energy futures [31], modelling and managing heating and cooling loads for energy-efficient building design [32], enabling energy conservation and efficiency in buildings [33–41]. Others have focused on the role of circular economy principles, business models and supply chains in: facilitating sustainable energy transitions [42–47]; decarbonising the built environment [48–50] and decarbonizing energy systems [51]. Although certain studies have explored the utility of AI in enhancing decarbonization through improved circularity performance, they have done this beyond the remit of the built environment and construction industry. For instance, Sankaran [52] explored the utility of circular economy principles, blockchain technology and AI in improving decarbonization and reducing plastic pollution during energy transitions. Similar studies by Oladapo et al., [53] and Jose et al. [54] focused on the use of circular economy principles to advance the contribution of sustainable materials towards successful decarbonization of renewable energy systems and for enabling sustainable energy management respectively. Also, extant studies which have sought to explore the role of AI in enabling sustainable energy management in the built environment have bothered mostly on achieving optimal levels of comfort for building occupants alongside energy efficiency and not decarbonisation [32–41]. In such circumstances, decarbonisation may be projected as an accidental outcome instead of the intended objective. Based on the foregoing, the limited nature of studies detailing the use of AI-enabled improved circularity performance of materials and energy for effective decarbonisation of the built environment and the construction industry can be discerned. This study is prompted by this reality.

Accordingly, this study seeks to address this gap by contributing to the ongoing discourse on the use of digital technologies in engendering improved systemic circularity performance in the contemporary built environment to achieve effective decarbonisation, albeit with an emphasis on materials and energy. Both facets have been singled out in this study due to the near consensus among scholars of their salient contributions towards the carbon footprint associated with the built environment [27]. Summarily, it is expected that the findings from this study would articulate the state-of-the-art as it pertains to the application of AI towards achieving carbon neutrality through improved circularity performance of materials and energy, highlight any limitations negating the use of AI towards achieving decarbonised built environment and elucidate any gaps in the extant literature worthy of further investigation in subsequent studies.

2. Research methodology

In understanding the contribution of AI to improve the circularity performance of construction to engender the decarbonisation of the built environment, this study adopted a scientometric and narrative review of existing studies with publications extracted from the Scopus database serving as the unit of analysis. The Scopus database was adopted based on its wide recognition among researchers in the field of science [55]. Moreover, it has been noted that this database overlaps considerably with other databases like Web of Science [56]. The bibliographic data for the scientometric and narrative reviews were gathered separately. Preliminary investigation has shown very limited works that have attempted to link AI, CE and decarbonisation as they relate to construction industry research and the built environment. As such, a scientometric review became paramount to understanding trends in general studies and linking this back to the set objectives of the current study. The scientometric review involves a text-mining of scientific publications wherein computer-assisted methods are used to review the available body of knowledge and unravel core research and their relationship within a given research field [56,57]. It also offers the opportunity to identify leading contributors through performance analysis determine impactful contributions through citations, co-authorships, and bibliographic coupling assessments and areas of focus and trends through science mapping and network visualisations [58].

The bibliographic data used in this scientometric review adopted related keywords carefully searched using major Boolean operators: “OR” and “AND”. The search entailed using the term Artificial intelligence along with other alternative terms, as proposed by Darko et al. [59]. The search protocol used includes Title-Abstract-Keywords: “Artificial intelligence” OR “Artificial general intelligence” OR “Case-based reasoning” OR “Computational intelligence” OR “Data mining” OR “Expert systems” OR “Fuzzy logic” OR “Fuzzy sets” OR “Genetic algorithms” OR “Knowledge-based systems” OR “Machine learning” OR “Machine intelligence” OR “Neural networks” OR “Robotics” AND “Circular Economy” OR decarbonisation. These keywords were designed to uncover studies that have explored AI and its related terms along with the concept of circular economy or decarbonisation within construction-related fields with a view to understanding their direction of focus. The timeframe was set from 2010 to 2024 to gather more recent works, while the subject area was limited to engineering, and document language was set to English as this is the major language of most publishing outlets. The document type was set at articles and conference papers as these have higher rigour in their review process [56,60]. Based on this selection criteria, the bibliographic data of 461 documents (articles = 314; conference paper = 147) were extracted and used for further scientometric analysis. The analyses of the extracted bibliographic data were conducted using R-Studio and the visualisation of Similarities Viewer (VOSviewer) software. VOSviewer helped determine trends using a map visualisation of the major terms in the documents. Also, Biblioshiny in R-Studio was used to uncover the word frequency and create a word cloud of the significant key terms from the extracted documents.

For the narrative review, it was necessary to carefully assess the only documents that have explored AI, circular economy, and decarbonisation as they relate to construction and/or built environment contexts. Using the search criteria Title-Abstract-Keywords: “Artificial intelligence” OR “Artificial general intelligence” OR “Case-based reasoning” OR “Computational intelligence” OR “Data mining” OR “Expert systems” OR “Fuzzy logic” OR “Fuzzy sets” OR “Genetic algorithms” OR “Knowledge-based systems” OR “Machine learning” OR “Machine intelligence” OR “Neural networks” OR “Robotics” AND Decarbonization AND “Circular Economy”, only nine articles emanated. However, after closely scrutinising the contents of these articles, only two were fit for purpose. As such, these two articles and other related articles uncovered from the search used in the scientometric analyses were used to map the available knowledge within the AI, circular economy, and decarbonisation in the construction domain. This review is presented using a thematic approach. The themes are structured in a manner that enables a chronologically sequenced flow designed to understand the nexus of AI, circularity performance and decarbonisation, uncover the application of AI for Improved circularity performance of construction, particularly in relation to material and energy, as well as determining the hindrances to the effective deployment of AI in enabling circularity performance of construction.

