Enhancing information standards for automated construction waste quantification and classification

Sivashanmugam, S., Rodriguez, S., Pour Rahimian, F., Elghaish, F., & Dawood, N. (2023). Enhancing information standards for automated construction waste quantification and classification. *Automation in Construction*, *152*, Article 104898. https://doi.org/10.1016/j.autcon.2023.104898

Published in:
Automation in Construction

Document Version:
Publisher's PDF, also known as Version of record

Queen's University Belfast - Research Portal:
Link to publication record in Queen's University Belfast Research Portal

Publisher rights
Copyright 2023 the authors.
This is an open access article published under a Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution and reproduction in any medium, provided the author and source are cited.

General rights
Copyright for the publications made accessible via the Queen's University Belfast Research Portal is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The Research Portal is Queen's institutional repository that provides access to Queen's research output. Every effort has been made to ensure that content in the Research Portal does not infringe any person's rights, or applicable UK laws. If you discover content in the Research Portal that you believe breaches copyright or violates any law, please contact openaccess@qub.ac.uk.

Open Access
This research has been made openly available by Queen's academics and its Open Research team. We would love to hear how access to this research benefits you. – Share your feedback with us: http://go.qub.ac.uk/oa-feedback

Download date:25. Mar. 2025

Automation in Construction 152 (2023) 104898

Contents lists available at ScienceDirect

Automation in Construction

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

Review

Enhancing information standards for automated construction waste quantification and classification

Subarna Sivashanmugam [a], Sergio Rodriguez [a], Farzad Pour Rahimian [a,*], Faris Elghaish [b], Nashwan Dawood [a]

[a] School of Computing, Engineering and Digital Technologies, Teesside University, United Kingdom
[b] Lecturer in Construction Project Management, School of Natural and Built Environment, Queen's University Belfast, United Kingdom

ARTICLE INFO

Keywords:
Construction and demolition waste
Quantification and classification
Information and communication technologies
Literature review
Conceptual framework

ABSTRACT

Accurate quantification and detailed classification of construction waste are paramount to improving their management. Over the last decades, various quantification models have been developed to measure, manage, and report construction waste generation. A detailed understanding of those models is essential to explore their applications across the life-cycle stages of a built asset. Existing reviews primarily focused on analysing the functions of quantification methodologies, but the digital and information standards to automate the quantification process are under-explored in the existing literature. A review is adopted to analyse papers published from 2012 to 2022. Out of 279 articles retrieved, 71 papers meeting the eligibility criteria were included. A critical analysis of the models indicates that unified data structure, standard information, life-cycle approach and interoperability between the BIM and waste knowledge bases are vital to automate and reinforce the quantification efficiency. Based on the review findings, a conceptual framework is developed to demonstrate the quantification workflow for building projects. The outcomes from the review will facilitate researchers to identify the prevailing gaps and enhance the waste quantification system to meet digital construction demands.

1. Introduction

Construction activities contribute to a large volume of solid waste globally. Around one-third of global solid waste is generated by the construction industry. For instance, construction waste in the UK contributes to 62% of total solid waste [1]. In the US, 600 million tonnes of construction debris were generated in 2018, twice the total municipal solid waste generated [2]. There are several definitions of waste. The European Union Waste Framework Directive defines 'waste' as '*any substance or object the holder discards or intends or is required to discard*' [3]. In general, waste is classified as construction, demolition, and excavation waste, depending on the type of activities causing waste. However, according to the statistical classification of economic activities in the European Community (NACE Rev. 2), 'Construction' includes excavation, construction, refurbishment, renovation, and demolition activities [4]. Therefore, this study adopts the term 'construction waste (CW)' to represent the material waste generated by the construction industry. Construction waste may be inert, non-inert and hazardous depending on its composition. Inert waste is widely used for site formation and land reclamation activities because of its non-reactive nature to the environment. Non-inert waste is chemically active and non-hazardous, while hazardous waste threatens the environment and human health [6]. The environmental impacts associated with waste are multi-fold, which include excessive raw material consumption, energy usage, greenhouse gas emissions, pollution, and landfilling. In the UK, for example, the construction sector consumes 25% of raw materials and contributes 32% of landfill waste [10]. In addition, waste generation significantly impacts time and cost overruns [11].

Attempts to enhance the flow of materials within construction projects gained momentum by introducing a circular economy approach. This approach aims to reduce raw material consumption, maximise the material life, and reduce waste generation and carbon emissions across the project life cycle [13]. Besides, Building Information Modelling (BIM), prefabrication, on-site waste reuse, recycling, and lean principles facilitate construction waste management (CWM) [6,17]. However, on top of all methods, accurate quantification and classification of waste are recognised as a primary part of CWM [29]. Thus, measuring waste generation amount, type, time, and place is essential for making

---

* Corresponding author.
E-mail address: f.rahimian@tees.ac.uk (F. Pour Rahimian).

https://doi.org/10.1016/j.autcon.2023.104898
Received 8 December 2022; Received in revised form 5 April 2023; Accepted 20 April 2023

informed WM decisions [27]. This led to the development of various quantification models to estimate waste generation at building and national levels. Each model is unique regarding its usage across the lifecycle stages, integration with project types, quantification methodology adopted, data types used, and application of digital technologies.

Earlier reviews conducted in the waste quantification (WQ) context focused on analysing the benefits and limitations of various quantification methods while overlooking the importance of data and digital implications to enhance WQ efficiency. For instance, Masudi et al. [28] discussed the six methods used to quantify waste generated from building projects by reviewing studies from 1996 to 2009. Wu et al. [29] examined the quantification methodologies, including site visits, generation rate calculation, life cycle analysis, classification system accumulation, and variable modelling, based on their review of papers published between 1996 and 2013. Meanwhile, other recent reviews [17,30–32] focused on reviewing the overall CW management process, which includes waste reduction, reuse, recycling, transport, disposal, quantification, and other standards and regulations. These reviews examine the applications of various technologies that facilitate the overall WM process, while the critical analysis of various elements of WQ models is limited.

Besides, evidence from existing research suggests that WQ is complex and challenging because of the diverse range of activities and materials involved across the project life cycle [33]. Moreover, there appears to be a transition towards using information and communication technologies (ICT) in the construction industry [36], which promotes a shift from fragmented traditional settings to integrated digital systems. The use of digital technologies has also been utilised to improve WM process [37–42]. However, despite the advancements of digital applications in the construction domain, there remains a lack of evidence on the information and digital standards in the WQ context in the burgeoning literature. Hence, a critical review of existing WQ models is significant to understand their key elements and limitations in digital construction. The study addressed three main research objectives stated thus:

Objective 1 – To explore the key factors influencing the applicability of construction WQ models.

Objective 2 - To identify the significant limitations of the current WQ system and propose future research directions to address the shortcomings.

Objective 3 - To propose a conceptual framework for improving information and digital standards of WQ systems through the application of ICTs.

The rest of the paper is structured as follows. Section 2 explains the methodology adopted in the study. Section 3 presents a detailed synthesis of the review. Section 4 discusses the limitations of current studies and provides recommendations for future studies to enhance the accessibility of WQ models. Finally, section 5 presents a BIM-assisted conceptual framework to automate the integration of the WQ process with project workflows.

2. Research methodology

The first two research objectives of the study were underpinned by a systematic literature review (SLR), which facilitated the identification of the gaps in the body of knowledge. The third research objective of the study was then addressed using a conceptual framework. This section overviews the SLR and its applications in this study. SLRs are advanced from traditional narrative reviews because of the transparent methodology adopted to collect and analyse data [43,44]. The critical aspect of SLR is that it allows researchers to filter articles based on pre-defined selection criteria, which reduces the ambiguities associated with data handling [45]. It can be defined as a systematic approach used to identify, evaluate, and synthesise research findings that aid in informed decision-making [46]. SLR is adopted in this study to compare and interpret patterns of existing WQ models. The five main elements of SLR that need to be defined before the review [45] are tabulated (Table 1).

Table 1
Review elements and their applications in this study.

Phases	Review elements	Applications in the current study
i)	Framing questions for review	a) What are the critical factors of WQ in global construction settings? b) What significant limitations are associated with the current WQ process? c) What are future research directions to enhance productivity in the overall WQ process?
ii)	Identifying relevant papers - search strategies	a) Source: Electronic databases (a detailed description of the type of database is given below) b) Selected keyword search using Boolean operators (Section 2.1)
iii)	Inclusion and exclusion criteria	a) Type - Research articles b) Language – English c) Year of publication – From 2012 to 2022 (December) d) Only papers with empirical evidence are included for review d) Papers that focus on solid construction waste are included, excluding liquid waste, general industrial waste, and municipal waste
iv)	Assessing the quality of papers - screening and eligibility	a) Duplicate screening b) Title, abstract and keywords were checked to identify the relevance of the paper with the scope of the study
v)	Data extraction	The relevant articles were extracted and coded in 'NVivo' based on the interpreted themes
vi)	Data analysis	Analysing the models based on the defined codes using tabulation, graphs, and qualitative description
vii)	Summarising the results	a) Describe the current settings of WQ models b) Propose future research advancements concerning WQ across the project life cycle

2.1. *Identifying relevant articles*

The articles were retrieved from widely accepted academic databases, Web of Science and Scopus [48]. In addition, the international journals with Q1 and Q2 Scopus indexes focusing on construction WM and ICT were added for further retrieval. The journals include 'Automation in Construction', 'Construction and Building Materials', 'Journal of Cleaner Production', 'Resources, Conservation and Recycling', 'Sustainability', 'Waste Management', and 'Waste Management and Research'. A bibliometric search method using keywords suggested by [30] is adopted to maximise the quality of search results. This method is adopted to collect relevant articles for review. The waste generated from the construction sector may be termed 'construction waste', 'C&D waste', and 'demolition waste'. Moreover, quantification includes 'generation rates', 'estimation', 'prediction', 'forecasting', and 'assessment'. Similarly, waste' classification' includes 'categorisation', 'sorting', and 'composition'. Therefore, the keywords were combined using the Boolean operators OR and (AND) to retrieve articles relevant to the review. E.g., 'construction waste' OR 'C&D waste' OR 'demolition waste' AND 'quantification', 'construction waste' OR 'C&D waste' OR 'demolition waste' AND 'categorisation'. The data collection and screening process adopted to retrieve articles for review are illustrated (Fig. 1).

