Automation in Construction 166 (2024) 105641

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Review

Artificial intelligence for deconstruction: Current state, challenges, and opportunities

Habeeb Balogun [a], Hafiz Alaka [a,*], Eren Demir [b], Christian Nnaemeka Egwim [a], Razak Olu-Ajayi [a], Ismail Sulaimon [a], Raphael Oseghale [a]

[a] Big Data Technologies and Innovation Laboratory, University of Hertfordshire, Hatfield, United Kingdom
[b] Business Analytics and Statistics groups, University of Hertfordshire Business School, United Kingdom

ARTICLE INFO

Keywords:
Artificial intelligence
Deconstruction
Sustainability
Challenges
Opportunities

ABSTRACT

Artificial intelligence and its subfields, such as machine learning, robotics, optimisation, knowledge-based systems, reality capture and extended reality, have brought remarkable advancements and transformative changes to various industries, including the building deconstruction industry. Acknowledging AI's benefits for deconstruction, this paper aims to investigate AI applications within this domain. A systematic review of existing literature focused on AI applications for planning, implementation and post-implementation activities within the context of deconstruction was carried out. Furthermore, the challenges and opportunities of AI for deconstruction activities were identified and presented in this paper. By offering insights into AI's application for key deconstruction activities, this paper paves the way for realising AI's potential benefits for this sector.

1. Introduction

Urban population projections indicate a looming crisis for the construction industry, with a doubling expected by 2050 [1]. This surge increases the demand for housing and brings about significant environmental and societal risks, including heightened pressure on natural resources, increased waste generation, and exacerbated pollution levels [2,3]. However, sustainable recovery practices, notably deconstruction, offer promising solutions by carefully dismantling buildings into reusable components and materials, thereby contributing to a circular economy [4].

In recent years, the global shift towards digitisation has witnessed a rise in data-driven technologies, with artificial intelligence (AI) emerging as a key player, especially in deconstruction. With its subfields like machine learning, robotics, and optimisation, AI has been instrumental in streamlining complex processes in this field. For instance, deep learning techniques have enabled the categorisation and organisation of construction end-of-life waste [5]. In contrast, machine learning predictive models have been applied to various aspects, such as predicting deconstruction costs [7], analysing the deconstruction process [8], assessing the technical reusability of building components [9], and estimating end-of-life waste [10]. Robotics has demonstrated effectiveness in tasks like component finish partitioning and removal, insulation partitioning and removal, and adhesion removal [11]. At the same time, optimisation techniques have enhanced deconstruction process planning [12,13], scheduling [14,15], and salvage material logistics [16].

AI can revolutionise decision-making and productivity in the deconstruction industry, unlocking insights from vast datasets previously archived for future reference. Data collected from smart devices, cameras, building information modelling (BIM), and other sources can be analysed by AI to optimise deconstruction implementation and promote sustainability. In line with this, Oluleye et al. [26] pointed out AI's role in automating the design for disassembly, material strength prediction, and reverse logistics, among the many benefits it can offer.

Owing to these benefits, AI has garnered significant attention from researchers in the field of deconstruction, leading to a surge in research works and publications. However, this proliferation of studies makes it challenging to grasp the current state of knowledge. To address this, a comprehensive review is essential to consolidate the latest advancements. Consequently, this paper aims to summarise the current state-of-the-art AI applications in deconstruction, focusing on (a) critically reviewing existing literature on AI in deconstruction, (b) identifying and discussing the application and challenges of AI in deconstruction, and

* Corresponding author.
E-mail addresses: h.balogun@herts.ac.uk (H. Balogun), h.alaka@herts.ac.uk (H. Alaka), e.demir@herts.ac.uk (E. Demir), c.n.egwim@herts.ac.uk (C.N. Egwim), r.olu-ajayi@herts.ac.uk (R. Olu-Ajayi), i.sulaimon@herts.ac.uk (I. Sulaimon), r.oseghale@herts.ac.uk (R. Oseghale).

https://doi.org/10.1016/j.autcon.2024.105641
Received 11 November 2023; Received in revised form 3 July 2024; Accepted 20 July 2024
Available online 30 July 2024

(c) identifying and discussing opportunities for AI in deconstruction.

While some related review studies in this area [18–27] have made valuable contributions, it's essential to note that these studies offer a comprehensive overview from a broader viewpoint. None of them, however, have undertaken an exhaustive examination of AI applications, particularly within the context of deconstruction, which is one of the significant end-of-life activities with many benefits within the construction industry [28–31]. This is crucial, as deconstruction presents unique challenges such as material audit, hazardous waste handling, and structural integrity assessment. These challenges require a focused analysis of AI applications explicitly tailored to deconstruction scenarios, which might differ significantly from broader construction contexts.

By offering an in-depth analysis focusing explicitly on the application of AI in deconstruction, this paper provides insight into the state of AI for deconstruction, identifying challenges and opportunities and presenting research directions for both industry professionals and researchers.

For clarification, this paper uses 'literature' and 'article' interchangeably. Additionally, within this context, 'deconstruction' encompasses all sustainable end-of-life activities, including selective demolition, partial demolition, and soft-stripping. Consequently, academic literature that focuses on these activities using AI will be deemed relevant to this review. Also, the categorisation of literature was established based on its alignment with one of three key stages/phases: planning, implementation, and post-implementation. These stages were framed through a comprehensive review of the literature by the authors, considering the specific activities each piece of literature highlights. These stages collectively serve as a framework for classifying the literature and were inspired by the works of [14,17].

The planning phase encompasses critical activities such as tactical and strategic decision-making, planning, and inspection. Implementation involves the actual implementation, encompassing separation, grasping, handling and more. Post-implementation concerns activities after successful implementation, including sorting, transportation to sites and recycling facilities.

2. Systematic review literature

To investigate the use of artificial intelligence for deconstruction, we conducted a systematic literature review following PRISMA guidelines, a method with established credibility and widespread use [3,23,32,33]. Fig. 1 shows the transparent and systematic data collection process following PRISMA.

From Fig. 1, several renowned databases, including Scopus, Association for Computing Machinery (ACM), IEEEXplore, ScienceDirect, and Google Scholar, were queried to retrieve relevant literature published until 2022. This timeframe was selected to gain insights into AI adoption's historical progression in deconstruction and identify associated challenges and opportunities.

The choice to utilise the Scopus database stemmed from its reputation as the most prominent academic database encompassing a wide range of scholarly topics. Scopus is renowned for indexing high-quality literature [35], which is another compelling reason for its inclusion in this paper. However, relying solely on Scopus could lead to omitting

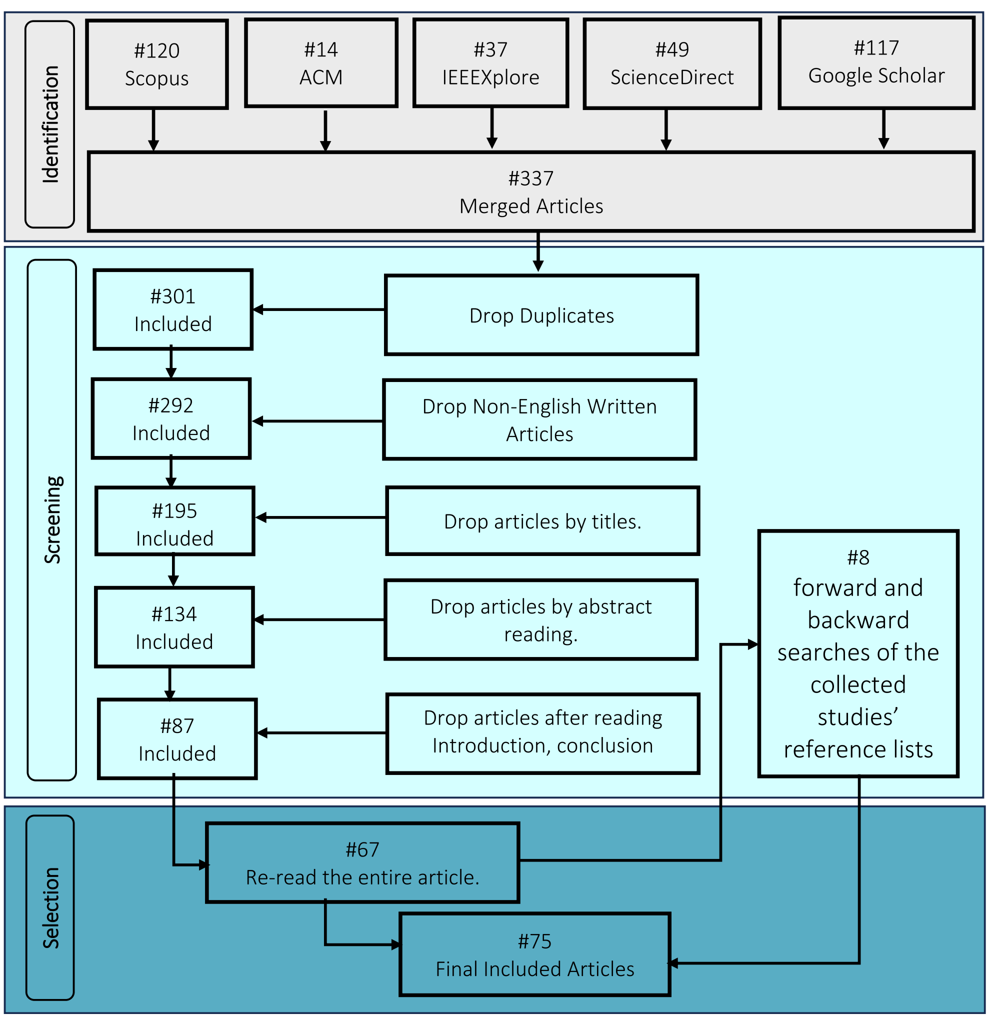

Fig. 1. Relevant article Identification, screening, and selection [34].

relevant literature. Consequently, additional databases such as ACM, IEEE Xplore, ScienceDirect, and Google Scholar were also searched. This deliberate search strategy aimed to mitigate the risk of overlooking pertinent literature by expanding the scope beyond Scopus. By employing a multi-database approach, this paper aimed to comprehensively gather literature on AI applications in deconstruction, ensuring a robust examination of the subject matter. Additionally, exploring multiple databases is fast becoming a norm, as can be seen in review studies, e.g., [23,36] within the architectural, engineering and construction (AEC) domain.

To comprehensively identify pertinent literature for inclusion in this review, we searched five databases. We structured our search strategy around three distinct collections of keywords, a methodology inspired by [37]. The design of these keyword clusters was carefully crafted to ensure a thorough search process.

Keyword Cluster 1 (KC1): comprises the term building, components, and materials. Other keywords, such as built structure and built environment, were unveiled as synonymous with building through a preliminary search on the internet.

Keyword Cluster 2 (KC2): incorporates keywords linked to deconstruction and sustainable recoveries such as disassembly dismantling recovery reuse recycling and demolition.

Keyword Cluster 3 (KC3): includes the elements of AI techniques. It involves general and specific keywords. Generic words such as artificial intelligence machine learning deep learning intelligence robotics and big data and exact terms such as neural network reinforcement learning model algorithm metaheuristics SVM clustering optimisation supervised learning unsupervised learning image recognition object detection semantic segmentation computer vision and video analytics were all incorporated into KC3.

The search criteria KC1 & KC2 & KC3 were applied to databases combining keywords within each cluster with "OR". However the overwhelming number of results and filter tool limitations within Google Scholar made us cease searching upon reaching a point where further search appeared redundant. As a result there is the possibility of missing literature in Google Scholar. However we anticipate that searching other databases will offset biases that may be present in the Google Scholar search.

The predetermined literature inclusion criteria include (1) literature involving the application of AI or any AI subfield for deconstruction and (2) literature involving the development or integration of AI or its subfield for activities synonymous with deconstruction or closely related. Conversely, literature was excluded based on the criteria: (1) not utilising AI or its subfield for deconstruction or closely related activities, (2) non-English, and (3) non-peer-reviewed journals, conferences, and textbooks.

Non-English language literature was excluded due to limitations in translation services, which could hinder accurate comprehension and analysis of research findings [3,32]. The decision to exclude other kinds of literature was based on the rationale that peer-reviewed journals, conferences and textbooks undergo a rigorous evaluation process by experts in the field [38]. By focusing solely on English-language peer-reviewed literature, this review sought to uphold rigorous/strict standards and minimise the risk of including potentially less reliable or lower-quality literature.

Following the refined search, we recorded the results in an Excel spreadsheet, including details such as author name, literature title, and abstract. Duplicate entries were removed, and further reviews involving the examination of each literature's topic and, in some cases, the abstract, introduction, and conclusion were considered to determine relevance. We added an Excel column for "include" or "exclude," along with an additional column for providing reasons for each decision. Independent reviewers performed this step, and Cohen's Kappa was calculated to assess inter-rater reliability [39]. In cases of disagreement between reviewers, discussions were held until a consensus was reached. Also, only pieces of literature readily accessible were considered.

Additionally, we thoroughly investigated the reference lists of the previously identified literature. This step was taken to uncover more literature following similar review studies [32,40,41]. As a result, eight more pieces of literature were retrieved and found relevant, totalling 75 literatures used for this review.