3. Discussion of findings

3.1. Scientometric analysis

3.1.1. Performance analysis of AI, circularity performance and decarbonisation research

The documents per year were evaluated to understand the attraction garnered by AI in relation to the circular economy or built environment decarbonisation. Fig. 1 shows that research relating AI to either circularity in construction or decarbonisation only gained prominence in 2019. Prior to this year, studies have been scant with 2011 and 2015 having no output at all. There has been a steady rise in the research interest in this area from 2019 with 2023 having 152 articles. The number of articles in 2024 is expected to increase as this analysis was conducted in January. There is the possibility of more papers being published before the year ends. The line graph in Fig. 1 also shows the mean total citations (TC) per year. 2017 has recorded the highest mean TC per year ($n = 32.5$) with lesser number of mean TC from 2018. This is unsurprising as it is expected that as more forthcoming publications leverage these already published documents and cite them, the mean TC per year will increase. This result implies that the concept of the nexus of AI and circularity in construction and AI and decarbonisation is gaining significant attention among researchers. Exploring AI to improve the circularity performance of construction materials and energy utilization to engender the decarbonisation of the built environment is a worthwhile research area that can bring significant contributions to the current decarbonisation of construction projects and built environment discourse.

The scientometric analysis also involved the countries of publications. This was done with a view to showcasing the major countries where the extracted documents emanated from and the need for further studies in countries with lesser publication frequency. In conducting this analysis, the corresponding authors’ countries were explored to give insight into where the studies were carried out. The 461 documents extracted had 1707 authors (main and co-authors), with the corresponding authors coming from 55 different countries. Table 1 shows the top countries with at least six documents, including an indication of the single country of publication (SCP) and multiple countries of publication (MCP) ratio. Overall, all documents extracted account for 29.72 % international co-authorship, thus confirming the wide range of interest across diverse countries and continents in this area of research. Also, from the MCP column on Table 1, it is evident that there is an appetite for studies of AI and circular economy or decarbonisation across diverse countries. Aside from Turkey, all other countries have at least 1 article that other countries have co-authored. The MCP ratio shows the strength of international collaboration. The closer the ratio is to 1, the higher the country’s international collaboration [61]. Looking at the MCP-ratio column, it can be concluded that Australia (0.67), Netherlands (0.50), Denmark (0.50), Iran (0.50) and Canada (0.44) are among the highest international collaborating countries. In terms of individual countries’ contributions to AI and circularity in construction as well as AI and decarbonisation, Table 1 shows China as the leading contributor, with 71 documents cited 1285 times. Also contributing significantly to this area of research are the United Kingdom ($n = 32$, TC = 659), USA ($n =$

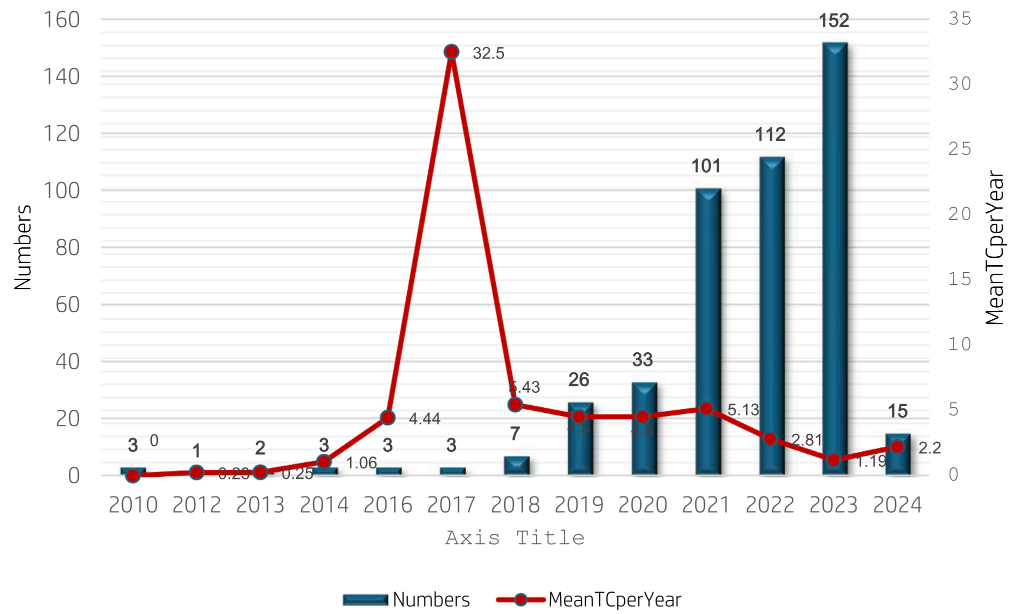

Fig. 1. Publication per year.

Table 1
Publications per country.

Country	n	SCP	MCP	MCP ratio	TC	Av. Art. Citations
China	71	49	22	0.31	1285	18.1
United Kingdom	32	23	9	0.28	659	20.6
USA	25	18	7	0.28	215	8.6
Italy	24	18	6	0.25	417	17.4
Germany	17	13	4	0.24	243	14.3
India	15	12	3	0.20	79	5.3
Spain	14	9	5	0.36	248	17.7
Australia	12	4	8	0.67	309	25.8
Sweden	10	8	2	0.20	87	8.7
Brazil	9	8	1	0.11	205	22.8
Canada	9	5	4	0.44	127	14.1
Greece	9	7	2	0.22	77	8.6
Portugal	9	6	3	0.33	92	10.2
Netherlands	8	4	4	0.50	118	14.8
Singapore	7	4	3	0.43	99	14.1
Turkey	7	7	0	0.00	24	3.4
Denmark	6	3	3	0.50	116	19.3
France	6	4	2	0.33	38	6.3
Iran	6	3	3	0.50	41	6.8

Note: n = number of publications; SCP = single country of publication; MCP = multiple countries publication

25, TC = 215), and Italy (n = 24, TC = 417). Again, this result further bolsters the need to explore the utilisation of AI to improve the circularity performance of construction to engender the decarbonisation of the built environment across diverse country-contexts.