2.2. *Screening and eligibility*

A two-step screening process was adopted to validate the eligibility of retrieved articles. In the first step, 82 duplicate articles were removed using the automated duplicate screening option in the "Endnote". The remaining 197 articles were retrieved for analysis. In the second stage of screening, the objectives of the articles were confirmed by scanning the

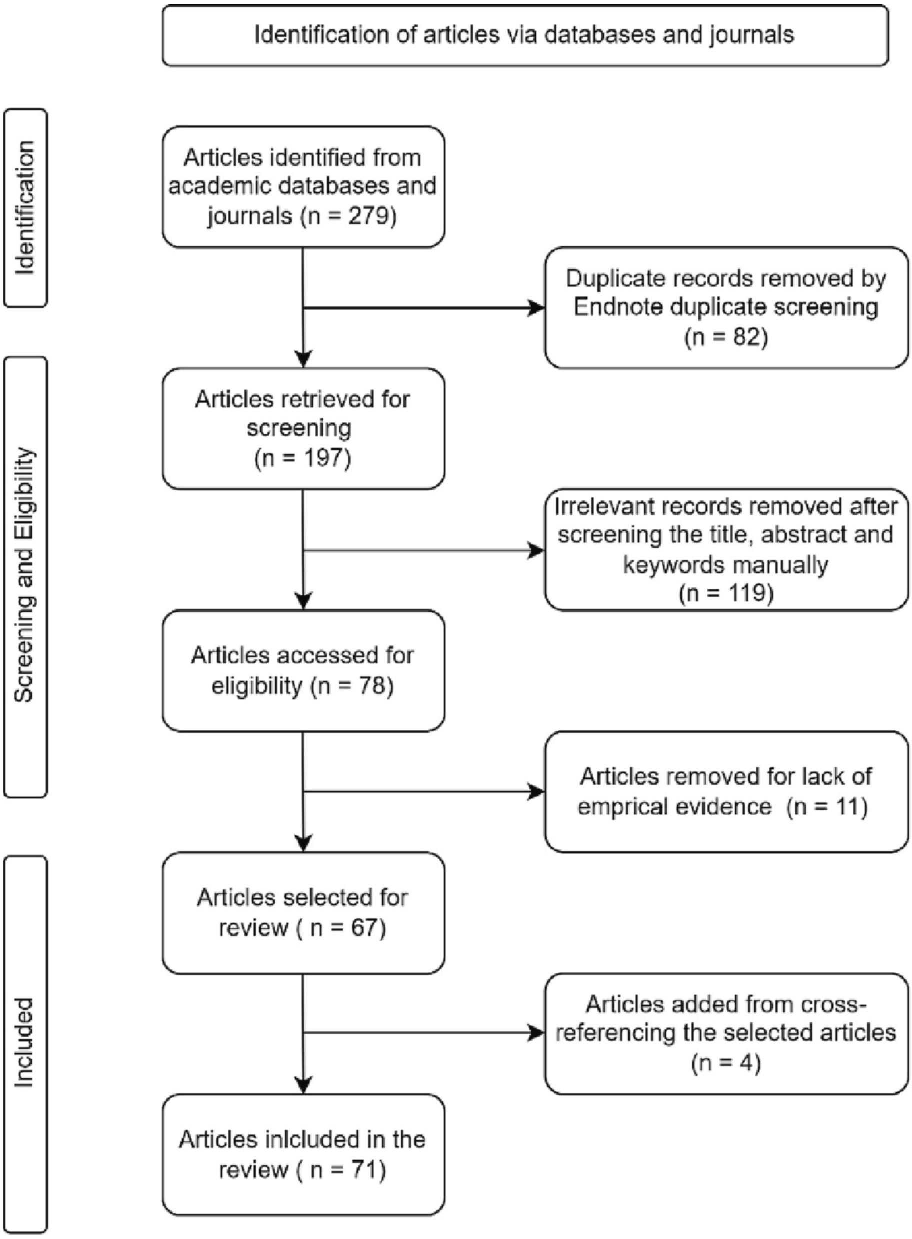

Fig. 1. Identification of articles via databases and journals - Flowchart.

title, abstract and keywords manually. The articles with empirical evidence on construction waste quantities, generation rates, and material composition were only accounted for review to allow a critical comparison of waste information across multiple scenarios. The articles discussing WM and associated innovations with limited or no information on the WQ data were excluded. The screening provided 67 articles meeting the eligibility criteria. Additionally, four articles aligning with the review objectives were retrieved from cross-referencing the filtered articles. Overall, 71 articles were included in the review.

2.3. Data extraction

This review compares the critical factors of WQ models to demonstrate their applicability and accessibility in the digital construction world. The models were categorised in a computer-aided qualitative data analysis platform, NVivo, based on critical factors identified (discussed in Section 4). The organised factors include,

(i) Distribution of papers: Publication year, geographical location, and journal list.
(ii) Sources of waste analysed and reporting metrics

a) Sources: Construction, refurbishment/renovation, and demolition waste
b) Reporting metrics used for classification: work packages, environmental values, chemical and reactive nature, recyclability levels, material distribution and legal waste codes.

(iii) Focus of the models: Buildings and infrastructure works.
(iv) Role of ICT within the WQ system: BIM, Artificial Intelligence (AI)-enabled WQ modelling, Geographical Information Systems (GIS), Big-data, Robotics, and Image recognition.

3. Data synthesis

This section presents the descriptive analysis of the reviewed papers based on publication year, geographical location, and list of journals.

3.1. Publication year

The importance of WQ in the construction sector has been gaining momentum among researchers across the globe in the last decade. As inferred from Fig. 2, the research trend shows a moderate variation each year with ups and downs. Nevertheless, the research conducted in recent years is higher than in previous years. More than half of the research studies were conducted from 2019 to 2022. This suggests increased recognition among the researchers is being given to CW quantification.

3.2. Geographical location

Based on the analysis, WQ research conducted in China ranks high among other countries, contributing to almost one-third of the total research outputs from 2012 to 2022 (Fig. 3). It is followed by HK and Spain, which also showed critical enhancements in research studies focusing on WQ across the region. Overall, half of the research conducted worldwide throughout the selected period is from these geographical locations.

However, the research studies in other countries have a large variation. For instance, in recent years, there has been extremely limited research in a few countries like Korea, Lebanon, and Portugal. In contrast, this trend is reversed in other countries like Bangladesh, the UK, Vietnam, and New Zealand, where there has been active research only in recent years (from 2019). However, various environmental, economic, technological, social, and legal drivers could manage these research gaps in the CW quantification context.

3.3. Journal list

The top five journals publishing papers in this area include *'Waste Management'* (25%), *'Waste Management and Research'* (18%), *'Journal of Cleaner Production* (15%), *'Resources, Conservation and Recycling' (11%)*, and *'Automation in Construction'* (8%). More than two-thirds of the retrieved articles are from these journals. Fig. 4. depicts the distribution of selected articles across the journals.

4. Results

This section presents the results and critical discussions of the findings. The results and discussion are organised into themes according to the review objectives. The themes explored include sources of waste and reporting metrics, application of project types included in WQ, and level of ICT adoption in the WQ process.

4.1. Sources of waste and reporting metrics

This section presents the results and discussion of the reviewed papers based on the sources of the waste and reporting metrics. This is in response to research objective 1, which explores the key factors influencing WQ in global construction settings.

4.1.1. Sources of waste selected for the study

The analysis of the papers showed that decision factors such as quantity and quality of waste vary with project activities. For instance, the waste generation rate (WGR) for the construction of new buildings was found to range from 10 to 135 kg/m^2, refurbishment of existing buildings varied from 20 to 397 kg/m^2, and demolition of existing buildings ranged from 195 to 1750 kg/m^2 [52]. Further, Lu et al. [50] reported that waste generated from maintenance and renovation works is likely to be non-inert. In contrast, demolition works contribute largely to inert and non-inert waste generation. So, to benchmark the WGR of different waste types, the three major types of project activities identified in the literature [19,33] were selected for analysis: construction, demolition, and refurbishment/renovation work. However, due to limited data, the excavation activities were excluded from the review.

As shown in Fig. 5, around half of the articles focused on measuring waste generated from the construction of new buildings [23,33,40,53,54], and 18% focused on demolition works [19,20,55,56]. In comparison, only 3% of the studies developed a WQ system specifically for refurbishment and renovation activities [57,58]. Besides, 8% of the studies focused on construction and demolition works [59–62], and 5% estimated waste generated from all three classified sources [50,52,63].

Further analysis of the papers showed that 23% of the articles [64–66] aggregated the quantification values without accounting for the project activities causing waste. For instance, Lu et al. [41] estimated that 364 million m^3 of construction waste was generated in Greater Bay Area, China, in 2018. Furthermore, Qiao et al. [65] forecasted the waste output from the construction industry to reach 141 million tons by 2025 in Shandong province. However, these studies lack sufficient information on the types of activities attributed to waste generation. Although the total waste value would be sufficient to set national waste reduction targets and policies, classifying waste based on the activities is critical for deciding the most appropriate WM routes. Hence, this variability in the measurement of WGRs may suggest that project phases and activities are critical in WQ.

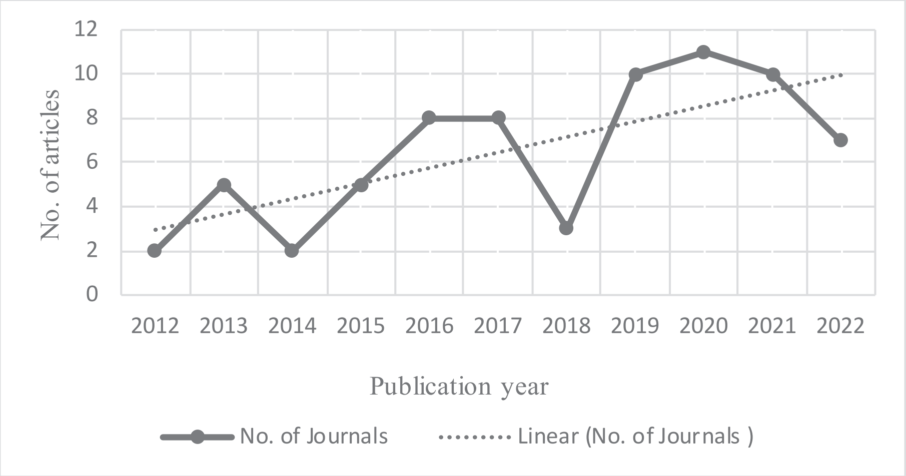

Fig. 2. Distribution of articles - Publication year.

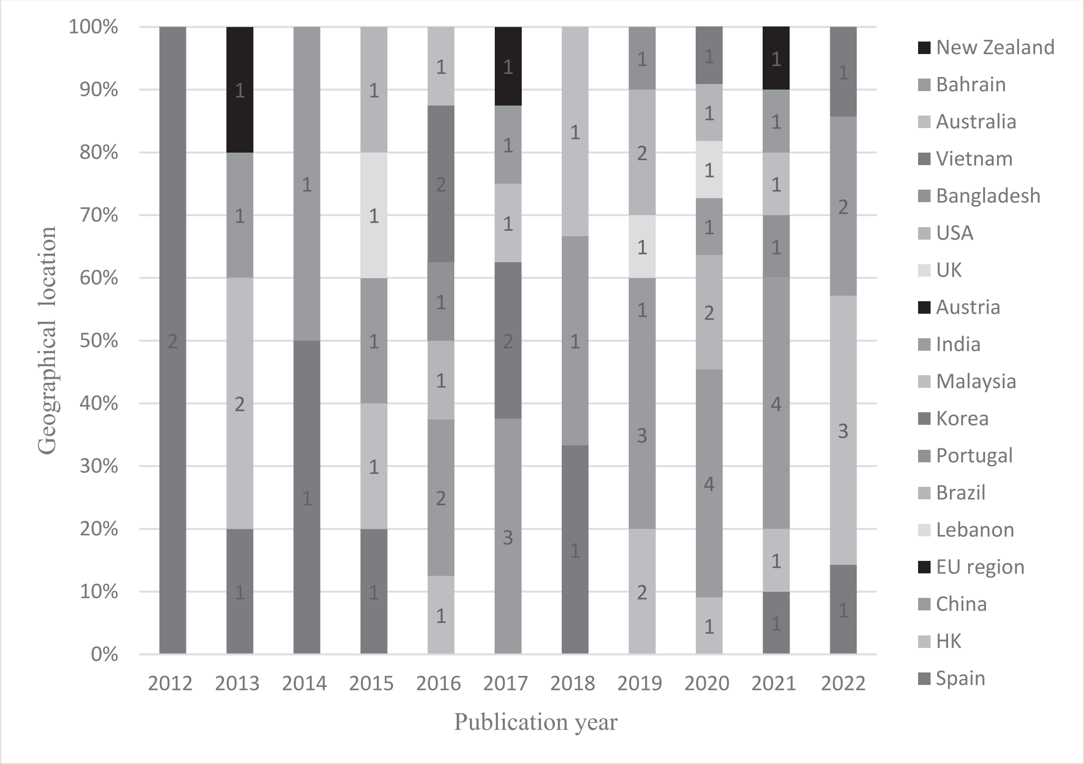

Fig. 3. Distribution of articles - Geographical location and publication year.