3. Results and discussion

3.1. Exploratory analysis

The exploratory analysis aimed to visualise/create a map of the current research landscape in AI for deconstruction. Consequently, we assessed the following perspectives: publication year and type, deconstruction activities, AI subfields, and the geographical distribution (i.e., first or corresponding author's affiliation), among others. The time horizon for this analysis was set until 2022, corresponding to the period during which the review was conducted.

Fig. 2 presents publication type and year, and we can see that an average of seven pieces of literature were published per year, which was consistently maintained from 2015 onwards, with a minor decline noted in 2016. The year 2022 had the highest number of publications, underscoring the recent emergence of AI for deconstruction.

Fig. 3 offers a comprehensive snapshot encompassing publication types, years, AI subtypes, deconstruction phase/stages and author's countries. Among 26 conference articles, nine focused on building inspection using deep learning, forming the most significant subset. Another five articles concentrated on material separation, predominantly leveraging robotics or a combination of robotics with other AI subsets. Also, conference articles featured a higher representation of separation, indicating its focus on actual deconstruction implementation, potentially due to robotics involvement.

In 48 journal articles, articles focused on inspection and deconstruction scheduling predominated, employing deep learning, knowledge-based systems, and robotics. Inventory and sorting were also significant areas, predominantly utilising deep learning. Overall, AI applications were prevalent in the planning phase (59 out of 75 identified articles), highlighting planning as the critical stage in deconstruction. Implementation (nine articles) and post-implementation (eight articles) received fewer mentions.

Regarding the geographical distribution of the articles, Germany and the United States emerged as primary frontrunners, boasting the highest aggregate of articles. An insightful scrutiny of the publication timeline reveals that Germany and the United States have consistently maintained their leading positions. Furthermore, Europe takes the lead in this specialised area of research. One plausible explanation could be the European Union's proactive strategy to promote circular economy approaches in 2015—a strategy that garnered extensive adoption and endorsement through national initiatives. This has positioned Europe at the forefront of advancements in AI for deconstruction, solidifying its preeminent status in the field.

Fig. 4 presents the distribution of articles by publishers. Additionally, the impact factor [42,43] and h-index [44] of publishers, which serve as metrics for academic article contribution and reputation, were provided. This confirms the quality of the articles—they originate from reputable journals and conferences.

The Journal of Automation in Construction leads with six publications, boasting an impressive impact factor of 10.3 and an h-index of 157. Other significant contributors include the Journal of Cleaner Production (three publications, impact factor: 11.1, h-index: 268), Sustainability (two publications, impact factor: 4.0, h-index: 136), Buildings (two publications, impact factor: 3.8, h-index: 45), and others, each contributing two articles.

The substantial presence of research literature in the Journal of Automation in Construction and other high-impact journals signifies remarkable advancement in this field, drawing attention to this research domain's newness and growing importance. The fact that a prestigious

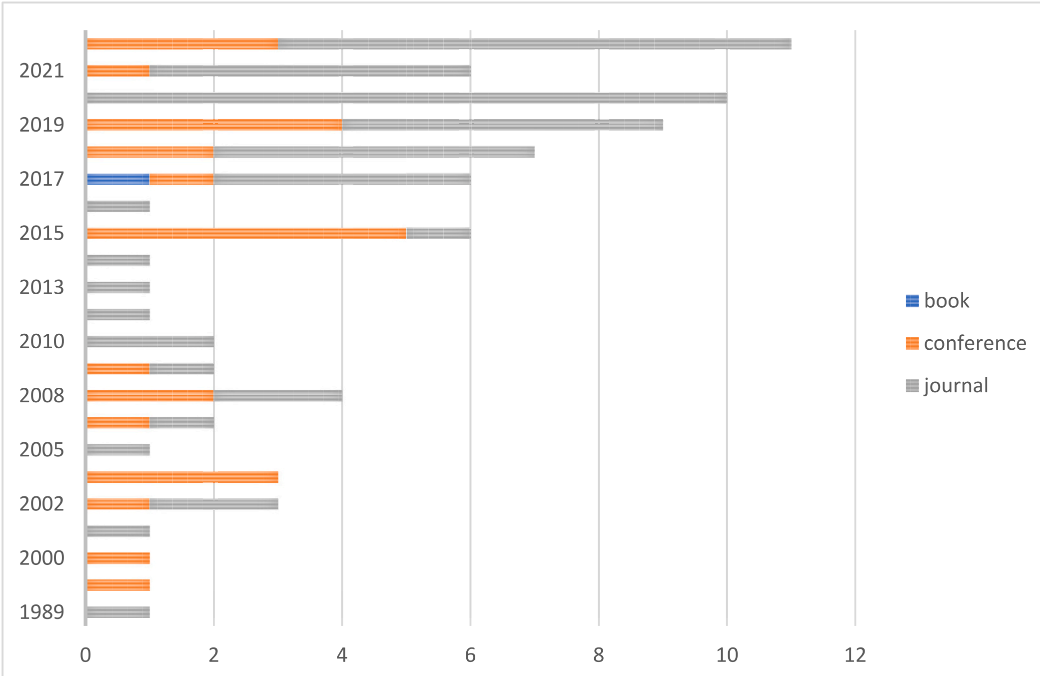

Fig. 2. Publication types against year.

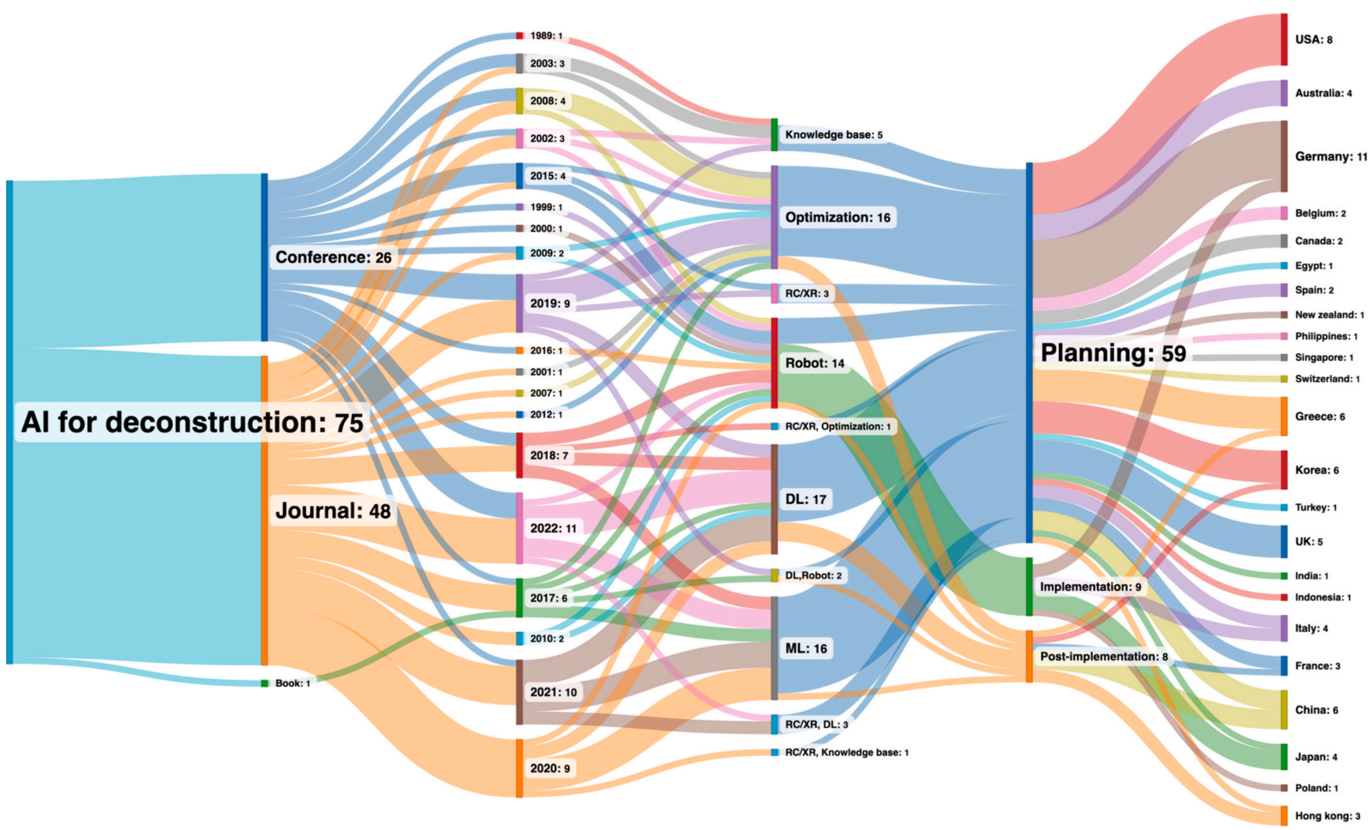

Fig. 3. Journal types, publication year, AI types, deconstruction stages and country of author/corresponding author.

journal has devoted many articles to this area underscores its increasing significance within the academic community. The journal's high h-index and impact factor, typically associated with respected academic publications, further validate the quality of the literature reviewed in this paper.

3.2. *Artificial intelligence and subfields used for deconstruction*

Artificial intelligence (AI) is the field of science and engineering dedicated to creating intelligent machines that can replicate human intelligence, with its origins dating back to 1956. Since its inception, AI

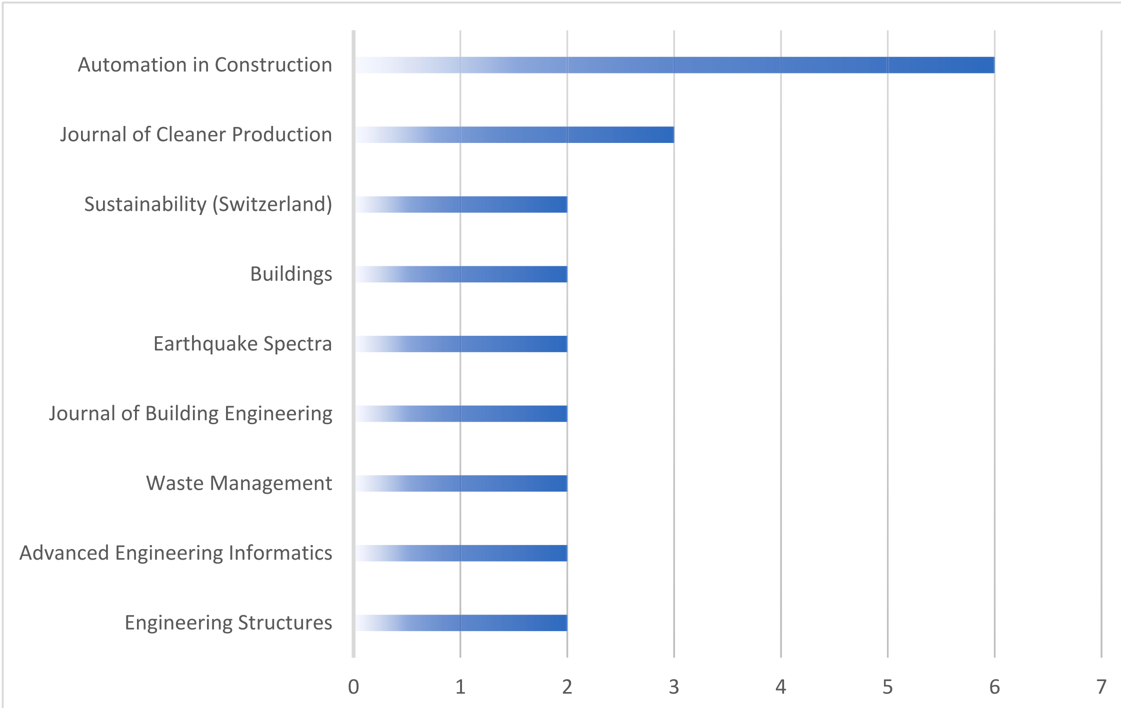

Fig. 4. Publication counts per publisher.

has steadily garnered the attention of both scholars and the public. This enduring interest results from computing power, systems, and techniques advancements. AI has consistently played a pivotal role in people's lives, facilitating the automation of activities that were once deemed impossible, especially in the fields of AEC [23,36].

There are many AI models and techniques. However, this section summarises the dominant AI techniques and models for deconstruction outlined within the selected literature, which were structured into subfields in line with Abioye et al. [23] categorisation. As a result, five prominent subfields stand out: Machine Learning (ML), Robotics, Optimization, Knowledge-based systems, and Reality capture & extended reality, as illustrated in Fig. 5.