3.1.2. Visualisation of the research area of focus on AI, circularity and decarbonisation in construction

In determining the key areas of focus of studies exploring AI and circularity in construction and AI and decarbonisation, a word cloud was developed using the top 50 common words from the extracted document, as seen in Fig. 2. Top among these common words include circular economy (n = 176), sustainable development (n = 93), machine learning (n = 73), artificial intelligence (n = 67), decision making (n = 63), decarbonisation (n = 56), energy efficiency (n = 43), recycling (n = 43), life cycle (n = 40), energy utilisation (n = 39), and genetic algorithms (n = 38). These common terms give an idea of the area of concentration of the extracted AI and circular economy or decarbonisation studies.

To further understand these research focus areas, VOSviewer was adopted due to its ease of use and ability to give a clear visualisation of keywords in a large bibliographic dataset. All the extracted documents revealed 4420 keywords used by authors and journals during indexing. The VOSviewer allowed regrouping this large number of keywords into

Fig. 2. Word cloud of most common keywords.

more coherent clusters using a set co-occurrence threshold. Aghimien et al. [62] have noted that there is no rule regarding the minimum threshold to be used, while Darko et al. [59] suggested a careful observation of the clarity of the visualisation map when setting a threshold for co-occurrence. As a result, a minimum co-occurrence threshold of 10 was set, and this revealed 86 keywords clustered into four major areas with a Total Link Strength (TLS) of 2036, as seen in Fig. 3.

Cluster 1 is in the red node on the visualisation map. This Cluster has 28 items, with the circular economy having the highest links of 80 with 211 occurrences, thus forming the focal point of this Cluster. This key term has a strong link with sustainable development (TLS = 57) and artificial intelligence (TLS = 42), thus indicating the significant focus of research on the relationship between AI and circular economy. Other prominent items in this cluster are sustainability, waste management, life cycle, recycling, reuse and demolition, which are critical terms in the concept of circular economy. Also prominent are industry 4.0, industrial economics, the internet of things, blockchain, robotics, digital technologies, and the construction industry. These terms show the exploration of other industry 4.0 technologies regarding CE in construction.

Cluster 2 is indicated in the green nodes on the map. This second Cluster has 24 items, with decarbonisation having the highest link of 69 with 56 occurrences. This key term shows a good link with other terms like greenhouse gases (TLS = 10), gas emissions (TLS = 9), carbon (TLS = 9), climate change (TLS = 9), and renewable energy resources (TLS = 8). Also, genetic algorithms have the strongest link with decarbonisation (TLS = 7) and optimisations (TLS = 5). This implies that whilst studies have continued to explore the decarbonisation of construction to eliminate greenhouse gases and combat climate change, others have explored the use of AI-related approaches to optimise the process of decarbonisation of the built environment.

Cluster 3 is indicated in the blue nodes on the map. This third cluster has 22 items, with machine learning sitting at the core with 78 links and 88 occurrences. This key term is strongly linked to learning systems (TLS = 16), energy utilisation (TLS = 16), forecasting (TLS = 16), neural networks (TLS = 14), learning algorithms (TLS = 14) and digital storage (TLS = 8) within the cluster. This research focuses on the use of AI-related approaches in the quest for energy efficiency and utilisation in the construction industry. Interestingly, machine learning also has a strong link with decarbonisation (TLS = 18) in Cluster 2 and circular economy (TLS = 29) in Cluster 1. Although this relationship exists separately, this link further emphasises the application of AI-related approaches in studies on circular economy and decarbonisation in the construction industry.

Cluster 4 is indicated in the yellow nodes on the visualisation map. This fourth cluster has 12 items, with decision-making sitting at the core with 79 links and 63 occurrences. Within the Cluster, this key term is strongly linked to supply chains (TLS = 15), fuzzy sets (TLS = 14), decision support systems (TLS = 13), investments (TLS = 7) and uncertainty analysis (TLS = 6). These relationships show the application of AI approaches in enabling effective decision-making in construction. Further assessment shows that decision-making is also strongly linked to circular economy (TLS = 41) and artificial intelligence (TLS = 16) in Cluster 1, as well as machine learning (TLS = 9) in Cluster 3.

4. Narrative review

The Scientometric analysis has noted the significant recognition garnered by AI in relation to circularity in construction as well as decarbonisation. The use of this technology in exploring these two areas has been significantly explored differently by researchers in diverse countries. The analysis has further revealed a strong relationship between AI-related approaches and circular economy as well as sustainable development, the use of AI to optimise the process of decarbonisation of construction, the application of AI-related approaches for energy efficiency and utilisation in construction, and AI approaches in enabling effective decision making in construction. However, none of the clusters in Fig. 3 revealed AI, circular economy and decarbonisation in the same cluster, thus confirming the absence of studies exploring AI in circularity performance and the decarbonisation of construction, particularly in relation to energy and material, which have been adjudged as the two main contributors to carbon emissions [63]. As such, the narrative review, which explored diverse articles helped map the available knowledge within the context of AI, circular economy, and decarbonisation in construction.