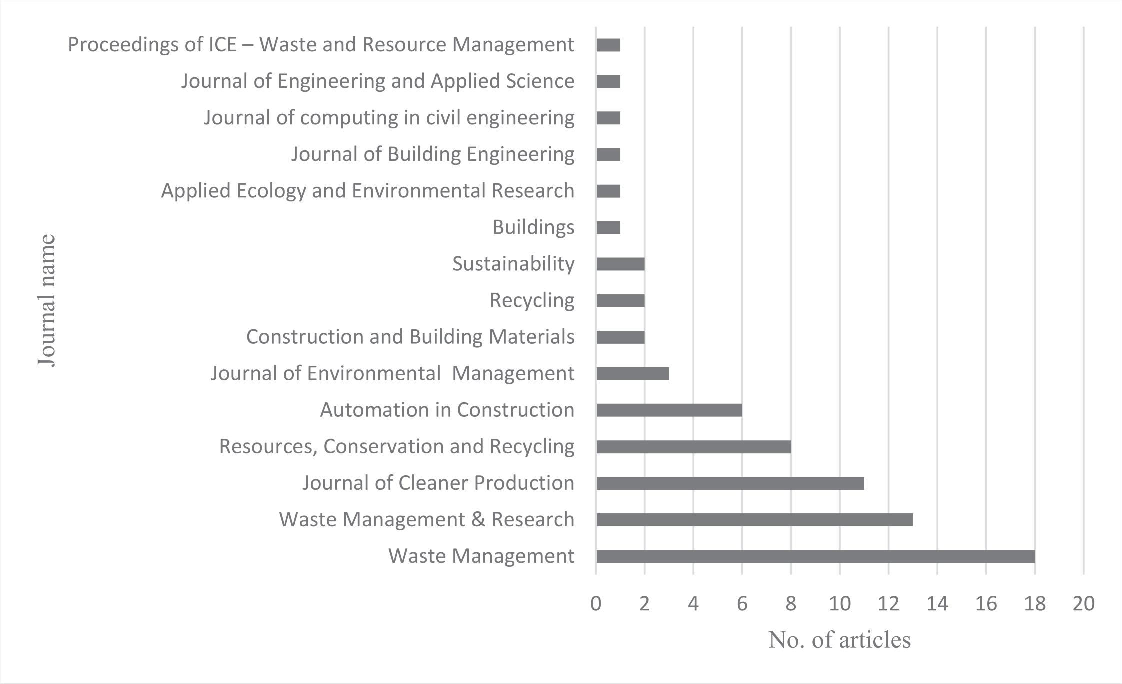

Fig. 4. Distribution of articles - Journal list.

4.1.2. *Classification of waste reporting*

The analysis of the reviewed papers identified that seven types of classifications were used to report waste compositions. It can be seen from Fig. 6 that 3% of the articles used WM routes (reusable, recyclable and landfillable) to report waste [24,37]; 3% used reactive nature and environmental values of waste material (inert, non-inert and hazardous) [50]; while 3% employed chemical properties (organic, inorganic, and metallic) in their classifications [8,67].

Reporting waste with a detailed description of material composition was found to be the most widely used (62%) in the current studies [20,23,34,68–70]. In addition to the material composition, 8% of studies carried out in the European Union (EU) region adopted waste classification systems called European Waste Codes (EWC) [52,57,71,72] to report waste. The EWCs are six-digit codes used for

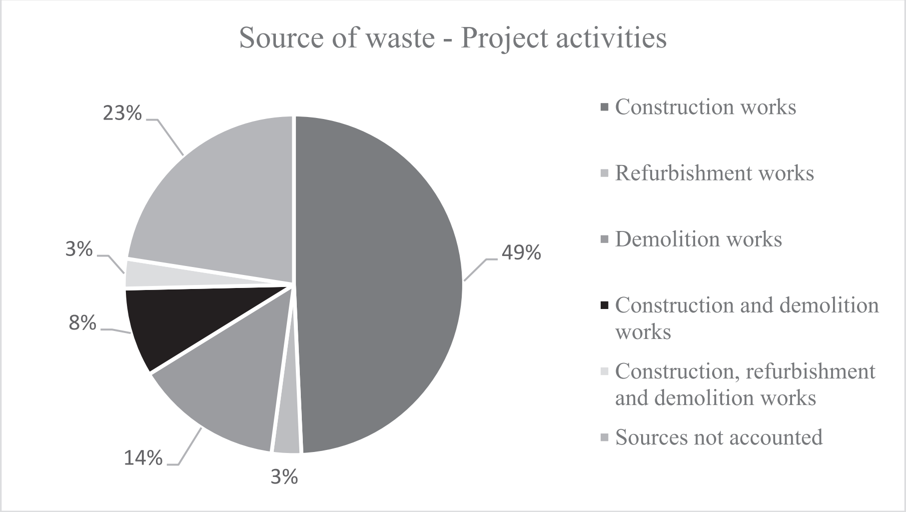

Fig. 5. Sources of waste according to project activities.

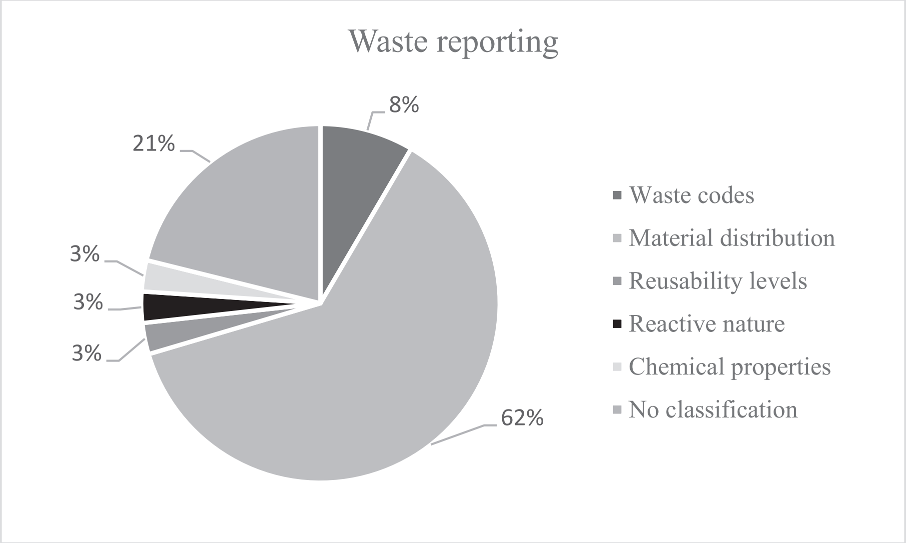

Fig. 6. Classifications of waste reporting.

waste classification and reporting across all EU member states [73]. However, nearly one-fourth of the articles have less or no information on material composition [33,65,74–76].

4.2. *Focus of WQ models based on project types*

This section presents the results and discussion of the reviewed papers based on the project types selected for the study. The analysis found that the four primary factors widely used in WQ include gross floor area (GFA), project type (building usage), structural frame type (concrete/steel/timber) and construction/demolition/deconstruction methodologies [20,72,77,78]. However, among all the factors, project type has been the most dominant factor in deciding waste quantity, quality, and frequency. For instance, comparing the WGRs for the demolition of masonry residential and non-residential buildings, Malia et al. [52] reported that the latter generates approximately twice the waste quantity of the former. Besides, Sun et al. [58] found that residential buildings' decoration and renovation WGR is significantly higher than other building types. These findings highlight the need to account for the project type along with project activities as one of the critical indicators for benchmarking waste performance. An overview of the focus of existing WQ models on different project types is presented in Fig. 7.

Only 1% of the studies focused on measuring waste from infrastructure works [79], while 86% of the articles focused on building projects [20,24,51,63,68,70,80,81]. Thus far, numerous studies [37,38,61,69] have extensively investigated building projects in general but have not adequately considered the usage of buildings. Notwithstanding, few studies included using residential, commercial, and industrial buildings as an indicator to measure waste [33,53,54,72,81,82]. However, considering building usage type is vital to benchmark waste performances. For instance, the WGR for demolition of *masonry 'residential'* and '*non-residential*' buildings in Spain are reported as 302to 664 kg/m^2 and 664to 825 kg/m^2, respectively [52]. This highlights the difference in waste levels according to building usage, thereby signifying the need for its consideration.

Further, the analysis showed that 18% of studies provided less information on project types selected for quantifying waste quantities and material composition. For example, Lu et al. [41] estimated that construction works generated 364 million m^3 of waste in 11 specific cities of the Greater Bay Area in China. This inability to scale the WGRs of various building usages and project activities presents a challenge for decision-makers and has ramifications for the validity of WQ results.

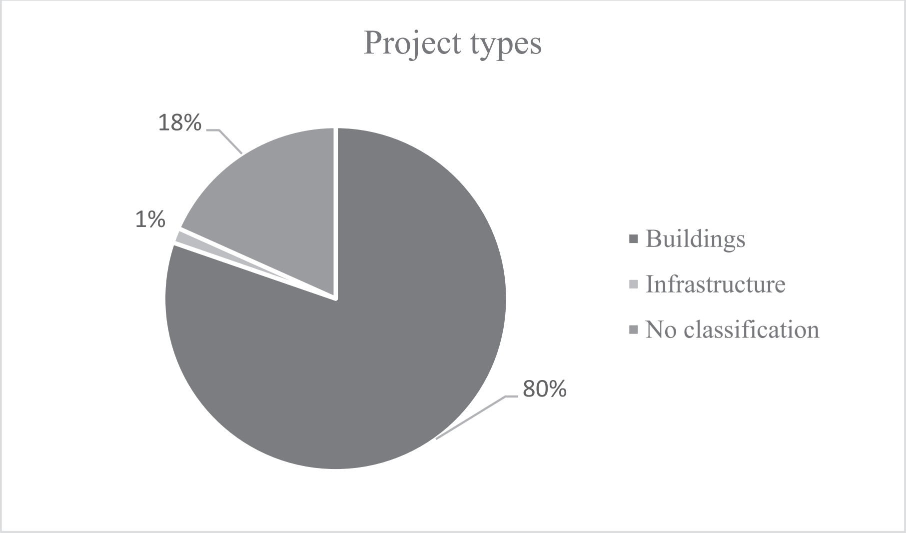

Fig. 7. Project types accounted for WQ.

4.3. Role of ICTs within the WQ system

This section presents the results and discussions of the reviewed papers based on ICT applications in WQ. An analysis of the reviewed articles showed the use of different ICT in various phases of WQ. The technologies primarily incorporated in the quantification process include BIM, AI-enabled WQ modelling, GIS, Big-data, Robotics, and Image recognition techniques.