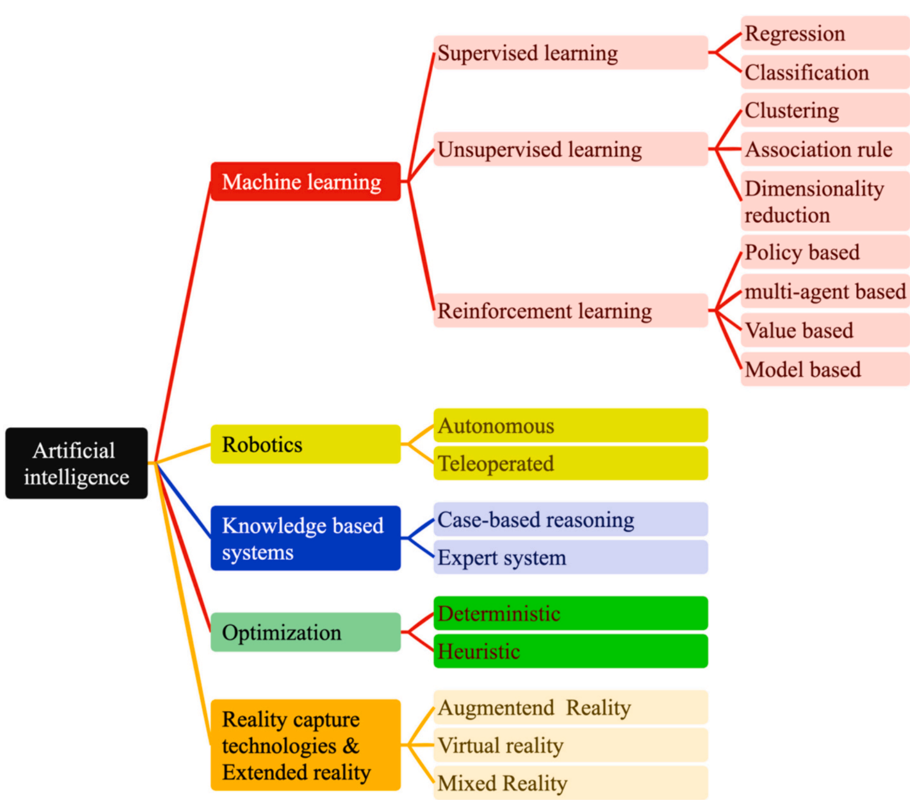

Fig. 5. Artificial intelligence and subfields.

3.2.1. Machine learning

Machine learning (ML) involves the application of computer systems to learn from past data and make predictions on new - unseen data. ML can be classified in several ways (Fig. 5). One way is to classify it based on the model's learning process, resulting in supervised, unsupervised, or reinforcement learning. Another classification criterion for ML is based on the complexity of the model, which can be either classical or deep learning [21].

1. Supervised learning necessitates labelled input data for training, making it suitable for solving regression or classification problems, depending on whether the labels are discrete or continuous values [45].
2. On the other hand, unsupervised learning operates without any labelled data, focusing on autonomously finding patterns within the data. Some well-known unsupervised learning techniques are clustering, association rule, and dimensionality reduction.
3. Reinforcement learning, the third category, involves a learning system, referred to as the agent, which interacts with the environment and receives rewards for its actions. Through this feedback mechanism, the agent learns to make decisions that maximise rewards [46]. Some well-known reinforcement techniques include value-based, model-based, multi-agent, and policy-based based, among others.

Additionally, ML may be classical ML or deep learning (DL). In classical ML, experts manually engineer features or attributes, which are then fed into the model. As a result, the model learns from the data and makes predictions. Examples of classical ML techniques include support vector machines, decision trees, and ensemble methods, to mention but a few. The effectiveness of classical ML models largely depends on the quality of the hand-engineered features [47–50].

Conversely, DL represents a specialised subfield of ML that centres around artificial neural networks (ANN). ANN is constructed with interconnected nodes, forming layers of neurons. Unlike classical ML, DL automatically learns feature representations directly from the data, eliminating manual feature engineering. This capability is one of the primary advantages of DL and has contributed to its widespread adoption in tackling intricate tasks across diverse domains. Classical ML and DL may still be formulated as supervised, unsupervised, or reinforcement learning, depending on the problem scoping and objectives.

3.2.2. Robotics

Robotics, another significant subfield of AI, concentrates on designing and constructing robots capable of emulating human activities in the real world. These robots are engineered to carry out highly specialised tasks that might pose challenges for humans, and they come in diverse shapes and forms. Based on the functionalities, robots can be autonomous or teleoperated.

1. Autonomous robots operate independently, making decisions using intelligence gathered through their sensors and programming without direct human interventions.
2. Teleoperated robots are controlled by humans from a remote location. This will be most useful in carrying out complex assignments in hazardous environments or situations where direct human presence is not feasible.

3.2.3. Knowledge-based

Knowledge-based systems (KBS) are inferential decision-making engines that draw upon expert knowledge or historical data to make informed decisions. KBS can be:

1. Case-based reasoning (CBR) learns by leveraging preceding problem-specific knowledge to solve new instances [51].
2. The expert system (ES) learns by amalgamating expert knowledge to devise evaluation rules for effective problem-solving [52].

3.2.4. Optimisation

Optimisation involves achieving the best possible outcomes while adhering to constraints [53]. It focuses on maximising or minimising a specific value or criterion by efficiently utilising available resources. It can be deterministic or stochastic (heuristics).

1. Deterministic refers to the systematic technique that guarantees finding optimal solutions for a given task, provided specific criteria are met. It follows a predefined set of rules and steps to search through the solution space and converges to the best possible solution. Some renowned examples of deterministic optimisation include gradient descent, linear programming, and integer programming, to mention but a few.
2. Conversely, stochastic (heuristic) methods are probabilistic methods that do not guarantee finding the global optimum. Instead, they attempt to find satisfactory solutions in a reasonable amount of time, especially for complex tasks where finding the global optimum might be computationally infeasible. Examples of methods include genetic algorithms, simulated annealing, and particle swarm optimisation, to mention but a few.

3.2.5. Reality capture and extended reality

Reality capture technologies include the techniques and tools used to collect and generate digital representations of an object, building inclusive. Within these technologies, laser scanners, unmanned aerial vehicles (UAVs), LiDAR (Light detection and ranging), photogrammetry, videogrammetry, and digital cameras are prominent. They gather images, videos, or 3D point cloud data. Furthermore, the extension of the reality captured refers to the extended reality (XR). XR can be Virtual reality (VR), Augmented reality (AR), Mixed reality (MR) and similar reality-altering technologies that immerse users in altered realities [54–56].

1. VR offers an immersive experience, replacing the real world with a wholly simulated or virtual environment.
2. AR augments reality with computer-generated content. In AR, digital content is overlaid onto the user's real-world surroundings, allowing users to see both the real-world and the additional content the AR device provides [57].
3. MR resembles AR but facilitates deeper engagement between the virtual and the actual environment, offering users a heightened sense of realism. In MR, users get a fusion of computer-generated content within their surroundings while also being able to engage with this content [54] actively.

To better understand these subfields, we provide some benefits and limitations of the identified AI subfields for deconstruction (Table 1). Shared benefits include optimised resource recovery combined with heightened productivity. However, limitations of these AI subfields for deconstruction include inadequate data accessibility and quality, ethical concerns, essential AI proficiency tailored for deconstruction purposes and seamless integration into practical applications, potential issues with generalization, and the criticality of validation, among other pertinent constraints.

3.3. AI application for deconstruction

Fig. 6 presents the identified areas of AI application for deconstruction, aligning precisely with the framework established in the introduction, delineating planning, implementation, and post-implementation phases. From Fig.6, ten distinct activities were presented, each correlated with their sub-activities and the relevant state-of-the-art models and subfields. Some identified activities include inventory feasibility assessment, project planning and scheduling, sorting, reverse logistics, separation, and recovery rate estimate. Additionally, sub-activities under inventory include data collection and audit, digital

Table 1
AI subfields, their benefits to deconstruction and limitations.

Subfield	Benefits to deconstruction	Limitations	Articles
Machine learning	1. Accurate predictive models 2. Enhanced resource management 3. Precision in dismantling techniques 4. Optimised material auditing 5. Streamlined planning. 6. Improved efficiency 7. Easy integration with other technology	1. Data availability and quality 2. Explainability/ interpretability 3. Generalization and validation 4. Computational complexity 5. Human expertise and integration 6. Ethical considerations	[7,58–60]
Robotics	1. Adaptability to various task 2. Enhance productivity. 3. Improve safety. 4. Precision and consistency 5. Handling heavy loads 6. Easy integration with other technology	1. Complexity of environment 2. Cost and scalability 3. Manipulation of variable materials	[61–64]
Knowledge based	1. Explainability 2. Adaptability to varied structures. 3. Documentation and knowledge sharing 4. Easy integration with other technology	1. Dependency on expert knowledge 2. Ethical and bias considerations 3. Inability to handle uncertainty	[65,66]
Optimization	1. Enhanced planning and decision making 2. Resource efficiency 3. Cost reduction 4. Adaptability to varied scenarios. 5. Optimal material recovery 6. Increased time efficiency	1. Computational Complexity 2. Data availability and quality 3. Trade-offs and conflicting objectives	[12,67–69]
Reality capture and extended reality	1. Accurate documentation 2. Enhanced visualization 3. Improved planning 4. Onsite assistance and support	1. Compatibility and interoperability	[70–74]

data generation, and as-built recognition.

3.3.1. Artificial intelligence application in deconstruction planning

The planning phase encompasses many activities, including inspection, project planning and scheduling for the deconstruction process, management of inventory, feasibility assessments, estimation of recovery rates, and thorough cost-benefit analyses (see Fig. 6).

3.3.2. Data collection/audit/inventory

Deconstruction is a complex engineering process, like construction, but more challenging due to lack of proper documentation. Comprehensive documentation should encompass a building's historical records, modifications, maintenance activities, and inventories. Examples of documents relevant to deconstruction include ownership and plot boundary documents, approval documents (e.g., permits and regulatory clearances), and strip plans of media lines and pipes (e.g., utility layouts) [14]. Facility management, retrofits, inspections, and sampling documents offer historical facility data, aiding in maintenance understanding. Specific exposure documents are critical for safety, containing information on hazardous materials. Lastly, documentation of neighbouring buildings helps assess potential impacts on adjacent structures. These documents collectively support safe, efficient, and compliant building deconstruction processes.

Unfortunately, many existing buildings do not have this information, and thus, they suffer from incomplete, outdated, or fragmented building information, resulting in partially unknown or uncertain details. Furthermore, building information is frequently stored unstructured, often needing more modern formats like computer-aided design (CAD) or building information modelling (BIM), and occasionally even in non-digital formats. More structured data is required to process building information directly. Consequently, material and components audits are manually possible, which implies manual measurements and examination of the existing building. A typical measurement and examination include the use of measuring tape, torchlight, and a camera for photographs or videos.

To tackle these inventory, material audit and documentation challenges, there has been a rise in the use of reality-capturing technologies like photogrammetry, videogrammetry, laser scanning, or combinations thereof to semi-automatically or automatically capture and process building information[6]. However, findings from this paper posited that many of these reality-capturing technologies function more effectively when integrated with other subfields of AI, such as classical ML and DL [75,76] and expert systems [77]. ANN-based models were among the prominent models mostly used to augment material recognition [78] and data extraction [72]. SVM and random forest were the other ML models discovered herein that are useful for data collection and material auditing in partnership with reality capture technologies such as 3D survey data, photogrammetry, and unmanned aerial vehicles, among others [70,71,76].

Despite the breakthroughs in ML and DL for recognition, detection and segmentation, its use, particularly for material audit and inventory, is still hindered by challenges, including the characteristics of the materials and components, typically inconsistent dimensions and standards, high similarity, and low variability (e.g., floor, ceiling, tiles and so on) [78]. Also, insufficient training data, particularly for classes that form the minority, may yield poor performances for such classes [76]. Collecting more data and/or augmenting available data may solve these challenges. Another challenge is the technical skills to annotate and prepare data correctly and the angle from which the data is captured [72,79]. Overcoming these challenges could facilitate the effective utilisation of reality-capture technology, robotics, ML and even extended and immersive reality for material inventory and auditing in deconstruction.

3.3.3. Deconstruction feasibility

Evaluating a building's deconstruction feasibility at the end of its useful life represents a pivotal activity within the planning phase. It revolves around the decision-making process of whether to proceed with deconstruction. This determination can be intricate, particularly for existing and conventional buildings not originally designed with deconstruction.

