Journal of Environmental Management 373 (2025) 123560

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Review

Applying digital technologies in construction waste management for facilitating sustainability

Wenbo Zhao [a,b], Jian Li Hao [a,c,*], Guobin Gong [a,c], Thomas Fischer [b], Yong Liu [d]

[a] Department of Civil Engineering, Design School, Xi'an Jiaotong-Liverpool University, Suzhou, China
[b] Department of Geography and Planning, School of Environmental Science, University of Liverpool, Liverpool, UK
[c] Department of Civil and Environmental Engineering, School of Engineering, University of Liverpool, Liverpool, UK
[d] School of Civil Engineering and Architecture, Zhejiang Sci-Tech University, Hangzhou, China

ARTICLE INFO

Keywords:
Construction waste management
Sustainability
Digital technologies
Science mapping

ABSTRACT

Although digital technologies (DTs) offer innovative sustainability solutions, their applications in construction waste (CW) management remain limited and face numerous challenges. Effective analysis of current applications, challenges, and future opportunities is crucial for advancing DTs in this field. Driven by four research questions, this paper reviews the application of DTs in CW management through a science mapping approach, analyzing 138 papers from 2014 to 2024. Influential journals, countries, and authors were analyzed. Then, a keyword co-occurrence analysis identified three latest primary research areas. The paper examines the current application and limitations of six commonly used DTs in CW management identified through keyword occurrence frequency: building information modeling (BIM), artificial intelligence (AI), geographic information systems (GIS), big data (BD), remote sensing (RS), and radio frequency identification (RFID). Research. This paper reviews the applications of DTs in CW management, advancing knowledge, informing decision-making, and guiding future research toward furthering sustainable CW management.

1. Introduction

Rapid urbanization has led to the depletion of natural resources and resulted in a significant accumulation of construction waste (CW). Climate change has increasingly become a global concern in recent times (Singh et al., 2023). The predominant disposal method for CW, landfilling, consumes land resources and contributes to greenhouse gas emissions (Hossain et al., 2017; Ottenhaus et al., 2023; Wang et al., 2019a). Despite 75% of CW having recycling potential, more than 35% of it globally is still being landfilled (Soto-Paz et al., 2023a). Increasing the reuse and recycling rates of CW is essential for achieving sustainability.

Achieving closed-loop management of construction materials involves implementing waste reduction, recycling, and reuse strategies as coming to the end of materials' lifecycle (Jacobsen et al., 2018). Despite research efforts to enhance CW management and optimize processes, various challenges remain unresolved, such as inadequate design quality, inefficient material handling, and deficiencies during purchasing and planning phase (Won and Cheng, 2017). CW management is transitioning from the basic material collection and sorting practices towards the implementation of sustainable recycling systems, with an increasingly high requirement for efficient waste management.

Due to their potential to enhance efficiency, reduce costs, and promote resource recycling, digital technologies (DTs) can be applied individually or in combination to effectively manage CW and thereby facilitate sustainable development. To achieve global sustainability goals, digital tools are increasingly being adopted to transform the operations, business models, and value-creation modes of companies involved in CW management (Ayub et al., 2021). Technological advancements offer resolutions for CW management, driving long-term societal benefits. By integrating circular economy principles, digitalization enhances resource recovery, reduces costs, and improves CW flow traceability (Kurniawan et al., 2022; Milios, 2021). DTs in CW management boost efficiency through automation, real-time monitoring, data-driven decisions, improving waste tracking, recycling processes, and resource recovery (Fang et al., 2023).

Previous studies have reviewed the applications of DTs in CW management. For example, Sepasgozar et al. (2021) employed social network analysis and statistical techniques to identify key authors, institutions, and research trends, revealing gaps in construction materials

* Corresponding author. Department of Civil Engineering, Design School, Xi'an Jiaotong-Liverpool University, Suzhou, China
E-mail addresses: jianli.hao@xjtlu.edu.cn, jianlhao@gmail.com (J.L. Hao).

https://doi.org/10.1016/j.jenvman.2024.123560
Received 4 August 2024; Received in revised form 22 October 2024; Accepted 30 November 2024
Available online 5 December 2024
0301-4797/

analysis and DTs applied in CW management. Cheah et al. (2022) explored how Industry 4.0 technologies can improve solid waste management through digital applications and machinery that facilitate a circular economy, emphasizing innovations in DTs for CW segregation and material traceability. Kannan et al. (2024) developed a framework for smart CW management 4.0 by integrating Industry 4.0 technologies and identifying key pillars for enhancing CW practices. However, despite the potential of DTs in CW management, there exists a gap in research comprehensively examining their application for enhancing sustainability (Li et al., 2020a; Sepasgozar et al., 2021). In addition, some papers focus on only one type of DTs or one step of the CW management process, which addresses specific challenges but may overlook the benefits of integrating multiple tools for improving overall performance (Lin et al., 2022; Maiurova et al., 2022). To address the gap, this paper conducts an extensive review to investigate existing knowledge and future directions regarding the utilization of DTs to advance sustainable CW management. A new approach is proposed by utilizing science mapping to explore the applications, challenges, and future directions of DTs in CW management. The paper solves the key research questions below to advance knowledge and guide future research, thereby enhancing sustainability and efficiency in CW management.

RQ1. Which journals, countries, and authors have made significant contributions to applying DTs in CW management?

RQ2. What are the interrelationships among these contributing journals, countries, and authors in the context of applying DTs in CW management?

RQ3. What are the current primary research topics related to the application of DTs in CW management?

RQ4. What are the status quo, limitations, and future research directions for the application of commonly used DTs in CW management?

2. Research methodology

This paper employs a science mapping approach, integrating quantitative and qualitative analyses to review DT applications in CW management. The science mapping approach includes qualitative discussion, scientometric analysis, and bibliometric search (Jin et al., 2019). Fig. 1

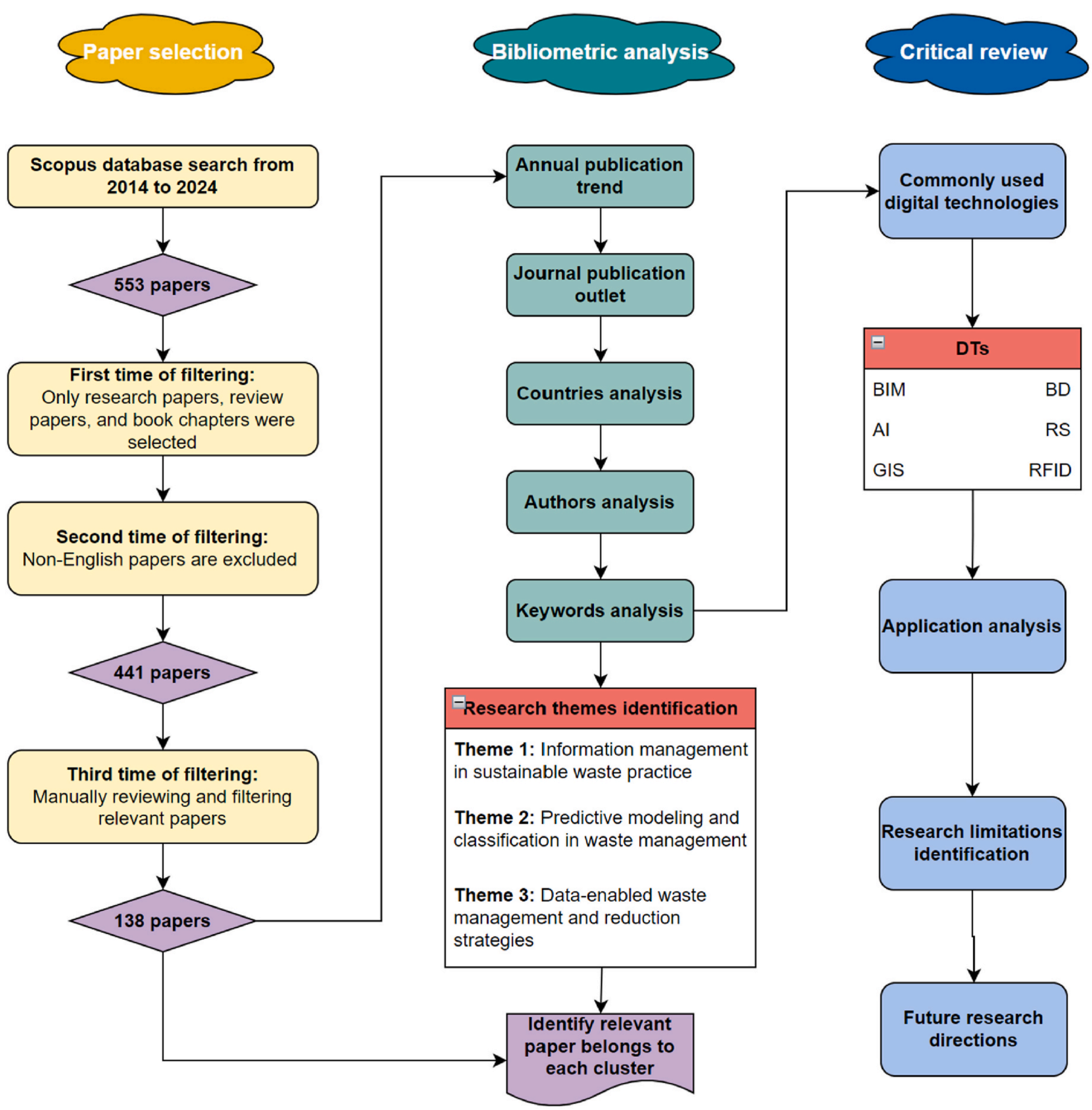

Fig. 1. Overall methodological framework.

depicts the overall methodological framework utilized in this study.

This paper reviews the application of DTs in CW management over the past 10 years, with 2014 chosen as the starting point due to the limited relevant research before 2014 and the significant advancements in DTs, along with the increased attention and usage in CW management thereafter. For the scientometric analysis, the Scopus database was applied to retrieve relevant papers from 2014 to 2024. Scopus is the largest peer-reviewed database, encompassing a larger number of papers, compared to other accessible databases (Nawaz et al., 2023; Song et al., 2016). The first step is developing a search syntax that includes essential terms associated with DTs utilized in CW. There are four types of waste that can be categorized as CW: construction waste, demolition waste (DW), renovation waste, (Hao and Ma, 2023), and decoration waste (Yu et al., 2023). The possible DTs that can be applied in CW have also been included in the research algorithm.

All keywords related to CW and DTs are included in the research algorithm for a comprehensive review. CW arises from activities involving the construction, demolition, renovation, decoration, and repair of facilities and infrastructures (Llatas, 2011; Lu et al., 2017; Wang et al., 2021). The research algorithm also encompasses all types of DTs, including their abbreviations and synonyms, applicable to CW management. Therefore, the research algorithm for this paper is TITLE-ABS-KEY ("construction and demolition waste" OR "building waste" OR "construction waste" OR "demolition waste" OR "renovation waste" OR "decoration waste") AND TITLE-ABS-KEY ("management") AND TITLE-ABS-KEY ("digital transformation" OR "technology" OR "technologies" OR "construction 4.0″ OR "digitalization" OR "digitalization" OR "digital construction" OR "BIM" OR "building information modeling" OR "building information modeling" OR "IoT" OR "Internet of Things" OR "blockchain" OR "digital twin" OR "digital twins" OR "AI" OR "artificial intelligence" OR "big data" OR "GIS" OR "geographic information system" OR "VR" OR "virtual reality" OR "AR" OR "augmented reality" OR "cloud computing" OR "robotics" OR "point cloud computing" OR "RFID" OR "radio frequency identification" OR "sensors" OR "digital platform" OR "machine learning" OR "deep learning" OR ″3D printing" OR ″3D scanning" OR "laser scanning" OR "laser scanner" OR "drone" OR "unmanned aerial vehicle" OR "UAV" OR "GPS" OR "global positioning system" OR "RTLS" OR "real-time location system" OR "CIM" OR "construction information modeling" OR "construction information modeling" OR "construction information management" OR "photogrammetry" OR "natural language processing" OR "artificial neural networks" OR "image segmentation" OR "remote sensing" OR "semantic segmentation" OR "computer vision" OR "transfer learning" OR "object detection" OR "computer vision" OR "information technology" OR "image recognition" OR "image analysis" OR "barcode technology").

The research initially retreived 553 results from Scopus in total from the year 2014–2024 including all document types as of April 5, 2024. To guarantee reliability and quanlity of the papers analyzed in this research, three filtering steps have been applied. Firstly, only articles, review papers, and book chapters are included, as these sources undergo a stringent peer-review process (Olawumi and Chan, 2018; Omrany et al., 2022). Secondly, the non-English papers are excluded from the analysis, leading to a total of 411 papers. Finally, all papers meeting the requirements were screened to ensure high relevance to the research content. Through a series of filtering and screenings, a total of 138 articles were ultimately chosen for analysis.

In this paper, VOSviewer software is used to analyze and visualize bibliometric networks, where VOS stands for "visualizing overlapping sets". VOSviewer can examine the bibliometric network connections within DTs related to CW management, covering aspects such as the number of publications, co-authorship, and country involvement. Then the co-occurrence of keywords was mapped, through which the main research topics were identified. Finally, a qualitative analysis was conducted to discuss the application, limitations, and future directions of the commonly used DTs.

3. Scientometric analysis

3.1. Annual publication trend and journal publication analysis

The trend of the number of publications regarding the application of DTs in CW management in the past 10 years is shown in Fig. 2. Omitting the incomplete information for 2024, the total of publications from 2014 to 2023 is generally increasing. This suggests that there has been a growing interest and output within the research domain regarding applying DTs in CW in recent years.

The 138 papers are distributed across 48 journals. For the analysis of journals, the minimum requirement is set at 5 documents per journal and 30 citations per journal. There are 7 journals that meet the threshold out of the 48 journals. The node sizes in network maps reflect the volume of publications from specific journals visually, with larger nodes denoting a greater number of publications (Jin et al., 2019). Fig. 3 illustrates the science mapping of journals of the selected papers, revealing the interrelationship among the journals. Analyzing annual publication trends and journal outputs visualize the increasing number of publications, which reflects a growing focus on applying DTs in CW management. The expanding number of literature not only reveals the advancing understanding of these technologies but also lays a foundation for future research. Mapping annual journal outputs helps identify key contributors and emerging themes, offering insights into how DTs can address the challenges in CW management.

Table 1 presents information on the 7 journals having the most publications. Ranked from highest to lowest, the top three journals with the highest number of published papers are WM, RCR, and JCP. Similarly, the total citations of journals, in descending order, are JCP, RCR, and WM. Average citation values are derived by dividing the overall citations by publication numbers. In terms of average citations, the journals rank highest to lowest are JCP, RCR, and AC.