4.3.1. Building information modelling (BIM)

BIM, one of the leading data-rich and object-oriented collaborative technologies, is incorporated into the WQ process. The application of BIM in WQ is underpinned by accounting BIM i) as an information bank for acquiring design, construction, and material information, ii) as a visualisation tool, and iii) for its computational API features.

i) **As an information bank.**

WQ is considered challenging due to the complex nature of projects, which requires a detailed understanding of the physical and functional properties of materials [90]. Witnessing the data richness in BIM models, researchers used BIM-based quantity take-off (QTO) details to obtain accurate and real-time dimensional and functional data of buildings. The multi-dimensional capability of BIM represents the building information across the life-cycle stages, ranging from 3D modelling to scheduling (4D), cost planning (5D), sustainability (6D), and facilities management (7D). Cheng and Ma [80] was the first research in WQ that incorporated 3D BIM to estimate building demolition and renovation waste quantities, pick-up truck requirements, and disposal costs. Later, the incorporation of 3D BIM to obtain material details required for waste estimation is adopted in future studies [24,38,85–87,89,91,92]. In addition, a few studies have incorporated higher dimensions of BIM to quantify waste. For instance, Guerra et al. [84] developed a 4D-BIM framework to estimate concrete and drywall waste quantities and schedule for its reuse and recycling during building construction. While, Bakchan et al. [83] adopted 7D BIM to estimate waste volume, schedule waste pick-up times, waste cost, and its reuse and recycling capabilities.

ii) **As a visualisation tool.**

Earlier studies highlighted the impact of design changes and design errors causing reworks and waste generation during construction, stating that design factors are responsible for one-third of total waste generation [25,93]. Besides, literature [17,32] proves that BIM's visualisation and design validation features facilitate architects and designers to identify clashes and develop error-free designs in the virtual environment, thereby avoiding reworks and wastage on-site. It is proved by [94] that 4.3% - 15.2% of waste is prevented by integrating the BIM-visualisation features to detect clashes in the design phase.

iii) **For its computational API features.**

In addition to the internal BIM applications, the functionality of BIM authoring tools is expanded to communicate with external applications through the Application Programming Interface (API) and plugins. The model developed by Cheng and Ma [80] was the first research to create a plugin using BIM-API to measure demolition and renovation waste assessment. Also, Akinade and Oyedele [38] developed a plugin to integrate the AI-based waste prediction model with the BIM platform to facilitate waste estimation and design simulation in the early design stages for new buildings. The API benefits the users by automatically extracting the design and material information, estimating waste, and inputting waste information into the model. This API enhances the bidirectional interaction between BIM and WQ models.

4.3.2. Artificial intelligence (AI)-based WQ modelling

AI modelling has proven to provide great value to a variety of application domains, including construction [49,95]. Similarly, various AI models that support WQ and classification processes are applied across the project life cycle. The AI models are widely used to generalise patterns from large datasets with less human intervention and high accuracy. The current studies use AI models to analyse and interpret patterns from the building [8,37–39,74] and regional [41,61] waste datasets. The main features of AI employed in WQ models include i) predictive analytics and ii) image analysis and computer vision.

i) **Predictive analytics.**

Depending on the project functionalities and the volume of existing data records, machine learning (ML), deep learning (DL), and hybrid models are adopted for predicting/forecasting waste generation levels. The two main pillars supporting AI modelling are input data and training algorithm(s). Based on the reviewed articles, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) are the main algorithms employed for mining small and large waste datasets. For instance, Hu et al. [8] used SVM to demonstrate the relationship between predictor variables (influencing factors of waste generation) and WGRs (from a small dataset). The data from 206 ongoing construction projects were used to develop a prediction model. SVM, a supervised ML algorithm, is used for classification, regression and outlier detection in given datasets [96]. While ANNs, a DL model, is used to generalise patterns from large datasets. For instance, Lu et al. [64] used ANNs to predict CW generation at early design stages. The waste patterns were interpreted from 37 K waste disposal records of multifamily residential buildings in Hong Kong. The study's results emphasise that WGRs are highly influenced by geographical location, project duration, project cost and public-private nature.

However, accuracy, time and estimation complexities are significant shortcomings of single AI models [74]. Hence, a few studies [38,74] developed hybrid AI models combining two different algorithms to overcome the limitations of single models. The application of hybrid models allowed the researchers to overcome the weakness of individual models and benefit from combining their strengths. For instance, Akinade and Oyedele [38] modelled an ANFIS system, a combination of neural networks and fuzzy inference systems, to develop an ideal neural network structure within a limited time, which otherwise would have been a significant shortcoming in the homogenous model. Further, Lee et al. [74] developed a hybrid model combining ANNs with Ant Colony Optimisation (ACO) to estimate waste in the early construction stages of residential buildings. By comparing simple ANNs with hybrid models, this study proved hybrid model shows less error rate, reduced calculation complexities, reduced training time and increased precision compared to the homogeneous ANN model. Though SVMs and ANNs seem to be dominant algorithms for working with CW datasets, it is worth exploring the options of developing hybrid models to work with fuzzy waste datasets.

ii) **Image analysis and computer vision.**

Besides, AI algorithms are integrated into waste analysis to discover patterns from digital waste images, thus facilitating on-site waste picking, classification, and sorting. Using AI models to recognise images enhances the classification and quantification of waste generated. The image data required for model training is mainly captured from waste skips placed on-site [21], waste dumps [100], truckload images [99,102], and generic google search images [98]. Depending on the type of image selected, the spatial features, visual aspects, and boundaries of waste materials are extracted to design the classification models. For instance, Dong et al. [97] developed a DL-integrated boundary transformer framework based on data collected from waste skips. Thus, integrating the semantic segmentation and object detection features of computer vision, this automated framework facilitates waste recognition in a cluttered state and supplements a fine granularity of material information within the given boundaries. This reduces human intervention, enhances waste reporting, and allows waste handlers to assign codes based on material types to undergo safe disposal.

Based on the analysis, the DL models like ANNs and CNNs are considered appropriate for working with unstructured and fuzzy waste data. However, the availability of waste records is a significant constraint to utilising AI's potential in the CWQ process. Accounting for the data limitation, the study conducted by (Na et al., 2022) employed data augmentation techniques to create new data points from the existing data to amplify the dataset. Thus, this amplification in this study (Na et al., 2022) reduced the overfitting of models and increased generalisation, thereby increasing the applications and accuracy of DL models. Hence, data, time, and accuracy factors should be considered while incorporating AI into the WQ process.

4.3.3. *Geographical information system (GIS)*

GIS is a spatial system that deals with data capture, storage, integration, and spatial and location information analysis. As such, GIS models developed by [24,55,103,104] are used to acquire data required for WQ. Wu et al. [103] developed a GIS model using the software ArcGIS to extract spatial and temporal data, including GFA of buildings, building type, type of structural frames, and design service life of buildings. This multi-dimensional information allowed researchers to estimate demolition waste from buildings at the regional level, its recycling potential and landfill requirements. Kleemann et al. [55] utilised the features of GIS databases and remote sensing to apply change detection based on image matching. Their findings show that statistical analysis underestimates the gross volume of demolished buildings by 1.1 million m3 per annum, which causes inaccuracy in WQ. In addition to measuring building layouts, the site locations and spatial features of waste recycling plants and landfilling sites were also analysed using GIS maps [24].

4.3.4. *Big data*

Big data, a data-driven decision-making approach, is adopted in the WQ to measure and benchmark waste performance. From the reviewed articles, Lu et al. [50] was the first study to incorporate BD to benchmark CWM performance by using consistent WGRs for construction, renovation and demolition works. This study classified waste as inert and non-inert and used a statistical approach to analyse patterns of those waste types. Likewise, Lee et al. [74] proposed an analytical model linked with AI and big data to discover relationships between project characteristics and automate the WQ process. Apart from waste estimation, the role of BD in waste classification is also demonstrated in the literature. Using 4.27 million truckload data, a BD model was developed by [42] to estimate the material composition of waste. The model development was facilitated by combining the statistical and probability approaches with big-data analytics.

4.3.5. *Robotics*

On-site waste segregation is a powerful WM method that facilitates the construction team to maximise the waste recovery potential [105]. Nevertheless, handling these waste materials is time-consuming, cost ineffective, and requires manual work [106]. To overcome these issues, autonomous robots are designed to pick up and sort waste according to the material type. Integrating computer vision into AI models has supported researchers in designing robots for waste picking and on-site sorting [107–109]. Using robots on-site for waste picking and sorting would likely reduce mixed-waste quantities, thereby increasing the waste reuse and recycling potentials. Further, automated sorting would help the construction industry overcome the health and safety accidents associated with manual waste handling.

4.3.6. *Image recognition*

One of the leading indicators influencing waste generation in building projects is GFA. The GFAs are generally obtained from 3D models and statistical records based on data availability. This data extraction method consumes more time, cost, and human resources. So, in order to overcome the limitations, Yu et al. [104] developed a hybrid method integrating building images obtained from Google Earth. The study focused on quantifying large-scale demolition waste during the urban renewal process. Thus, acquiring real-time geometric information about the building could mitigate quantification errors, reduce human intervention, and enhance the efficiency of the whole WQ process.

5. Discussions – Limitations and future research directions

Although existing research has studied various dimensions of WQ, some critical issues remain unaddressed, which are explored in the section. This section will highlight the significant gaps in the current studies and promising research directions for future researchers.

5.1. *Enhance the attention on refurbishment/renovation activities*

Existing WQ studies have focused on new constructions and demolition activities, while refurbishments and renovations of existing structures received limited attention. This is despite the fact that the WGR of refurbishment/renovation and demolition works are three times higher than those of new constructions [52]. Further, national laws on net-zero carbon targets appear to have driven the reuse of existing structures in some countries for their potential benefits across energy, cost, social, and health values. For instance, 70% of the UK's non-residential building stock is already built and will require refurbishing one million homes yearly for the next three decades to meet the 2050 net-zero target [110]. The waste generation during the in-use stages increase as refurbishment and renovation activities expand. This suggests the demand for a shift in focus; waste from renovation and refurbishment should be considered as a crucial component of WQ practices.

5.2. *Employ a standardised waste classification approach*

Overall, it was identified that seven different classification methods were followed by researchers to report waste. Each classification system is unique and satisfies different purposes. For instance, waste classification based on its environmental values is appropriate to determine the CWM routes, whereas estimating waste generated from the work packages facilitates the construction team in allocating the required resources required on time [70]. However, the terms used to describe the composition/distribution of waste materials have been inconsistent. For instance, a few studies [18,111] used the terms' masonry/masonry debris/masonry blocks' to report the waste generation of 'bricks/blocks'. Likewise, 'plasterboard' is referred to as 'drywall/gypsum wallboard/wall panels' [40,112] based on geographical location. Although the properties of these materials are similar, there is a less semantic definition for these terms to make informed decisions. With the growing usage of ICT techniques, research studies [88] ascertain that reliable waste data representation is essential for lowering errors brought on by inconsistent definitions. A few studies, including [8], maintained a uniform structure to integrate data collected from various projects for WQ. Yet, the representation of defined vocabularies to automate the overall system is lacking. Thus, the semantic characterisation of waste material data could be improved using a standard waste code system. For instance, a few studies [72,79,85,86] conducted in the EU region rely on European Waste Catalogue (EWC) coding system (E.g., 17_01_01 for non-hazardous concrete) to classify waste. These codes provide a standardised waste description to ensure accuracy and consistency in waste classification. Hence, initiatives incorporating standardised waste codes could ease information exchange between multiple platforms, thus improving automation across the WQ process.

5.3. *Incorporate life-cycle impact values into waste analysis and reporting*

Each quantification model is unique in the way they measure and report waste. WGR is widely used in existing research studies to quantify and benchmark waste performance. Based on the WGRs of building materials, it was suggested in the reviewed studies that inert waste materials contribute to a large volume of construction waste, and the quantity of hazardous waste is negligible [8,67]. According to the articles evaluated, the major waste-contributing materials in terms of volume/weight are concrete, bricks/blocks, ceramics, and timber [18,55,56,58,77,113]. However, a few studies [58,89,92] observed that emission levels of other waste materials like metals, gypsum, and asphalt are higher than the 'major waste contributing' materials. For instance, Xu et al. [89] estimated that asphalt contributed to one-fourth of the CO2 emissions, although the material was the lowest in total waste generated. The recycling of aluminium waste contributes to 45% of carbon emissions despite its weight being 1% of total waste generation. This scenario is vice versa in masonry waste, which contributes to 90% of the total waste volume, but its emission levels are less than 1% of the total emission [92]. Therefore, reducing emission levels (E.g., embodied carbon levels) from the conclusions reached using volume/weight-based WQ approaches will have limited impacts.