As part of the solution to this challenge, Abdullah et al. [80] proposed an intelligent decision support system using expert knowledge to select the most appropriate building end-of-life techniques, which include deconstruction, using criteria such as structural characteristics, site conditions, costs, experience, reusability, and time. Anumba et al. [81] extended the work of Abdulla et al. [82] by subjecting the different criteria to a quantitative evaluation in terms of cost. The outcome was a ranking of overall deconstruction feasibility based on their cost-effectiveness. Notably, both studies include social criteria like the health and safety of on-site workers and public acceptance. Additionally,

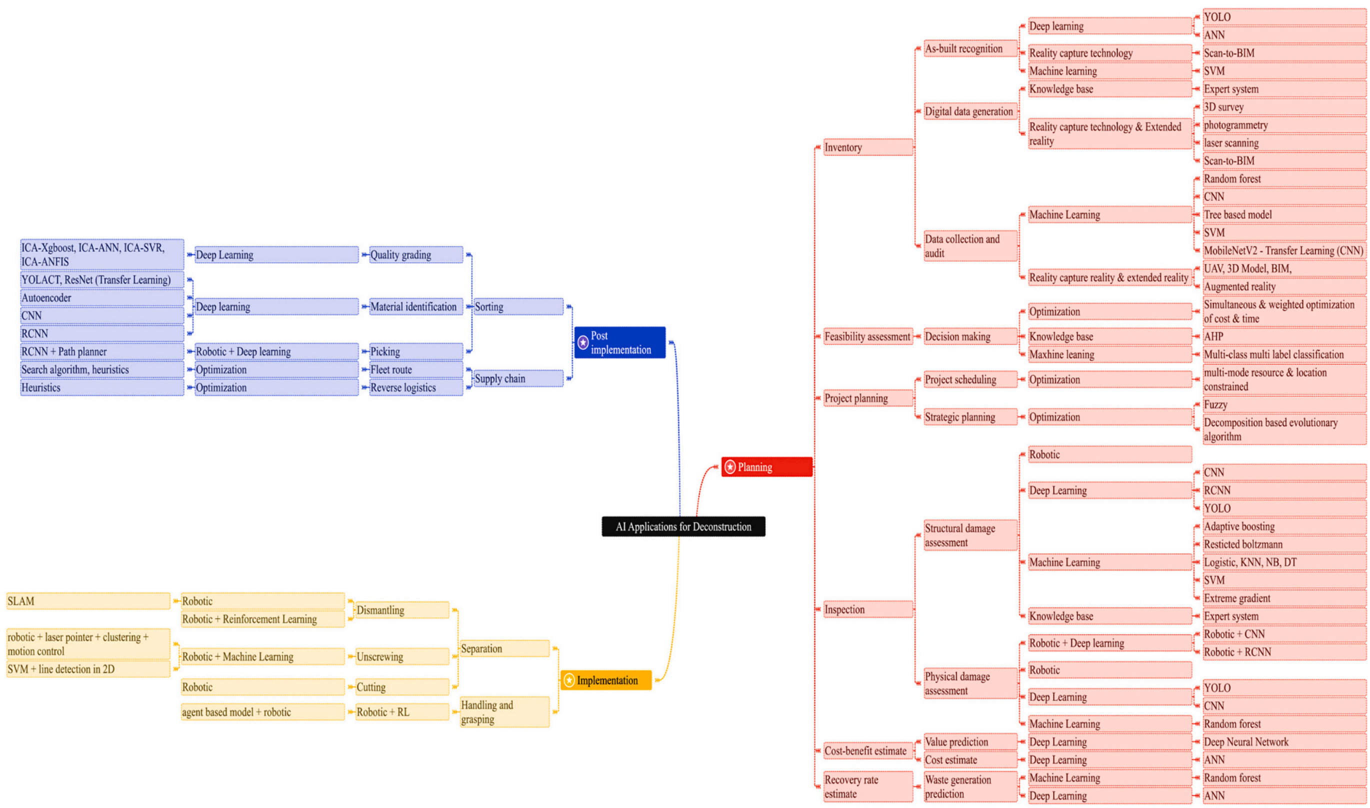

Fig. 6. Summary of AI application for deconstruction.

workers' skills and prior experiences were considered factors contributing to economic criteria.

Similar literature surfaced afterwards, though they explored deconstruction feasibility from different points using different AI subfields. For example, deconstruction feasibility with a focus on economic gain and time optimisation [83], economic reuse potential prediction [58] and technical reuse potential of components [9], among others.

Drawing from the reviewed articles, deconstruction feasibility assessment is possible using different subfields, mainly depending on the problem formulation and criteria. It is possible using optimisation algorithms [84], expert systems [80,85], and machine learning [9,86]. However, the multifaceted nature of deconstruction makes the state-of-the-art feasibility assessment almost impractical, and this is because no known model has developed a holistic view of the criteria that influence deconstruction [3]. Based on this, an AI-driven predictive model considering all significant criteria from different standpoints may provide a realistic and practical feasibility assessment for deconstruction.

3.3.4. *Project planning*

Effective planning is fundamental for all deconstruction activities and crucial in attaining specific project objectives. These objectives may involve cost reduction, material recovery maximisation, or both. The precise goals will vary and be influenced by factors like the building's type, urgency, stakeholder preferences, etc. Given the unique characteristics of each deconstruction project, personalised planning approaches are indispensable to address each building's distinct requirements comprehensively.

Deconstruction project planning consists of finding an optimal and feasible path for deconstruction under given constraints [12]. As a result, it is often framed as an optimisation challenge and is typically categorised into two dimensions: strategic and operational [87]. Strategic planning delivers decision support for the entire project, considering factors like time, cost, quality, resources, risk, etc. In contrast, operational planning predominantly concentrates on individual project activities, and its key objective is often to shorten the project's duration, which is commonly addressed as a resource-constrained project scheduling problem (RCPSP). Common heuristics and algorithms used for planning, generating sequences and scheduling include search techniques, optimisation techniques and genetic algorithms.

Despite the progress and utility of the optimisation techniques presented in these sources, some limitations have been observed, including limited real-life validation and a lack of automated learning of deconstruction knowledge from existing records without extensive human involvement [12,88,89].

3.3.5. *Structure and material inspection*

The challenge of manually inspecting buildings, especially considering structural and non-structural components and safety concerns, has led to traction among researchers [90]. Some have focused on AI-driven inspections of structural [91,92], and non-structural components [93], while others covered both aspects [94].

Various AI subfields, notably classical ML and DL, have been utilised, especially for image recognition and segmentation, often in integration with robotics and expert systems. For instance, Liu et al. [95] proposed an autonomous robot system employing recurrent neural networks for real-time visual defect detection.

Robotics has also played a pivotal role in inspection. Balaguer et al. [96] introduced a teleoperated robot for high-rise metallic structure inspection, while Inoue et al. [97] employed robots for wall inspection and deterioration estimation. Several studies have introduced expert systems for defect prediction [98] and utilised machine learning models for seismic vulnerability assessments [99,100].

From the retrieved articles, classification problems were predominantly tackled, except for strength and capacity predictions [92]. Convolutional neural networks (CNNs) were the primary choice for image detection and recognition. The most prevalent robot types used for inspections were teleoperated and semi-autonomous systems.

3.3.6. Cost-benefit estimate

Cost estimation is a complex task, primarily due to uncertainties associated with the building's condition and the availability of comprehensive information regarding material states and values. This inherent complexity has led to the adoption of AI techniques. Subfields of AI, such as ML and DL, have proven valuable for analysing historical project data and various variables to generate highly accurate estimates of material yields, costs, and benefits. Utilising AI in this manner helps reduce the likelihood of unforeseen expenses during the deconstruction process.

Studies have demonstrated the relevance and accuracy of artificial neural networks and case-based reasoning in cost estimation [7]. The precise valuation of materials through artificial intelligence has also been proposed [101]. Among the predictive models employed for cost and benefit estimation, ANN with built-in layers emerged as the most used. This preference is attributed to the complexity of the variables involved. Furthermore, DL techniques like ANN were advantageous because they automatically extract features from the input data without requiring manual feature selection.

3.3.7. Recovery rate estimate

Accurately predicting the rates of salvageable and waste materials presents a considerable challenge, as the decision to proceed with deconstruction often hinges on the assessed value and quality/quantity of recoverable materials within the building slated for deconstruction. In response to this challenge, AI has been increasingly explored to predict waste and salvageable material before commencing the deconstruction process.

As identified, Akanbi et al. [10], Cha et al. [102], and Cha et al. [103] have delved into the realm of AI, explicitly employing supervised DL and ensemble ML (made up of weaker ML models) to achieve accurate predictions of waste and recoverable material.

Table 2 summarises AI subfields in planning phase activities and sub-activities, alongside the potential opportunities. Noteworthy opportunities include leveraging robotics and DL algorithms to streamline material audits and optimise building material recovery. Furthermore, the prospect of a predictive model for assessing deconstruction feasibility using multidimensional criteria and applying extended and immersive reality for virtual feasibility assessments and material potential identification stands out.

Table 2 shows the limited utilisation of robotics in planning activities, primarily attributed to cost and expertise constraints [23]. Additionally, while reality capturing exhibits substantial benefits within inventory activities, its integration and use with extended reality still need to be explored, showcasing the untapped potential of extended reality in enhancing deconstruction planning activities. Thus, robotics integrated with ML, DL, digital technologies like IoT, and extended reality should be more utilised in deconstruction planning activities. This underscores a critical gap in harnessing these advanced technologies to their full potential within deconstruction planning activities.

3.3.8. Artificial intelligence application for implementation

Robotics plays a pivotal role across various deconstruction implementation activities. It is instrumental in tasks such as separation, dismantling, handling, and grasping, as well as sub-activities like denailing and cutting, as illustrated in Fig. 6. This is due to the inherent physical nature of typical deconstruction implementation tasks.

Robots have been developed for dismantling interior components, such as ceiling panels [61,117], ceiling beams [64] and partition removal [118]. Conversely, robots designed for dismantling structural components, like walls, have also been developed [63]. They have also been explored for multitasking purposes [119], aiming to maximise productivity and reduce deconstruction implementation times.

The integration of robots with other subfields, mainly classical ML, DL, reality-capturing technology, and expert systems, is evident in most of these studies. For instance, Leea et al. [63] introduced an autonomous deconstruction robot equipped with a vision system capable of collecting environmental feedback. While considering hardware capabilities and human expert inputs, this system can automatically and precisely cut concrete walls. Additionally, it includes a grasping module to ensure safe wall cutting without damaging other building elements. Similarly, Biggs et al. [64] developed a teleoperated robot designed explicitly for unscrewing suspended ceiling beams. This robot utilises laser scanning and clustering techniques to locate beams and features a motion control module for navigating between screws. While the robot performed admirably, occasional issues with skipped screws were encountered.

The findings from these studies underscore that most developed robots for various deconstruction activities largely remain in their experimental stages, posing a challenge in evaluating their practicality for real-world deconstruction practices. Furthermore, while these robots hold promising potential applications, their deployment on actual deconstruction sites faces hurdles due to the inherent unstructured nature of building end-of-life scenarios [120]. Despite the potential for reinforcement learning to address these challenges, its exploration in this domain still needs to be explored.

3.3.9. Artificial intelligence application for post-implementation

The aftermath of deconstruction implementation presents several challenges, some of which can be strenuous, dangerous, or technically demanding. Post-implementation involves sorting and grading salvageable materials to separate reusable items from waste, picking and loading, planning logistics for the recovered materials, and more, as

Table 2
State-of-the-art AI applications for deconstruction planning activities, sub-activities, subfields, and opportunities.

S/N	Activity	Sub activities	ML	RB	KBS	OP	RC/XR	Opportunities
1	Inventory	1. As-built recognition [15,59,78]	X					1. Robotics and Deep learning streamlined material audit
		2. Digital data generation [73,77]			X			
		3. Data collection and material audit [72,75]	X					
2	Feasibility assessment	1. Decision making [85,104]	X		X	X		1. Predictive model for feasibility assessment
		2. Reuse potential assessment [9,86]	X					2. Virtual feasibility assessment and material potential
3	Project planning	1. Schedule planning [105,106]				X		1. AI-driven insights for strategic planning and task prioritization
		2. Strategic planning [107]				X		
4	Inspection	1. Structural damage assessment [100,108–110]	X	X	X			1. XR-enabled building inspection
		2. Physical damage assessment [111,112]	X					
5	Cost-benefit estimate	1. Value prediction [113]	X					1. AI and XR high-value material recognition
		2. Cost estimate [114]	X		X			2. Knowledge-based market demand estimate
6	Recovery rate estimate	1. Waste generation estimate [115,116]	X					1. Deep learning for the material recovery rate

ML - Machine learning includes deep learning, RB – robotics, KBS-knowledge-based systems, OP-Optimization, and RC/XR – reality capture technology and extended reality.

illustrated in Fig. 6.

Studies in this field have explored the use of AI, including classical ML, DL and robotics, to address these challenges. Table 3 presents the summary of the subfields used for post-implementation.

Findings in this study revealed the use of AI subfields such as optimisation for post-implementation activities. For instance, Xanthopoulos et al. [124] proposed and formulated the supply chain task for recovered materials as an optimisation problem. Also, Duan et al. [125] investigated the prediction of compressive strength in recycled aggregate using meta-heuristic search techniques (ICA) and XGBoost. They developed a hybrid model called ICA-XGBoost, which was argued to outperform other models such as ICA-ANN, ICA-SVR, and ICA-ANFIS.

Additionally, studies have explored using classical ML and DL with robotics for sorting and classifying salvageable materials. Examples include real-time waste classification and sorting systems using deep learning techniques like YOLACT and ResNet-50 [5]. In a similar study, Wang et al. [126] introduced a robot capable of identifying materials, picking them up, and loading them. This robot utilised a Recurrent Convolutional Neural Network (RCNN) for object detection and employed DL techniques for path planning and motion control. Several other studies, such as those by [122,127,128], adopted a similar approach involving robots, DL, and image-based technologies. Convolutional Neural Networks (CNN) and its variants, including Faster CNN, Recurrent CNN, Region-based CNN, and Masked RCNN, were among these studies' commonly used DL models for object and image recognition. While these proposed solutions demonstrate relevance, it's important to note that most are still in their experimental stages and may require further refinement for practical on-site use.