3.2. Science mapping of countries

The science mapping of countries shown in Fig. 4 demonstrates the most productive nations in the research area of implementing DTs in CW management. Understanding these leading countries is crucial for fostering research funding and collaborations, as well as identifying influential contributors to the field (Tariq et al., 2021). The minimum requirement for the number of publications every country is set at 4, and for citations, it is set at 5. Out of the 42 countries, 13 meet the thresholds. Table 2 provides detailed information about these 13 countries. The science mapping of countries identifies the most productive nations and potential collaboration opportunities among countries. Additionally, it reveals influential contributors, enabling stakeholders to connect with leading researchers and institutions globally. This mapping enhances understanding of global research dynamics and informs strategic decisions for sustainable practices in CW management.

There are four clusters of countries categorized by the frequency with which they reference each other. For instance, Mainland China, the United States, Hong Kong, and Saudi Arabia are grouped together in a cluster identified by the color red. The other three clusters are denoted in green, blue, and yellow. Mainland China has the largest node, indicating it has the highest number of relevant publications, totaling 45. Following Mainland China, Hong Kong and Australia have 23 and 19 publications, respectively. However, countries with a large number of publications do not necessarily have a high average citation count. The average citations per paper in the United States is the highest, at 77 citations, followed by Nigeria, Hong Kong, and the United Kingdom.

3.3. Science mapping of authors

In conducting the co-authorship analysis in CW, the criteria for the minimum publications per author is set to 5, and the minimum citations received by an author is set to 30. A total of 9 authors out of the 442

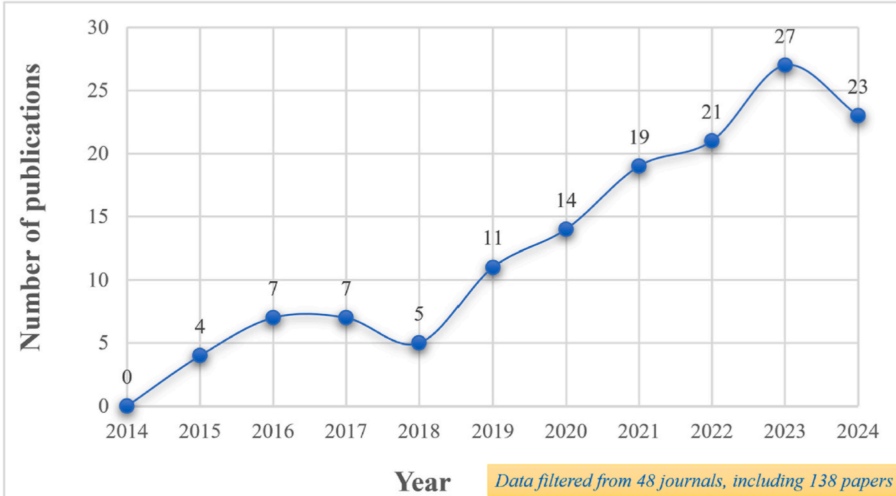

Fig. 2. Yearly publications from 2014 to 2024.

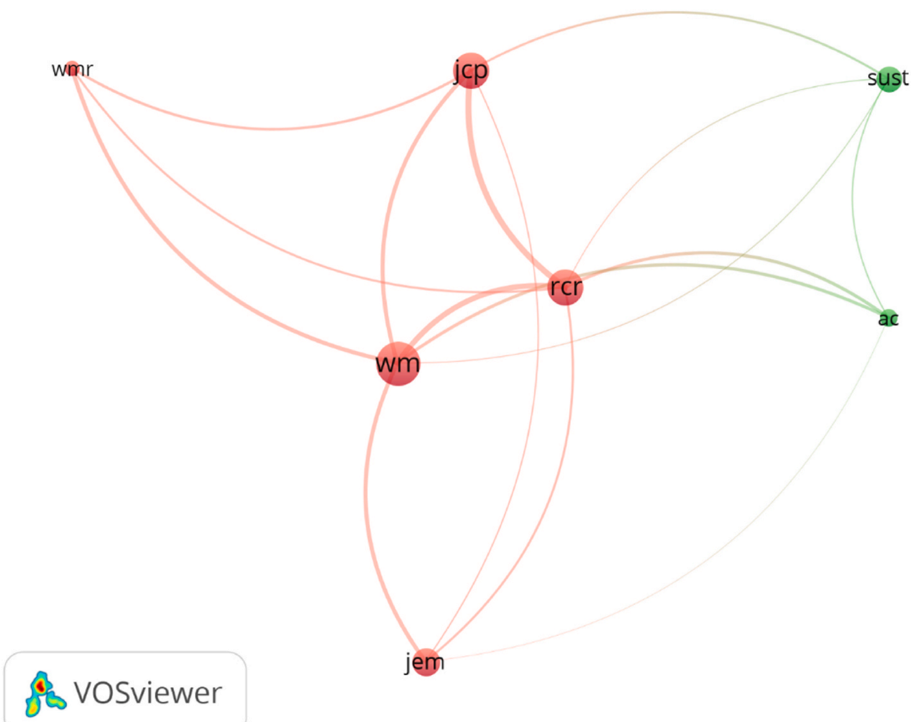

Fig. 3. Science mapping of journals* * WM=Waste Management; RCR=Resources, Conservation and Recycling; JCP = Journal of Cleaner Production; JEM = Journal of Environmental Management; SUST=Sustainability; AC=Automation in Construction; WMR=Waste Management and Research.

authors meet these thresholds. The science mapping of the authors is depicted in Fig. 5. The science mapping of authors identifies key contributors, influential researchers, and collaboration patterns, guiding future studies and promoting cooperation in CW management. It also reveals gaps and supports the advancement of digital tools for managing CW.

Table 3 presents detailed information about the contributions of the 9 authors in the area. Lu W. is identified as the most productive author, having contributed 18 relevant papers with a total of 867 citations. Akinade O. has contributed 5 relevant papers, achieving the highest average citations among all nine authors, indicating a high impact. Oyedele L. is also a highly influential author, ranking second in both average citations, with 94, and total citations, with 565, among the nine authors.

4. Major research area analysis

The main research areas for applying DTs in CW management are identified through the co-occurrence of keyword analysis. A keyword network can provide visualization of significant research topics and their mutual association (Wuni et al., 2019). A thesaurus file is developed to combine similar and redundant keywords, ensuring alignment with matching terms (Oluleye et al., 2022). A substantial node size denotes frequent item occurrence, while thick connection lines indicate strong item relationships, with different colors distinguishing nodes into separate clusters (Li et al., 2020a).

Tables S1, S2, and S3 of the supplementary material provide detailed summaries of relevant papers categorized under each research theme, demonstrating applied DTs and their applications in CW management.

Table 1
Quantitative measurements of journals.

Acronym	Journal	Documents	Citations	Average citations	Total link strength
WM	Waste Management	17	717	42	48
RCR	Resources, Conservation and Recycling	14	727	52	44
JCP	Journal of Cleaner Production	14	1007	72	36
JEM	Journal of Environmental Management	11	193	18	18
SUST	Sustainability (Switzerland)	10	78	8	12
AC	Automation in Construction	7	353	50	18
WMR	Waste Management and Research	6	158	26	20

The minimum occurrence times of keywords is set as 7. Of all the 1377 keywords, 49 keywords meet the threshold. Through the co-occurrence of keywords using VOSviewer, all keywords associated with each cluster have been identified. This analysis revealed recurring themes and patterns, which were classified into three distinct clusters based on the frequency and relationships of keywords within each cluster. Three clusters were identified each representing a different research area, as shown in Fig. 6.

4.1. Cluster 1: Strategic information management in sustainable CW practice

There are 18 items belonging to the first cluster: architectural design, BIM, CW, charge density waves, circular economy, construction, construction and building industry, decision making, demolition, economics, environmental impact, GIS, image analysis, information management, information theory, life cycle, recycling, sustainable development. The 18 keywords in Cluster 1 emphasize the crucial role of information in optimizing CW management strategies. For example,

Table 2
Quantitative measurements of top countries.

Country	Documents	Citations	Average citations	Total link strength
Mainland China	45	1419	32	201
Hong Kong	23	1471	64	194
Australia	19	573	30	111
United Kingdom	16	908	57	71
South Korea	13	465	36	69
United States	8	618	77	96
India	8	42	5	15
Brazil	6	82	14	22
Malaysia	5	85	17	26
Canada	5	55	11	21
Nigeria	4	188	47	39
Pakistan	4	257	64	24
Egypt	4	8	2	9

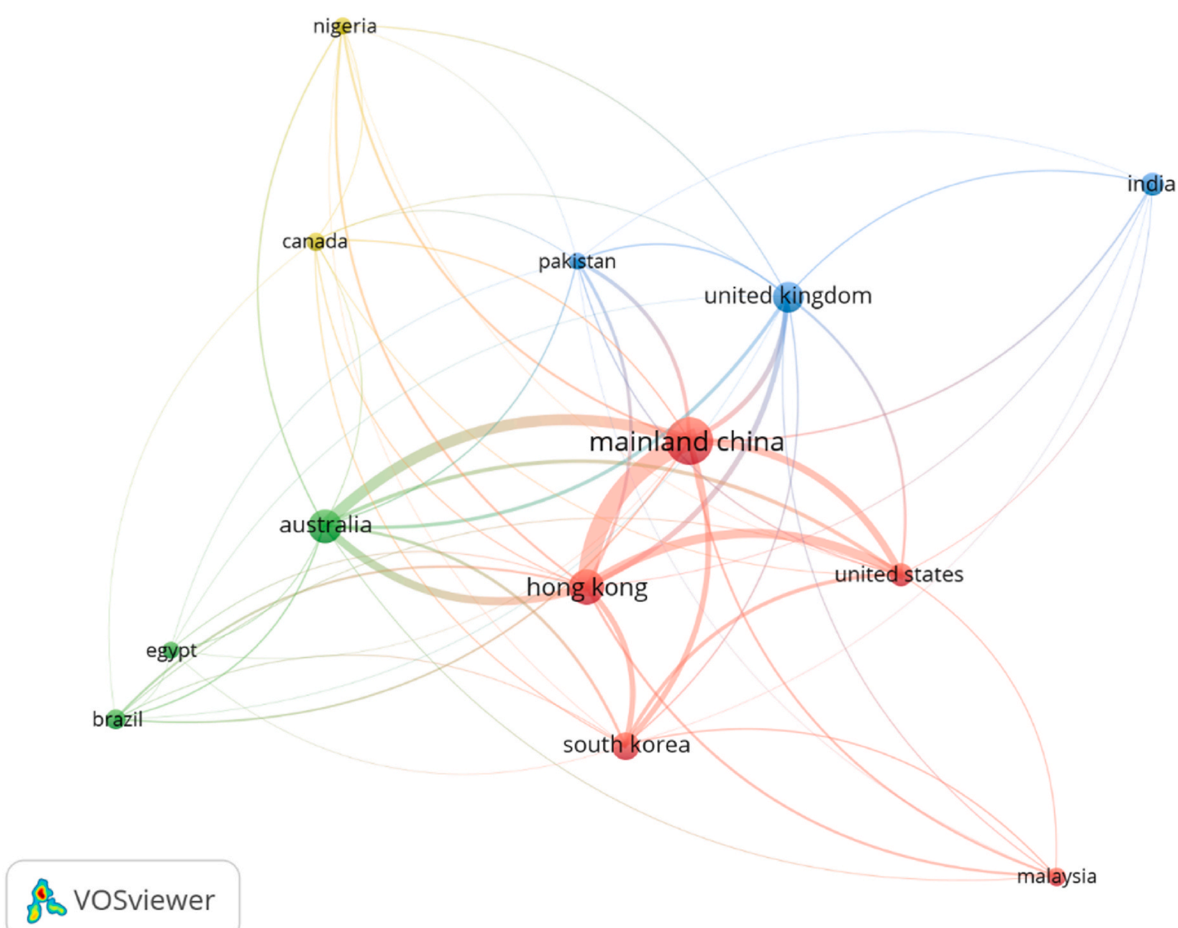

Fig. 4. Science mapping of productive countries.

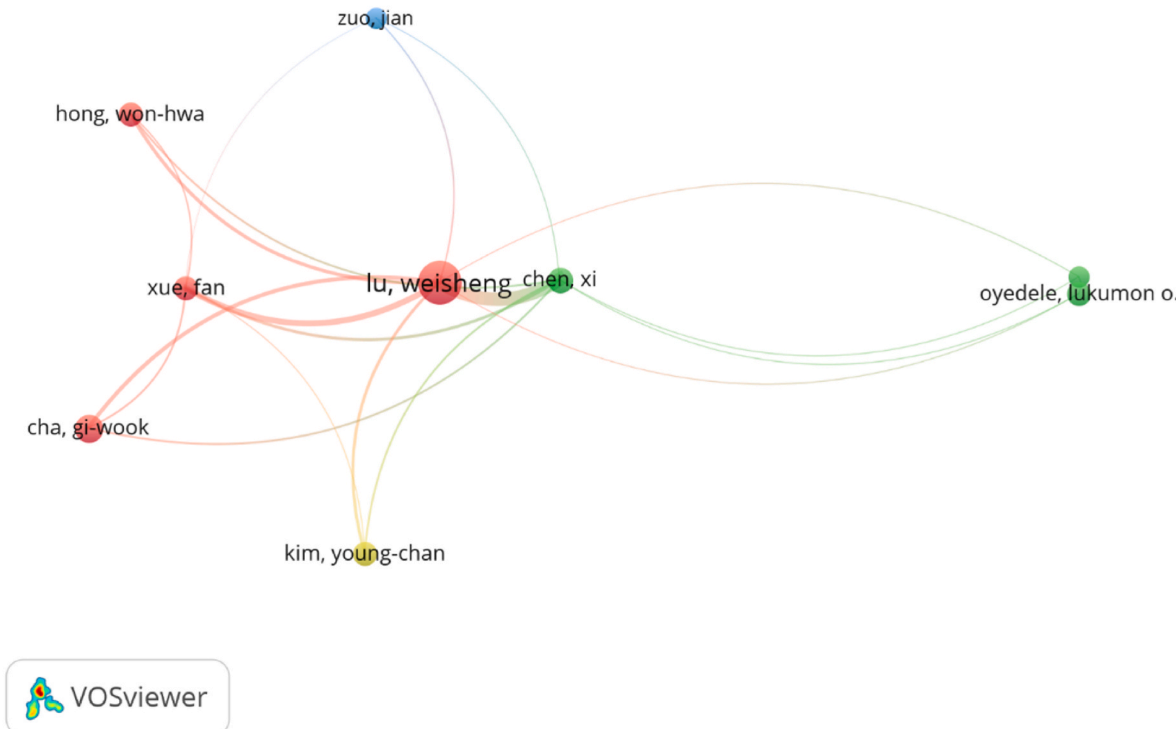

Fig. 5. Science mapping of influential authors.