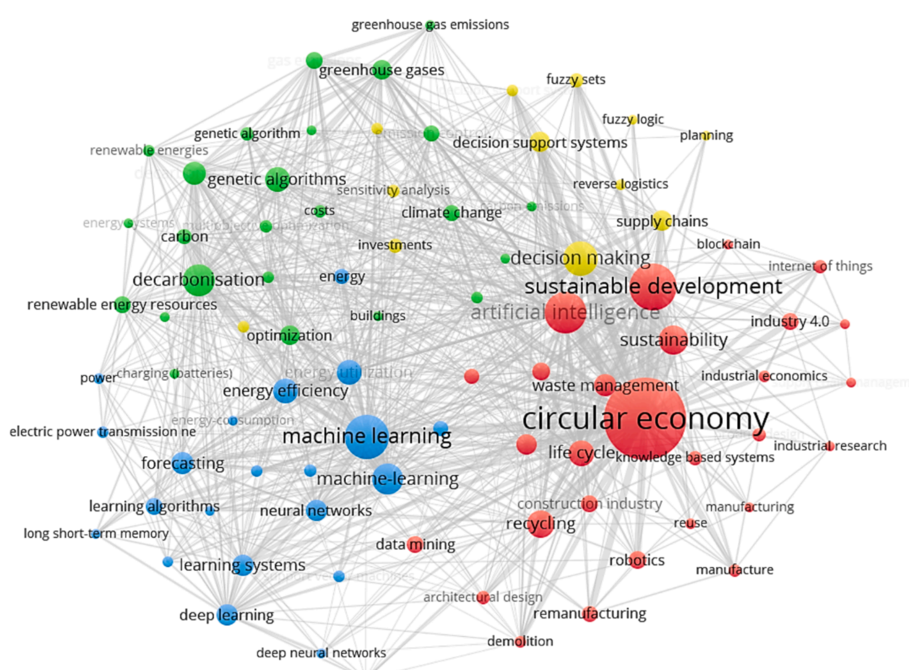

Fig. 3. Network visualisation of co-occurring keywords in AI and circular economy or decarbonisation.

4.1. Understanding the AI, circularity performance and decarbonisation nexus

AI as a technology comprises computer algorithms deployed towards actualising tasks that normally require human cognitive functions or intelligence [64,65]. It exhibits these capabilities because of four basic facets of data processing, namely, the ability to sense, comprehend, act, and learn [66]. Furthermore, it resolves complex problems through the development of computing systems with the capacity to perform tasks that require human intelligence, such as learning and visual perception [67]. AI and associated techniques like Artificial Neural Networks, Machine Learning, Deep Learning, etc., have been applied to analyse and model vast amounts of relevant data which are then used for effective decision-making [68]. Potential applications of AI include monitoring and diagnoses, trends and forecasts, clustering, and regression analyses, planning and scheduling, industrial and household robotics, speech conversion into textual data and vice versa, chatbots and virtual assistants, image and video analysis, as well as environment and landscape analysis [66].

Also, AI enables data mining, relying extensively on the extraction of patterns therein [27,69]. Machine Learning (ML), a subset of AI, has been consistently deployed towards facial recognition, speech recognition etc.[68], autonomously driven vehicles, web search and anomaly detection, etc. [70]. Moreover, ML algorithms such as Artificial Neural Networks (ANN) are considered powerful due to their versatile learner concepts, which allow for handling non-linear relationships between variables without econometric intuition [68]. Similarly, Deep-Learning Neural Network (DNN) is driving the current exponential growth in ML due to its ability for intuitive decision-making. DNNs entail learning high-level abstractions in data and address the ANN's inability to handle selectivity variance [71]. AI's potential to assist with actualising specific construction objectives has been reported. For instance, AI's ability to automate construction tasks, connect sensors using IoTs, predict and manage construction-related risks and uncertainties, and monitor building and construction project performance has been reported [72]. AI's potential to facilitate effective decarbonisation of the built environment through contributing towards effective decision-making for improved circularity performance of construction, particularly around materials and energy, has been elucidated [73].

Anchored mostly on the tenets of the closed-loop system and a cradle-to-cradle approach to production, the circular economy has continued defying any broadly accepted definition [74], making implementation of the concept very subjective. Also, Ramakrishna et al., [75] maintain that although multiple definitions have been observed in the literature, the concept connotes a paradigmatic shift from the traditional make-use-dispose production paradigm towards the reduce-reuse-recycle approach. However, the definition proffered by Kirchherr et al [74], seems to capture the entirety of the concept. The scholars defined CE as 'a regenerative economic system which necessitates a paradigm shift to replace the 'end of life' concept with reducing, alternatively reusing, recycling, and recovering materials throughout the supply chain, with the aim to promote value maintenance and sustainable development, creating environmental quality, economic development, and social equity, to the benefit of current and future generations [74:4]. Furthermore, Kirchherr et al., [74] highlighted the essential role of stakeholders and their technological innovations and capabilities as enablers of the CE. Therefore, circularity performance can be described as the measure by which improved product longevity, more intensive product use, material efficiency, material substitution, and demand change has been achieved at both product and project levels, respectively [24]. It was further posited that energy and materials-related circularity remain major contributors to the high carbon footprint attributed to the industry [24]. The ability of relevant actors to derive maximum levels of circularity performance from the built environment towards decarbonisation has been negated by their inability to bridge the decisions made at the front-end of the asset delivery phase and the end-of-life phase (systemic circularity) [27,76]. These scholars stress the need for decisions on material choices to be made at the outset of the procurement phase of the construction process, with adequate consideration given to the circularity performance of the material during the deconstruction of the building. While this may be considered a difficult decision based on data availability, Oluleye et al. [27] highlighted the capability of various AI technologies to achieve this feat. This perspective is shared by Agrawal et al. [77], wherein the potential of AI, blockchain, and the Internet of Things (IoT) to contribute to achieving carbon neutrality using circular economy principles was highlighted.