4. Challenges facing AI for deconstruction

So far, this paper has pinpointed potential prospects and upcoming patterns in using AI for deconstruction. Recognising and deliberating on the leading obstacles is crucial to deepen our understanding in this domain. Fig. 7 illustrates the opportunities, challenges, directions for future research, and the evolving trends. Five notable challenges affecting the utilisation of AI for deconstruction are presented below.

4.1. Data availability and quality

This review uncovered a significant issue: there needs to be more publicly available real-life datasets suitable for training AI in deconstruction. Most of the existing data used for developing AI in this field is privately owned. This scarcity of accessible data has hindered the adoption of AI in deconstruction, as AI heavily rely on ample data [47,49,129–131]. Furthermore, there needs to be more focus on sustainable end-of-life, which has limited data availability specifically tailored for deconstruction [132]. Although some studies utilised a few open-source datasets, especially for waste classification and sorting, many needed more quality [5]. Other efforts have been made to collect datasets from the internet, but these often fall short of representing real-world deconstruction sites [112].

Table 3
Summary of subfields used for post-implementation activities and sub-activities.

Activities	Sub-activities	ML	RB	KBS	OP	RC/XR	Opportunities
Sorting	Grading [121]	X			X		Sorting and grading automation through adaptive learning
	Material classification [122]	X	X				
Supply chain	Reverse logistics [123]				X		AI-driven Reverse logistics
	Fleet route [123]				X		

Furthermore, using transfer learning and pre-trained models streamlines AI model training, particularly in machine and deep learning, and minimises data requirements by leveraging existing knowledge for new tasks. Adapting prior model learning to related tasks or domains is beneficial, especially for activities like material sorting [5,133]. However, despite these advantages, the data quality problem still needs to be solved [134].

Overall, the absence of a tailored dataset for deconstruction poses a significant challenge in leveraging AI for deconstruction. If this challenge remains unaddressed, it could stagnate the evolution of digital deconstruction. To overcome this obstacle, we recommend establishing a secure data-sharing platform to encourage developing and validating more AI solutions tailored for deconstruction. Additionally, data challenges may be tackled shortly with the rise in the use and integration of reality-capturing technologies, including unmanned aerial vehicles (UAV), sensors, laser scanners, and others.

4.2. Cost and scalability

The undeniable benefits of AI in deconstruction are offset by substantial initial expenses, dissuading smaller firms and subcontractors, significant players in the industry [135,136]. This leaves firms with the trade-off between AI adoption's return on investment and associated expenses. Additionally, ensuring AI's adaptability to diverse deconstruction workflows and project sizes is pivotal for broad acceptance. However, integrating these AI applications smoothly across different projects and firms poses a scalability challenge, adding complexity to their widespread application.

4.3. Human expertise and explainability

Deconstruction, a specialised field, makes finding individuals proficient in deconstruction and AI development challenging. AI's intricate nature creates a barrier as its inner workings are often hard to interpret, hindering adoption. This lack of transparency may lead deconstruction professionals to hesitate to trust AI solutions without understanding how they arrive at conclusions. Addressing this requires developing AI models that are not just effective but also transparent and interpretable.

Collaborations between AI experts and deconstruction industry professionals can bridge these gaps by fostering innovation tailored to the unique needs of deconstruction. Such collaborations aim to create models offering insights into decision-making processes, fostering trust among deconstruction stakeholders and potentially accelerating AI adoption in the industry.

4.4. Complicated site conditions and uncertainties in buildings at the end of life

Over time, buildings naturally deteriorate due to factors like weather and accidents, among others, rendering their conditions uncertain. Furthermore, typical sites are mostly complex and complicated [21]. These challenges significantly impact the feasibility and effectiveness of adopting AI for deconstruction. The unpredictable state of buildings complicates the use of AI solutions, which rely on accurate data for decision-making. The uncertainties hinder the AI's ability to predict and assess salvageable materials and optimise strategies effectively, among other possibilities.

To boost AI adoption in deconstruction, it's vital to tackle uncertainties and complex site conditions. Leveraging advanced technologies like IoT, sensors, and adaptive and reinforcement learning for autonomous decision-making and accurate building assessments can mitigate these challenges.

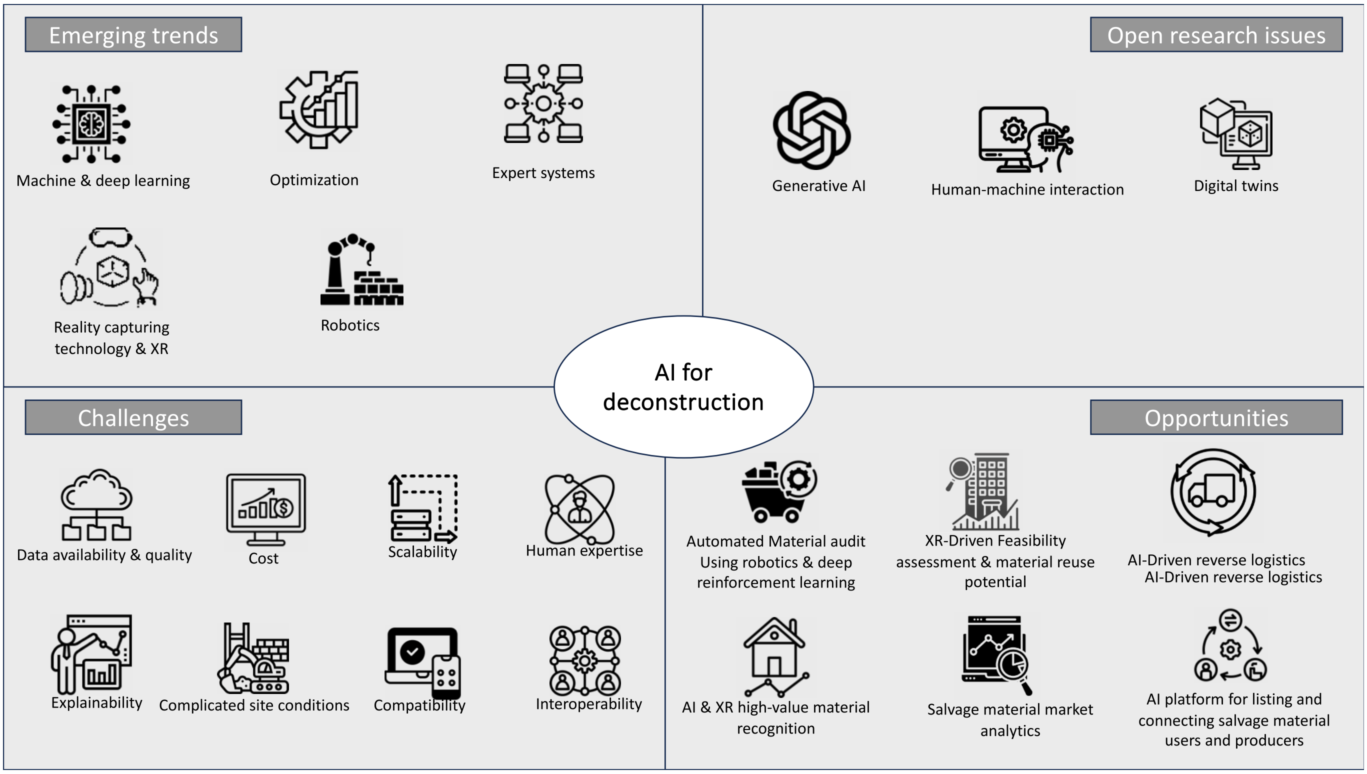

Fig. 7. AI for deconstruction: opportunities, challenges, trends, and future directions.

4.5. Compatibility and interoperability

Deconstruction is a specialised domain within construction, and like construction, professionals within deconstruction are conventional in their ways, so ensuring AI solutions seamlessly integrate with existing tools and systems used in the deconstruction process is essential. Challenges arise when AI solutions need help fitting into current workflows or more efficient data exchange with other on-site tools.

Addressing these challenges involves tailoring AI applications for easy integration within the industry's infrastructure. This aims to have AI systems complement/enhance, rather than disrupt, established practices. For instance, when AI tools seamlessly communicate with inventory management or structural analysis systems, they optimise decision-making during deconstruction. Ultimately, prioritising compatibility and interoperability not only streamline operations but also significantly boosts efficiency in deconstruction activities.

5. Opportunities and future direction

The paper's findings suggest the need for further research to explore AI's potential in deconstruction. Therefore, some opportunities and future research directions are outlined below (See Fig. 7).

5.1. Robotics and deep reinforcement learning for material audit

Integrating deep reinforcement learning (DRL) for material audit during deconstruction can revolutionise how robots identify, classify, and handle various building materials. By utilising DRL, robots equipped with sensors and cameras can learn to accurately classify materials which are typically difficult to distinguish [78]. This technology allows the robots to continuously improve their material recognition abilities over time, enhancing the precision and efficiency of material audits. Additionally, DRL empowers these robots to develop optimised sorting strategies, learning how to prioritise materials for recycling, reuse, or specific processing based on their properties. This approach streamlines the material audit process, maximises resource recovery, and promotes a circular economy.

5.2. XR-driven feasibility assessment and material reuse potential

Exploring extended reality (XR) in assessing material reuse potential and evaluating deconstruction feasibility is a significant opportunity for future research. By leveraging XR technologies like augmented reality (AR) and virtual reality (VR), researchers can create immersive mock-ups that analyse and visualise potential salvageable material for reuse or recycling from buildings. These simulations could provide valuable insights into recovered materials' condition, usability, and suitability for repurposing. Additionally, XR-driven feasibility assessments can virtually simulate and evaluate the deconstruction process, allowing stakeholders to assess challenges, optimise methodologies, and make informed decisions before physically undertaking the deconstruction. This innovative approach streamlines decision-making processes and contributes to more efficient and cost-effective practices within the deconstruction industry.

5.3. AI-driven reverse logistics

Integrating AI subfields like robotics, optimisation, reality-capturing systems, and machine learning models presents a transformative opportunity for reverse logistics. By deploying these innovations, the intelligent screening of recovered materials at collection points can be readily automated. Furthermore, the advanced capabilities in optimisation algorithms can help solve complex tasks as intricate as path and route optimisation. This streamlines the redirection of the retrieved materials to locations suitable for repurposing/further processing. Leveraging this innovative approach to select the most efficient routes would reduce transportation time while maximising opportunities for material recovery. This convergence of AI-driven technologies would significantly contribute towards more efficient, sustainable, and streamlined materials management in reverse logistics operations within deconstruction.

6. Conclusion

The potential impact of AI on various industries, particularly in tackling and enhancing overall productivity, is undeniable. The deconstruction sector, facing productivity issues and numerous hurdles, stands to benefit significantly from AI's transformative capabilities. With the rapid evolution of digital technologies, AI has the potential to synergise and magnify the effects of these technological advancements within the deconstruction process.

This paper thoroughly investigates the application of AI for deconstruction, encompassing an analysis of recent and relevant studies covering various uses of AI within deconstruction. Our research aims to gauge the extent to which AI has been employed for deconstruction processes, exploring its utilisation across diverse activities. We provided an overview covering AI concepts, types, and subfields, revealing their uses within deconstruction. Furthermore, we outlined the limitations and benefits of each AI subfield, offering a concise summary of their contributions to the field of deconstruction.

Several well-known databases, including Scopus, Association for Computing Machinery (ACM), IEEEXplore, ScienceDirect, and Google Scholar, were searched to retrieve relevant literature/articles published until 2022. This decision was reached to have a comprehensive collection of studies on AI applications for deconstruction, ensuring a robust examination of the subject.

Based on the retrieved literature (i.e., the gathered data), we categorised AI subfields into five: machine learning, robotics, optimisation, knowledge-based systems, reality-capture technologies, and extended reality. Additionally, we organised the applications of these subfields within the context of deconstruction into three stages/phases: planning, implementation, and post-implementation. This structuring allows for a comprehensive understanding of how these AI subfields are utilised at different stages of the deconstruction process, from initial planning to actual implementation and subsequent post-implementation activities.

The paper's findings underscored that machine learning, deep learning, optimisation, and knowledge-based systems emerged as prominent AI subfields extensively employed in deconstruction activities. Conversely, the exploration/ utilisation of robotics, reinforcement learning, and extended reality remained comparatively limited within the AI literature dedicated to deconstruction. Furthermore, despite generative AI's advancement and hype in other studies [137], their potential contributions to deconstruction processes remain largely unexplored and underutilised.

The paper highlights that AI integration in deconstruction is gaining momentum owing to emerging trends like reality-capturing technologies and BIM. However, many are still in their conceptual or laboratory phases. Moreover, we identified challenges impeding the adoption of AI for deconstruction and provided actionable recommendations to overcome these hurdles. Overall, this paper is a valuable resource for researchers and industry professionals, offering insights into relevant AI uses and ongoing research within deconstruction.

