Automated Scan-to-BIM for Construction Digital Transformation: Conceptual Framework, Processing Methods and Best-Practice Guidelines

Ke You [a,b], Ke Chen [c], Fan Xue [a,b*]

This is the peer-reviewed post-print version of the paper:
You, K., Chen, K., & Xue, F. (2026). Automated scan-to-BIM for construction digital transformation: Conceptual framework, processing methods and best-practice guidelines. *Automation in Construction*, 182, 106755. Doi: 10.1016/j.autcon.2025.106755
The final version of this paper is available at: https://doi.org/10.1016/j.autcon.2025.106755
The use of this file must follow the Creative Commons Attribution Non-Commercial No Derivatives License, as required by Elsevier's policy.

a. Department of Real Estate and Construction, The University of Hong Kong, Pokfulam, Hong Kong, China
b. National Center of Technology Innovation for Digital Construction Hong Kong Branch, The University of Hong Kong, Pokfulam, Hong Kong, China
c. School of Civil and Hydraulic Engineering, Huazhong University of Science and Technology, Wuhan, Hubei, China.
* Corresponding author. Fan Xue. E-mail addresses: xuef@hku.hk

Abstract

The global Architecture, Engineering, and Construction (AEC) industry has witnessed surging demand for Construction Digital Transformation (CDT) over the past decade. Scan-to-BIM delivers accurate as-is conditions and reconstructs detailed BIM for diverse CDT applications. Researchers have proposed automated scan-to-BIM using algorithms and AI to minimize labor demands, but a comprehensive review with systematic guidelines is lacking. This paper presents a conceptual model of scan-to-BIM processes and reviews development patterns and trends based on 58 cases. Based on the model, this paper offers a four-step guideline for AEC practitioners to adopt automated scan-to-BIM effectively. The contribution of this paper is three-fold. First, the conceptual model offers a comprehensive and simplified overview of scan-to-BIM processes for beginners. Secondly, trends emerge, e.g., transformation from rigid rules to AI methods. Thirdly, the best-practice guidelines empower AEC practitioners to maximize scan-to-BIM advantages tailored to their needs.

Keywords

Building Information Modeling (BIM); Scan-to-BIM; Systematic review; Guidelines; Digital transformation

1 Introduction

The Architecture, Engineering, and Construction (AEC) is a pillar industry in almost every nation's economy, and occupies a central position in global sustainable development [1, 2]. Construction Digital Transformation (CDT) is pivotal to the development of the AEC industry [3, 4]. The core of CDT lies in integrating digital technologies throughout the entire lifecycle of construction projects, aiming to enhance efficiency, enhance sustainability and increase resilience, thereby advancing the United Nations Sustainable Development Goals (SDGs) [5]. CDT encompasses the key stages of design, construction, operation, and maintenance, each stage relying on advanced technologies such as Building Information Modeling (BIM), the Internet of Things (IoT), and Artificial Intelligence (AI) to optimize processes, while BIM provides comprehensive services throughout the entire lifecycle [6]. With its increasing success and deep use, such as BIM Level 2/3 in the UK [7], over 20 mandatory BIM uses in Hong Kong [8], and 'positive design' in mainland China, BIM has demonstrated significant advancements. Among the top BIM uses, scan-to-BIM has become essential, as highlighted by the Hong Kong Construction Industry Council (HKCIC), which lists it among the 6 most popular BIM uses [9].

Despite these advancements, there are often many deviations between the as-designed BIM and the as-built BIM, which poses challenges to the operation and maintenance of buildings. Technical barriers stem from manual operations in traditional scan-to-BIM, which are prone to errors and labor-intensive. Findings show that 60% of a building's lifecycle costs focus on the operation phase, but manually creation of as-built BIM can delay maintenance [10].The creation and application of as-built BIM models has gradually become a research hotspot [6, 11, 12]. Scan-to-BIM is the main method for obtaining as-built BIM, which can provide digital assets for the construction, maintenance of buildings [13-15]. During the construction phase, scan-to-BIM can be used for progress monitoring and quality inspection to ensure that the construction process proceeds as planned [16]. During the maintenance phases, scan-to-BIM can provide detailed building information to support facility management (FM) and maintenance [17, 18].