Table 3
Quantitative measurements of high-influential authors.

Author	Documents	Citations	Average citations	Total link strength
Lu, Weisheng	18	867	48	67
Cha, Gi-wook	8	176	22	16
Chen, Xi	7	529	76	51
Hong, Won-hwa	6	118	20	14
Kim, Young-chan	6	166	28	12
Oyedele, Lukumon	6	565	94	6
Xue, Fan	6	184	31	28
Okinade, Olugbenga	5	478	96	6
Zuo, Jian	5	176	35	6

terms like ‘life cycle’ and ‘recycling’ underscore the importance of understanding material flows and resource recovery within a circular economy framework. Terms such as ‘BIM’, ’GIS’, and ‘image analysis’ highlight advanced technological tools for effective information visualization and decision-making. Additionally, keywords like ‘sustainable development’ and ‘environmental impact’ reflect a focus on integrating information management strategies to enhance sustainability outcomes in CW management. By linking these keywords, the cluster theme reveals the role of DTs in information management for developing CW strategies.

Information on waste is useful for managing waste strategies, including landfilling planning, subsidies for recycling, fees for pollution behavior, and waste management policies (Lu et al., 2021a). Relevant DTs for CW information management include BIM, GIS, CIM, blockchain, material passports, radio frequency identification (RFID), internet of things (IoT), and remote sensing (RS). Cluster 1 emphasizes the strategic use of information to support long-term decision-making in sustainable CW management, utilizing standardized data and structured information flows to achieve sustainability goals at policy and management levels. The details of the relevant papers in Cluster 1 can be found in Table S1 of the supplementary material. The three main research topics under cluster 1 are summarized in sections 4.1.1 to 4.1.3.

4.1.1. Developing a decision-making system for site selection

One of the most important research topics in information management is developing a decision-making system, for determining the location of waste recycling or disposal sites and predicting illegal dumping places. Securing environmental and social sustainability requires prioritizing strategies that reduce waste and promote circularity (Matlin et al., 2020; Song et al., 2024; Yu et al., 2022). GIS is effective for managing geographic data (Khater et al., 2022; Mousavi et al., 2023; Singh, 2019), which is crucial when making decisions for CW management (Paul and Bussemaker, 2020). The utilization of GIS with other DTs, such as RS and IoT, can assist in spatial data analysis, decision-making processes, and resource management.

RS and GIS are increasingly utilized in the management of landfills (Singh, 2019). RS technologies, such as radar, satellite imagery, and aerial photography, can monitor real-time factors including waste accumulation, landfilling sites, and landfilling rates (Fraternali et al., 2024; Sharma and Sood, 2024). IoT technology can promote smart waste management systems by providing real-time data (Hussain et al., 2024; Olawade et al., 2024). The expansion of IoT and interconnected devices has increased data collection, enhancing decision-making systems (Garcia-de-Prado et al., 2017; Koot et al., 2021; Louis and Dunston, 2018). The fusion of GIS with real-time data-collecting technologies not only enables spatial analysis but also facilitates real-time decision-making, making it a prominent research area.

4.1.2. Storing, sharing, and visualizing life cycle building information

Another research topic in the information management of CW is the storing and sharing of building life cycle data. Buildings can generate large quantities of data throughout their life cycle, including the end-of-life phase. Using parametric modeling, data on waste such as type and quantity can be extracted and stored in an information platform (Guerra et al., 2019). BIM transforms information into three-dimensional (3D) models, representing both the functional and physical attributes of construction projects within collaborative digital formats (Su et al.,

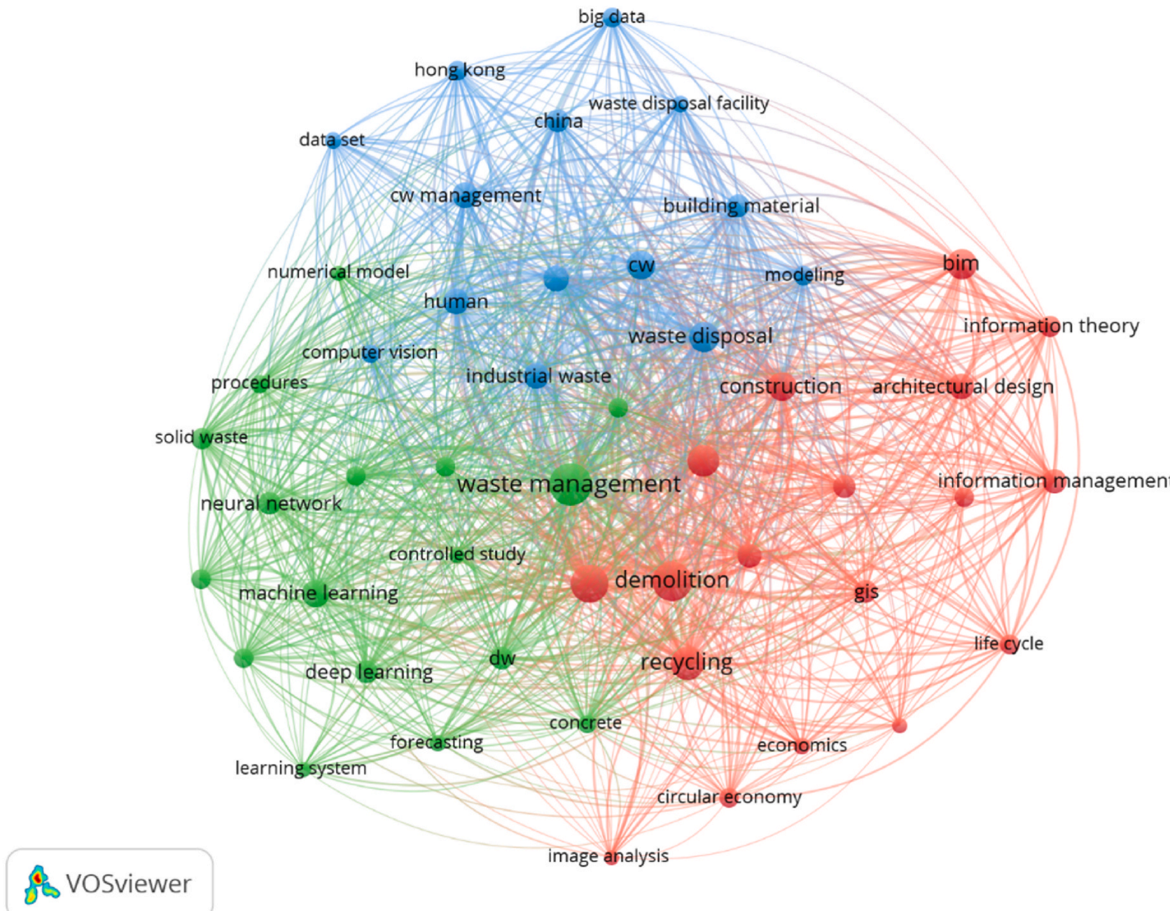

Fig. 6. Major research areas of DTs in CW management.

2021). Promoting the sharing of data between involved parties through the BIM platform results in enhanced coordination and decreased errors (Aziz et al., 2024). Leveraging BIM aids stakeholders in making informed decisions regarding CW management (Hao et al., 2024), such as taxes, transportation costs, and landfilling fees (Cheng and Ma, 2013; Kim et al., 2017). The proper management of building information enhances the efficiency and effectiveness of managing CW, enabling better decision-making and resource allocation over the life cycle of buildings.

Apart from BIM-relevant technologies, other information-related technologies, such as CIM, can also be applied in storing, sharing, and visualizing building information. CIM has been commonly applied in CW management, such as waste quantification (Guerra et al., 2019), integration and collaboration of models for information sharing (Ghaffarianhoseini et al., 2017; Liu et al., 2015), and 3D visualization (Li et al., 2017). The storing, sharing, and visualization functions of relevant information management technologies allow for a more holistic approach to waste management, enabling stakeholders to optimize resource allocation, minimize waste generation, and adhere to sustainability goals.

4.1.3. Developing material passport for effective CW management

Efficient information management is crucial in the administration of CW, and material passports are emerging as a promising solution in this regard. Typically, a material passport can provide detailed information about the materials used in buildings (Honic et al., 2021). The development of material passports should be based on several technologies, such as BIM, blockchain, and RFID. Material passports gather information on different types of waste materials, thereby promoting the reusing or recycling of waste, leading to a decrease in environmental pollution and landfilling rate (Vahidi et al., 2024).

Blockchain technology offers promising capabilities for the development and implementation of material passports. Although material passports provide comprehensive building information, there are several problems regarding the cross-border trading of CW, such as duplicated passports, low transparency, lack of coordination, lack of platform for providing supply information, and digital information being tampered with (Wu et al., 2023). Blockchain integrates distributed ledgers, consensus mechanisms, and cryptography (Risius and Spohrer, 2017). Blockchain features, such as tamper-proof records, can reduce data manipulation and enhance CW tracking process (Elghaish et al., 2023). Blockchain used in material passports can help establish a secure, decentralized ledger that records the origin, composition, and disposal of construction materials, ensuring supply chain transparency and authenticity.

4.2. Cluster 2: Prediction and classification in CW management

There are 17 keywords included in the second cluster: algorithm, artificial intelligence, concrete, construction and demolition, controlled study, deep learning, DW, forecasting, learning system, machine learning, neural network, numerical model, prediction, procedures, solid waste, waste generation, waste management. Cluster 2 focuses on predictive modeling and classification algorithms using AI technologies, to forecast CW, optimize recycling, and improve recovery processes while enhancing efficiency and reducing CW. The details of the relevant papers in Cluster 2 are shown in Table S2 of the supplementary material. The two main research topics under cluster 2 are summarized in sections 4.2.1 to 4.2.2.

4.2.1. Predicting the quantity of CW

The first research topic within the second cluster is the prediction of CW quantity. Forecasting the quantity of waste generated in a construction project aids project managers in strategizing CW management, minimizing waste production, and ultimately lowering the overall expenses of construction projects (Ujong et al., 2022; Zhao et al., 2024). This process may require a comprehensive analysis of the quantities, types, and timing of CW during the construction process. By employing digital tools like machine learning, waste generation can be forecasted, enabling the implementation of appropriate measures to minimize CW generation and mitigate environmental impacts.

AI technologies have become increasingly utilized for precise prediction of CW generation (Abdallah et al., 2020), as their advanced algorithms provide distinctive capabilities in data analysis, training, and forecasting (Coskuner et al., 2021). As an important tool in AI, machine learning models are commonly adopted in developing predictive models for CW management (Cha et al., 2020; Gulghane et al., 2023; Ye et al., 2020). Song et al. (2017) improved the forecasting accuracy of a gray model for waste prediction by integrating the support vector regression technique and a transition matrix to adjust the residual series. Elshaboury AlMetwaly (2023) employed machine learning to quantity CW using geographic data gathered via GIS and RS, enabling the extraction of information on agricultural, built-up, and vacant areas. Integrating AI to improve the accuracy and efficiency of predicting CW generation is important for CW management and resource allocation.

4.2.2. Automatic CW classification

The second research topic within this cluster is the automatic classification of CW. Since sorting accuracy significantly influences the amount of recycled materials, CW classification plays a crucial role in CW management. The automatic sorting consists of two primary phases: initially, the CW is categorized into specific groups, and then it undergoes mechanical sorting according to its composition (Satav et al., 2023). AI possesses the ability to detect patterns and offer predictions, with deep learning methodologies being applicable for identifying waste objects by analyzing the visual and chemical attributes of waste (Moon et al., 2023). Following CW identification, robotics can be utilized to categorize components according to their specific classifications (Dodampegama et al., 2024). Research into both stages is crucial, as they contribute to achieving an automated and efficient waste sorting process. By categorizing waste initially and then mechanically sorting based on its composition, a streamlined waste sorting system can be realized, enhancing overall efficiency and effectiveness.

AI has become increasingly popular as a viable solution for automating manual waste segregation through the use of intelligent robotics (Sirimewan et al., 2024b). The majority of research concerning CW sorting emphasizes the early stage of waste item identification (Dodampegama et al., 2024), underscoring the potential for the application of robotic systems in CW sorting. Advancements in AI can substitute humans with robots in tasks that are hazardous and repetitive (Sarc et al., 2019). According to Chen et al. (2023), integrating robots into waste sorting can decrease the likelihood of risks that workers may suffer and streamline the sorting process. Intelligent robots equipped with the capability to identify distinct material types, positions, and dimensions could potentially automate the sorting of CW materials, offering a viable alternative to human workers (Lu et al., 2022).

Robotics powered by deep neural waste identification revolutionize traditionally labor-intensive waste sorting methods. Although robotics can achieve automatic waste classification, human involvement is important for assisting the robots in various aspects, such as intervening promptly when facing detection errors, thereby enhancing sorting accuracy (Chen et al., 2023). Enhanced waste sorting leads to better recycling outcomes and reduces landfill waste (Weber et al., 2020), facilitated by process automation and the integration of digital platforms (Maiurova et al., 2022). Predicting and sorting CW helps improve the recycling rate, promoting sustainable development.

4.3. Cluster 3: Advanced data analytics in CW management

There are 14 items that are included in cluster 3: big data (BD), building material, China, computer vision, construction material, CW, CW management, data set, Hong Kong, human, industrial waste, modeling, waste disposal, and waste disposal facility. The construction and building industry, a major source of solid waste, requires strategic interventions for efficient waste handling and resource recovery. The technologies commonly applied in this research direction include BD, computer vision, image analysis, segmentation, and data mining. Cluster 3 centers on advanced data analytics to optimize the operational aspects of CW management, focusing on how technological advancements enable data-driven tools to enhance resource recovery and efficiency. The details of the relevant papers in Cluster 3 are shown in Table S3 of the supplementary material. The two main research topics under cluster 3 are summarized in sections 4.3.1 to 4.3.2.

4.3.1. Strategic planning for future CW management

The first research topic within this cluster is the development of future strategies. Large volumes of data can be accumulated over the life cycle of construction projects, making BD analysis a promising method for deriving insights and informing decision-making processes. Historical data is crucial in CW management for identifying trends in waste accumulation, optimizing resource utilization, and ensuring compliance with relevant regulations and standards. Using historical data can help stakeholders in making effective strategies for future CW management.

BD is significant in analyzing historical data and supporting future strategy development. BD analysis involves gathering, merging, and examining extensive datasets to generate insights and experience that inform decision-making processes (Saggi and Jain, 2018). Compared to a semi-automated approach or artificial input, BD analysis is more accurate, integrating real-time information via the IoT (Bilal et al., 2016a). BD analysis can identify trends, irregularities, and forms in construction data, offering effective strategies for future waste management based on historical data.