In addition, economic aspects of waste, as evidenced by the higher tax pricing [114] for hazardous waste (£96.7/t) compared to inert waste (£3.10/t), suggest that the former should also be prioritised within the waste flows. Thus, future research needs to address incorporating impact values of waste materials during quantification to align with other environmental impact assessments. Besides, the impact-based analysis will seamlessly integrate WQ models with the design, construction, carbon, and cost workflows.

5.4. *Focus on infrastructure projects*

Unlike buildings, the studies focusing on WQ from infrastructure works are deficient. Among the evaluated studies, only one paper [79] focused on measuring waste from infrastructure (railway) projects in Spain. Given the wide variety of materials used in buildings in the real world, a thorough analysis of waste from buildings is essential [55]. However, it has been suggested that because of the size and complexity, infrastructure projects also produce significant waste, which must be prioritised for analysis [116]. In addition, the waste-generating factors, including design features, construction techniques and other environmental and social factors, impact the infrastructure works. So, adequate planning in the early project stages is significant for controlling the waste generation in the infrastructure works [116]. This indicates a potential field for future scientific research to concentrate on measuring waste from infrastructure projects.

5.5. *Unified data structure to increase interoperability between BIM and WQ-knowledge bases*

The role of ICT applications is increasing in waste assessment for its benefits across data collection, predictive analysis, modelling and simulation, categorisation, and visualisation. Despite its advantages, the continuous evolution of computational systems has led to the deployment of heterogenous data and technologies, which will keep growing in the future. Accounting BIM as a source of building information, different technologies, and databases, including historical and regional waste databases, site-waste reports, Government records, GIS and LCA data, are integrated to different extents to facilitate WQ. This large volume of data extracted from various sources to assess waste holds different structures, challenging an effortless and automated data exchange across multiple platforms. For instance, the current WQ model plugins [38,80] rely highly on specific BIM and waste databases, which confines the interoperability of developed systems across other platforms [117]. Thus, constructing a unified open data structure for BIM—WQ that can accommodate data from multiple platforms opens doors for increasing interoperability. Future research in this direction could further facilitate the development of reliable and compatible waste databases, thus expanding the dynamics between WQ models and BIM platforms.

5.6. *Establish complex relationships between project characteristics and WGRs in AI-WQ modelling*

The productivity of construction projects is progressively improved by adopting automated and flexible techniques, which reduces human intervention across the project life-cycle stages [118]. Similarly, different levels of AI applications are deployed to facilitate the quantification and classification of CW. The AI-based modelling allows researchers to establish the relationships between the input (project characteristics) and output (WGRs) variables. The three primary variables used for analysis include GFA, building usage, and structural frame. However, in real cases, WGR is influenced by various factors, including architectural form, procurement type, stages of construction, installation methods, and temporal aspects [11,25,120]. For instance, in conventional construction, the super-structure stage generates a large volume of steel reinforcement, brick and block waste due to offcuts. These waste types are prevented in prefabricated structures, but the volume of plastic packing waste used to transport these components increases [121], further becoming a concern. Although the building usage and structural frames are similar, this hypothesis shows that the WGR of brick, block and steel in conventional construction will vary from prefabricated constructions. Moreover, adopting the same WGRs in both cases could lead to inaccurate results. Therefore, a comprehensive assessment of CW and its inherent relationship with multiple project features is paramount to enhance the granularity and appropriateness of AI-WQ models.

6. Waste quantification and classification: a conceptual framework

This section proposes a conceptual framework for improving the WQ system through the application of ICTs, in response to the final objective of the study. The conceptual framework is informed by the shortcomings

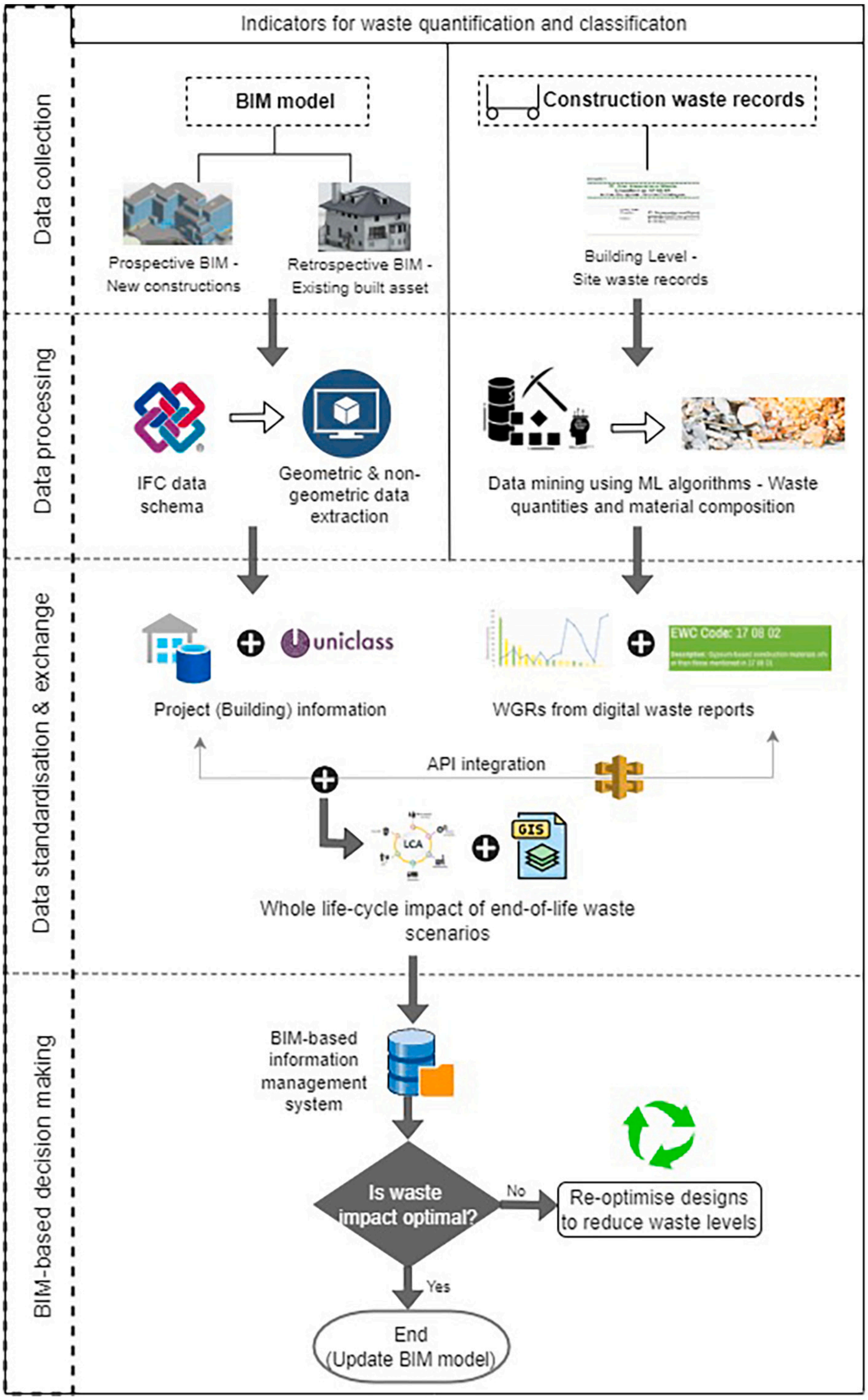

Fig. 8. Waste quantification and classification – BIM-assisted workflow.

of the existing WQ system and the future research directions discovered from the literature review.

6.1. Overview of existing frameworks

The previous BIM-enabled frameworks in the WM context have significant limitations, i) In the first case, most existing frameworks [10,17,94,120,122] only provide guidelines to utilise BIM strategies in CWM and the critical elements of the quantification process using BIM are limited in those frameworks. ii) In the second scenario, the frameworks [38,84,87,123,124] implemented to facilitate WQ are constrained to run only with specific BIM software and waste databases. Although these frameworks could digitalise the WQ process, the automation and interoperability achieved in the quantification process are insignificant. For instance, the hybrid AI-integrated BIM framework developed by [38] integrates WQ into the design process. Though this framework enables automated data extraction and processing, it depends on a specific 3D BIM platform, and thus the interoperability of the model with other BIM platforms is limited. Hence, a framework to overcome the limitations associated with digital data formats, information standards, and interoperability is vital to integrate the WQ into actual project workflows.

6.2. Framework development

Based on the systematic review, it can be inferred that each activity across the project life cycle will have varying waste generation levels and material compositions. This indicates that WQ models should be highly versatile for various applications. Here, a framework is proposed that leverages the possibilities of ICTs to enhance the accessibility of WQ models throughout the life-cycle stages. The framework is underpinned by the conceptual framework analysis methodology proposed by [125]. This offers a theorisation procedure for building frameworks based on the reflections of the grounded theory method. Accounting for the qualitative nature of the review, including the assumed relationships among concepts and addressed future directions of WQ research, this approach is selected for framework development. As shown in Fig. 8, the framework consists of four main layers: data collection, data processing, data standardisation and exchange, and the BIM-based decision-making layer. All layers are interconnected so that the output of each layer will be used as an input for the following layer. The sections that follow provide a brief description of the layers.

i) **Data collection:**

The data source layer of the framework illustrates the data required for WQ in the early project stages. The first indicator, project information, including the building's geometric and functional properties, emanates from the BIM model. BIM, being the digital asset of a building [126], holds loads of information required for quantification. Around 40% of the AEC professionals in the UK credit "*BIM as a norm for project information*" [127]. Hence, the BIM model is a rich data source in this proposed WQ framework. Given that the project has a digital BIM model, the primary data source is typical for new and existing buildings.

The waste factor for building materials is available in various repositories, including existing site waste records, statistical reports, waste disposal records, and secondary data sources. Since there is no sole source for extracting waste data, it is necessary to consider the accessibility, availability, and completeness of datasets before choosing a suitable source.

ii) **Data processing:**

Based on the reviewed studies, the building data used for WQ is obtained from a specific software format, which lacks interaction with other BIM software(s). This limits the integration of WQ models across the project life cycle. Hence, the data collected from the BIM software is transferred to Industry Foundation Classes (IFC) format. IFC is an official standard recognised by International Organization for Standardisation (ISO 16739-1:2018) for easy information exchange [128]. It is a platform-independent open data structure that enhances interoperability across multiple BIM platforms. The IFC data consist of dimensions, element quantities, material details, schedules, and spatial relationships between them, thus facilitating WQ. The IFC data schemas are available in the STEP, physical structure, and XML. Besides, IFC can be expressed in labelled RDF graphs using ifcOWL (web ontology language), which supports the user in structuring the waste data extracted from multiple web databases [129]. Thus, adopting IFC would ease information exchange across multiple BIM platforms.

Since WQ is a complex data-intensive process, reviewed studies proved that handling them manually is time-consuming, inaccurate, requires a high level of human intervention, and yields random waste results. These challenges are addressed by introducing a data processing layer that enhances automation in the WQ process. Automation is achieved by incorporating AI algorithms into quantification and classification process. As research [130,131] proves that each algorithm best fits only with a specific dataset type, the most suitable one should be selected depending on the volume of waste data available.