The term 'decarbonisation' describes the process of reducing carbon emissions and other GHGs [19]. The IPCC's 6th Assessment Report highlights the urgency of climate change, projecting that global warming will exceed the Paris Goal of limiting temperature rise to 1.5 °C above pre-industrial levels by as early as 2035 [78]. The criticality of decarbonization efforts in mitigating these risks has been elucidated [78]. The crucial need to address climate change has led to a growing focus on decarbonization strategies through the promotion of sustainable and low-carbon pathways to global development. As highlighted previously, the construction industry and the built environment contribute significant amounts of carbon emissions from the anthropogenic activities associated with the duo [63,79]. Chou and Bui [32] attributed 60 % of carbon emissions experienced in Hong Kong to electricity generation whilst noting that buildings accounted for 89 % consumption of the total amount of electricity generated therein. The dominance of buildings in the energy consumption matrix is corroborated by various scholars [38,40].

To mitigate the incidence of rising carbon emissions from the built environment, Zhong et al. [63] suggested two main approaches. These approaches include the decarbonisation and reduction in the amount of energy required for building operations and the production of materials and energy required during building construction [63,79]. Suffice it to state that construction materials and energy are two main contributors to the built environment's carbon footprint. While construction materials entail all materials used in the delivery of construction products, energy in this context consists of that which is utilised not just to produce the construction materials but also for the equipment used during the construction process and that which is being used for the operation of the electrical and electronic appliances during the in-use phase of the building. Cottafava and Ritzen [80] delineated energy into two main facets, embodied energy and operational energy. The former which is related to the energy expended on a material's lifecycle across the construction, maintenance and demolition phases of the project was further divided into initial embodied energy, recurrent embodied energy and demolition embodied energy respectively.

It has been argued that the capabilities of AI models can be applied towards making construction materials to become more responsive to climatic conditions and energy utilisation (smart materials) [4,81,82]. In turn, this can result in improved materials and energy circularity performance. Similarly, AI's predictive and generative capabilities can be used to establish a material's circularity performance across its lifecycle [83]. Having this understanding can assist managers with the determination of which material to utilise and for what purpose. It can also lead to an understanding of the energy that would be dissipated towards the production and usage of this material. Using platforms like Building Information Modelling and Digital Twin, AI can be used to determine the perfect energy mix for the decarbonisation of buildings across their lifecycles in various climatic contexts and according to the building typology [84–87]. It can also be used to determine the strength of materials after having been recovered from existing buildings at the end-of-life stage, establishing their utility for new construction or highlighting possible areas for improvement to engender durability [88,89].

Based on the foregoing, Nikkas et al. [83] established the nexus between circularity performance and decarbonisation. The study alludes to the outcome of the impact assessment of the European Union's 2050 decarbonisation agenda, wherein circularity and behavioural change trumped investments in high technological innovations as they concerned contributions towards a cheaper and efficient decarbonisation agenda. However, the useful contribution of AI models towards enabling effective and efficient decarbonisation from a managerial perspective cannot be overemphasised. Also, decarbonisation strategies identified by Sbahieh et al. [9], like the use of alternative fuels, substituting the cement clinker, energy efficiency, carbon capture and storage technology, and use of alternative cement, all bear attributes of the circular economy principles.

5. Application of AI for improved circularity performance of construction materials and energy

In this section, the reportage of the application of various AI models and technologies for the purposes of achieving improved circularity performance of construction materials and energy are presented, albeit separately.

5.1. Construction materials

The construction of built assets has been known to consume a lot of materials. The production of these materials, such as steel and cement, remains pivotal for the sustenance of the industrial sector in various economies and requires a lot of energy [25]. Depending on the energy source used, the production process generates a lot of carbon and other GHGs, which are subsequently emitted into the atmosphere. Studies have put the percentage of emitted and embodied carbon associated with building materials at 10 % of the total carbon footprint of developed countries, whilst developing countries are expected to have a larger share due to the significant developments taking place in those countries [90]. Corroborating this assertion, Zhong et al. [63] maintained that the production of building materials accounted for an estimated 11 % of global energy and process-related GHG emissions. As such, there has been a clamour for extending a building's lifespan to prevent early demolition and encouraging building retrofits to reduce the demand for building materials [90]. Accordingly, Oluleye et al.[27], through a review of extant literature, established thirteen built environment delivery facets where AI models can be deployed to improve the circularity performance thereof. These facets and the types of AI models to be deployed are presented in Table 2.

Table 1 alludes to the successful deployment of various AI models for improving construction material circularity performance.

For instance, the study by Rakhshan et al [91] sought to develop a probabilistic model using advanced supervised machine learning techniques like, random forest, K-Nearest Neighbours algorithm, Gaussian process, and support vector machine (SVM) to predict the reuse potential of structural elements at the end-of-life of a building. The study's results culminated in the identification and ranking of the critical factors enabling the reusability of structural elements of buildings as derived from the perspectives of relevant stakeholders. Furthermore, the results led to the development of a learning platform for assisting prospective users with an assessment of the technical reusability of the load-bearing structural elements of buildings. In another study, Lu et al [92] compared the strengths and weakness of different AI models namely, artificial neural network (ANN), the multiple linear regression (MLR), decision tree (DT) and grey models (GM) when deployed towards the estimation and/or prediction of waste generation tendencies of construction materials. The study's results indicated that whereas all the AI models showed high levels of accuracy regarding waste generation predictions, the ANN and GM displayed a higher level of prediction accuracy [92].