Scan-to-BIM involves acquiring the current building data through light detection and ranging (LiDAR) or other 3D capture technologies, and then converting the data into a digital BIM model [6]. Traditional scan-to-BIM relies on manual operations by engineers, which is often time-consuming and labor-intensive, and prone to human errors. With the development of artificial intelligence, these manual tasks can be gradually completed automatically by computers [19, 20]. Ideal automated scan-to-BIM involves the automation of data collection and data processing. Based on the automatic semantic segmentation and clustering of 3D point clouds, automatic object detection can be achieved by combining spatial relationships, and then BIM can be automatically obtained using parametric algorithms [21]. Due to extensive research efforts, the application scenarios of automated scan-to-BIM processes are also constantly expanding, covering many fields such as historical building protection [22-24], urban planning [25, 26], and construction progress monitoring [27].

Automated scan-to-BIM is a complex but demanded task. The initial stage of this process involves the collection of 3D point cloud data, which can capture high-precision 3D representations of buildings or construction sites [28, 29]. Although the raw data points are dense and rich in geometric information, they also contain a lot of noise and redundant information. Consequently, data cleaning and down-sampling form a critical step [30-32]. Data cleaning aims to remove noise, erroneous points and redundant data to ensure the accuracy and efficiency of subsequent processing [33, 34]. Down-sampling regularizes the density of point cloud data and reduces the amount of data while maintaining the geometric structure [31]. Then, semantic segmentation is conducted to identify various architectural elements and structures from 3D point clouds, thereby enriching the model with semantic information, and adding to the geometric data [35-37]. The final stage involves converting the processed 3D point clouds into a BIM model through parametric modeling, along with model layout and registration [6, 38].

Many general architectural elements, such as walls, floors, or ceilings, equip with vertical or horizontal extrusions from regular 2D shapes. Rule-based methods, therefore, can extract the vertical or horizontal geometries and topological information from 3D point clouds using algorithms like random sample consensus (RANSAC) or geometric hashing. RANSAC searches for the minimum bounding box of a point cloud to infer the shape of the object [39], while geometric hashing generates lines or surfaces from the point cloud distribution to determine object shapes [40]. Although rule-based methods have high classification performance for defined elements [41], they have great limitations for objects with special structures, such as chairs or tables [42]. Occlusion during the scanning process poses additional challenges for extracting information from 3D point clouds [43, 44]. Semantic segmentation based on deep learning can extract information from point clouds where various objects coexist, effectively making up for the shortcomings of rule-based methods [45-47]. 3D point cloud semantic segmentation, as a core step in automation, faces challenges such as reliance on large-scale training data, difficulty in handling complex structures (such as irregular building elements), and occlusion problems.

Existing reviews and surveys on scan-to-BIM in the literature have primarily focused on specific aspects of the technology, including its principles, methods, and typical applications. Volk et al. [48] analyzed the Scan-to-BIM applications for existing buildings. Rashdi et al. [49] focused on the impact of scanning technologies such as LiDAR and oblique photography on Scan-to-BIM. Bassiere et al. [50] reviewed the existing methods for reconstructing BIM walls in an unsupervised manner. In addition, case studies mainly focus of existing research [51], such as rule-based scan-to-BIM method [41], and the scan-to-BIM workflow for cultural heritage [52]. However, there is still a significant gap in the comprehensive understanding of the automation processes involved in scan-to-BIM, especially the integration of advanced artificial intelligence (AI) technologies and the optimization of the scan-to-BIM process. Existing literature often lacks a detailed comparative analysis of the latest automation methods, including their advantages, limitations, and practical implementation challenges. In practice, AEC practitioners lack clear guidelines, which hinders the selection of suitable technologies for project scenarios and leads to inefficient resource use.

This paper aims to address three research questions as follows: (1) What are the core components, technical approaches, and their interrelationships in automated scan-to-BIM? (2) What are the recent trends and research hotspots in automated scan-to-BIM? (3) How can best-practice guidelines be formulated to accommodate varied applications and project requirements? In order to answer these questions, this paper aims to comprehensively review the latest advances in automated scan-to-BIM. A conceptual model is proposed to provide a comprehensive and abstract overview of the scan-to-BIM process for newcomers. Then, a technological analysis summarizes recent trends, such as a paradigm shift from rigid decision rules to artificial intelligence approaches. Finally, this paper compiles best practice guidelines that enable AEC practitioners to benefit the most from adopting scan-to-BIM processes based on the given work scenario and application needs. The rest of the paper consists of four sections. Section 2 introduces the research methodology, Section 3 compares the automated scan-to-BIM processes, and Section 4 gives guidance for selecting a suitable automated scan-to-BIM processes. Section 5 is the conclusion of this review.