4.3.2. CW Composition identification

Accurate composition identification is important for efficient CW management. Data regarding the composition of CW is vital for automatic CW classification (Davis et al., 2021; Lu et al., 2022). Conventionally, features of waste materials are crafted manually and subsequently input into machine learning models like SVM (Özkan et al., 2015; Wang et al., 2019b), which is time-consuming and lacks accuracy.

Computer vision is effective in identifying the composition of CW, utilizing technologies such as image analysis and image segmentation. The basis of image analysis lies in the identification of visual characteristics of objects, such as shape, patterns, gradients, dimensions, and other attributes (Califice et al., 2013; Hoang et al., 2020). Image classification is a form of image analysis that primarily focuses on assigning images to different categories or labels. Image classification categorizes images, object detection locates, and image segmentation labels each pixel in an image (Sirimewan et al., 2024a). Waste recognition through image classification can categorize a provided waste image into predefined classes (Dong et al., 2022). Accurate composition data is crucial for efficient CW management, and image classification is increasingly being employed to automate the process, improving both speed and accuracy.

Image segmentation has become a cornerstone step in computer vision, aiding in object recognition, shape reconstruction, classification, and estimating object volumes (Sirimewan et al., 2024b). In recent years, a growing number of publications have centered on the applications of semantic segmentation and object detection in CW management (Liang and Gu, 2021; Panwar et al., 2020; Wang et al., 2019a). Semantic segmentation models using deep learning in computer vision have demonstrated remarkable effectiveness in identifying objects within images (Yong et al., 2023). Semantic segmentation labels each pixel in an image concerning its designated category, providing spatial geometry for both 'objects' and 'stuff' (Sirimewan et al., 2024a; Wang et al., 2022c). This capability aids in detecting and identifying waste materials within cluttered settings, as semantic segmentation provides detailed pixel-level information (Dong et al., 2022; Lu et al., 2022). Overall, computer vision is gaining attention in CW management for its ability to provide precise identification and localization of waste materials within complex scenes.

5. Critical review and discussion

Through a systematic review of the 138 papers, eight DTs commonly used in CW management have been identified: BIM, GIS, machine learning, BD, deep learning, AI, image analysis, blockchain, and RFID. Table 4 presents the quantitative measurement of the identified keywords related to DTs. Neural networks are a method within deep learning, which is a branch of machine learning (Hoong et al., 2020). Machine learning, a subset of AI, is an information analysis approach through trainings (Gao et al., 2024). Therefore, machine learning, neural networks, and deep learning are categorized as AI technologies. The identified six main DTs from keyword analysis are BIM, AI, GIS, BD, RS, and RFID.

5.1. Building information modeling (BIM)

5.1.1. Application of BIM

By leveraging comprehensive information on CW, BIM enables the establishment of material and component banks, fostering sustainable construction practices through material recycling and component reuse. BIM provides many capabilities, including estimating demolition costs, offering decision-making tools for CW management, calculating carbon emissions, and devising schedules, thereby improving the rate of recycling (Shi and Xu, 2021; Wang et al., 2021).

BIM can assist in estimating CW. Guerra et al. (2019) created automated algorithms for estimating CW in drywall and concrete waste. Using the estimated volume of CW attributable to design changes, Won et al. (2016) calculated the potential reduction in CW achievable through BIM-assisted validations. Cheng and Ma (2013) highlighted BIM facilitates CW management through collaboration, quantity surveying, 3D visualization, and design review. Kim et al. (2017) offered detailed insights into a BIM-centered framework for predicting CW generated from design, aimed at enhancing planning, processing, and management procedures. Ge et al. (2017) introduced a DW management system leveraging a reconstructed 3D model, facilitating the measurement of recyclable materials and the planning of recycling processes. Xu et al. (2019) generated a BIM-assisted CW management system to accurately calculate CW types, quantities, and other relevant data, while transparently illustrating the derivation of CW data from BIM models. The estimation of CW is an important application of BIM.

BIM can also be applied in material tracking. BIM shows great potential in supplying stock material data for upcoming demolitions and efficiently organizing demolition-related information (Rašković et al., 2020). BIM can provide comprehensive data, including geometric, physical, and visual characteristics, enabling the creation of a virtual model that represents the real structure (Nizam et al., 2018). Information can be distributed to stakeholders over the life cycle of construction projects. For example, Akanbi et al. (2018) generated a BIM-centered platform for assessing the remaining value of CW throughout the lifecycle of buildings. Guerra et al. (2019) utilized BIM alongside procurement records to generate CW calculation algorithms for drywall and concrete. Detailed information provided by BIM can be leveraged for effective material tracking in demolition projects.

Table 4
Details of keywords related to DTs in CW management.

keyword	occurrences	total link strength	Cluster no.
BIM	36	274	1
machine learning	28	250	2
GIS	19	185	1
deep learning	17	166	2
artificial intelligence	14	154	2
BD	14	132	3
computer vision	11	115	3
image analysis	7	65	3
RS	5	40	1
RFID	5	30	1

BIM can be applied together with other methodologies to enhance efficiency and effectiveness in various aspects of CW. BIM can be used with a combination of sustainability concepts for sustainability evaluation. For example, Jalaei and Jrade (2015) combined BIM with leadership in energy and environmental design (LEED) to calculate credits related to energy, atmosphere, materials, and resources. BIM can also integrate with the principles of the circular economy, allowing for effective resources utilization and CW reduction over the building's lifespan (Soust-Verdaguer et al., 2017). Additionally, integrating BIM with lean methods optimizes the construction process by using BIM's digital capabilities to eliminate waste, streamline workflows, and enhance team collaboration (Aziz et al., 2024). Research indicates that integrating BIM with sustainable concepts like LEED, lean principles, and the circular economy promotes the sustainable management of CW.

BIM can also be integrated with methods like life cycle assessment (LCA) and geographic information system (GIS) for environmental assessment and route design. Environmental assessment is a participatory process that evaluates the environmental impacts of policies, plans, programs, and projects to ensure these impacts are considered in decision-making, with growing attention worldwide (Fischer et al., 2023). Han et al. (2024) integrated LCA and multi-criteria decision analysis (MCDA) into a DW management platform based on BIM for visualization and sustainability assessment. Su et al. (2021) generated a system for predicting and calculating DW, utilizing BIM for detailed building characterization, GIS for waste transportation route design, and LCA for environmental performance evaluation. The methods can serve as tools to assess and verify the sustainability of construction projects, and when integrated with BIM, they offer a comprehensive approach to ensuring sustainable building practices (Schamne et al., 2024). BIM and its integration with other methodologies are effective and widely applied in CW management.

5.1.2. Limitations and future research directions

However, BIM has predominantly emphasized technological aspects, often overlooking the socio-economic dimensions of construction projects (Charef et al., 2021). Moreover, due to dataset limitations, current BIM-based CW estimation methods focus on individual buildings at a project level, overlooking waste generation at regional or wider levels (Li et al., 2020a). While many tools are available for quantifying the environmental performance of waste management in residential areas, none effectively integrate and manage diverse data in a BIM environment (Mercader-Moyano et al., 2021). Therefore, solving challenges related to socio-economic aspects and dataset limitations is crucial.

Future studies should integrate interdisciplinary collaboration, case studies, and implementation strategies into technological advancements with sustainable waste management practices in construction. Developing scalable BIM-based CW estimation methods that aggregate data across multiple projects can help assess waste generation at regional or wider levels. Future studies should also explore the advancement of BIM-enabled tools for CW collection, which will incorporate CW information into BIM models (Akinade and Oyedele, 2019). Finally, information technologies are still in their initial phase of application in CW management, with certain limitations (Li et al., 2020a). In future research, BIM should be applied with other DTs, such as GIS or BD to ensure a large-scale waste accurate prediction of CW. To address dataset limitations in BIM-based CW estimation, comprehensive data collection, augmentation, crowdsourcing, remote sensing, machine learning, and collaborative sharing should be employed to enhance data coverage and accuracy for improved waste management assessments.

5.2. Artificial intelligence (AI)

The keywords of machine learning, deep learning, image analysis, and computer vision shown in Table 4 belong to AI technologies. AI has been widely used in CW management, particularly in the collection and sorting phases (Singh et al., 2024). Deep learning is a subset of machine learning, which is crucial in AI applications. Computer vision, an important part of AI, allows for analyzing and utilizing visual data. Image analysis, a subset of computer vision, extracts useful information from images. The applications of these AI technologies in CW management are reviewed in this section.

5.2.1. Machine learning

Machine learning is commonly used for developing prediction models for CW quantification. Choosing the right machine learning algorithms is crucial, as the predominantly categorical independent variables significantly influence the model outcomes (Ram and Kalidindi, 2017). There are several algorithms such as logistic regression, support vector machine, random forest, decision trees, K-nearest neighbor, multiple linear regression, and neural networks (Abdallah et al., 2020; Elshaboury and AlMetwaly, 2023; Gulghane et al., 2023). Artificial neural networks are commonly adopted in predicting CW generation (Cha et al., 2022; Golbaz et al., 2019; Song et al., 2017; Soni et al., 2019). Support vector machine algorithms (Abbasi and El Hanandeh, 2016; Abunama et al., 2019; Cha et al., 2022; Dai et al., 2011; Golbaz et al., 2019; Hu et al., 2021; Kumar et al., 2018; Noori et al., 2009; Song et al., 2017) and linear regression are commonly adopted in developing prediction models (Afon and Okewole, 2007; Ali Abdoli et al., 2012; AzaDi Maria et al., 2016; Chhay et al., 2018; Golbaz et al., 2019; Kumar and Samadder, 2017; Montecinos et al., 2018).

Deep learning, a subset of machine learning, specializes in artificial neural networks and learning representations of data through multiple layers. Deep learning utilizes several processing layers to acquire data structures and relationships across different levels of abstraction (LeCun et al., 2015). Deep learning enables the prediction of CW by providing access to information on potential waste generation, thereby supporting effective reusing and recycling of materials (Akanbi et al., 2020). Generally, deep learning can forecast CW quantity, optimize material recycling and reusing, automatic CW sorting, and enhance process efficiency through data-driven insights and decision support tools.

5.2.2. Computer vision

Computer vision is commonly used in waste composition recognition. The emergence of deep learning has improved computer vision's capability to recognize a wide range of objects within images, enhancing its effectiveness in identifying diverse objects related to CW (Prasad and Arashpour, 2024; Sirimewan et al., 2024a). The unique absorbance and color characteristics of different waste materials enable their differentiation through visual recognition methods (Lu et al., 2022). For example, a mask region-based convolutional neural network and a faster region-based convolutional neural network were trained by Wang et al. (2020) to detect waste materials dispersed throughout the construction site. Advancements in computer vision can enhance the efficiency and accuracy of CW identification, promoting sustainable resource recycling and reuse.

Computer vision can also aid in managing workers on construction sites. Luo et al. (2019) created a platform that adopts computer vision to detect and visualize agile work environments. Park and Brilakis (2012) developed a video frame detection algorithm to automate the initialization of visual trackers for construction workers. Yu et al. (2019) combined computer vision with biomechanics to identify behavior to enhance worker safety on construction sites. These innovative approaches demonstrate the potential of computer vision in enhancing worker safety, productivity, and overall management on construction sites, leading to an increment in the reduction or recycling rate of CW.

5.2.3. Image analysis

Through image analysis, researchers can gain deeper into the composition, distribution, and potential trends of CW. Using satellite-based image analysis, Wang et al. (2022a) evaluated the susceptibility of landfills to landslides in Shenzhen. Hoang et al. (2020) employed image analysis to identify CW components and quantify waste generation rates based on the layout of CW. Bogoviku Waldmann (2021) proposed utilizing image analysis to extract a historical life cycle profile showcasing building demolition behavior, aiding in projecting potential mineral CW from the building stock under stochastic scenarios. Additionally, Di Maria et al. (2016) employed image analysis to evaluate the size distribution of recycling aggregates in CW.

Assessing building stock using image analysis provides an effective approach to understanding the lifetime dynamics of buildings (Bogoviku and Waldmann, 2021). A geographical perspective is crucial in this regard, as demolition patterns are closely linked to the socio-economic context. Image analysis is becoming essential in CW management, providing comprehensive and precise data for effective handling, thereby promoting resource utilization and recycling.

5.2.4. Limitations and future research directions

Implementing AI systems necessitates extensive datasets, and limited data availability can pose a challenge to achieving accurate predictive performance (Abdallah et al., 2020). Insufficient dataset size and poor data quality, including image noise, imbalanced class distributions, or labeling inaccuracies, can undermine meaningful patterns in deep learning models, resulting in biased outcomes (Lu et al., 2022). In addition, in different data environments, such as those with small datasets or qualitative variables, the predictive performance observed in prior research may not be assured, as predictive models utilizing machine learning algorithms on small datasets can be prone to estimation error and large variability (Cha et al., 2021). Finally, 2D-based computer vision may face challenges with objects not situated on flat surfaces, necessitating additional algorithms. Existing methods relying on pre-existing 3D models for training are less practical for CW, where deformations may occur, impacting the accuracy of algorithms (Wang et al., 2020).

Additional features need to be created to strengthen the forecasting models for CW that exhibited relatively poor predictive performance (Cha et al., 2021). In addition, integrating deep learning with BIM will enhance their usability among stakeholders, with future refinements considering additional building features such as room count, building elements, and components (Akanbi et al., 2020). Future research should develop robust computer vision algorithms that can accurately locate and estimate CW in dynamic environments without pre-existing 3D models. Leveraging techniques like point cloud processing, semantic segmentation, and deep learning can enhance the adaptability and generalization of these algorithms to diverse real-world scenarios, ultimately improving the efficiency and reliability of CW management.

5.3. Geographic information system (GIS)

5.3.1. Application of GIS and its integration with other methods

GIS is normally used in disposal site selection and environmental assessment of different waste management strategies, assisting decision-making for stakeholders. GIS serves as an assessment tool that can collaborate with various models to evaluate the environmental impacts and future outcomes of projects or activities. Environmental impact assessment can reduce adverse environmental effects and maximize the positive benefits associated with development projects (Sibale Fischer, 2024). Since many factors can affect the determination of a waste disposal or recycling site, different MCDA methods like fuzzy logic, analytic hierarchy process (AHP), dynamic modeling, and analytical network process are extensively used with GIS in waste management studies (Yalcinkaya and Kirtiloglu, 2021).