Furthermore, this paper provides an overview of what is already in existence (i.e., the AI application areas and the subfields that were employed) and some challenges from the existing literature affecting AI for deconstruction; also, we have suggested possible areas in deconstruction professional can exploit AI for efficiency and productivity (please see Fig. 7). This paper highlights areas that are yet to be explored, and open for research. This will help and serve as a starting point for deconstruction practitioners and researchers in the following ways. For example, support the AI skill force without deconstruction domain expertise to understand areas where AI can be used for deconstruction purposes and help deconstruction practitioners just starting on AI adoption to note subfields and methods that are relevant/feasible for deconstruction activities.

Despite its contributions, it is essential to acknowledge the limitations of this paper. The paper focused solely on journals, conferences, and textbooks, possibly neglecting valuable insights from other literature types. Consequently, the research findings may not present a complete overview of the available literature on AI for deconstruction. Furthermore, the paper primarily examined the methodologies employed in the literature rather than focusing on their results. This narrow focus may have limited our discussion and hindered the thorough validation of the methods used.

These limitations highlight areas for future research. Future studies should address these shortcomings by incorporating data from various sources, evaluating the results, and validating the methods employed in the literature.

CRediT authorship contribution statement

Habeeb Balogun: Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Hafiz Alaka:** Writing – review & editing, Supervision, Software, Resources. **Eren Demir:** Writing – review & editing, Supervision. **Christian Nnaemeka Egwim:** Writing – review & editing, Project administration. **Razak Olu-Ajayi:** Writing – review & editing, Project administration. **Ismail Sulaimon:** Writing – review & editing. **Raphael Oseghale:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

None.

Data availability

No data was used for the research described in the article.

Acknowledgement

We would like to thank Godoyon Wusu, Wasiu Yusuf, and Muideen Adegoke of BDTILab for their insightful feedback/expertise in de/construction and digital technology.

References

[1] World Bank, Urban Development. https://www.worldbank.org/en/topic/urbandevelopment, Mar. 10, 2023.
[2] G. Bertino, J. Kisser, J. Zeilinger, G. Langergraber, T. Fischer, D. Österreicher, Fundamentals of building deconstruction as a circular economy strategy for the reuse of construction materials, Appl. Sci. (Switzerland) 11 (3) (2021) 1–31, https://doi.org/10.3390/app11030939.
[3] H. Balogun, H. Alaka, C.N. Egwim, S. Ajayi, Systematic review of drivers influencing building deconstructability: towards a construct-based conceptual framework, Waste Manag. Res. 41 (2022) 512–530, https://doi.org/10.1177/0734242X221124078.
[4] M. Geissdoerfer, P. Savaget, N.M.P. Bocken, E.J. Hultink, The circular economy – a new sustainability paradigm? J. Clean. Prod. 143 (2017) 757–768, https://doi.org/10.1016/j.jclepro.2016.12.048.
[5] S. Na, S. Heo, S. Han, Y. Shin, M. Lee, Development of an artificial intelligence model to recognise construction waste by applying image data augmentation and transfer learning, Buildings 12 (2) (2022), https://doi.org/10.3390/buildings12020175.
[6] M. Gordon, A. Batallé, C. De Wolf, A. Sollazzo, A. Dubor, T. Wang, Automating building element detection for deconstruction planning and material reuse: a case study, Autom. Constr. 146 (2023) 104697, https://doi.org/10.1016/j.autcon.2022.104697.
[7] A. Tatiya, D. Zhao, M. Syal, G.H. Berghorn, R. LaMore, Cost prediction model for building deconstruction in urban areas, J. Clean. Prod. 195 (2018) 1572–1580, https://doi.org/10.1016/j.jclepro.2017.08.084.
[8] L.A. Akanbi, L.O. Oyedele, K. Omoteso, M. Bilal, O.O. Akinade, A.O. Ajayi, J.M. D. Delgado, H.A. Owolabi, Disassembly and deconstruction analytics system (D-DAS) for construction in a circular economy, J. Clean. Prod. 223 (2019) 386–396, https://doi.org/10.1016/j.jclepro.2019.03.172.
[9] K. Rakhshan, J.-C. Morel, A. Daneshkhah, Predicting the technical reusability of load-bearing building components: a probabilistic approach towards developing a circular economy framework, J. Build. Eng. 42 (2021) 102791, https://doi.org/10.1016/j.jobe.2021.102791.

[10] L.A. Akanbi, A.O. Oyedele, L.O. Oyedele, R.O. Salami, Deep learning model for demolition waste prediction in a circular economy, J. Clean. Prod. 274 (2020) 122843, https://doi.org/10.1016/j.jclepro.2020.122843.

[11] E. Lublasser, L. Hildebrand, A. Vollpracht, S. Brell-Cokcan, Robot assisted deconstruction of multi-layered façade constructions on the example of external thermal insulation composite systems, Constr. Robot. 1 (1–4) (2017) 39–47, https://doi.org/10.1007/s41693-017-0001-7.

[12] B. Sanchez, C. Haas, A novel selective disassembly sequence planning method for adaptive reuse of buildings, J. Clean. Prod. 183 (2018) 998–1010, https://doi.org/10.1016/j.jclepro.2018.02.201.

[13] B. Sanchez, C. Rausch, C. Haas, Deconstruction programming for adaptive reuse of buildings, Autom. Constr. 107 (2019), https://doi.org/10.1016/j.autcon.2019.102921.

[14] R. Volk, Proactive-Reactive, Robust Scheduling, and Capacity Planning of Deconstruction Projects under Uncertainty vol. 20, KIT Scientific Publishing, 2017. ISBN: 3731505924.

[15] R. Volk, N. Sevilmis, F. Schultmann, Deconstruction project planning based on automatic acquisition and reconstruction of building information for existing buildings, in: Smart and Sustainable Built Environment (SASBE) Conference, 2015, p. 47. https://publica.fraunhofer.de/handle/publica/391619.

[16] N. Akbarpour, A. Salehi-Amiri, M. Hajiaghaei-Keshteli, D. Oliva, An innovative waste management system in a smart city under stochastic optimization using vehicle routing problem, Soft. Comput. 25 (2021) 6707–6727, https://doi.org/10.1007/s00500-021-05669-6.

[17] H. Poschmann, H. Brueggemann, D. Goldmann, Disassembly 4.0: a review on using robotics in disassembly tasks as a way of automation, Chem. Ing. Tech. 92 (4) (2020) 341–359, https://doi.org/10.1002/cite.201900107.

[18] A.B. Saka, L.O. Oyedele, L.A. Akanbi, S.A. Ganiyu, D.W.M. Chan, S.A. Bello, Conversational artificial intelligence in the AEC industry: a review of present status, challenges and opportunities, Adv. Eng. Inform. 55 (2023) 101869, https://doi.org/10.1016/j.aei.2022.101869.

[19] A. Darko, A.P.C. Chan, M.A. Adabre, D.J. Edwards, M.R. Hosseini, E.E. Ameyaw, Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities, Autom. Constr. 112 (2020) 103081, https://doi.org/10.1016/j.autcon.2020.103081.

[20] T.D. Akinosho, L.O. Oyedele, M. Bilal, A.O. Ajayi, M.D. Delgado, O.O. Akinade, A. A. Ahmed, Deep learning in the construction industry: a review of present status and future innovations, J. Build. Eng. 32 (2020) 101827, https://doi.org/10.1016/j.jobe.2020.101827.

[21] Y. Xu, Y. Zhou, P. Sekula, L. Ding, Machine learning in construction: from shallow to deep learning, Developm. Built Environ. 6 (2021) 100045, https://doi.org/10.1016/j.dibe.2021.100045.

[22] Y. Pan, L. Zhang, Roles of artificial intelligence in construction engineering and management: a critical review and future trends, Autom. Constr. 122 (2021) 103517, https://doi.org/10.1016/j.autcon.2020.103517.

[23] S.O. Abioye, L.O. Oyedele, L. Akanbi, A. Ajayi, J.M.D. Delgado, M. Bilal, O. O. Akinade, A. Ahmed, Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges, J. Build. Eng. 44 (2021) 103299, https://doi.org/10.1016/j.jobe.2021.103299.

[24] M. Regona, T. Yigitcanlar, B. Xia, R.Y.M. Li, Opportunities and adoption challenges of AI in the construction industry: a PRISMA review, J. Open Innov.: Technol. Mark. Complex. 8 (1) (2022) 45, https://doi.org/10.3390/joitmc8010045.

[25] S.K. Baduge, S. Thilakarathna, J.S. Perera, M. Arashpour, P. Sharafi, B. Teodosio, A. Shringi, P. Mendis, Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications, Autom. Constr. 141 (2022) 104440, https://doi.org/10.1016/j.autcon.2022.104440.

[26] B.I. Oluleye, D.W.M. Chan, P. Antwi-Afari, Adopting artificial intelligence for enhancing the implementation of systemic circularity in the construction industry: a critical review, Sustain. Prod. Consumpt. 35 (2023) 509–524, https://doi.org/10.1016/j.spc.2022.12.002.

[27] A.B. Saka, L.O. Oyedele, L.A. Akanbi, S.A. Ganiyu, D.W.M. Chan, S.A. Bello, Conversational artificial intelligence in the AEC industry: a review of present status, challenges and opportunities, Adv. Eng. Inform. 55 (2023) 101869, https://doi.org/10.1016/j.aei.2022.101869.

[28] R. Charef, Supporting construction stakeholders with the circular economy: a trans-scaler framework to understand the holistic approach, Clean. Eng. Technol. 8 (2022) 100454, https://doi.org/10.1016/j.clet.2022.100454.

[29] K. Rakhshan, J.C. Morel, H. Alaka, R. Charef, Components reuse in the building sector – a systematic review, Waste Manag. Res. 38 (4) (2020) 347–370, https://doi.org/10.1177/0734242X20910463.

[30] R. Charef, E. Ganjian, S. Emmitt, Socio-economic and environmental barriers for a holistic asset lifecycle approach to achieve circular economy: a pattern-matching method, Technol. Forecast. Soc. Chang. 170 (2021) 120798, https://doi.org/10.1016/j.techfore.2021.120798.

[31] R. Charef, J. Morel, K. Rakhshan, Barriers to implementing the circular economy in the construction industry: a critical review, Sustainability 13 (23) (2021) 12989, https://doi.org/10.3390/su132312989.

[32] C.N. Egwim, H. Alaka, E. Demir, H. Balogun, S. Ajayi, Systematic review of critical drivers for delay risk prediction: towards a conceptual framework for BIM-based construction projects, Front. Eng. Built Environ. 3 (1) (2022) 16–31, https://doi.org/10.1108/FEBE-05-2022-0017.

[33] R. Khallaf, M. Khallaf, Classification and analysis of deep learning applications in construction: a systematic literature review, Autom. Constr. 129 (2021) 103760, https://doi.org/10.1016/j.autcon.2021.103760.

[34] M.J. Page, D. Moher, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews, BMJ 372 (2021), https://doi.org/10.1136/bmj.n160.

[35] M. Thelwall, P. Sud, Scopus 1900–2020: growth in articles, abstracts, countries, fields, and journals, Quant. Sci. Stud. 3 (1) (2022) 37–50, https://doi.org/10.1162/qss_a_00177.

[36] M. Bilal, L.O. Oyedele, J. Qadir, K. Munir, S.O. Ajayi, O.O. Akinade, H. A. Owolabi, H.A. Alaka, M. Pasha, Big data in the construction industry: a review of present status, opportunities, and future trends, Adv. Eng. Inform. 30 (3) (2016) 500–521, https://doi.org/10.1016/j.aei.2016.07.001.

[37] K. Meng, G. Xu, X. Peng, K. Youcef-Toumi, J. Li, Intelligent disassembly of electric-vehicle batteries: a forward-looking overview, Resour. Conserv. Recycl. 182 (2022) 106207, https://doi.org/10.1016/j.resconrec.2022.106207.

[38] H. Alaka, L.O. Oyedele, O. Hakeem, S.O. Ajayi, M. Bilal, O.O. Akinade, Methodological approach of construction business failure prediction studies: a review, Constr. Manag. Econ. 34 (11) (2016) 808–842, https://doi.org/10.1080/01446193.2016.1219037.

[39] J. Belur, L. Tompson, A. Thornton, M. Simon, Interrater reliability in systematic review methodology: exploring variation in coder decision-making, Sociol. Methods Res. 50 (2) (2018) 837–865, https://doi.org/10.1177/0049124118799372.

[40] C.N. Egwim, H. Alaka, L.O. Toriola-Coker, H. Balogun, S. Ajayi, R. Oseghale, Extraction of underlying factors causing construction projects delay in Nigeria, J. Eng. Design Technol. 21 (5) (2021) 1323–1342, https://doi.org/10.1108/JEDT-04-2021-0211.

[41] C.N. Egwim, H. Alaka, E. Demir, H. Balogun, R. Olu-Ajayi, I. Sulaimon, G. Wusu, W. Yusuf, A.A. Muideen, Artificial intelligence in the construction industry: a systematic review of the entire construction value chain lifecycle, Energies 17 (1) (2023) 182, https://doi.org/10.3390/en17010182.

[42] S. Olavarrieta, Using single impact metrics to assess research in business and economics: why institutions should use multi-criteria systems for assessing research, J. Econom. Finance Administr. Sci. 27 (53) (2022) 6–33, https://doi.org/10.1108/JEFAS-04-2021-0033.