Depending on the review, results from existing literature suggest that building GFA, usage and architecture type, and type of structural frames are the leading indicators for waste generation. However, the most appropriate predictor variables should be selected by establishing the complex relationship between each project characteristic. For instance, the WGR of 'concrete' for 'prefabricated construction' will be less than the 'in-situ methods' in a 'concrete frame' building. Though the structural frame type is similar in both cases, the construction methodology differs. This inherent correlation between each predictor variable should be used for applying suitable WGRs. As can be seen from Fig. 9, the inherent relation between multiple project characteristics and waste generation should be established to develop a custom machine learning algorithm for predicting construction waste for new projects. The inputs from the previous layer and the selected AI algorithm will enable the development of analytical models that allow the user to quantify waste based on project characteristics. The final output of this layer will support digitalisation and accuracy in WQ.

iii) **Data standardisation and exchange:**

Integrating WQ models with BIM platforms is essential to demonstrate seamless communication between design, construction, and waste knowledge bases. Before that, it is crucial to verify that material/waste terminologies used for computational analyses between various digital platforms are standardised. *Concrete blocks*, for instance, are also known as *masonry blocks*, *concrete bricks*, and *concrete masonry units* in different BIM libraries and waste databases. Although the properties of these materials are similar, the semantics for these terms must be clearly defined to ease automation. Hence data mapping is required to preserve the level of detail across the information sources. The coding system is considered to be one of the viable options for reducing manual data handling. For instance, the studies conducted by [85,86] used BCCA (Base de Costes de la Construcción de Andalucía (BCCA), an Andalusian Construction Costs Database) coding system to map data between the BIM library and the selected waste database. In this framework, the Uniclass 2015 codes are mapped to materials to ease communication between the BIM, waste and LCA datasets. In addition, the EWC is incorporated into the analyses to enhance waste reporting. This standardised and consistent information further leads to the development of reliant and complaint waste databases in the future.

Besides, it is worth considering the life cycle impacts of waste materials and the selected WM route. The International Organization for Standardisation (ISO 14040:2006) highlights that the impact values extracted from life cycle assessment (LCA) databases could facilitate the

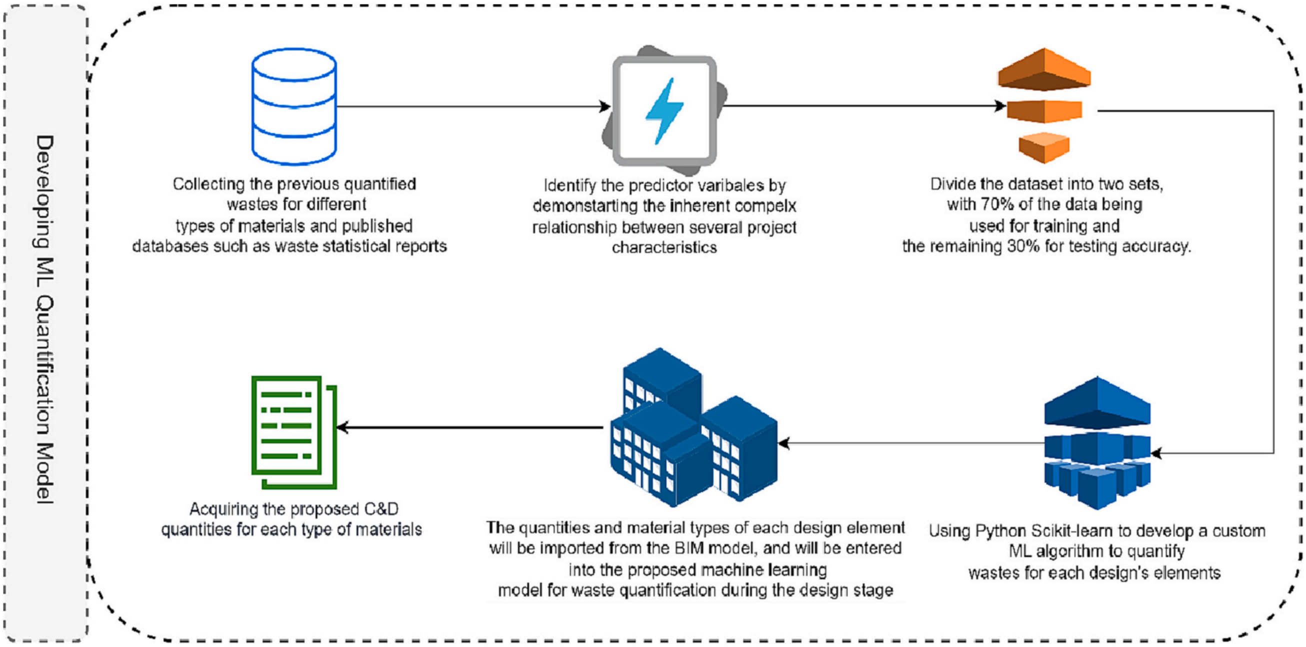

Fig. 9. The process of developing an ML model for WQ.

assessment of environmental impacts of waste materials and end-of-life waste scenarios [132]. Hence, the communication of waste in terms of its impacts can be achieved by incorporating impact data into the analysis. Besides, the selection of WM routes also decides transportation emissions. To facilitate this estimation, the GIS maps could be used to calculate the distance between the construction sites and waste treatment plants, thus, providing the impacts associated with selected end-of-life scenarios.

The exchange of waste, LCA and GIS data with BIM platforms could be facilitated through API and plugin extensions of BIM, given the capabilities of the selected software. This third layer ensures standardisation and interoperability across these multiple data repositories. The results of the data exchange will be stored in the BIM model as additional custom parameters to allow users to comprehensively assess the overall impacts of the building's technical and material characteristics.

iv) **BIM-based decision-making:**

The decision layer will provide a user-based interface for selecting an optimal design or re-selecting another design option should the initial design be deemed highly wasteful. The decision layer interface will prompt the user to select optimised materials based on a given set of project scenarios. The quantified waste results incorporated into the BIM model allow the user to make informed decisions on waste from the initial stages of a project. The decision layers allow users to adopt necessary design and construction process changes to reduce waste based on impact levels. This further allows designers to benchmark and compare multiple design options. The end-of-life scenarios of each waste material and its life-cycle impacts are presented to allow users to select an optimised design meeting the project requirements.

The overall idea of the framework is to enhance the level of digitalisation, standardisation, automation, and interoperability across the data sources to enhance bi-directional communication between waste analysis and BIM. Moreover, to achieve the goals of working in a collaborative data environment across the life-cycle stages.

6.3. *Limitations of the framework*

i) The current framework is limited to new and existing buildings with available BIM data. Given that the project has a digital BIM model, the primary data source is typical for new and existing buildings. For existing buildings with no BIM models, it is likely to employ diverse data capture techniques such as image processing, optical character recognition, and 3D scanning to reconstruct enriching digital information for the building, a retrospective BIM [133]. So, an 'as-built' BIM model can be integrated within the proposed conceptual framework once available. However, the current framework is limited to new and existing buildings designed with BIM.

ii) The data mapping using standardised waste coding system like EWC are applicable only in geographical locations where the codes exist. However, recognising the importance of minimal manual data handling, coding systems could be encouraged in other geographical areas to ease and automate information flows across the WQ workflows.

iii) The proposed conceptual framework covers only the environmental impacts of waste materials and WM methods, while the economic and social dimensions are excluded. Contemporary studies suggest that all three dimensions of WQ could influence the development and selection of optimal WQ models, which is likely to impact decision-making related to its application in construction and demolition sites. Future studies could expand the framework presented in this study to account for the other sustainable pillars.

7. Research significance and novelty

It is evident from the research that accurate WQ is vital for managing waste across the project life cycle. Although existing WQ models were developed to satisfy specific requirements, they appear to ignore the critical factors influencing the automation of the whole system across the whole life cycle of the built asset. Despite the importance given in previous studies for selecting an appropriate quantification method, the focus on information standards to utilise the maximum power of ICTs is less valued. This gap is filled in the review by identifying the significant limitations and proposing future research directions to automate the whole WQ process. The novel framework proposed in this research fills the current gap by conceptualising an automated digital life-cycle approach for quantifying and classifying waste. Also, the proposed conceptual framework recognises the importance of unified structure, information standards, and ICTs to guarantee seamless data mapping and exchange between multiple platforms employed in the quantification process. This study prioritises developing the construction sector to achieve an integrated digital collaboration system and enable users to connect within a common data platform to increase interoperability. Moreover, the proposed conceptual framework seeks to enable integrated digital systems, standardise data structures, ensure consistency in information flows, automate the WQ workflows and produce sustainable results from ICT integration. In addition to exploring 'what' technologies could facilitate automated WQ systems in the digital construction era, 'how' the overall process should be improved to obtain the full potential of innovation is presented in this study.

8. Conclusions and limitations

A systematic literature review of 71 papers was conducted to analyse the key factors influencing waste generation levels. The paper critically reviewed existing WQ models intending to understand their key elements and limitations in the digital construction era. The limitations of existing WQ models are provided, and promising future directions are recommended. The review witnessed the growing importance of CW quantification and classification among the researchers. Several innovative digital approaches are introduced to enhance the accuracy and flexibility of the WQ system. However, the consistency of data structures and information standards to enhance automation across the quantification process requires attention. Hence, a unified data architecture contextualising diversified data from multiple sources would enhance interoperability and facilitate more robust and granular analysis. This data structure also allows the integration of waste analysis with actual project workflows, including time, cost, and other supply chain indicators that aid in informed decision-making. Although it is evident from the existing studies that a range of ICTs influences the WQ process, further improvements to overcome the shortcomings of seamless and consistent information flows would ensure automation and efficiency of the overall system.

By incorporating the future research directions, a conceptual framework which exploits the potential of ICT to enhance the flexibility of WQ models is developed. This study concludes that WQ in the construction sector could be enhanced through the ubiquitous adoption of innovative ICT tools underpinned by a unified data structure and standardised classification and coding system. These are critical pillars to enhance interoperability and automate the overall WQ process. The review outputs allow researchers to understand the current scenario of WQ across different project types and activities and develop innovative solutions to overcome the issues. The limitations of the review cannot be ignored. Although the review focuses on proposing an automated solution to enhance the information flow and accuracy of WQ models, the availability of waste data is critical to achieving maximum potential from the proposed solutions. Therefore, there could be a limitation to applying the suggested technologies in the geographical locations where the CW data is not recorded. Secondly, it is possible that the findings of other articles not included in the applied search criteria could affect the conclusions drawn in this study. However, the overall trend of WQ in the construction sector is reflected in the paper to facilitate future studies to understand the importance of data and interoperability in the quantification and classification system.

The outcome of this paper will be used to provide empirical evidence based on the validation of the proposed conceptual framework with a real-life case study building.

Declaration of Competing Interest

None.

Data availability

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

Acknowledgements

This paper contains research which is part of the lead author's ongoing PhD research project, partially funded by Teesside University.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.autcon.2023.104898.

References

[1] DEFRA, Department of Environment Food And Rural Statistics, UK Statistics on Waste, 2021. Retrieved from: https://www.gov.uk/government/statistics/uk-waste-data/uk-statistics-on-waste. Last Access: 17 May 2022.

[2] EPA (United States Environmental Protection Agency), Construction and Demolition Debris: Material-Specific Data, Retrieved from: https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/construction-and-demolition-debris-material, 2021. Last Access: 17 May 2022.

[3] DEFRA (Department of Environment Food And Rural Statistics), Definition of Waste: 2018 Waste Framework Directive amendments, Retrieved from: https://www.gov.uk/government/publications/legal-definition-of-waste-guidance/definition-of-waste-2018-waste-framework-directive-amendments, 2020. Last Access: 17 May 2022.

[4] EC (European Commission), NACE Rev 2. Statistical classification of economic activities in the European Community, Retrieved from: https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF, 2008. Last Access: 17 May 2022.