The integrated approach of GIS and MCDA is commonly used in site determination for waste disposal or treatment based on a range of criteria and preferences of decision-makers (Ali et al., 2023; Elshaboury et al., 2024). For example, AlZaghrini et al. (2019) generated a decision support system that optimizes facility location for CW through a combined approach of GIS and multi-criteria analysis. Biluca et al. (2020) determined the optimal places for landfilling or recycling of CW using GIS and MCDA. Soto-Paz et al. (2023b) integrated GIS, fuzzy-AHP, and Monte Carlo simulation to facilitate site selections.

GIS can also be combined with LCA to provide a comprehensive spatial and environmental analysis framework. GIS provides spatial analysis capabilities, while LCA evaluates environmental impacts across the lifecycle of waste. Komkova and Habert (2023) combined GIS with the LCA approach for identifying optimal waste supply chain networks. Li et al. (2020b) integrated the approach of GIS with LCA to assess the environmental impact of mobile recycling of CW. The integrated approach provides a robust framework for CW management, offering comprehensive assessments, aiding decision-making, and facilitating the formulation of sustainable CW management strategies.

5.3.2. Limitations and future research directions

However, there has been limited exploration of integrating GIS with hybrid simulation systems and a lack of research on assessing the environmental performance of city-scale waste management in both temporal and spatial dimensions. In addition, geographic data in some cities are not comprehensive enough or updated quickly enough for a thorough spatial analysis (MaDi Maria et al., 2016), leading to a limited research area. Finally, since the effective use of GIS relies on high-quality, large-volume data for accurate analysis, data security issues must be solved when handling sensitive data in GIS.

To solve the problem of lacking comprehensive and integrated data used in GIS, some technologies can be applied together with GIS. For example, Kleemann et al. (2017) used change detection through image matching, enabling the identification of building demolition activities that may not have been reported to municipal departments. Collaborative initiatives between government agencies, research institutions, and private organizations could help address data gaps and ensure access to comprehensive and current geographic data. Given the reliance of GIS on large quantities of data, future research should also focus on data management and security issues. This includes developing robust data management frameworks that ensure the integrity, accessibility, and privacy of spatial data. Since within decision-making systems, a critical determinant influencing choices is the promptness and transparency of information (Wang et al., 2021), GIS can be integrated with other real-time data collection technologies, like IoT. Innovative approaches to data security, such as encryption and access control mechanisms, should be explored to protect sensitive information while enabling collaboration.

5.4. Big data (BD)

5.4.1. Application of BD in CW management

With the rapid advancement of hardware, software, devices, and diverse sensors, the building sector has transitioned into the period of BD, facilitating the digitization of CW management processes (Bilal et al., 2016b; Xue et al., 2021). BD has been created to explore extensive datasets, unveiling patterns, non-linear relationships, and causal effects, thereby facilitating more informed decision-making (Xu et al., 2020). There is significant enthusiasm for leveraging BD, to uncover hidden trends and to allow predictive and prescriptive analytics, enabling the anticipation and shaping of prospective events (Bilal et al., 2016a).

BD is commonly adopted in illegal dumping supervision. Lu et al. (2016) utilized BD consisting of two million CW disposal statistics of 5700 projects in Hong Kong to compare CW management performance between public and private sectors, revealing a notable disparity and informing strategies for improving waste management practices. Research also showed that BD analytics is promising for addressing the challenge of waste composition recognition (Yuan et al., 2021). For example, Lu et al. (2021b), highlighted non-random patterns in CW composition within regions, suggesting that BD analytics could predict waste composition based on bulk density. BD can also be applied in promoting the sustainability of CW management. Xu et al. (2020) utilized BD to analyze the CW management efficiency disparity between private and public sectors in Hong Kong, based on CW disposal information from 132 projects. Chen and Lu (2017) applied BD analytics to identify the factors influencing DW generation specifically in Hong Kong, thereby promoting sustainable waste management. These studies highlight big data’s pivotal role in informing evidence-based strategies for optimizing CW management and advancing sustainable development.

5.4.2. Limitations and future research directions

Data quality and comprehensiveness are important for effective data analysis (Sattari et al., 2017). Nevertheless, missing data and occasional inaccuracies due to information barriers pose challenges to CW management (Bilal et al., 2016b; Callistus and Clinton, 2016). To address this challenge, future studies could integrate more advanced technologies for data collection and validate the integrity and validity of the collected data. Additionally, researchers could explore the development of statistical models and algorithms to solve the issue of missing information.

The integration of BD with BIM holds the promise of developing a resilient CW simulation tool (Bilal et al., 2016a). However, the integration of BD with BIM for CW management is still limited, with the application of new DTs in waste management being at an early stage. Future research directions should further investigate on integrating BD and BIM, enhancing the application of new DTs, and advancing comprehensive approaches to effectively manage CW. Moreover, regional variations in CW management, influenced by regulatory environments, economic conditions, geography, and environmental concerns, highlight the necessity for region-specific big data analysis to customize waste management strategies effectively.

5.5. Remote sensing (RS)

5.5.1. Application of RS in waste management

RS has emerged as a crucial means of acquiring up-to-date regional data (Chen et al., 2021; Cusworth et al., 2020). Firstly, RS can detect illegal CW dumping, aiding authorities to prevent environmental damage and ensure compliance with waste management regulations. For example, Yong et al. (2023) achieved the automatic identification of illegal dumping sites for CW using RS. Secondly, RS can be used to predict the volume of CW accumulated from construction activities. Elshaboury AlMetwaly (2023) predicted the quantity of CW in Egypt using the integrated approach of RS, GIS, and machine learning. Guo et al. (2022) predicted the amount of excavated soil and construction sludge in geotechnical and underground engineering projects. In addition, RS can be applied for environmental impact monitoring. RS was utilized by Li et al. (2022) to assess the effectiveness of dust-proof nets in mitigating pollution from CW, utilizing multispectral satellite data and advanced classification methods for urban environmental monitoring and governance. Finally, RS can also be applied for waste composition detection. Chen et al. (2021) utilized RS, specifically high-resolution imagery, to extract and identify urban CW using a multi-feature analysis method.

In summary, RS offers a cost-effective and efficient means of monitoring CW due to its wide coverage, high timeliness, and stable data support. With its ability to objectively depict the earth’s surface conditions, RS provides insights into the spatial distribution and dynamic CW accumulation. As such, RS can assist in enhancing waste management practices by providing reliable and comprehensive data for informed decision-making.

5.5.2. Limitations and future research directions

RS data often lacks the necessary spatial and temporal resolution for precise monitoring of small-scale CW activities, leading to the integration approach such as GIS and RS a promising trend. Secondly, achieving high classification accuracy is challenging due to the complexity of variability in CW types. Future directions could center on advanced sorting algorithms, such as adopting machine learning to promote accurate data and effectiveness in waste detection.

Chen et al. (2021) summarized three difficulties in identifying CW using RS: (1) waste displays heterogeneous spectral and texture properties; (2) interfering elements like buildings and bare soil hinder accurate identification; and (3) reliable evaluation methods are lacking. To address these challenges, advanced spectral and texture analysis methods, along with improved feature classification techniques, are necessary to accurately differentiate heterogeneous waste properties from interfering elements like buildings and bare soil, while establishing reliable evaluation methodologies. In addition, accessing high-quality RS data, can be expensive and limited in availability, constraining CW monitoring efforts. Integrating RS data with ground-based observations, such as field surveys and sensor networks, could enhance the reliability and comprehensiveness of CW monitoring systems and can be useful in solving the problem.

5.6. Radio frequency identification (RFID)

5.6.1. Application of RFID and its integration with other methods

RFID technology facilitates tracking and archiving construction components' properties, promoting their reuse and minimizing wastage in the construction sector. RFID operates as a wireless sensor, transmitting data through signals to or from physical "tags" affixed to items (Iacovidou et al., 2018). An RFID communication system necessitates several key components. An RFID communication system requires several key components: a reader, one or more tags, and antennas that enable information transmission (Domdouzis et al., 2007). RFID's ability to store and transmit information enhances CW traceability (Vahidi et al., 2024). RFID improves the traceability of different kinds of CW by providing accurate and real-time data throughout the waste management process.

RFID's integration with technologies like BIM, GIS, and GPS showcases numerous valuable applications in the CW domain. RFID technology enables the tracking and tracing of various items in the building sector, including equipment, materials, components, tools, and personnel (Iacovidou et al., 2018). RFID, with its real-time information and traceability, can be integrated with BIM to streamline information management over the life cycle of a component, minimizing duration and labor for data retrieval and reducing ineffective decisions due to information gaps (Ergen et al., 2007; Iacovidou et al., 2018). Tracking component lifecycle data through RFID and BIM can enhance the assessment of recyclability (Akbarnezhad et al., 2014). Integrating GIS or GPS with RFID enhances spatial awareness and location-tracking capabilities, enabling real-time tracking of items. This integration provides geographical information about movement and utilization, aiding resource allocation, logistical planning, and management efficiency in construction projects.

5.6.2. Limitations and future research directions

The performance of RFID could be affected by reliability issues stemming from tag placement, signal distortions caused by densely arranged readers, and the material composition to which the tags are attached (Lim et al., 2013). According to Iacovidou et al. (2018), RFID faces limitations such as communication issues among components, data overload from repeated readings, difficulties in accurately identifying component positions, signal degradation from component fixation, the need for reevaluating tag placement, the lack of common technical standards, and frequency range incompatibility between countries.

As technology advances, incorporating technologies like GPS and sensors alongside policy development for regulated and sustainable use, RFID's potential as a facilitator for mainstream adoption in structural construction component reuse becomes more achievable (Iacovidou et al., 2018). Future research should focus on developing algorithms for dynamically adjusting reader settings based on environmental conditions and exploring novel protocols for efficient data transmission and error correction mechanisms. Additionally, leveraging blockchain for transparent information management and IoT for real-time monitoring of construction projects could further enhance RFID. Blockchain can be used to enhance data security and integrity in construction-related documents by providing a decentralized, immutable ledger that records transactions transparently (Das et al., 2022). A comprehensive construction process involves multiple stakeholders (Ma and Hao, 2024), and the advancement of IoT can be used to monitor construction processes by connecting sensors and devices to a network, enabling continuous data collection, transmission, and instant analysis (Jiang et al., 2023; Rao et al., 2022). IoT enables real-time tracking of RFID tags, while blockchain ensures data integrity and prevents fraud in the supply chain (Baygin et al., 2022). Therefore, integrating IoT and blockchain into RFID can improve its functionality and security.

6. Conclusion

This study employs a science mapping method to review the application of DTs in CW management. Through a comprehensive review of the identified 138 articles from 2014 to 2024, the objectives of the study were accomplished: to uncover the evolution and reveal the main research trends within the research domain; to identify the primary current research areas; to review the application of the most widely adopted DTs in CW management; to identify the limitations of these DTs and propose future directions. The findings offer valuable insights into the evolution, current and future research trends, and limitations of DTs in CW management, aiding researchers, policymakers, and industry professionals in making informed decisions and advancing the field.

Bibliometric analysis reveals a significant increase in research on DTs in CW management, identifying leading contributions from major journals. The findings show that mainland China has the most published papers, while the US boasts the highest average citation rate. Key research themes identified include strategic information management, predictive modeling, and advanced data analytics in CW management. CW management can benefit from various DTs by enhancing efficiency, transparency, and decision-making processes over the entire life cycle. By integrating DTs, CWM practices can improve waste estimation, optimize resource recovery, and streamline planning processes, leading to reduced environmental impact. Furthermore, these technologies facilitate better monitoring and tracking of CW flows, enabling more effective compliance with policies in achieving sustainability goals. However, current limitations include challenges related to data integration, varying standards across technologies, the integration of multiple systems, the need for skilled personnel to effectively collaborate using these tools, relatively high implementation costs, and resistance to change within companies, all of which impede the application of DTs in promoting sustainable CW management.

This review covers BIM, AI, GIS, BD, RS, and RFID, exploring their applications, identifying limitations, and suggesting future research directions. BIM can be utilized for waste estimation, visual planning, and material tracking, and when combined with methods like LEED, circular economy, lean, and LCA, it aids in sustainability evaluation and environmental assessment of CW. Future research should integrate socioeconomic dimensions, develop comprehensive tools for quantifying environmental impacts, and collaborate with GIS and BD for accurate CW prediction and management. AI technologies, including machine learning, deep learning, computer vision, and image analysis, are vital for CW management. Machine learning predicts waste generation, deep learning improves material reuse, computer vision aids in waste composition recognition and worker management, and image analysis provides waste trend insights. Future research should enhance data quality and availability, optimize feature groups, integrate deep learning with BIM software, and improve computer vision algorithms. GIS, often used for site selection and environmental assessment with MCDA or LCA, faces limitations in integration with hybrid simulation systems and outdated data for city-scale assessments. Collaborative efforts are needed to improve data quality and robust management frameworks. BD analytics optimize CW management by revealing trends, predicting composition, and informing strategies, with future research focusing on statistical models for missing data and integrating BD with BIM for resilient waste simulation. RS detects illegal dumping, estimates waste volume, and monitors impacts, with future research on advanced algorithms to address waste variability. RFID technology enhances traceability and monitoring, with integration into BIM, GIS, and GPS improving information management and resource allocation. Future research should address tag placement, signal distortions, dynamic reader settings, and secure data management through blockchain or IoT.

While this review offers comprehensive insights, it has certain limitations. Firstly, it exclusively considered literature published in English, ignoring studies and outputs in other languages. Secondly, the focus was primarily on journal papers and book chapters, excluding some other relevant research sources. Future research could broaden the scope to include a wider range of sources. Additionally, while the paper mainly examined commonly used DTs based on keyword occurrence, there is potential to explore less common but still applicable DTs in CW management in future studies.

CRediT authorship contribution statement

Wenbo Zhao: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jian Li Hao:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Guobin Gong:** Writing – review & editing, Supervision, Investigation, Data curation. **Thomas Fischer:** Writing – review & editing, Supervision, Methodology. **Yong Liu:** Supervision, Investigation, Funding acquisition.

Declaration of competing interest

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

Acknowledgment

This work was supported by the National Natural Science from the National Natural Science Foundation of China [grant number 72374182]; and Xi’an Jiaotong-Liverpool University [grant number XJTLU RDF 2016–32].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.123560.

Data availability

Data will be made available on request.

References

Abbasi, M., El Hanandeh, A., 2016. Forecasting municipal solid waste generation using artificial intelligence modelling approaches. Waste Manage. (Tucson, Ariz.) 56, 13–22. https://doi.org/10.1016/j.wasman.2016.05.018.

Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdalla, H., Mahfood, B., 2020. Artificial intelligence applications in solid waste management: a systematic research review. Waste Manage. (Tucson, Ariz.) 109, 231–246. https://doi.org/10.1016/j.wasman.2020.04.057.