[43] I.D. Craig, L. Ferguson, A.T. Finch, Journals ranking and impact factors: how the performance of journals is measured, Future Academ. J. (Second Edition) (2014) 259–298, https://doi.org/10.1533/9781780634647.259.

[44] J. Mingers, F. Macri, D. Petrovici, Using the h-index to measure the quality of journals in the field of business and management, Inf. Process. Manag. 48 (2) (2012) 234–241, https://doi.org/10.1016/j.ipm.2011.03.009.

[45] D. Spathis, I. Perez-Pozuelo, L. Marques-Fernandez, C. Mascolo, Breaking away from labels: the promise of self-supervised machine learning in intelligent health, Patterns 3 (2) (2022), https://doi.org/10.1016/j.patter.2021.100410.

[46] V. Uc-Cetina, N. Navarro-Guerrero, A. Martin-Gonzalez, C. Weber, S. Wermter, Survey on reinforcement learning for language processing, Artif. Intell. Rev. 56 (2022) 1543–1575, https://doi.org/10.1007/s10462-022-10205-5.

[47] H. Balogun, H. Alaka, C. Egwim, Boruta-grid-search least square support vector machine for NO2 pollution prediction using big data analytics and IoT emission sensors, Appl. Comp. Inform. (2021), https://doi.org/10.1108/ACI-04-2021-0092.

[48] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, S. Ajayi, Machine learning for energy performance prediction at the design stage of buildings, Energy Sustain. Dev. 66 (2022) 12–25, https://doi.org/10.1016/j.esd.2021.11.002.

[49] R. Olu-Ajayi, H. Alaka, I. Sulaimon, H. Balogun, G. Wusu, W. Yusuf, M. Adegoke, Building energy performance prediction: a reliability analysis and evaluation of feature selection methods, Expert Syst. Appl. 225 (2023) 120109, https://doi.org/10.1016/j.eswa.2023.120109.

[50] H. Alaka, L. Oyedele, H. Owolabi, O. Akinade, M. Bilal, S. Ajayi, A big data analytics approach for construction firms failure prediction models, IEEE Trans. Eng. Manag. 66 (4) (2018) 689–698, https://doi.org/10.1109/TEM.2018.2856376.

[51] M. Chen, R. Qu, W. Fang, Case-based reasoning system for fault diagnosis of aero-engines, Expert Syst. Appl. 202 (2022) 117350, https://doi.org/10.1016/j.eswa.2022.117350.

[52] X. Ye, W.W. Yu, W.H. Yu, L.N. Lv, Simulating urban growth through case-based reasoning, Europ. J. Remote Sens. 55 (1) (2022) 277–290, https://doi.org/10.1080/22797254.2022.2056518.

[53] A.J. Kulkarni, G. Krishnasamy, A. Abraham, "Introduction to Optimization," Cohort Intelligence: A Socio-inspired Optimization Method, Springer International Publishing, 2017, https://doi.org/10.1007/978-3-319-44254-9_1. ISBN. 978–3–319-44253-2.

[54] N. Verdelho Trindade, A. Ferreira, J. Madeiras Pereira, S. Oliveira, Extended reality in AEC, Autom. Constr. 154 (2023) 105018, https://doi.org/10.1016/j.autcon.2023.105018.

[55] M. Al-Adhami, S. Wu, L. Ma, Extended reality approach for construction quality control, in: Proceedings of the 21st CIB World Building Congress. Constructing Smart Cities, Hong Kong SAR, China, 2019, pp. 1127–1135. http://www.irbnet.de/daten/iconda/CIB_DC33672.pdf.

[56] S. Alizadehsalehi, A. Hadavi, J.C. Huang, From BIM to extended reality in AEC industry, Autom. Constr. 116 (2020) 103254, https://doi.org/10.1016/j.autcon.2020.103254.

[57] X. Wang, M.J. Kim, P.E.D. Love, S.-C. Kang, Augmented reality in built environment: classification and implications for future research, Autom. Constr. 32 (2013) 1–13, https://doi.org/10.1016/j.autcon.2012.11.021.

[58] K. Rakhshan, J.-C. Morel, A. Daneshkhah, A probabilistic predictive model for assessing the economic reusability of load-bearing building components:

developing a circular economy framework, Sustain. Prod. Consumpt. 27 (2021) 630–642, https://doi.org/10.1016/j.spc.2021.01.031.
[59] B. Ekanayake, A. Ahmadian Fard Fini, J.K.W. Wong, P. Smith, A deep learning-based approach to facilitate the as-built state recognition of indoor construction works, Constr. Innov. (2022), https://doi.org/10.1108/ci-05-2022-0121.
[60] L.A. Akanbi, A.O. Oyedele, L.O. Oyedele, R.O. Salami, Deep learning model for demolition waste prediction in a circular economy, J. Clean. Prod. 274 (2020) 122843, https://doi.org/10.1016/j.jclepro.2020.122843.
[61] S.R. Cruz-Ramírez, Y. Mae, T. Arai, T. Takubo, K. Ohara, Vision-based hierarchical recognition for dismantling robot applied to interior renewal of buildings, Comput. Aided Civ. Inf. Eng. 26 (5) (2010) 336–355, https://doi.org/10.1111/j.1467-8667.2010.00689.x.
[62] F. Corucci, E. Ruffaldi, Toward autonomous robots for demolitions in unstructured environments, in: Intelligent Autonomous Systems 13, Springer International Publishing, 2015, pp. 1515–1532, https://doi.org/10.1007/978-3-319-08338-4_109.
[63] H.J. Leea, C. Heuera, S. Brell-Cokcana, Concept of a robot assisted on-site deconstruction approach for reusing concrete walls, in: 39th International Symposium on Automation and Robotics in Construction (ISARC), Bogota, Columbia, 2022, pp. 422–429, https://doi.org/10.22260/ISARC2022/0058.
[64] G. Biggs, T. Kotoku, T. Tanikawa, Ceiling beam screw removal using a robotic manipulator, Adv. Robot. 25 (11–12) (2011) 1451–1472, https://doi.org/10.1163/016918611X579484.
[65] A.W. Sadek, M.K. Swailem, A knowledge based expert system for seismic assessment of existing reinforced concrete buildings, in: Proceedings of the Third International Conference on Engineering Computational Technology, 2002, pp. 17–18, https://doi.org/10.4203/ccp.76.6.
[66] S.J. Fenves, E. Ibarra-Anaya, A knowledge-based system for evaluating the seismic resistance of existing buildings, in: Computer Utilization in Structural Engineering, ASCE, 1989, pp. 428–437. ISBN: 0872626989.
[67] E. Queheille, F. Taillandier, N. Saiyouri, Optimization tool of waste management in building deconstruction with environmental criteria, in: 7th International Conference on Sustainable Solid Waste Management, Heraklion, Greece, 2019. https://hal.inrae.fr/hal-02951230.
[68] E. Queheille, F. Taillandier, N. Saiyouri, Optimization of strategy planning for building deconstruction, Autom. Constr. 98 (2019) 236–247, https://doi.org/10.1016/j.autcon.2018.11.007.
[69] B. Sanchez, C. Rausch, C. Haas, Deconstruction programming for adaptive reuse of buildings, Autom. Constr. 107 (2019) 102921, https://doi.org/10.1016/j.autcon.2019.102921.
[70] F. Banfi, A. Mandelli, Computer vision meets image processing and UAS photogrammetric data integration: from HBIM to the eXtended reality project of Arco della Pace in Milan and its decorative complexity, J. Imag. 7 (7) (2021) 118, https://doi.org/10.3390/jimaging7070118.
[71] V. Croce, G. Caroti, L. De Luca, K. Jacquot, A. Piemonte, P. Véron, From the semantic point cloud to heritage-building information modelling: a semiautomatic approach exploiting machine learning, Remote Sens. 13 (3) (2021), https://doi.org/10.3390/rs13030461.
[72] D. Shon, B. Noh, N. Byun, Identification and extracting method of exterior building information on 3D map, Buildings 12 (4) (2022) 452, https://doi.org/10.3390/buildings12040452.
[73] X. Hu, Y. Zhou, S. Vanhullebusch, R. Mestdagh, Z. Cui, J. Li, Smart building demolition and waste management frame with image-to-BIM, J. Build. Eng. 49 (2022) 104058, https://doi.org/10.1016/j.jobe.2022.104058.
[74] Y. Wei, A. Pushkar, B. Akinci, Supporting deconstruction waste management through 3D imaging: a case study, in: Proceedings of the 36th International Symposium on Automation and Robotics in Construction (ISARC), International Association for Automation and Robotics in Construction (IAARC), Canada, 2019, pp. 438–445, https://doi.org/10.22260/ISARC2019/0059.
[75] G. Kaplan, R. Comert, O. Kaplan, D.K. Matci, U. Avdan, Using machine learning to extract building inventory information based on LiDAR data, ISPRS Int. J. Geo Inf. 11 (10) (2022) 517, https://doi.org/10.3390/ijgi11100517.
[76] M. Bassier, M. Vergauwen, B. Van Genechten, Automated classification of heritage buildings for as-built BIM using machine learning techniques, in: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences 4, 2017, pp. 25–30, https://doi.org/10.5194/isprs-annals-IV-2-W2-25-2017.
[77] O. Doukari, D. Greenwood, Automatic generation of building information models from digitized plans, Autom. Constr. 113 (2020) 103129, https://doi.org/10.1016/j.autcon.2020.103129.
[78] I. Brilakis, M. Lourakis, R. Sacks, S. Savarese, S. Christodoulou, J. Teizer, A. Makhmalbaf, Toward automated generation of parametric BIMs based on hybrid video and laser scanning data, Adv. Eng. Inform. 24 (4) (2010) 456–465, https://doi.org/10.1016/j.aei.2010.06.006.
[79] D. Raghu, A. Markopoulou, M. Marengo, I. Neri, A. Chronis, C. De Wolf, Enabling component reuse from existing buildings through machine learning, using google street view to enhance building databases, in: Proceedings of the 27th CAADRIA Conference, Sydney, 2022, pp. 577–586, https://doi.org/10.52842/conf.caadria.2022.2.577.
[80] A. Abdullah, C. Anumba, E. Durmisevic, Decision tools for demolition techniques selection, in: Proceedings of the 11th Rinker International Conference, 2003, pp. 55–72. https://www.irbnet.de/daten/iconda/CIB854.pdf.
[81] C.J. Anumba, A. Abdullah, K. Ruikar, An integrated system for demolition techniques selection, Archit. Eng. Des. Manag. 4 (2) (2008) 130–148, https://doi.org/10.3763/aedm.2008.0071.
[82] A. Abdullah, C. Anumba, E. Durmisevic, Decision tools for demolition techniques selection, in: Proceedings of the 11th Rinker International Conference, 2003, pp. 55–72. https://www.irbnet.de/daten/iconda/CIB854.pdf.
[83] D. Aidonis, Multiobjective mathematical programming model for the optimization of end-of-life buildings deconstruction and demolition processes, Sustainability 11 (5) (2019) 1426, https://doi.org/10.3390/su11051426.
[84] D. Aidonis, Multiobjective mathematical programming model for the optimization of end-of-life buildings deconstruction and demolition processes, Sustainability 11 (5) (2019) 1426, https://doi.org/10.3390/su11051426.
[85] O.L. Sari, T.J.W. Adi, A. Munif, Selection model of building demolition method based on expert system, in: Third International Conference on Sustainable Innovation 2019 – Technology and Engineering (IcoSITE 2019), Atlantis Press, 2019, pp. 58–61, https://doi.org/10.2991/icosite-19.2019.12.
[86] K. Rakhshan, J.-C. Morel, A. Daneshkhah, A probabilistic predictive model for assessing the economic reusability of load-bearing building components: developing a circular economy framework, Sustain. Prod. Consumpt. 27 (2021) 630–642, https://doi.org/10.1016/j.spc.2021.01.031.
[87] F. Hübner, R. Volk, A. Kühlen, F. Schultmann, Review of project planning methods for deconstruction projects of buildings, Built Environ. Project Asset Manag. 7 (2) (2017) 212–226, https://doi.org/10.1108/BEPAM-11-2016-0075.
[88] E. Queheille, F. Taillandier, N. Saiyouri, Optimization of strategy planning for building deconstruction, Autom. Constr. 98 (2019) 236–247, https://doi.org/10.1016/j.autcon.2018.11.007.
[89] E. Queheille, F. Taillandier, N. Saiyouri, Optimization tool of waste management in building deconstruction with environmental criteria, in: 7th International Conference on Sustainable Solid Waste Management, 2019. https://hal.inrae.fr/hal-02951230.
[90] S. Roeslin, Q. Ma, H. Juárez-Garcia, A. Gómez-Bernal, J. Wicker, L. Wotherspoon, A machine learning damage prediction model for the 2017 Puebla-Morelos, Mexico, earthquake, Earthquake Spectra 36 (2) (2020) 314–339, https://doi.org/10.1177/8755293020936714.
[91] D.-C. Feng, Z.-T. Liu, X.-D. Wang, Z.-M. Jiang, S.-X. Liang, Failure mode classification and bearing capacity prediction for reinforced concrete columns based on ensemble machine learning algorithm, Adv. Eng. Inform. 45 (2020) 101126, https://doi.org/10.1016/j.aei.2020.101126.
[92] S. Mangalathu, J.-S. Jeon, Classification of failure mode and prediction of shear strength for reinforced concrete beam-column joints using machine learning techniques, Eng. Struct. 160 (2018) 85–94, https://doi.org/10.1016/j.engstruct.2018.01.008.
[93] R. Yadhunath, S. Srikanth, A. Sudheer, C. Jyotsna, J. Amudha, Detecting surface cracks on buildings using computer vision: An experimental comparison of digital image processing and deep learning, in: V.S. Reddy, V.K. Prasad, J. Wang, K.T. V. Reddy (Eds.), Soft Computing and Signal Processing, Springer Singapore, Singapore, 2022, pp. 197–210, https://doi.org/10.1007/978-981-16-1249-7_20.
[94] M.H. Rafiei, H. Adeli, A novel machine learning-based algorithm to detect damage in high-rise building structures, Struct. Design Tall Spec. Build. 26 (18) (2017) e1400, https://doi.org/10.1002/tal.1400.
[95] L. Liu, R.-J. Yan, V. Maruvanchery, E. Kayacan, I.-M. Chen, L.K. Tiong, Transfer learning on convolutional activation feature as applied to a building quality assessment robot, Int. J. Adv. Robot. Syst. 14 (3) (2017), https://doi.org/10.1177/1729881417712620, 172988141771262.
[96] C. Balaguer, A. Gimenez, C.M. Abderrahim, ROMA robots for inspection of steel based infrastructures, Industr. Robot Int. J. 29 (3) (2002) 246–251, https://doi.org/10.1108/01439910210425540.
[97] F. Inoue, A. Honjo, T. Makino, S. Kwon, Inspection robot system using duct fan and deterioration estimation of building wall that can be applied even in disaster, in: 2018 18th International Conference on Control, Automation and Systems (ICCAS), 2018, pp. 331–334. https://ieeexplore.ieee.org/document/8571997.
[98] S. Terenchuk, A. Pashko, B. Yeremenko, S. Kartavykh, N. Ershova, Modeling an intelligent system for the estimation of technical state of construction structures, East. Europ. J. Adv. Technol. 3 (2) (2018) 47–53. http://nbuv.gov.ua/UJRN/Vejpte_2018_3(2)__7.
[99] K. Morfidis, K. Kostinakis, Approaches to the rapid seismic damage prediction of r/c buildings using artificial neural networks, Eng. Struct. 165 (2018) 120–141, https://doi.org/10.1016/j.engstruct.2018.03.028.
[100] Y. Xu, X. Lu, Y. Tian, Y. Huang, Real-time seismic damage prediction and comparison of various ground motion intensity measures based on machine learning, J. Earthq. Eng. 26 (8) (2022) 4259–4279, https://doi.org/10.1080/13632469.2020.1826371.
[101] L. Haifeng, P. Baoming, An evaluation model of demolished houses based on improved deep learning, in: 2021 7th International Conference on Computer and Communications (ICCC), 2021, pp. 1249–1255, https://doi.org/10.1109/ICCC54389.2021.9674495.
[102] G.-W. Cha, S.-H. Choi, W.-H. Hong, C.-W. Park, Development of machine learning model for prediction of demolition waste generation rate of buildings in redevelopment areas, Int. J. Environ. Res. Public Health 20 (1) (2022) 107, https://doi.org/10.3390/ijerph20010107.
[103] G.W. Cha, H.J. Moon, Y.M. Kim, W.H. Hong, J.H. Hwang, W.J. Park, Y.C. Kim, Development of a prediction model for demolition waste generation using a random forest algorithm based on small DataSets, Int. J. Environ. Res. Public Health 17 (19) (2020) 6997, https://doi.org/10.3390/ijerph17196997.
[104] A. Abdullah, C. Anumba, E. Durmisevic, Decision tools for demolition techniques selection, in: Proceedings of the 11th Rinker International Conference, 2003, pp. 55–72. https://www.irbnet.de/daten/iconda/CIB854.pdf.
[105] F. Schultmann, Dealing with uncertainties in (de-)construction management, the contribution of fuzzy scheduling, in: Deconstruction and Materials Reuse -