[6] H. Yuan, W. Lu, J.J. Hao, The evolution of construction waste sorting on-site, Renew. Sust. Energ. Rev. 20 (2013) 483–490, https://doi.org/10.1016/j.rser.2012.12.012.

[8] R. Hu, K. Chen, W. Chen, Q. Wang, H. Luo, 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 Manag. 126 (2021) 791–799, https://doi.org/10.1016/j.wasman.2021.04.012.

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

[11] S. Nagapan, I.A. Rahman, A. Asmi, A.H. Memon, I. Latif, Issues on construction waste: The need for sustainable waste management, in: 2012 IEEE Colloquium on Humanities, Science and Engineering (CHUSER), IEEE, 2012, pp. 325–330, https://doi.org/10.1109/CHUSER.2012.6504333.

[13] K.T. Adams, M. Osmani, T. Thorpe, J. Thornback, Circular economy in construction: current awareness, challenges and enablers, in: Proceedings of the Institution of Civil Engineers-Waste and Resource Management 170, Thomas Telford Ltd, 2017, pp. 15–24, https://doi.org/10.1680/jwarm.16.00011.

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

[18] A. Bakshan, I. Srour, G. Chehab, M. El-Fadel, A field based methodology for estimating waste generation rates at various stages of construction projects, Resour. Conserv. Recycl. 100 (2015) 70–80, https://doi.org/10.1016/j.resconrec.2015.04.002.

[19] M. Bernardo, M.C. Gomes, J. de Brito, Demolition waste generation for development of a regional management chain model, Waste Manag. 49 (2016) 156–169, https://doi.org/10.1016/j.wasman.2015.12.027.

[20] G.-W. Cha, Y.-C. Kim, H.J. Moon, W.-H. Hong, New approach for forecasting demolition waste generation using chi-squared automatic interaction detection (CHAID) method, J. Clean. Prod. 168 (2017) 375–385, https://doi.org/10.1016/j.jclepro.2017.09.025.

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

[23] Y. Li, X. Zhang, Web-based construction waste estimation system for building construction projects, Autom. Constr. 35 (2013) 142–156, https://doi.org/10.1016/j.autcon.2013.05.002.

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

[25] B. Bossink, H. Brouwers, Construction waste: quantification and source evaluation, J. Constr. Eng. Manag. 122 (1) (1996) 55–60, https://doi.org/10.1061/(ASCE)0733-9364(1996)122:1(55).

[27] H. Yuan, L. Shen, Trend of the research on construction and demolition waste management, Waste Manag. 31 (4) (2011) 670–679, https://doi.org/10.1016/j.wasman.2010.10.030.

[28] A.F. Masudi, C.R. Che Hassan, N.Z. Mahmood, S.N. Mokhtar, N.M. Sulaiman, Quantification methods for construction waste generation at construction sites: a review, Adv. Mater. Res. 163 (2011) 4564–4569, https://doi.org/10.4028/www.scientific.net/AMR.163-167.4564.

[29] Z. Wu, T. Ann, L. Shen, G. Liu, Quantifying construction and demolition waste: an analytical review, Waste Manag. 34 (9) (2014) 1683–1692, https://doi.org/10.1016/j.wasman.2014.05.010.

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

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

[32] B. Nikmehr, M.R. Hosseini, J. Wang, N. Chileshe, R. Rameezdeen, BIM-based tools for managing construction and demolition waste (CDW): a scoping review, Sustainability 13 (15) (2021) 8427, https://doi.org/10.3390/su13158427.

[33] A.P. Kern, M.F. Dias, M.P. Kulakowski, L.P. Gomes, Waste generated in high-rise buildings construction: a quantification model based on statistical multiple regression, Waste Manag. 39 (2015) 35–44, https://doi.org/10.1016/j.wasman.2015.01.043.

[34] J.K. Liu, Y.D. Liu, S.M. Zhao, S.M. Li, Estimation of construction wastes based on the bill of quantitiy in South China, Appl. Ecol. Environ. Res. 17 (1) (2019) 123–146, https://doi.org/10.15666/aeer/1701_123146.

[36] X. Zhao, A scientometric review of global BIM research: analysis and visualization, Autom. Constr. 80 (2017) 37–47, https://doi.org/10.1016/j.autcon.2017.04.002.

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

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

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

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

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

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

[43] C. Okoli, A guide to conducting a standalone systematic literature review, Commun. Assoc. Inf. Syst. 37 (1) (2015) 43, https://doi.org/10.17705/1CAIS.03743.

[44] Y. Xiao, M. Watson, Guidance on conducting a systematic literature review, J. Plan. Educ. Res. 39 (1) (2019) 93–112, https://doi.org/10.1177/0739456X17723971.

[45] D. Gough, S. Oliver, J. Thomas, An Introduction to Systematic Reviews, Sage, 2017. ISBN: 9781473929432.

[46] M.J. Grant, A. Booth, A typology of reviews: an analysis of 14 review types and associated methodologies, Health Inf. Libr. J. 26 (2) (2009) 91–108, https://doi.org/10.1111/j.1471-1842.2009.00848.x.

[48] A. Aghaei Chadegani, H. Salehi, M. Yunus, H. Farhadi, M. Fooladi, M. Farhadi, N. Ale Ebrahim, A comparison between two main academic literature collections: web of science and Scopus databases, Asian Soc. Sci. 9 (5) (2013) 18–26, https://doi.org/10.5539/ass.v9n5p18.

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

[50] W. Lu, X. Chen, Y. Peng, L. Shen, Benchmarking construction waste management performance using big data, Resour. Conserv. Recycl. 105 (2015) 49–58, https://doi.org/10.1016/j.resconrec.2015.10.013.

[51] C.M. Mah, T. Fujiwara, C.S. Ho, Construction and demolition waste generation rates for high-rise buildings in Malaysia, Waste Manag. Res. 34 (12) (2016) 1224–1230, https://doi.org/10.1177/0734242X16666944.

[52] M. Malia, J. de Brito, M.D. Pinheiro, M. Bravo, Construction and demolition waste indicators, Waste Manag. Res. 31 (3) (2013) 241–255, https://doi.org/10.1177/0734242X12471707.

[53] L.M.F. Maues, B.D.O. do Nascimento, W.S. Lu, F. Xue, Estimating construction waste generation in residential buildings: a fuzzy set theory approach in the Brazilian Amazon, J. Clean. Prod. 265 (2020), https://doi.org/10.1016/j.jclepro.2020.121779.

[54] P.V. Saez, C. Porras-Amores, M.D. Merino, New quantification proposal for construction waste generation in new residential constructions, J. Clean. Prod. 102 (2015) 58–65, https://doi.org/10.1016/j.jclepro.2015.04.029.

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

[56] H. Wu, H. Duan, L. Zheng, J. Wang, Y. Niu, G. Zhang, Demolition waste generation and recycling potentials in a rapidly developing flagship megacity of South China: prospective scenarios and implications, Constr. Build. Mater. 113 (2016) 1007–1016, https://doi.org/10.1016/j.conbuildmat.2016.03.130.

[57] P.V. Saez, J.S.C. Astorqui, M.D. Merino, M.D.M. Moyano, A.R. Sanchez, Estimation of construction and demolition waste in building energy efficiency retrofitting works of the vertical envelope, J. Clean. Prod. 172 (2018) 2978–2985, https://doi.org/10.1016/j.jclepro.2017.11.113.

[58] P. Sun, N. Zhang, J. Zuo, R. Mao, X. Gao, H. Duan, Characterizing the generation and flows of building interior decoration and renovation waste: a case study in Shenzhen City, J. Clean. Prod. 260 (2020), 121077, https://doi.org/10.1016/j.jclepro.2020.121077.

[59] T. Ding, J. Xiao, Estimation of building-related construction and demolition waste in Shanghai, Waste Manag. 34 (11) (2014) 2327–2334, https://doi.org/10.1016/j.wasman.2014.07.029.

[60] R. Islam, T.H. Nazifa, A. Yuniarto, A.S.M. Shanawaz Uddin, S. Salmiati, S. Shahid, An empirical study of construction and demolition waste generation and implication of recycling, Waste Manag. 95 (2019) 10–21, https://doi.org/10.1016/j.wasman.2019.05.049.

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

[62] L. Zheng, H. Wu, H. Zhang, H. Duan, J. Wang, W. Jiang, B. Dong, G. Liu, J. Zuo, Q. Song, Characterizing the generation and flows of construction and demolition waste in China, Constr. Build. Mater. 136 (2017) 405–413, https://doi.org/10.1016/j.conbuildmat.2017.01.055.

[63] W.S. Lu, C. Webster, Y. Peng, X. Chen, X.L. Zhang, Estimating and calibrating the amount of building-related construction and demolition waste in urban China, Int. J. Constr. Manag. 17 (1) (2017) 13–24, https://doi.org/10.1080/15623599.2016.1166548.

[64] W. Lu, Y. Peng, X. Chen, M. Skitmore, X. Zhang, The S-curve for forecasting waste generation in construction projects, Waste Manag. 56 (2016) 23–34, https://doi.org/10.1016/j.wasman.2016.07.039.

[65] L. Qiao, D.D. Liu, X.L. Yuan, Q.S. Wang, Q. Ma, Generation and prediction of construction and demolition waste using exponential smoothing method: a case study of Shandong Province, China, Sustainability 12 (12) (2020) 12, https://doi.org/10.3390/su12125094.

[66] Z. Wu, H. Fan, G. Liu, Forecasting construction and demolition waste using gene expression programming, J. Comput. Civ. Eng. 29 (5) (2015) 04014059, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000362.

[67] Q.K. Wang, L. Chen, R.B. Hu, Z.G. Ren, Y.T. He, D.R. Liu, Z.Q. Zhou, An empirical study on waste generation rates at different stages of construction projects in China, Waste Manag. Res. 38 (4) (2020) 433–443, https://doi.org/10.1177/0734242X19886635.

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

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

[70] Y.S. Li, X.Q. Zhang, G.Y. Ding, Z.Q. Feng, Developing a quantitative construction waste estimation model for building construction projects, Resour. Conserv. Recycl. 106 (2016) 9–20, https://doi.org/10.1016/j.resconrec.2015.11.001.

[71] P. Mercader-Moyano, A. Ramirez-de-Arellano-Agudo, Selective classification and quantification model of C&D waste from material resources consumed in residential building construction, Waste Manag. Res. 31 (5) (2013) 458–474, https://doi.org/10.1177/0734242x13477719.

[72] P.V. Saez, M.D. Merino, C. Porras-Amores, Estimation of construction and demolition waste volume generation in new residential buildings in Spain, Waste Manag. Res. 30 (2) (2012) 137–146, https://doi.org/10.1177/0734242X11423955.

[73] EC (European Commission), Guidance on classification of waste according to EWC-Stat categories, in: Supplement to the Manual for the Implementation of the Regulation (EC) No 2150/2002 on Waste Statistics, 2010. Retrieved from: https://ec.europa.eu/eurostat/documents/342366/351806/Guidance-on-EWCStat-categories-2010.pdf/0e7cd3fc-c05c-47a7-818f-1c2421e55604. Last Access: 18 February 2023.

[74] D. Lee, S. Kim, S. Kim, Development of hybrid model for estimating construction waste for multifamily residential buildings using artificial neural networks and ant Colony optimization, Sustainability 8 (9) (2016), https://doi.org/10.3390/su8090870.

[75] D.H. Paz, K.P. Lafayette, Forecasting of construction and demolition waste in Brazil, Waste Manag. Res. 34 (8) (2016) 708–716, https://doi.org/10.1177/0734242X16644680.