2. Research methods

This study employed an archival study framework comprising five steps: (1) Development of conceptual model; (2) Literature collection and case interpretation; (3) Bibliometric analysis; (4) Comparative evaluation of different technologies; and (5) Compilation of the best-practice guideline.

2.1 Conceptual model

Fig. 1 shows the generalized conceptual model of automated scan-to-BIM workflow to elucidate the research objectives and provide supporting materials for the guideline. This conceptual model comprises five interrelated components: (1) data acquisition method, (2) data processing and semantic enrichment, (3) general architectural elements (AEs) and detailed BIM objects, (4) software, and (5) CDT stage.

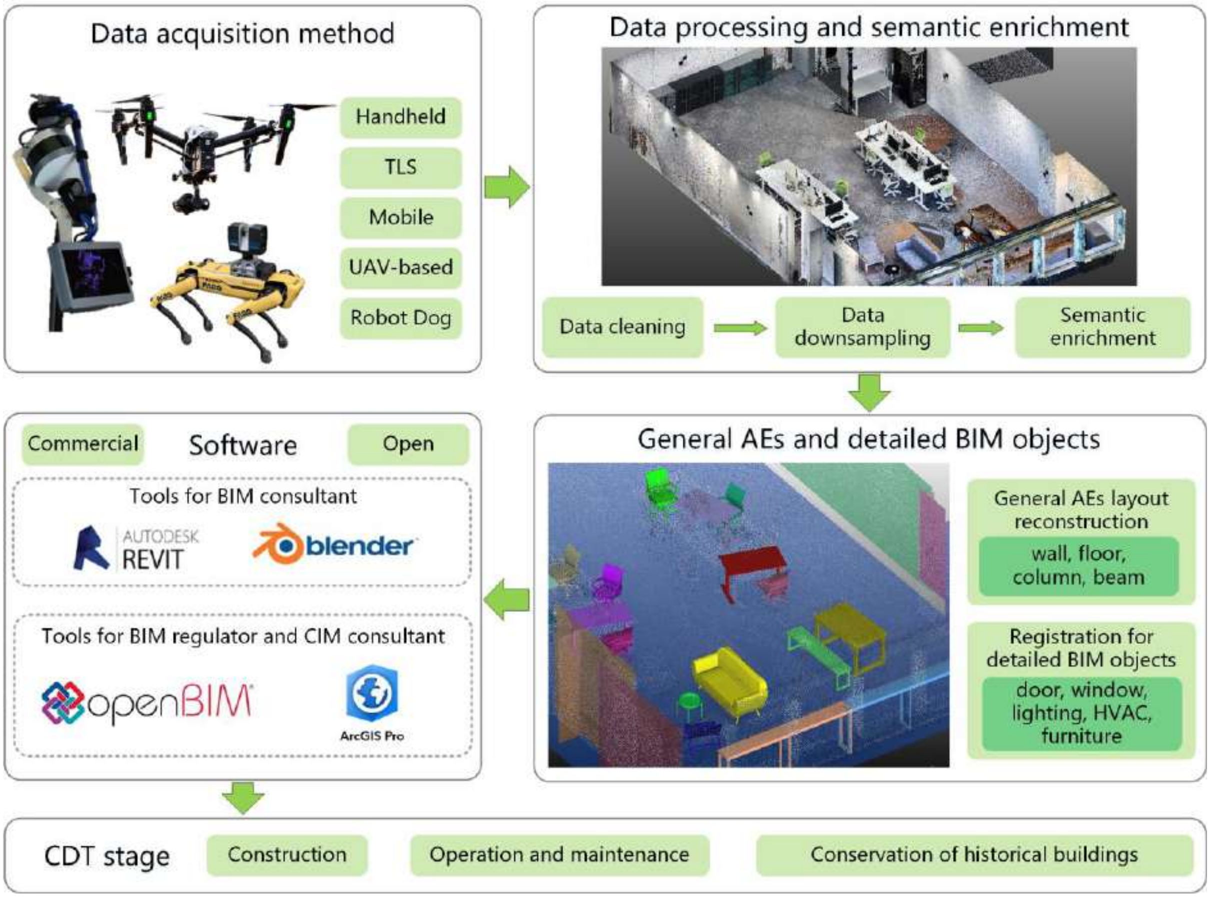

Fig. 1. Guiding conceptual model of scan-to-BIM.