Furthermore, Nunez et al., [93] relied on a mix of gradient boosting regression and particle swarm optimization to develop a machine learning based model for enhancing the mixture design of recycled concrete aggregates to cater to different classes of compressive strength.

Table 2
AI models deployed for activities in the built environment.

Built environment delivery and management facet (activity)	Type of AI model
Selection of circular materials	Artificial Neural Network
Design for waste prevention, disassembly/ deconstruction	Artificial Neural Network; Genetic Algorithm
Prediction of technical and economical circularity performance of materials.	K-Nearest Neighbours; Gaussian Process; Artificial Neural Network; Support Vector Machine; Random Forest
Prediction of hazardous materials	Logistic Regression; Support Vector Machine
Operation of circular business models	Unspecified AI models
Estimation of building construction demolition waste generation	Linear Regression; Artificial Neural Network; Decision Tree; Grey Models
Onsite waste recycling	Convolutional Neural Network
Pre-demolition auditing in a circular economy	Deep Neural Network; Convolutional Neural Network;
Prediction of materials' (aggregate) strength for reuse and recycling post-EoL	Recurrent Neural Network, Gaussian Processes, Decision Tree, Gradient Boosting; Support Vector Machine.
Demolition waste sorting, composition, and segmentation;	Deep Neural Network; Convolutional Neural Network
Reverse Logistics	Unspecified AI Models
Missing building construction and demolition waste data management and analysis	Decision Tree
Optimisation of waste collection and site selection for building construction and demolition waste recycling plant	Artificial Neural Network; Genetic Algorithm

Source: Adapted from Oluleye et al. [27].

This was in the aftermath of determining the utility of the machine learning models in tackling the challenge faced with achieving mixture optimisation of recycled concrete aggregates due to low accuracy levels of compressive strength estimation [93].

Judging from these examples, the prevalent applications of AI models have been geared towards improving circularity performance of construction materials for purposes relating to resource recoverability and strength of recycled or recovered materials. None of these examples and other examples detailed in the literature highlighted the use of AI-enabled circular economy principles in material's selection and management to engender decarbonisation of the built environment and associated construction processes, thereby confirming the existence of the gap upon which this study was predicated.

5.2. Energy

The energy system comprising of electricity, heat and transport remains responsible for an estimated 73.2 % of greenhouse gas emissions [18]. These facets are significantly associated with the development, management/operation and decommissioning of the built environment. Also, Horup et al [94] in highlighting the impact that the decarbonization of the electricity grid can confer on the mitigation of climate change challenges, admit the potential of such impacts to be undermined by the increment in building stock globally. They propose the reduction in the demand for new buildings (sufficiency)as a potent decarbonization strategy [94]. As such, reducing these emissions within the built environment sphere will post significant contributions on the attainment of the society's decarbonization agenda.

Decarbonising the built environment through the energy pathway usually takes any of the following transformative pathways: the electrification of end-uses, electricity supply decarbonisation, and associated efficiency improvements [16]. To achieve these outcomes, AI has been mostly deployed to control, monitor, and optimise the operations of energy systems. Scholars have mentioned the following as pathways for improving the circularity performance of energy systems; a) use of innovative technologies and practices to engender a reduction in energy demand; b) support for the increased implementation of renewable energy technologies; c) implementation of policies that seek to incentivise the reduction, recycling and reuse of energy sources, d). enhancing collaboration of the energy sector with other economic sectors of production in a manner that is supportive of the closed loop system, and; e) increased investments in research and development [31].

Danish and Seniyu [31] noted areas where AI models have been implemented to achieve the previously mentioned pathways. These include economic load dispatch analysis, stabilisation and regulation of voltage, fault identification and restoration of energy systems, planning and forecasting, observability of networks, frequency regulation and stability, system storage and power management, demand-side management/forecasting, electricity theft control, unit commitment and power management, grid optimisation, and building energy management systems. Whilst different categories of AI models can be applied to a variety of applications domiciled within energy systems, the choice of what model to apply is usually guided by parameters such as the preference of focus or decision-making preference based on their automation level, energy type, energy policy type, application type, and technique type.

Regardless of the multiplicity of facets within which AI models can be deployed for effective energy system management towards a decarbonised built environment, Danish and Senjyu [31] highlighted the significance of the use of an AI-enabled policy framework in governing the energy decarbonisation agenda. The authors opined that such a framework would provide a multi- and transdisciplinary approach for an effective outcome in terms of decarbonisation, energy conservation, renewable energy generation, and integration across various phases of the energy lifecycle. Continuing, Danish and Senjyu [31] posited that these policies direct the use of various mechanisms such as carbon pricing, renewable energy portfolio standards, and incentivisation of pro-energy efficient behaviours of stakeholders within the built environment using subsidies and regulations that are mostly tailored towards the characteristics and requirements of these stakeholders.

The circular economy contributes significantly to the energy sector's decarbonisation efforts. It does so by broadening the scope of emission reduction beyond just energy production to include the entire supply chain of energy sources, thereby targeting emissions from the fundamental energy infrastructure as well [51].