Abunama, T., Othman, F., Ansari, M., El-Shafie, A., 2019. Leachate generation rate modeling using artificial intelligence algorithms aided by input optimization method for an MSW landfill. Environ. Sci. Pollut. Res. 26, 3368–3381. https://doi.org/10.1007/s11356-018-3749-5.

Afon, A.O., Okewole, A., 2007. Estimating the quantity of solid waste generation in Oyo, Nigeria. Waste Manag. Res. 25 (4), 371–379. https://doi.org/10.1177/0734242X0707828.

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

Akanbi, L.A., Oyedele, L.O., Akinade, O.O., Ajayi, A.O., Delgado, M.D., Bilal, M., Bello, S.A., 2018. Salvaging building materials in a circular economy: a BIM-based whole-life performance estimator. Resour. Conserv. Recycl. 129, 175–186. https://doi.org/10.1016/j.resconrec.2017.10.026.

Akbarnezhad, A., Ong, K.C.G., Chandra, L.R., 2014. Economic and environmental assessment of deconstruction strategies using building information modeling. Autom. ConStruct. 37, 131–144. https://doi.org/10.1016/j.autcon.2013.10.017.

Akinade, O.O., Oyedele, L.O., 2019. Integrating construction supply chains within a circular economy: an ANFIS-based waste analytics system (A-WAS). J. Clean. Prod. 229, 863–873. https://doi.org/10.1016/j.jclepro.2019.04.232.

Ali Abdoli, M., Falah Nezhad, M., Salehi Sede, R., Behboudian, S., 2012. Longterm forecasting of solid waste generation by the artificial neural networks. Environ. Prog. Sustain. Energy 31 (4), 628–636. https://doi.org/10.1002/ep.10591.

Ali, I., Islam, A., Ali, S.M., Adnan, S., 2023. Identification and selection of suitable landfill sites using GIS-based multi-criteria decision analysis in the Peshawar District, Pakistan. Waste Manag. Res. 41 (3), 608–619. https://doi.org/10.1177/0734242X221124069.

AlZaghrini, N., Srour, F.J., Srour, I., 2019. Using GIS and optimization to manage construction and demolition waste: the case of abandoned quarries in Lebanon. Waste Manage. (Tucson, Ariz.) 95, 139–149. https://doi.org/10.1016/j.wasman.2019.06.011.

Ayub, M., Othman, M.H.D., Khan, I.U., Hubadillah, S.K., Kurniawan, T.A., Ismail, A.F., Rahman, M.A., Jaafar, J., 2021. Promoting sustainable cleaner production paradigms in palm oil fuel ash as an eco-friendly cementitious material: a critical analysis. J. Clean. Prod. 295, 126296. https://doi.org/10.1016/j.jclepro.2021.126296.

Aziz, R.M., Nasreldin, T.I., Hashem, O.M., 2024. The role of BIM as a lean tool in design phase. J. Eng. Appl. Sci. 71 (1), 23. https://doi.org/10.1186/s44147-023-00340-3.

Baygin, M., Yaman, O., Baygin, N., Karakose, M., 2022. A blockchain-based approach to smart cargo transportation using UHF RFID. Expert Syst. Appl. 188, 116030. https://doi.org/10.1016/j.eswa.2021.116030.

Bilal, M., Oyedele, L.O., Akinade, O.O., Ajayi, S.O., Alaka, H.A., Owolabi, H.A., Qadir, J., Pasha, M., Bello, S.A., 2016a. Big data architecture for construction waste analytics (CWA): a conceptual framework. J. Build. Eng. 6, 144–156. https://doi.org/10.1016/j.jobe.2016.03.002.

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

Biluca, J., de Aguiar, C.R., Trojan, F., 2020. Sorting of suitable areas for disposal of construction and demolition waste using GIS and ELECTRE TRI. Waste Manage. (Tucson, Ariz.) 114, 307–320. https://doi.org/10.1016/j.wasman.2020.07.007.

Bogoviku, L., Waldmann, D., 2021. Modelling of mineral construction and demolition waste dynamics through a combination of geospatial and image analysis. J. Environ. Manag. 282, 111879. https://doi.org/10.1016/j.jenvman.2020.111879.

Califice, A., Michel, F., Dislaire, G., Pirard, E., 2013. Influence of particle shape on size distribution measurements by 3D and 2D image analyses and laser diffraction. Powder Technol. 237, 67–75. https://doi.org/10.1016/j.powtec.2013.01.003.

Callistus, T., Clinton, A., 2016. Evaluating barriers to effective implementation of project monitoring and evaluation in the Ghanaian construction industry. Procedia Eng. 164, 389–394. https://doi.org/10.1016/j.proeng.2016.11.635.

Cha, G.W., Moon, H.J., Kim, Y.C., 2021. Comparison of random forest and gradient boosting machine models for predicting demolition waste based on small datasets and categorical variables. Int. J. Environ. Res. Publ. Health 18 (16), 8530. https://doi.org/10.3390/ijerph18168530.

Cha, G.W., Moon, H.J., Kim, Y.C., 2022. A hybrid machine-learning model for predicting the waste generation rate of building demolition projects. J. Clean. Prod. 375, 134096. https://doi.org/10.1016/j.jclepro.2022.134096.

Cha, G.W., Moon, H.J., Kim, Y.M., Hong, W.H., Hwang, J.H., Park, W.J., Kim, Y.C., 2020. Development of a prediction model for demolition waste generation using a random forest algorithm based on small datasets. Int. J. Environ. Res. Publ. Health 17 (19), 6997. https://doi.org/10.3390/ijerph17196997.

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

Cheah, C.G., Chia, W.Y., Lai, S.F., Chew, K.W., Chia, S.R., Show, P.L., 2022. Innovation designs of industry 4.0 based solid waste management: machinery and digital circular economy. Environ. Res. 213, 113619. https://doi.org/10.1016/j.envres.2022.113619.

Chen, J., Fu, Y., Lu, W., Pan, Y., 2023. Augmented reality-enabled human-robot collaboration to balance construction waste sorting efficiency and occupational safety and health. J. Environ. Manag. 348, 119341. https://doi.org/10.1016/j.jenvman.2023.119341.

Chen, Q., Cheng, Q., Wang, J., Du, M., Zhou, L., Liu, Y., 2021. Identification and evaluation of urban construction waste with VHR remote sensing using multi-feature analysis and a hierarchical segmentation method. Rem. Sens. 13 (1), 158. https://doi.org/10.3390/rs13010158.

Chen, X., Lu, W., 2017. Identifying factors influencing demolition waste generation in Hong Kong. J. Clean. Prod. 141, 799–811. https://doi.org/10.1016/j.jclepro.2016.09.164.

Cheng, J.C., Ma, L.Y., 2013. A BIM-based system for demolition and renovation waste estimation and planning. Waste Manage. (Tucson, Ariz.) 33 (6), 1539–1551. https://doi.org/10.1016/j.wasman.2013.01.001.

Chhay, L., Reyad, M.A.H., Suy, R., Islam, M.R., Mian, M.M., 2018. Municipal solid waste generation in China: influencing factor analysis and multi-model forecasting. J. Mater. Cycles Waste Manag. 20, 1761–1770. https://doi.org/10.1007/s10163-018-0743-4.

Coskuner, G., Jassim, M.S., Zontul, M., Karateke, S., 2021. Application of artificial intelligence neural network modeling to predict the generation of domestic, commercial and construction wastes. Waste Manag. Res. 39 (3), 499–507. https://doi.org/10.1177/0734242X20935181.

Cusworth, D.H., Duren, R.M., Thorpe, A.K., Tseng, E., Thompson, D., Guha, A., Newman, S., Foster, K.T., Miller, C.E., 2020. Using remote sensing to detect, validate, and quantify methane emissions from California solid waste operations. Environ. Res. Lett. 15 (5), 054012. https://doi.org/10.1088/1748-9326/ab7b99.

Dai, C., Li, Y., Huang, G., 2011. A two-stage support-vector-regression optimization model for municipal solid waste management–a case study of Beijing, China. J. Environ. Manag. 92 (12), 3023–3037. https://doi.org/10.1016/j.jenvman.2011.06.038.

Das, M., Tao, X., Liu, Y., Cheng, J.C., 2022. A blockchain-based integrated document management framework for construction applications. Autom. ConStruct. 133, 104001. https://doi.org/10.1016/j.autcon.2021.104001.

Davis, P., Aziz, F., Newaz, M.T., Sher, W., Simon, L., 2021. The classification of construction waste material using a deep convolutional neural network. Autom. ConStruct. 122, 103481. https://doi.org/10.1016/j.autcon.2020.103481.

Di Maria, F., Bianconi, F., Micale, C., Baglioni, S., Marionni, M., 2016. Quality assessment for recycling aggregates from construction and demolition waste: an image-based approach for particle size estimation. Waste Manage. (Tucson, Ariz.) 48, 344–352. https://doi.org/10.1016/j.wasman.2015.12.005.

Dodampegama, S., Hou, L., Asadi, E., Zhang, G., Setunge, S., 2024. Revolutionizing construction and demolition waste sorting: insights from artificial intelligence and robotic applications. Resour. Conserv. Recycl. 202, 107375. https://doi.org/10.1016/j.resconrec.2023.107375.

Domdouzis, K., Kumar, B., Anumba, C., 2007. Radio-Frequency Identification (RFID) applications: a brief introduction. Adv. Eng. Inf. 21 (4), 350–355. https://doi.org/10.1016/j.aei.2006.09.001.

Dong, Z., Chen, J., Lu, W., 2022. Computer vision to recognize construction waste compositions: a novel boundary-aware transformer (BAT) model. J. Environ. Manag. 305, 114405. https://doi.org/10.1016/j.jenvman.2021.114405.

Elghaish, F., Hosseini, M.R., Kocaturk, T., Arashpour, M., Ledari, M.B., 2023. Digitalised circular construction supply chain: an integrated BIM-Blockchain solution. Autom. ConStruct. 148, 104746. https://doi.org/10.1016/j.autcon.2023.104746.

Elshaboury, N., AlMetwaly, W.M., 2023. Modeling construction and demolition waste quantities in Tanta City, Egypt: a synergistic approach of remote sensing, geographic information system, and hybrid fuzzy neural networks. Environ. Sci. Pollut. Res. 30 (48), 106533–106548. https://doi.org/10.1007/s11356-023-29735-8.

Elshaboury, N., Hesham, A., AlMetwaly, W.M., 2024. Optimal site selection for construction and demolition waste disposal using GIS-FAHP: a case study from Kafr El Sheikh City, Egypt. Environ. Sci. Pollut. Res. 1–17. https://doi.org/10.1007/s11356-023-31637-8.

Ergen, E., Akinci, B., Sacks, R., 2007. Life-cycle data management of engineered-to-order components using radio frequency identification. Adv. Eng. Inf. 21 (4), 356–366. https://doi.org/10.1016/j.aei.2006.09.004.

Fang, B., Yu, J., Chen, Z., Osman, A.I., Farghali, M., Ihara, I., Hamza, E.H., Rooney, D.W., Yap, P.-S., 2023. Artificial intelligence for waste management in smart cities: a review. Environ. Chem. Lett. 21 (4), 1959–1989. https://doi.org/10.1007/s10311-023-01604-3.

Fischer, T.B., Fonseca, A., Geißler, G., Jha-Thakur, U., Retief, F., Alberts, R., Jiricka-Pürrer, A., 2023. Simplification of environmental and other impact assessments–results from an international online survey. Impact Assess. Proj. Apprais. 41 (3), 181–189. https://doi.org/10.1080/14615517.2023.2198839.

Fraternali, P., Morandini, L., González, S.L.H., 2024. Solid waste detection, monitoring and mapping in remote sensing images: a survey. Waste Manage. (Tucson, Ariz.) 189, 88–102. https://doi.org/10.1016/j.wasman.2024.08.003.

Gao, Y., Wang, J., Xu, X., 2024. Machine learning in construction and demolition waste management: progress, challenges, and future directions. Autom. ConStruct. 162, 105380. https://doi.org/10.1016/j.autcon.2024.105380.

Garcia-de-Prado, A., Ortiz, G., Boubeta-Puig, J., 2017. COLLECT: COLLaborativE ConText-aware service oriented architecture for intelligent decision-making in the Internet of Things. Expert Syst. Appl. 85, 231–248. https://doi.org/10.1016/j.eswa.2017.05.034.

Ge, X.J., Livesey, P., Wang, J., Huang, S., He, X., Zhang, C., 2017. Deconstruction waste management through 3D reconstruction and BIM: a case study. Visual. Eng 5, 1–15. https://doi.org/10.1186/s40327-017-0050-5.

Ghaffarianhoseini, A., Tookey, J., Ghaffarianhoseini, A., Naismith, N., Azhar, S., Efimova, O., Raahemifar, K., 2017. Building Information Modelling (BIM) uptake: clear benefits, understanding its implementation, risks and challenges. Renew. Sustain. Energy Rev. 75, 1046–1053. https://doi.org/10.1016/j.rser.2016.11.083.

Golbaz, S., Nabizadeh, R., Sajadi, H.S., 2019. Comparative study of predicting hospital solid waste generation using multiple linear regression and artificial intelligence. Journal of Environmental Health Science and Engineering 17, 41–51. https://doi.org/10.1007/s40201-018-00324-z.

Guerra, B.C., Bakchan, A., Leite, F., Faust, K.M., 2019. BIM-based automated construction waste estimation algorithms: the case of concrete and drywall waste streams. Waste Manage. (Tucson, Ariz.) 87, 825–832. https://doi.org/10.1016/j.wasman.2019.03.010.

Gulghane, A., Sharma, R., Borkar, P., 2023. Performance analysis of machine learning-based prediction models for residential building construction waste. Asian J. Civ. Eng. 24 (8), 3265–3276. https://doi.org/10.1007/s42107-023-00708-z.

Guo, Q., Zhan, L., Shen, Y., Wu, L., Chen, Y., 2022. Classification and quantification of excavated soil and construction sludge: a case study in Wenzhou, China. Front. Struct. Civ. Eng. 16 (2), 202–213. https://doi.org/10.1007/s11709-021-0795-8.

Han, D., Kalantari, M., Rajabifard, A., 2024. The development of an integrated BIM-based visual demolition waste management planning system for sustainability-oriented decision-making. J. Environ. Manag. 351, 119856. https://doi.org/10.1016/j.jenvman.2023.119856.

Hao, J.L., Ma, W., 2023. Evaluating carbon emissions of construction and demolition waste in building energy retrofit projects. Energy 281, 128201. https://doi.org/10.1016/j.energy.2023.128201.

Hao, J.L., Zhao, W., Gong, G., Ma, W., Li, L., Zhang, Y., 2024. Catalyzing sustainability through prefabrication: integrating BIM-LCA for assessing embodied carbon in timber formwork waste. Sustain. Chem. Pharm. 41, 101698. https://doi.org/10.1016/j.scp.2024.101698.