The data collection of 3D point cloud data is realized through the use of LiDAR technology. The LiDAR system calculates the distance of the target object by emitting laser pulses and measuring their return time, thereby generating accurate 3D coordinates. LiDAR can be fixed on different mobile platforms such as unmanned aerial vehicles (UAVs) and robots, or can be utilized as handheld equipment for data collection. Given the substantial volume of 3D point clouds, it is necessary to process the raw data with data cleaning and down-sampling. The semantic information of the 3D point clouds needs to be obtained, and deep learning-based algorithms have proven to be effective for the automated processing of semantic enrichment.

Geometric representations of general AEs, such as walls, floors, and beams, can be generated using plane fitting or surface fitting techniques. However, for architectural elements with complex structures, such as chairs, sofas, and tables, the processes of surface fitting and parametric modeling can be time-consuming and cumbersome. To address this, registration is employed to match the 3D point cloud data with the BIM model. This involves using sampling algorithms to generate 3D point cloud data from the surface of the BIM model. Common sampling methods include uniform sampling, random sampling and curvature-based sampling. Subsequently, feature extraction and comparison are performed to obtain accurate BIM models of architectural elements with intricate structures through point cloud registration. The components within the conceptual model can be further categorized by different classifications, as illustrated in Table 1.

Table 1. Descriptors of five components of scan-to-BIM conceptual model.

Component	Descriptor	Code	Examples
Scene	Infrastructure	Infra.	Bridges, Tunnels
	Buildings	Bldgs.	Apartment Building, Office
Data acquisition method	Handheld Laser Scanners	HLS	Geosys PX-80
	Terrestrial Laser Scanners	TLS	Faro Focus 3D X 130
	Mobile Scanning Systems	MSS	Nav-Vis M6
	UAV-based Scanning Systems	USS	DJI Phantom Four
	Robotic Scanning Systems	RSS	Boston Dynamics BigDog
	Established dataset	ED	S3DIS
Semantic segmentation of scans	Handcrafted Annotation	HA	-
	Rule-based	RB	-
	Traditional Machine Learning	TML	HDBSCAN
	Deep learning	DL	PointNet
BIM Software	Commercial	Comm.	Autodesk Revit
	Open	Open	Blender
CDT stage	Construction	Const.	-
	Operation and maintenance	O&M	-
	Conservation of historical buildings	CHB	-

Data acquisition method encompasses handheld equipment, mobile systems, UAV-based platforms, robot-based systems, and terrestrial laser scanning (TSL). A significant challenge impeding the automation of the scan-to-BIM process is the semantic segmentation of 3D point clouds. Although algorithms such as PointNet [53] and Mask3D [45] have demonstrated commendable performance on public datasets, the software-assisted acquisition of semantic information from 3D point clouds remains a prevalent method in contemporary research. The use of software significantly enhances the automation capabilities of the scan-to-BIM process. Commonly utilized commercial software includes Autodesk Revit, Autodesk Recap, and Trimble RealWorks, whereas open-source platforms include Blender and CloudCompare. Current research primarily focuses on the application of automated scan-to-BIM in infrastructure, industrial facilities, and urban architecture. Additionally, these applications involve the preservation of historical buildings, as well as the construction management and maintenance of existing buildings

2.2 Literature collection

Based on the criteria provided by the preferred reporting items for systematic reviews and meta-analyses (PRISMA), a literature search was conducted using the keywords mentioned in the conceptual model. The databases used for the literature search included Web of Science, Google Scholar, and Scopus database. The search strategy of this study covers popular algorithms involved in AI by focusing on keywords such as semantic segmentation and point cloud classification. The query strings were "scan-to-BIM" ("Scans to Parametric BIM*" OR "Scan-vs-BIM") AND "Point Cloud Modelling" ("3D laser scanning*" OR "Scanning Technologies*" OR "LiDAR") OR "3D point clouds classification" ("Semantic Segmentation*" OR "Instance segmentation") OR "artificial intelligence" ("deep learning*" OR "machine learning"). The search results of this review covered journal and conference papers, books, dissertations, and reports published in recent years, but did not include patents and legal cases. The screening and data extraction for this review were performed independently by two researchers to reduce the risk of human error and subjective bias. The search period was from 2015.01 to 2025.08, and the search language was English.