Whereas the study by Danish and Senjyu [31] focused on the articulation of an AI-policy framework for governing transitions towards a decarbonised energy sector, other studies have viewed the role of AI in engendering energy efficiency within the built environment. In their study, Farzaneh et al [36] highlighted the usefulness of AI models and big data in optimising demand response and end-use energy efficiency. In their study, the authors identified areas such as renewable energy forecasting, energy efficiency management, and energy accessibility as constituting opportunities for the integration of AI models [36]. For renewable energy forecasting, the use of AI models in collating and analysing data from relevant sources to provide accurate predictions of real-time availability of renewable energy based on estimated weather conditions, lighting density, temperature and wind was elucidated [36]. It is expected that such prediction will enable the balancing of energy supply and demand from these sources alongside the conventional grid. The deployment of AI models for energy efficiency in buildings relates to the use of AI to monitor, collate information regarding energy consumption in buildings at different intervals (peak and off-peak) and to outline probable means of reducing energy consumption levels based on this information [34,35,39]. With regards to energy accessibility, Seljak et al [45] advocates for the harvesting of renewable and renewable energy resulting from the use of waste heat in buildings or surrounding infrastructure. Also, Zhu et al [95] suggests the use of distributed energy systems (DES) to improve the percentage of renewable energy obtained in the energy mix whilst reducing the cost of energy. However, both studies did not explain how AI models can assist in improving the waste heat capture and reuse model, improving the renewable energy share in the energy mix or how such conversion activities can contribute to decarbonisation of the built environment. It should be reiterated that whereas a plethora of studies have explored the use of AI models to enable efficient energy use in buildings, a greater percentage of these studies have focused on occupant comfort and not improved circularity performance of energy systems and decarbonisation of the built environment.

In acknowledging the drive for decarbonisation of energy systems using a shift to renewable energy and efficient energy use, Sen et al.,[51] mention the need for more attention to paid to material efficiency, a critical contributor to improved circularity performance as such shifts would result in more material usage within supply chains. Accordingly, they advocate the improvement of material efficiency levels through reuse of components, use of less raw materials to achieve same purpose, and use of longer-lasting products and services as well as remanufacturing [51]. Other approaches which are in conformity with circular economy principles suggested include: ensuring ease of maintenance, repair, upgrade, remanufacture or recycle during product design; encouraging broader and better consumer choice towards ensuring increased intensity of use of products and services; preventing the transition of byproducts into waste items through the clustering of activities which have the potential to utilize such byproducts; and substituting materials which are either hazardous, adjudged difficult to recycle or ascribed low recovery rates [51].

The foregoing is indicative that the adoption of innovative practices and techniques within energy systems in the built environment can facilitate improved circularity performance therein for the purposes of successful decarbonisation. However, the integration of digital technologies such as AI will ensure more robust processes. Suffice it to state that using AI in this context would enable improved circularity performance of the energy systems and foster a 4 % reduction in global emissions by 2030 [96] in a manner that engenders reliability.

6. Challenges hindering the effective deployment of AI in enabling circularity performance of materials and energy

Despite the seeming utility of AI models in facilitating effective built environment decarbonisation, the implementation of this technology towards achieving improved circularity performance of materials and energy has been hindered by certain factors. Some of these factors are:

6.1. Data-related challenges

Data remains an integral component for the successful implementation of AI models. According to Baduge et al. [64], these models utilise massive amounts of data to carry out predictive analysis. For this purpose, the pre-processing of the data remains pivotal to achieving high accuracy levels. However, the absence of publicly available real-life datasets has been reported [25]. Similarly, a lack of databases concerning buildings, especially concerning the end-of-life phases of the construction project, makes using these datasets for predictive analytics and sensory capabilities challenging. Also, Oluleye et al. [27] enthused about the need for the development of a privacy protocol for data-sharing among relevant stakeholders in a digitised environment. Such a protocol is currently lacking.

In furtherance to the foregoing, the literature reviewed revealed the lack of a widely accepted set of indicators for measuring the circularity performance of the built environment, especially as it concerns materials and energy [51,80,89,97,98]. Corona et al. [97] maintains that the none of the extant set of indicators engenders a systemic manner thereby facilitating 'burden shifting' across a diverse range of facets. Most of these indicators focus on environmental considerations to the neglect of social and economic considerations. This shortcoming also observed in the set of indicators outlined by Sen et al., [51] for assessing the circularity performance of materials within energy systems. This poses another challenge to effective use of data to enhance the application of

AI models for improved circularity performance of materials and energy and ultimately, the achievement of the built environment decarbonisation agenda.

6.2. Cultural issues and the Blackbox nature of AI

The construction industry's reputation as a slow adopter of digital innovation persists. This culture, alongside the stakeholders' suspicion of the reasons behind AI-enabled judgements, has hindered the rate of adoption and deployment of various AI models. According to Oluleye et al. [27], the lack of explainable AI models has further exacerbated the adoption of AI in the construction industry, as extant models do not highlight the information upon which each judgement, they make is predicated. They insist that despite the culture-related challenge negating the adoption of digital technologies in the construction industry, the presence of explainable AI models which are easily comprehendible and manageable will engender trust among stakeholders, thereby enabling them to overcome some of these cultural barriers [27].

6.3. Slow shifts from the traditional approach to the deep learning approach in the construction industry

The lack of research funding to engender the transition towards the use of deep learning approaches in the construction industry has been reported as a barrier to the quick-paced adoption of modern AI platforms in the construction industry [27]. Similarly, the slim profit margins experienced by construction organisations have limited their ability to invest in forward-looking research and development for AI model development.

6.4. Ineffective life cycle management in the construction industry

Oluleye et al. [27] identified the inability of extant lifecycle management frameworks in the construction industry to clearly detail material properties and waste management processes as a potential obstacle to using AI models for improved circularity performance in the industry. According to the study, it is expected that understanding the transformation of materials and their properties (material flow) during various stages of the construction lifecycle remains critical for the effective implementation of AI models in engendering improved circularity performance of materials and energy [27].