Proceedings of the 11th Rinker International Conference on Deconstruction and Materials Reuse, University of Florida, Gainesville, USA 2003, 2003. Ed.: A. Chini, CIB. 15-S, www.irbnet.de/daten/iconda/CIB855.pdf.

[106] F. Hübner, F. Schultmann, Robust multi-mode resource constrained project scheduling of building deconstruction under uncertainty, in: MISTA, 2015, pp. 638–644. https://publikationen.bibliothek.kit.edu/1000052683.

[107] A. Xanthopoulos, D. Aidonis, D. Vlachos, E. Iakovou, A planning optimisation framework for construction and demolition waste management, Int. J. Ind. Syst. Eng. 10 (3) (2012) 257, https://doi.org/10.1504/ijise.2012.045675.

[108] M. Mousavi, A. TohidiFar, A. Alvanchi, BIM and machine learning in seismic damage prediction for non-structural exterior infill walls, Autom. Constr. 139 (2022) 104288, https://doi.org/10.1016/j.autcon.2022.104288.

[109] E. Harirchian, T. Lahmer, V. Kumari, K. Jadhav, Application of support vector machine modeling for the rapid seismic hazard safety evaluation of existing buildings, Energies (Basel) 13 (13) (2020) 3340, https://doi.org/10.3390/en13133340.

[110] S.-H. Hwang, S. Mangalathu, J. Shin, J.-S. Jeon, Machine learning-based approaches for seismic demand and collapse of ductile reinforced concrete building frames, J. Build. Eng. 34 (Aug. 2021) 101905, https://doi.org/10.1016/j.jobe.2020.101905.

[111] M.H. Rafiei, H. Adeli, A novel machine learning-based algorithm to detect damage in high-rise building structures, Struct. Design Tall Spec. Build. 26 (18) (2017) e1400, https://doi.org/10.1002/tal.1400.

[112] B. Ekanayake, A deep learning-based building defects detection tool for sustainability monitoring, in: Proceedings of the 10th World Construction Symposium, 2022, pp. 2–13, https://doi.org/10.31705/WCS.2022.1.

[113] L. Haifeng, P. Baoming, An evaluation model of demolished houses based on improved deep learning, in: 2021 7th International Conference on Computer and Communications (ICCC), 2021, https://doi.org/10.1109/iccc54389.2021.9674495.

[114] A. Tatiya, D. Zhao, M. Syal, G.H. Berghorn, R. LaMore, Cost prediction model for building deconstruction in urban areas, J. Clean. Prod. 195 (2018) 1572–1580, https://doi.org/10.1016/j.jclepro.2017.08.084.

[115] L.A. Akanbi, A.O. Oyedele, L.O. Oyedele, R.O. Salami, Deep learning model for demolition waste prediction in a circular economy, J. Clean. Prod. 274 (2020) 122843, https://doi.org/10.1016/j.jclepro.2020.122843.

[116] G.-W. Cha, S.-H. Choi, W.-H. Hong, C.-W. Park, Development of machine learning model for prediction of demolition waste generation rate of buildings in redevelopment areas, Int. J. Environ. Res. Public Health 20 (1) (2022) 107, https://doi.org/10.3390/ijerph20010107.

[117] S.R. Cruz-Ramirez, Y. Ishizuka, Y. Mae, T. Takubo, T. Arai, Dismantling interior facilities in buildings by human robot collaboration, in: 2008 IEEE International Conference on Robotics and Automation, 2008, https://doi.org/10.1109/robot.2008.4543602.

[118] E. Lublasser, L. Hildebrand, A. Vollpracht, S. Brell-Cokcan, Robot assisted deconstruction of multi-layered façade constructions on the example of external thermal insulation composite systems, Constr. Robot. 1 (1–4) (2017) 39–47, https://doi.org/10.1007/s41693-017-0001-7.

[119] S. Lee, W. Pan, T. Linner, T. Bock, A framework for robot assisted deconstruction: process, sub-systems and modelling, in: 32nd ISARC: Proceedings of the International Symposium on Automation and Robotics in Construction, 2015, https://doi.org/10.22260/ISARC2015/0093.

[120] E. Lublasser, K. Iturralde, T. Linner, S. Brell Cokcan, T. Bock, Automated refurbishment & end-of-life processes research approaches in German and Japanese construction, in: Proceedings of the CIB* IAARC W119 CIC 2016 Workshop, 2016. https://publications.rwth-aachen.de/record/679386.

[121] D. Van Dao, H.-B. Ly, S.H. Trinh, T.-T. Le, B.T. Pham, Artificial intelligence approaches for prediction of compressive strength of geopolymer concrete, Materials 12 (6) (2019) 983, https://doi.org/10.3390/ma12060983.

[122] W. Xiao, J. Yang, H. Fang, J. Zhuang, Y. Ku, X. Zhang, Development of an automatic sorting robot for construction and demolition waste, Clean Techn. Environ. Policy 22 (9) (2020) 1829–1841, https://doi.org/10.1007/s10098-020-01922-y.

[123] A. Xanthopoulos, E. Iakovou, On the optimal design of the disassembly and recovery processes, Waste Manag. 29 (5) (2009) 1702–1711, https://doi.org/10.1016/j.wasman.2008.11.009.

[124] A. Xanthopoulos, D. Aidonis, D. Vlachos, E. Iakovou, A planning optimisation framework for construction and demolition waste management, Int. J. Ind. Syst. Eng. 10 (3) (2012) 257–276, https://doi.org/10.1504/IJISE.2012.045675.

[125] J. Duan, P.G. Asteris, H. Nguyen, X.-N. Bui, H. Moayedi, A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model, Eng. Comput. 37 (4) (2021) 3329–3346, https://doi.org/10.1007/s00366-020-01003-0.

[126] Z. Wang, H. Li, X. Zhang, Construction waste recycling robot for nails and screws: computer vision technology and neural network approach, Autom. Constr. 97 (2019) 220–228, https://doi.org/10.1016/j.autcon.2018.11.009.

[127] Z. Wang, H. Li, X. Yang, Vision-based robotic system for on-site construction and demolition waste sorting and recycling, J. Build. Eng. 32 (2020) 101769, https://doi.org/10.1016/j.jobe.2020.101769.

[128] Y. Ku, J. Yang, H. Fang, W. Xiao, J. Zhuang, Deep learning of grasping detection for a robot used in sorting construction and demolition waste, J. Mater. Cycles Waste Manage. 23 (1) (2021) 84–95, https://doi.org/10.1007/s10163-020-01098-z.

[129] H. Balogun, H. Alaka, N.C. Egwim, S. Ajayi, Random forest feature selection for particulate matter (PM10) pollution concentration, in: Environmental Design and Management Conference (EDMIC), 2021, pp. 576–587. http://hdl.handle.net/2299/27125.

[130] H. Balogun, H. Alaka, N.C. Egwim, S. Ajayi, An application of machine learning with Boruta feature selection to improve NO2 pollution prediction, in: Environmental Design and Management Conference (EDMIC), Bristol, United Kingdom, 2021, pp. 551–561. http://hdl.handle.net/2299/27086.

[131] C.N. Egwim, H. Alaka, L.O. Toriola-Coker, H. Balogun, F. Sunmola, Applied artificial intelligence for predicting construction projects delay, Mach. Learn. Appl. 6 (2021) 100166, https://doi.org/10.1016/j.mlwa.2021.100166.

[132] A. Akbarieh, L.B. Jayasinghe, D. Waldmann, F.N. Teferle, BIM-based end-of-lifecycle decision making and digital deconstruction: literature review, Sustainability 12 (7) (2020) 2670, https://doi.org/10.3390/su12072670.

[133] L. Liu, R.-J. Yan, V. Maruvanchery, E. Kayacan, I.-M. Chen, L.K. Tiong, Transfer learning on convolutional activation feature as applied to a building quality assessment robot, Int. J. Adv. Robot. Syst. 14 (3) (2017), https://doi.org/10.1177/1729881417712620, 1729881417712620.

[134] Y. Sun, Z. Gu, Using computer vision to recognize construction material: a trustworthy dataset perspective, Resour. Conserv. Recycl. 183 (2022) 106362, https://doi.org/10.1016/j.resconrec.2022.106362.

[135] J.K. Low, S.L. Wallis, G. Hernandez, I.S. Cerqueira, G. Steinhorn, T.-A. Berry, Encouraging circular waste economies for the New Zealand construction industry: opportunities and barriers, Front. Sustain. Cities 2 (2020) 35, https://doi.org/10.3389/frsc.2020.00035.

[136] M.E. Aguilar-Fernández, J.R. Otegi-Olaso, Firm size and the business model for sustainable innovation, Sustainability 10 (12) (2018), https://doi.org/10.3390/su10124785.

[137] A. Saka, R. Taiwo, N. Saka, B.A. Salami, S. Ajayi, K. Akande, H. Kazemi, GPT models in construction industry: opportunities, limitations, and a use case validation, Developm. Built Environ. 17 (2024) 100300, https://doi.org/10.1016/j.dibe.2023.100300.