Hoang, N.H., Ishigaki, T., Kubota, R., Tong, T.K., Nguyen, T.T., Nguyen, H.G., Yamada, M., Kawamoto, K., 2020. Waste generation, composition, and handling in building-related construction and demolition in Hanoi, Vietnam. Waste Manage. (Tucson, Ariz.) 117, 32–41. https://doi.org/10.1016/j.wasman.2020.08.006.

Honic, M., Kovacic, I., Aschenbrenner, P., Ragossnig, A., 2021. Material Passports for the end-of-life stage of buildings: challenges and potentials. J. Clean. Prod. 319, 128702. https://doi.org/10.1016/j.jclepro.2021.128702.

Hoong, J., Lux, J., Mahieux, P.-Y., Turcry, P., Ait-Mokhtar, A., 2020. Determination of the composition of recycled aggregates using a deep learning-based image analysis. Autom. ConStruct. 116, 103204. https://doi.org/10.1016/j.autcon.2020.103204.

Hossain, M.U., Wu, Z., Poon, C.S., 2017. Comparative environmental evaluation of construction waste management through different waste sorting systems in Hong Kong. Waste Manage. (Tucson, Ariz.) 69, 325–335. https://doi.org/10.1016/j.wasman.2017.07.043.

Hu, R., Chen, K., Chen, W., Wang, Q., Luo, H., 2021. Estimation of construction waste generation based on an improved on-site measurement and SVM-based prediction model: a case of commercial buildings in China. Waste Manage. (Tucson, Ariz.) 126, 791–799. https://doi.org/10.1016/j.wasman.2021.04.012.

Hussain, I., Elomri, A., Kerbache, L., El Omri, A., 2024. Smart city solutions: comparative analysis of waste management models in IoT-enabled environments using multiagent simulation. Sustain. Cities Soc. 103, 105247. https://doi.org/10.1016/j.scs.2024.105247.

Iacovidou, E., Purnell, P., Lim, M.K., 2018. The use of smart technologies in enabling construction components reuse: a viable method or a problem creating solution? J. Environ. Manag. 216, 214–223. https://doi.org/10.1016/j.jenvman.2017.04.093.

Jacobsen, R., Willeghems, G., Gellynck, X., Buysse, J., 2018. Increasing the quantity of separated post-consumer plastics for reducing combustible household waste: the case of rigid plastics in Flanders. Waste Manage. (Tucson, Ariz.) 78, 708–716. https://doi.org/10.1016/j.wasman.2018.06.025.

Jalaei, F., Jrade, A., 2015. Integrating building information modeling (BIM) and LEED system at the conceptual design stage of sustainable buildings. Sustain. Cities Soc. 18, 95–107. https://doi.org/10.1016/j.scs.2015.06.007.

Jiang, P., Zhang, L., You, S., Van Fan, Y., Tan, R.R., Klemeš, J.J., You, F., 2023. Blockchain technology applications in waste management: overview, challenges and opportunities. J. Clean. Prod. 421, 138466. https://doi.org/10.1016/j.jclepro.2023.138466.

Jin, R., Yuan, H., Chen, Q., 2019. Science mapping approach to assisting the review of construction and demolition waste management research published between 2009 and 2018. Resour. Conserv. Recycl. 140, 175–188. https://doi.org/10.1016/j.resconrec.2018.09.029.

Kannan, D., Khademolqorani, S., Janatyan, N., Alavi, S., 2024. Smart waste management 4.0: the transition from a systematic review to an integrated framework. Waste Manage. (Tucson, Ariz.) 174, 1–14. https://doi.org/10.1016/j.wasman.2023.08.041.

Khater, E.G., Ali, S.A., Afify, M.T., Bayomy, M.A., Abbas, R.S., 2022. Using of geographic information systems (GIS) to determine the suitable site for collecting agricultural residues. Sci. Rep. 12 (1), 14567. https://doi.org/10.1038/s41598-022-18850-0.

Kim, Y., Hong, W., Park, J., Cha, G., 2017. An estimation framework for building information modeling (BIM)-based demolition waste by type. Waste Manag. Res. 35 (12), 1285–1295. https://doi.org/10.1177/0734242X17736381.

Kleemann, F., Lehner, H., Szczypińska, A., Lederer, J., Fellner, J., 2017. Using change detection data to assess amount and composition of demolition waste from buildings in Vienna. Resour. Conserv. Recycl. 123, 37–46. https://doi.org/10.1016/j.resconrec.2016.06.010.

Komkova, A., Habert, G., 2023. Optimal supply chain networks for waste materials used in alkali-activated concrete fostering circular economy. Resour. Conserv. Recycl. 193, 106949. https://doi.org/10.1016/j.resconrec.2023.106949.

Koot, M., Mes, M.R., Iacob, M.E., 2021. A systematic literature review of supply chain decision making supported by the Internet of Things and Big Data Analytics. Comput. Ind. Eng. 154, 107076. https://doi.org/10.1016/j.cie.2020.107076.

Kumar, A., Samadder, S., 2017. An empirical model for prediction of household solid waste generation rate–A case study of Dhanbad, India. Waste Manage. (Tucson, Ariz.) 68, 3–15. https://doi.org/10.1016/j.wasman.2017.07.034.

Kumar, A., Samadder, S., Kumar, N., Singh, C., 2018. Estimation of the generation rate of different types of plastic wastes and possible revenue recovery from informal recycling. Waste Manage. (Tucson, Ariz.) 79, 781–790. https://doi.org/10.1016/j.wasman.2018.08.045.

Kurniawan, T.A., Othman, M.H.D., Hwang, G.H., Gikas, P., 2022. Unlocking digital technologies for waste recycling in Industry 4.0 era: a transformation towards a digitalization-based circular economy in Indonesia. J. Clean. Prod. 357, 131911. https://doi.org/10.1016/j.jclepro.2022.131911.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. nature 521 (7553), 436–444. https://doi.org/10.1038/nature14539.

Li, C.Z., Zhao, Y., Xiao, B., Yu, B., Tam, V.W., Chen, Z., Ya, Y., 2020a. Research trend of the application of information technologies in construction and demolition waste management. J. Clean. Prod. 263, 121458. https://doi.org/10.1016/j.jclepro.2020.121458.

Li, J., Liang, J., Zuo, J., Guo, H., 2020b. Environmental impact assessment of mobile recycling of demolition waste in Shenzhen, China. J. Clean. Prod. 263, 121371. https://doi.org/10.1016/j.jclepro.2020.121371.

Li, X., Xu, J., Zhang, Q., 2017. Research on construction schedule management based on BIM technology. Procedia Eng. 174, 657–667. https://doi.org/10.1016/j.proeng.2017.01.214.

Li, Z., Guo, H., Zhang, L., Liang, D., Zhu, Q., Liu, X., Zhou, H., 2022. Time-series monitoring of dust-proof nets covering urban construction waste by multispectral images in Zhengzhou, China. Rem. Sens. 14 (15), 3805.

Liang, S., Gu, Y., 2021. A deep convolutional neural network to simultaneously localize and recognize waste types in images. Waste Manage. (Tucson, Ariz.) 126, 247–257. https://doi.org/10.1016/j.wasman.2021.03.017.

Lim, M.K., Bahr, W., Leung, S.C., 2013. RFID in the warehouse: a literature analysis (1995–2010) of its applications, benefits, challenges and future trends. Int. J. Prod. Econ. 145 (1), 409–430. https://doi.org/10.1016/j.ijpe.2013.05.006.

Lin, K., Zhao, Y., Kuo, J.H., Deng, H., Cui, F., Zhang, Z., Zhang, M., Zhao, C., Gao, X., Zhou, T., 2022. Toward smarter management and recovery of municipal solid waste: a critical review on deep learning approaches. J. Clean. Prod. 346, 130943. https://doi.org/10.1016/j.jclepro.2022.130943.

Liu, Z., Osmani, M., Demian, P., Baldwin, A., 2015. A BIM-aided construction waste minimisation framework. Autom. ConStruct. 59, 1–23. https://doi.org/10.1016/j.autcon.2015.07.020.

Llatas, C., 2011. A model for quantifying construction waste in projects according to the European waste list. Waste Manage. (Tucson, Ariz.) 31 (6), 1261–1276. https://doi.org/10.1016/j.wasman.2011.01.023.

Louis, J., Dunston, P.S., 2018. Integrating IoT into operational workflows for real-time and automated decision-making in repetitive construction operations. Autom. ConStruct. 94, 317–327. https://doi.org/10.1016/j.autcon.2018.07.005.

Lu, W., Chen, J., Xue, F., 2022. Using computer vision to recognize composition of construction waste mixtures: a semantic segmentation approach. Resour. Conserv. Recycl. 178, 106022. https://doi.org/10.1016/j.resconrec.2021.106022.

Lu, W., Chen, X., Ho, D.C., Wang, H., 2016. Analysis of the construction waste management performance in Hong Kong: the public and private sectors compared using big data. J. Clean. Prod. 112, 521–531. https://doi.org/10.1016/j.jclepro.2015.06.106.

Lu, W., Lou, J., Webster, C., Xue, F., Bao, Z., Chi, B., 2021a. Estimating construction waste generation in the Greater Bay Area, China using machine learning. Waste Manage. (Tucson, Ariz.) 134, 78–88. https://doi.org/10.1016/j.wasman.2021.08.012.

Lu, W., Webster, C., Chen, K., Zhang, X., Chen, X., 2017. Computational Building Information Modelling for construction waste management: moving from rhetoric to reality. Renew. Sustain. Energy Rev. 68, 587–595. https://doi.org/10.1016/j.rser.2016.10.029.

Lu, W., Yuan, L., Xue, F., 2021b. Investigating the bulk density of construction waste: a big data-driven approach. Resour. Conserv. Recycl. 169, 105480. https://doi.org/10.1016/j.resconrec.2021.105480.

Luo, X., Li, H., Wang, H., Wu, Z., Dai, F., Cao, D., 2019. Vision-based detection and visualization of dynamic workspaces. Autom. ConStruct. 104, 1–13. https://doi.org/10.1016/j.autcon.2019.04.001.

Ma, W., Hao, J.L., 2024. Enhancing a circular economy for construction and demolition waste management in China: a stakeholder engagement and key strategy approach. J. Clean. Prod. 450, 141763. https://doi.org/10.1016/j.jclepro.2024.141763.

Maiurova, A., Kurniawan, T.A., Kustikova, M., Bykovskaia, E., Othman, M.H.D., Singh, D., Goh, H.H., 2022. Promoting digital transformation in waste collection service and waste recycling in Moscow (Russia): applying a circular economy paradigm to mitigate climate change impacts on the environment. J. Clean. Prod. 354, 131604. https://doi.org/10.1016/j.jclepro.2022.131604.

Matlin, S.A., Mehta, G., Hopf, H., Krief, A., Keßler, L., Kümmerer, K., 2020. Material circularity and the role of the chemical sciences as a key enabler of a sustainable post-trash age. Sustain. Chem. Pharm. 17, 100312. https://doi.org/10.1016/j.scp.2020.100312.

Mercader-Moyano, P., Morat, O., Serrano-Jiménez, A., 2021. Urban and social vulnerability assessment in the built environment: an interdisciplinary index-methodology towards feasible planning and policy-making under a crisis context. Sustain. Cities Soc. 73, 103082. https://doi.org/10.1016/j.scs.2021.103082.

Milios, L., 2021. Towards a circular economy taxation framework: expectations and challenges of implementation. Circ. Econ. Sustainability. 1 (2), 477–498. https://doi.org/10.1007/s43615-020-00002-z.

Montecinos, J., Ouhimmou, M., Chauhan, S., Paquet, M., 2018. Forecasting multiple waste collecting sites for the agro-food industry. J. Clean. Prod. 187, 932–939. https://doi.org/10.1016/j.jclepro.2018.03.127.

Moon, S., Hou, L., Han, S., 2023. Empirical study of an artificial neural network for a manufacturing production operation. Oper. Manage. Res. 16 (1), 311–323. https://doi.org/10.1007/s12063-022-00309-0.

Mousavi, S., Hosseinzadeh, A., Golzary, A., 2023. Challenges, recent development, and opportunities of smart waste collection: a review. Sci. Total Environ. 886, 163925. https://doi.org/10.1016/j.scitotenv.2023.163925.

Nawaz, A., Chen, J., Su, X., 2023. Exploring the trends in construction and demolition waste (C&DW) research: a scientometric analysis approach. Sustain. Energy Technol. Assessments 55, 102953. https://doi.org/10.1016/j.seta.2022.102953.

Nizam, R.S., Zhang, C., Tian, L., 2018. A BIM based tool for assessing embodied energy for buildings. Energy Build. 170, 1–14. https://doi.org/10.1016/j.enbuild.2018.03.067.

Noori, R., Abdoli, M., Ghasrodashti, A.A., Jalili Ghazizade, M., 2009. Prediction of municipal solid waste generation with combination of support vector machine and principal component analysis: a case study of Mashhad. Environ. Prog. Sustain. Energy: An Official Publication of the American Institute of Chemical Engineers 28 (2), 249–258. https://doi.org/10.1002/ep.10317.

Olawade, D.B., Fapohunda, O., Wada, O.Z., Usman, S.O., Ige, A.O., Ajisafe, O., Oladapo, B.I., 2024. Smart waste management: a paradigm shift enabled by artificial intelligence. Waste Management Bulletin. https://doi.org/10.1016/j.wmb.2024.05.001.

Olawumi, T.O., Chan, D.W., 2018. A scientometric review of global research on sustainability and sustainable development. J. Clean. Prod. 183, 231–250. https://doi.org/10.1016/j.jclepro.2018.02.162.

Oluleye, B.I., Chan, D.W., Saka, A.B., Olawumi, T.O., 2022. Circular economy research on building construction and demolition waste: a review of current trends and future research directions. J. Clean. Prod. 357, 131927. https://doi.org/10.1016/j.jclepro.2022.131927.

Omrany, H., Chang, R., Soebarto, V., Zhang, Y., Ghaffarianhoseini, A., Zuo, J., 2022. A bibliometric review of net zero energy building research 1995–2022. Energy Build. 262, 111996. https://doi.org/10.1016/j.enbuild.2022.111996.

Ottenhaus, L.M., Yan, Z., Brandner, R., Leardini, P., Fink, G., Jockwer, R., 2023. Design for adaptability, disassembly and reuse–A review of reversible timber connection systems. Construct. Build. Mater. 400, 132823. https://doi.org/10.1016/j.conbuildmat.2023.132823.