[76] E.D.C. Teixeira, M.A.S. González, L.F.M. Heineck, A.P. Kern, G.M. Bueno, Modelling waste generated during construction of buildings using regression analysis, Waste Manag. Res. 38 (8) (2020) 857–867, https://doi.org/10.1177/0734242x19893012.

[77] J. Li, Z. Ding, X. Mi, J. Wang, A model for estimating construction waste generation index for building project in China, Resour. Conserv. Recycl. 74 (2013) 20–26, https://doi.org/10.1016/j.resconrec.2013.02.015.

[78] U.A. Umar, N. Shafiq, M.H. Isa, Investigation of construction wastes generated in the Malaysian residential sector, Waste Manag. Res. 36 (12) (2018) 1157–1165, https://doi.org/10.1177/0734242X18790359.

[79] A.D. Baez, P.V. Saez, M.D. Merino, J.G. Navarro, Methodology for quantification of waste generated in Spanish railway construction works, Waste Manag. 32 (5) (2012) 920–924, https://doi.org/10.1016/j.wasman.2012.01.007.

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

[81] P.V. Saez, M.D. Merino, C. Porras-Amores, A.S.A. Gonzalez, Assessing the accumulation of construction waste generation during residential building construction works, Resour. Conserv. Recycl. 93 (2014) 67–74, https://doi.org/10.1016/j.resconrec.2014.10.004.

[82] A. Bakchan, K.M. Faust, Construction waste generation estimates of institutional building projects: leveraging waste hauling tickets, Waste Manag. 87 (2019) 301–312, https://doi.org/10.1016/j.wasman.2019.02.024.

[83] A. Bakchan, K.M. Faust, F. Leite, Seven-dimensional automated construction waste quantification and management framework: integration with project and site planning, Resour. Conserv. Recycl. 146 (2019) 462–474, https://doi.org/10.1016/j.resconrec.2019.02.020.

[84] B.C. Guerra, F. Leite, K.M. Faust, 4D-BIM to enhance construction waste reuse and recycle planning: case studies on concrete and drywall waste streams, Waste Manag. 116 (2020) 79–90, https://doi.org/10.1016/j.wasman.2020.07.035.

[85] R. Quiñones, C. Llatas, M.V. Montes, I. Cortés, A multiplatform BIM-integrated construction waste quantification model during design phase. The case of the structural system in a Spanish building, Recycling 6 (3) (2021) 62, https://doi.org/10.3390/recycling6030062.

[86] R. Quiñones, C. Llatas, M.V. Montes, I. Cortés, Quantification of construction waste in early design stages using Bim-based tool, Recycling 7 (5) (2022) 63, https://doi.org/10.3390/recycling7050063.

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

[88] V.W. Tam, Y. Zhou, C. Illankoon, K.N. Le, A critical review on BIM and LCA integration using the ISO 14040 framework, Build. Environ. 213 (2022), 108865, https://doi.org/10.1016/j.buildenv.2022.108865.

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

[90] F. Jalaei, M. Zoghi, A. Khoshand, Life cycle environmental impact assessment to manage and optimize construction waste using building information modeling (BIM), Int. J. Constr. Manag. 21 (8) (2021) 784–801, https://doi.org/10.1080/15623599.2019.1583850.

[91] M.T.H. Khondoker, Automated reinforcement trim waste optimization in RC frame structures using building information modeling and mixed-integer linear programming, Autom. Constr. 124 (2021), 103599, https://doi.org/10.1016/j.autcon.2021.103599.

[92] J. Wang, H. Wu, H. Duan, G. Zillante, J. Zuo, H. Yuan, Combining life cycle assessment and building information modelling to account for carbon emission of building demolition waste: a case study, J. Clean. Prod. 172 (2018) 3154–3166, https://doi.org/10.1016/j.jclepro.2017.11.087.

[93] O. Faniran, G. Caban, Minimizing waste on construction project sites, Eng. Constr. Archit. Manag. 5 (2) (1998) 182–188, https://doi.org/10.1108/eb021073.

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

[95] R. Sacks, M. Girolami, I. Brilakis, Building information modelling, artificial intelligence and construction tech, Develop. Built Environ. 4 (2020), 100011, https://doi.org/10.1016/j.dibe.2020.100011.

[96] T.O. Ayodele, Types of machine learning algorithms, New Adv. Mach. Learn. 3 (2010) 19–48, https://doi.org/10.5772/225.

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

[98] K. Lin, T. Zhou, X. Gao, Z. Li, H. Duan, H. Wu, G. Lu, Y. Zhao, Deep convolutional neural networks for construction and demolition waste classification: VGGNet structures, cyclical learning rate, and knowledge transfer, J. Environ. Manag. 318 (2022), 115501, https://doi.org/10.1016/j.jenvman.2022.115501.

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

[100] S. Na, S. Heo, S. Han, Y. Shin, M. Lee, Development of an artificial intelligence model to recognise construction waste by applying image data augmentation and transfer learning, Buildings 12 (2) (2022) 175, https://doi.org/10.3390/buildings12020175.

[102] J. Chen, W. Lu, L. Yuan, Y. Wu, F. Xue, Estimating construction waste truck payload volume using monocular vision, Resour. Conserv. Recycl. 177 (2022), 106013, https://doi.org/10.1016/j.resconrec.2021.106013.

[103] H. Wu, J. Wang, H. Duan, L. Ouyang, W. Huang, J. Zuo, An innovative approach to managing demolition waste via GIS (geographic information system): a case study in Shenzhen city, China, J. Clean. Prod. 112 (2016) 494–503, https://doi.org/10.1016/j.jclepro.2015.08.096.

[104] B. Yu, J.Y. Wang, J. Li, J.R. Zhang, Y.N. Lai, X.X. Xu, Prediction of large-scale demolition waste generation during urban renewal: a hybrid trilogy method, Waste Manag. 89 (2019) 1–9, https://doi.org/10.1016/j.wasman.2019.03.063.

[105] S.O. Ajayi, L.O. Oyedele, M. Bilal, O.O. Akinade, H.A. Alaka, H.A. Owolabi, Critical management practices influencing on-site waste minimization in construction projects, Waste Manag. 59 (2017) 330–339, https://doi.org/10.1016/j.wasman.2016.10.040.

[106] C.S. Poon, T. Ann, L. Ng, On-site sorting of construction and demolition waste in Hong Kong, Resour. Conserv. Recycl. 32 (2) (2001) 157–172, https://doi.org/10.1016/S0921-3449(01)00052-0.

[107] X. Chen, H. Huang, Y. Liu, J. Li, M. Liu, Robot for automatic waste sorting on construction sites, Autom. Constr. 141 (2022), 104387, https://doi.org/10.1016/j.autcon.2022.104387.

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

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

[110] UKGBC (UK Green Building Council), The Importance of Retrofitting in Advancing Net Zero, Retrieved from: https://www.ukgbc.org/news/the-importance-of-retrofitting-in-advancing-net-zero/, 2021. Last Access: 25 Feb 2023.

[111] V. Ram, S.N. Kalidindi, Estimation of construction and demolition waste using waste generation rates in Chennai, India, Waste Manag. Res. 35 (6) (2017) 610–617, https://doi.org/10.1177/0734242X17693297.

[112] P.T. Lam, T. Ann, Z. Wu, C.S. Poon, Methodology for upstream estimation of construction waste for new building projects, J. Clean. Prod. 230 (2019) 1003–1012, https://doi.org/10.1016/j.jclepro.2019.04.183.

[113] A. Vilventhan, V. Ram, S. Sugumaran, Value stream mapping for identification and assessment of material waste in construction: a case study, Waste Manag. Res. 37 (8) (2019) 815–825, https://doi.org/10.1177/0734242X19855429.

[114] HMRC (HM Revenues & Customs), Landfill Tax Rates, Retrieved from: https://www.gov.uk/government/publications/rates-and-allowances-landfill-tax/landfill-tax-rates-from-1-april-2013, 2022. Last Access: 08 August 2022.

[116] R.F. de Magalhães, Â.D.M.F. Danilevicz, T.A. Saurin, Reducing construction waste: a study of urban infrastructure projects, Waste Manag. 67 (2017) 265–277, https://doi.org/10.1016/j.wasman.2017.05.025.

[117] S. Sivashanmugam, S. Rodriguez, F. Rahimian, N. Dawood, Maximising the construction waste reduction potential–how to overcome the barriers, in: Proceedings of the Institution of Civil Engineers-Civil Engineering, Thomas Telford Ltd, 2022, pp. 1–9, https://doi.org/10.1680/jcien.22.00163.

[118] T. Bock, The future of construction automation: technological disruption and the upcoming ubiquity of robotics, Autom. Constr. 59 (2015) 113–121, https://doi.org/10.1016/j.autcon.2015.07.022.

[120] M. Osmani, J. Glass, A.D. Price, Architects' perspectives on construction waste reduction by design, Waste Manag. 28 (7) (2008) 1147–1158, https://doi.org/10.1016/j.wasman.2007.05.011.

[121] N.G. Pericot, P.V. Sáez, M.D.R. Merino, O.L. Carrasco, Production patterns of packaging waste categories generated at typical Mediterranean residential building worksites, Waste Manag. 34 (11) (2014) 1932–1938, https://doi.org/10.1016/j.wasman.2014.06.020.

[122] S. Gupta, K.N. Jha, G. Vyas, Proposing building information modeling-based theoretical framework for construction and demolition waste management: strategies and tools, Int. J. Constr. Manag. 22 (12) (2022) 2345–2355, https://doi.org/10.1080/15623599.2020.1786908.

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

[124] J.K. Liu, Y.D. Li, S.M. Zhao, S.M. Li, Estimation of construction wastes based on the bill of quantitiy in South China, Appl. Ecol. Environ. Res. 17 (1) (2019) 123–146, https://doi.org/10.15666/aeer/1701_123146.

[125] Y. Jabareen, Building a conceptual framework: philosophy, definitions, and procedure, Int J Qual Methods 8 (4) (2009) 49–62, https://doi.org/10.1177/160940690900800406.

[126] S. Hamil, What is Building Information Modelling (BIM), Retrieved from: https://www.thenbs.com/knowledge/what-is-building-information-modelling-bim, 2021. Last Access: 09 August 2022.

[127] NBS (National Building Specification), 10th Annual BIM Report, Retrieved from: https://www.thenbs.com/knowledge/national-bim-report-2020, 2020. Last Access: 09 August 2022.

[128] ISO, Industry Foundation Classes (IFC) for Data Sharing in the Construction and Facility Management Industries, Retrieved from: https://www.iso.org/standard/51622.html, 2013. Last Access: 20 February 2023.

[129] buildingSMART, Industry Foundation Classes (IFC) – An Introduction, Retrieved from: https://technical.buildingsmart.org/standards/ifc/, 2023. Last Access: 20 February.

[130] B. Mahesh, Machine learning algorithms-a review, Int. J. Sci. Res. (IJSR) 9 (2020) 381–386, https://doi.org/10.21275/ART20203995 [Internet].

[131] F. Osisanwo, J. Akinsola, O. Awodele, J. Hinmikaiye, O. Olakanmi, J. Akinjobi, Supervised machine learning algorithms: classification and comparison, Int. J.

Comp. Trends and Technol. (IJCTT) 48 (3) (2017) 128–138, https://doi.org/10.14445/22312803/IJCTT-V48P126.

[132] ISO, Environmental Management — Life cycle Assessment — Principles and Framework, Retrieved from: https://www.iso.org/obp/ui/#iso:std:iso:14040:ed-2:v1:en, 2006. Last Access: 22 July 2022.

[133] R. Volk, J. Stengel, F. Schultmann, Building information modeling (BIM) for existing buildings—literature review and future needs, Autom. Constr. 38 (2014) 109–127, https://doi.org/10.1016/j.autcon.2013.10.023.