6.5. Limited artificial intelligence studies in implementing systemic circularity

The limited number of studies focusing on the application of AI models towards the enhancement of the circularity performance of materials and energy, as well as the decarbonisation agenda, has been identified as constituting a hindrance to the implementation of AI models within the context [27,99]. Such paucity of relevant literature limits the depth of knowledge concerning the phenomenon being investigated, hence heightening the apprehension regarding adopting these models for the intended purpose.

6.6. Limited digital infrastructures

According to Oluleye et al. [27], the lack of the required infrastructure to engender effective material recovery would negate the adoption of AI for improving the circularity performance of materials and energy and, by extension, the decarbonisation of the built environment. This infrastructure should cater to the digitisation of waste sorting, identification, and segmentation across the entire lifecycle of the built asset.

7. Gaps in AI, circularity performance and decarbonisation research in construction-related studies

As mentioned previously, a narrative review is intended for the mapping of the research carried out in a particular knowledge to determine the gap that exists within that particular domain, thereby providing a scope for further studies to bridge any observed gaps. This study is no exception. Based on a review of carefully selected literature, certain critical gaps have been observed and are articulated below.

Firstly, it was observed that there is a lack of studies on systemic circularity performance involving a whole-life cycle analysis of construction materials with due consideration to the contributions of the energy involved in their production, utilisation, and decommissioning. Following from the search strings presented in the research methodology section and the outcomes of this search (only two papers were identified as aligning with the theme of the current study), it can be discerned that there is a paucity of studies seeking to deepen investigations into the role of AI in improving systemic circularity performance of the materials and energy towards the decarbonisation of the built environment. This observation calls for attention as the opportunities availed by the deployment of AI into this domain appear limitless. Further studies focusing on the elucidation of this nexus should be encouraged.

Also, there is a lack of studies seeking to explore the impact of contextual variables on the application of AI towards improving material and energy circularity performance. Based on the findings from the narrative review, which elucidate the important role of AI in improving the circularity performance of materials and energy in the built environment context, it was discovered that the impact of the contextual variables like the institutional, regulatory and legislative contexts was not considered. Similarly, the impact of the climatic conditions on the judgements arrived at by the AI models concerning energy efficiency, circularity performance, and materials were not considered. There is a need for studies to address this gap as materials and energy sources, as well as the amount of emitted and embodied carbon, would ordinarily differ across climatic zones. There is also a need to elicit data that better reflects these contextual variables during the training of the AI model.

There is also the absence of a holistic framework for articulating literature on AI, and circularity performance for effective decarbonisation. Furthermore, a lack of a Project Data Responsibility Framework was also observed. The effectiveness of AI models has been traced to the integrity and comprehensiveness of the data set upon which the judgements made by AI models are predicated. As such, the issue of project data responsibility must be considered. This concept provides an insight into the nature of the responsibility borne by various project stakeholders towards ensuring data integrity. This area is underexplored within the corpus of relevant literature, particularly as it pertains to the use of AI to engender improved circularity performance of materials and energy for effective decarbonisation of the built environment.

8. Conclusion

This study set out to explore the role of AI models in enabling improved circularity performance of material and energy for effective decarbonisation of the built environment. This study had become imperative due to the increasing role of digital technologies in facilitating the attainment of otherwise challenging construction industry objectives. Construction material and energy circularity and decarbonisation remain areas where such contributions are mostly needed due to their topical nature and society's sustainability aspirations. The absence of sufficient studies exploring AI, circular economy and decarbonisation together led to the use of a scientometric review to first analyse works that have explored AI in relation to either circular economy or decarbonisation in the built environment. Based on the findings from the scientometric analysis, it was concluded that AI plays an important role in the circular economy as studies have continued to explore the impact of AI approaches in improving the circularity performance of built environment activities. It was also observed that studies on AI for effective decarbonisation have also continued to emerge. However, the findings reinforced the absence of studies exploring these three concepts within the built environment and the need for such studies to be conducted.

The scoping of a few studies on AI models to improve circularity performance for effective decarbonisation of the built environment was also conducted and presented in the narrative review. Based on the findings, it is concluded that the effective decarbonisation of the built environment is attainable through AI and improved material and energy circularity performance. An array of AI models needed to improve material and energy circularity and promote decarbonisation were uncovered. As such, built environment professionals, organisations and researchers seeking to improve the attainment of decarbonisation can explore these noted models and approaches. Further review revealed that the effective use of AI for improved circularity performance and decarbonisation of built environment activities is challenged by issues relating to data, culture and the Blackbox nature of AI, the slow shifts from the traditional approach to the deep learning approach in the construction industry, ineffective life cycle management in the construction industry, limited artificial intelligence studies in implementing systemic circularity, and limited digital infrastructures. As such, tackling these challenges is paramount if the actualisation of effective decarbonisation of the built environment is to be achieved.

In addition, the study noted areas wherein more studies can be conducted. The absence of existing works on AI, circularity performance and decarbonisation in the built environment means there is an opportunity for future works to make meaningful contribution in this area of research. Moreover, there is a need for studies exploring the impact of contextual variables on the application of AI towards improving material and energy circularity performance. Developing a holistic framework for articulating literature on AI, and circularity performance for effective decarbonisation can also prove to be an important contribution for future works. Lastly, studies on the Project Data Responsibility Framework are needed to decarbonise the built environment effectively through AI and circular economy models.

CRediT authorship contribution statement

Bankole Awuzie: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Alfred Ngowi:** Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing – review & editing. **Douglas Aghimien:** Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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