Özkan, K., Ergin, S., Işık, Ş., Işıklı, İ., 2015. A new classification scheme of plastic wastes based upon recycling labels. Waste Manage. (Tucson, Ariz.) 35, 29–35. https://doi.org/10.1016/j.wasman.2014.09.030.

Panwar, H., Gupta, P., Siddiqui, M.K., Morales-Menendez, R., Bhardwaj, P., Sharma, S., Sarker, I.H., 2020. AquaVision: automating the detection of waste in water bodies using deep transfer learning. Case Stud. Chem. Environ. Eng. 2, 100026. https://doi.org/10.1016/j.cscee.2020.100026.

Park, M.W., Brilakis, I., 2012. Construction worker detection in video frames for initializing vision trackers. Autom. ConStruct. 28, 15–25. https://doi.org/10.1016/j.autcon.2012.06.001.

Paul, M., Bussemaker, M.J., 2020. A web-based geographic interface system to support decision making for municipal solid waste management in England. J. Clean. Prod. 263, 121461. https://doi.org/10.1016/j.jclepro.2020.121461.

Prasad, V., Arashpour, M., 2024. Optimally leveraging depth features to enhance segmentation of recyclables from cluttered construction and demolition waste streams. J. Environ. Manag. 354, 120313. https://doi.org/10.1016/j.jenvman.2024.120313.

Ram, V., Kalidindi, S.N., 2017. Estimation of construction and demolition waste using waste generation rates in Chennai, India. Waste Manag. Res. 35 (6), 610–617. https://doi.org/10.1177/0734242X176932.

Rao, A.S., Radanovic, M., Liu, Y., Hu, S., Fang, Y., Khoshelham, K., Palaniswami, M., Ngo, T., 2022. Real-time monitoring of construction sites: sensors, methods, and applications. Autom. ConStruct. 136, 104099. https://doi.org/10.1016/j.autcon.2021.104099.

Rašković, M., Ragossnig, A.M., Kondracki, K., Ragossnig-Angst, M., 2020. Clean construction and demolition waste material cycles through optimised pre-demolition waste audit documentation: a review on building material assessment tools. Waste Manag. Res. 38 (9), 923–941. https://doi.org/10.1177/0734242X20936763.

Risius, M., Spohrer, K., 2017. A blockchain research framework: what we (don't) know, where we go from here, and how we will get there. Business & information systems engineering 59, 385–409. https://doi.org/10.1007/s12599-017-0506-0.

Saggi, M.K., Jain, S., 2018. A survey towards an integration of big data analytics to big insights for value-creation. Inf. Process. Manag. 54 (5), 758–790. https://doi.org/10.1016/j.ipm.2018.01.010.

Sarc, R., Curtis, A., Kandlbauer, L., Khodier, K., Lorber, K.E., Pomberger, R., 2019. Digitalisation and intelligent robotics in value chain of circular economy oriented waste management–A review. Waste Manage. (Tucson, Ariz.) 95, 476–492. https://doi.org/10.1016/j.wasman.2019.06.035.

Satav, A.G., Kubade, S., Amrutkar, C., Arya, G., Pawar, A., 2023. A state-of-the-art review on robotics in waste sorting: scope and challenges. Int. J. Interact. Des. Manuf. 17 (6), 2789–2806. https://doi.org/10.1007/s12008-023-01320-w.

Sattari, M.T., Rezazadeh-Joudi, A., Kusiak, A., 2017. Assessment of different methods for estimation of missing data in precipitation studies. Nord. Hydrol 48 (4), 1032–1044. https://doi.org/10.2166/nh.2016.364.

Schamne, A.N., Nagalli, A., Soeiro, A.A.V., Martins, J.P.d.S.P., 2024. BIM in construction waste management: a conceptual model based on the industry foundation classes standard. Autom. ConStruct. 159, 105283. https://doi.org/10.1016/j.autcon.2024.105283.

Sepasgozar, S.M., Mair, D.F., Tahmasebinia, F., Shirowzhan, S., Li, H., Richter, A., Yang, L., Xu, S., 2021. Waste management and possible directions of utilising digital technologies in the construction context. J. Clean. Prod. 324, 129095. https://doi.org/10.1016/j.jclepro.2021.129095.

Sharma, K., Sood, M., 2024. Monitoring, classification and analysis of waste disposal sites using Machine Learning. Procedia Comput. Sci. 235, 1558–1567. https://doi.org/10.1016/j.procs.2024.04.147.

Shi, Y., Xu, J., 2021. BIM-based information system for econo-enviro-friendly end-of-life disposal of construction and demolition waste. Autom. ConStruct. 125, 103611. https://doi.org/10.1016/j.autcon.2021.103611.

Sibale, J.L., Fischer, T.B., 2024. Does matrilineality reduce gender inequality in Environmental and Social Impact Assessment (ESIA) public participation? Some evidence from Malawi. Environ. Manag. 1–12. https://doi.org/10.1007/s00267-024-01971-9.

Singh, A., 2019. Remote sensing and GIS applications for municipal waste management. J. Environ. Manag. 243, 22–29. https://doi.org/10.1016/j.jenvman.2019.05.017.

Singh, M., Singh, M., Singh, S.K., 2024. Tackling municipal solid waste crisis in India: insights into cutting-edge technologies and risk assessment. Sci. Total Environ. 170453. https://doi.org/10.1016/j.scitotenv.2024.170453.

Singh, N., Farina, I., Petrillo, A., Colangelo, F., De Felice, F., 2023. Carbon capture, sequestration, and usage for clean and green environment: challenges and opportunities. Int. J. Sustain. Eng. 16 (1), 248–268. https://doi.org/10.1080/19397038.2023.2256379.

Sirimewan, D., Bazli, M., Raman, S., Mohandes, S.R., Kineber, A.F., Arashpour, M., 2024a. Deep learning-based models for environmental management: recognizing construction, renovation, and demolition waste in-the-wild. J. Environ. Manag. 351, 119908. https://doi.org/10.1016/j.jenvman.2023.119908.

Sirimewan, D., Harandi, M., Peiris, H., Arashpour, M., 2024b. Semi-supervised segmentation for construction and demolition waste recognition in-the-wild: adversarial dual-view networks. Resour. Conserv. Recycl. 202, 107399. https://doi.org/10.1016/j.resconrec.2023.107399.

Song, J., Zhang, H., Dong, W., 2016. A review of emerging trends in global PPP research: analysis and visualization. Scientometrics 107, 1111–1147. https://doi.org/10.1007/s11192-016-1918-1.

Song, P., Wu, L., Zhao, W., Ma, W., Hao, J., 2024. Life cycle sustainability assessment: an index system for building energy retrofit projects. Buildings 14 (9), 2817. https://doi.org/10.3390/buildings14092817.

Song, Y., Wang, Y., Liu, F., Zhang, Y., 2017. Development of a hybrid model to predict construction and demolition waste: China as a case study. Waste Manage. (Tucson, Ariz.) 59, 350–361. https://doi.org/10.1016/j.wasman.2016.10.009.

Soni, U., Roy, A., Verma, A., Jain, V., 2019. Forecasting municipal solid waste generation using artificial intelligence models—a case study in India. SN Appl. Sci. 1 (2), 162. https://doi.org/10.1007/s42452-018-0157-x.

Soto-Paz, J., Arroyo, O., Torres-Guevara, L.E., Parra-Orobio, B.A., Casallas-Ojeda, M., 2023a. The circular economy in the construction and demolition waste management: a comparative analysis in emerging and developed countries. J. Build. Eng. 107724. https://doi.org/10.1016/j.jobe.2023.107724.

Soto-Paz, J., Hernandez, A., Mejía-Parada, C.A., Mora-Ruiz, V., Hernández, W., Luna-Guevara, F., Casallas-Ojeda, M., Parra-Orobio, B.A., 2023b. A hybrid decision tool for site selection of construction and demolition waste (CDW) facilities in developing countries. Environ. Processess. 10 (2), 35. https://doi.org/10.1007/s40710-023-00633-y.

Soust-Verdaguer, B., Llatas, C., García-Martínez, A., 2017. Critical review of bim-based LCA method to buildings. Energy Build. 136, 110–120. https://doi.org/10.1016/j.enbuild.2016.12.009.

Su, S., Li, S., Ju, J., Wang, Q., Xu, Z., 2021. A building information modeling-based tool for estimating building demolition waste and evaluating its environmental impacts. Waste Manage. (Tucson, Ariz.) 134, 159–169. https://doi.org/10.1016/j.wasman.2021.07.025.

Tariq, S., Hu, Z., Zayed, T., 2021. Micro-electromechanical systems-based technologies for leak detection and localization in water supply networks: a bibliometric and systematic review. J. Clean. Prod. 289, 125751. https://doi.org/10.1016/j.jclepro.2020.125751.

Ujong, J.A., Mbadike, E.M., Alaneme, G.U., 2022. Prediction of cost and duration of building construction using artificial neural network. Asian J. Civ. Eng. 23 (7), 1117–1139. https://doi.org/10.1007/s42107-022-00474-4.

Vahidi, A., Gebremariam, A.T., Di Maio, F., Meister, K., Koulaeian, T., Rem, P., 2024. RFID-based material passport system in a recycled concrete circular chain. J. Clean. Prod. 442, 140973. https://doi.org/10.1016/j.jclepro.2024.140973.

Wang, H., Zhang, J., Lin, H., 2022a. Satellite-based analysis of landfill landslide: the case of the 2015 Shenzhen landslide. Int. J. Geotech. Eng. 16 (3), 293–300. https://doi.org/10.1080/19386362.2019.1610605.

Wang, T., Wu, Z., Luo, C., 2021. Multi-participant construction waste demolition and transportation decision-making system. Resour. Conserv. Recycl. 170, 105575. https://doi.org/10.1016/j.resconrec.2021.105575.

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

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

Wang, Z., Peng, B., Huang, Y., Sun, G., 2019b. Classification for plastic bottles recycling based on image recognition. Waste Manage. (Tucson, Ariz.) 88, 170–181. https://doi.org/10.1016/j.wasman.2019.03.032.

Wang, Z., Zhang, Y., Mosalam, K.M., Gao, Y., Huang, S.L., 2022c. Deep semantic segmentation for visual understanding on construction sites. Comput. Aided Civ. Infrastruct. Eng. 37 (2), 145–162. https://doi.org/10.1111/mice.12701.

Weber, K., Quicker, P., Hanewinkel, J., Flamme, S., 2020. Status of waste-to-energy in Germany, Part I–Waste treatment facilities. Waste Manag. Res. 38 (1_Suppl. l), 23–44. https://doi.org/10.1177/0734242X1989463.

Won, J., Cheng, J.C., 2017. Identifying potential opportunities of building information modeling for construction and demolition waste management and minimization. Autom. ConStruct. 79, 3–18. https://doi.org/10.1016/j.autcon.2017.02.002.

Won, J., Cheng, J.C., Lee, G., 2016. Quantification of construction waste prevented by BIM-based design validation: case studies in South Korea. Waste Manage. (Tucson, Ariz.) 49, 170–180. https://doi.org/10.1016/j.wasman.2015.12.026.

Wu, L., Lu, W., Peng, Z., Webster, C., 2023. A blockchain non-fungible token-enabled 'passport'for construction waste material cross-jurisdictional trading. Autom. ConStruct. 149, 104783. https://doi.org/10.1016/j.autcon.2023.104783.

Wuni, I.Y., Shen, G.Q., Osei-Kyei, R., 2019. Scientometric review of global research trends on green buildings in construction journals from 1992 to 2018. Energy Build. 190, 69–85. https://doi.org/10.1016/j.enbuild.2019.02.010.

Xu, J., Lu, W., Ye, M., Xue, F., Zhang, X., Lee, B.F.P., 2020. Is the private sector more efficient? Big data analytics of construction waste management sectoral efficiency. Resour. Conserv. Recycl. 155, 104674. https://doi.org/10.1016/j.resconrec.2019.104674.

Xu, J., Shi, Y., Xie, Y., Zhao, S., 2019. A BIM-Based construction and demolition waste information management system for greenhouse gas quantification and reduction. J. Clean. Prod. 229, 308–324. https://doi.org/10.1016/j.jclepro.2019.04.158.

Xue, F., Wu, L., Lu, W., 2021. Semantic enrichment of building and city information models: a ten-year review. Adv. Eng. Inf. 47, 101245. https://doi.org/10.1016/j.aei.2020.101245.

Yalcinkaya, S., Kirtiloglu, O.S., 2021. Application of a geographic information system-based fuzzy analytic hierarchy process model to locate potential municipal solid waste incineration plant sites: a case study of Izmir Metropolitan Municipality. Waste Manag. Res. 39 (1), 174–184. https://doi.org/10.1177/0734242X20939636.

Ye, Z., Yang, J., Zhong, N., Tu, X., Jia, J., Wang, J., 2020. Tackling environmental challenges in pollution controls using artificial intelligence: a review. Sci. Total Environ. 699, 134279. https://doi.org/10.1016/j.scitotenv.2019.134279.

Yong, Q., Wu, H., Wang, J., Chen, R., Yu, B., Zuo, J., Du, L., 2023. Automatic identification of illegal construction and demolition waste landfills: a computer vision approach. Waste Manage. (Tucson, Ariz.) 172, 267–277. https://doi.org/10.1016/j.wasman.2023.10.023.

Yu, S., Awasthi, A.K., Ma, W., Wen, M., Di Sarno, L., Wen, C., Hao, J.L., 2022. In support of circular economy to evaluate the effects of policies of construction and demolition waste management in three key cities in Yangtze River Delta. Sustain. Chem. Pharm. 26, 100625. https://doi.org/10.1016/j.scp.2022.100625.

Yu, S., Hao, J.L., Di Sarno, L., Ma, W., Guo, N., Liu, Y., 2023. Enhancing pro-environmental behaviour of employees towards renovation waste for a circular economy: the role of external supervision and corporate environmental responsibility. Sustain. Chem. Pharm. 33, 101103. https://doi.org/10.1016/j.scp.2023.101103.

Yu, Y., Li, H., Yang, X., Kong, L., Luo, X., Wong, A.Y., 2019. An automatic and non-invasive physical fatigue assessment method for construction workers. Autom. ConStruct. 103, 1–12. https://doi.org/10.1016/j.autcon.2019.02.020.

Yuan, L., Lu, W., Xue, F., 2021. Estimation of construction waste composition based on bulk density: a big data-probability (BD-P) model. J. Environ. Manag. 292, 112822. https://doi.org/10.1016/j.jenvman.2021.112822.

Zhao, W., Hao, J.L., Gong, G., Ma, W., Zuo, J., Di Sarno, L., 2024. Decarbonizing prefabricated building waste: scenario simulation of policies in China. J. Clean. Prod. 458, 142529. https://doi.org/10.1016/j.jclepro.2024.142529.