The initial search yielded 812 articles, and initial screening was performed by examining titles, abstracts and keywords, which resulted in 369 articles. Studies not related to the AEC industry, such as agriculture or medicine, were excluded. All articles were subjected to full-text screening based on specific eligibility criteria. The criteria were (1) original research contributions rather than literature reviews, and (2) incorporation of automated scan-to-BIM into practical applications within the AEC industry, described in sufficient detail in the literature. The automated scan-to-BIM within 58 publications were analyzed, guided by the conceptual model, and data were extracted using the basic information of the selected empirical studies presented in Table 1 to produce Table 2.

Table 2. List of 58 actual cases of automating scan-to-BIM.

No.	Reference	Year	Scene	Data acquisition method	Semantic segmentation of scans	BIM Software	CDT stage
1	Mahmoud et al. [55]	2025	Bldgs.	HLS	DL	Comm.	O&M

2	Luo et al. [56]	2025	Infra.	USS	RB	Comm.	O&M
3	Elsharkawi et al. [57]	2025	Bldgs.	Multi	DL	Comm.	O&M
4	Patil et al. [58]	2025	Bldgs.	ED	DL	Open	O&M
5	Liu et al. [59]	2025	Bldgs.	MSS	DL	Open	O&M
6	Ma et al. [51]	2025	Bldgs.	ED	DL	Comm.	O&M
7	Kang et al. [60]	2025	Bldgs.	USS	DL	Comm.	O&M
8	Elsharkawi et al. [57]	2025	Bldgs.	USS	HA	Comm.	Const.
9	Chen et al. [42]	2024	Bldgs.	HLS	TML	Open	O&M
10	Cho et al. [61]	2024	Bldgs.	Multi	HA	Comm.	O&M
11	Rocha et al. [62]	2024	Bldgs.	USS	HA	Comm.	CHB
12	Yang et al. [63]	2024	Infra.	Multi	TML	Multi	O&M
13	Mahmoud et al. [54]	2024	Bldgs.	MSS	DL	Comm.	O&M
14	Pan et al. [64]	2024	Bldgs.	Multi	DL	Comm.	CHB
15	Pepe et al. [65]	2024	Bldgs.	HLS	HA	Open	CHB
16	Wang et al. [66]	2024	Bldgs.	TLS	DL	Comm.	O&M
17	Rocha et al. [67]	2024	Bldgs.	Multi	HA	Comm.	CHB
18	Birkeland et al. [68]	2024	Bldgs.	TLS	DL	Comm.	O&M
19	Zhu et al. [69]	2024	Bldgs.	TLS	DL	Comm.	O&M
20	Kellner et al. [32]	2023	Bldgs.	TLS	DL	Multi	O&M
21	Kim et al. [70]	2023	Infra.	ED	DL	Multi	O&M
22	Stanga et al. [71]	2023	Infra.	Multi	DL	Multi	CHB
23	Aftab et al. [72]	2023	Bldgs.	TLS	HA	Comm.	O&M
24	Jarzabek et al. [73]	2023	Bldgs.	TLS	HA	Open	O&M
25	Abreu et al. [74]	2023	Bldgs.	TLS	HA	Open	O&M
26	Martens et al. [75]	2023	Bldgs.	TLS	RB	Multi	O&M
27	Hu et al. [76]	2023	Bldgs.	RSS	DL	Multi	Const.
28	Kim et al. [77]	2023	Bldgs.	TLS	DL	Comm.	O&M
29	Croce et al. [78]	2023	Infra.	TLS	TML	Comm.	CHB
30	Xie et al. [79]	2023	Bldgs.	TLS	DL	Comm.	O&M
31	Campagnolo et al. [80]	2023	Bldgs.	ED	DL	Comm.	CHB
32	Wang et al. [81]	2022	Bldgs.	ED	DL	Multi	O&M
33	Park et al. [47]	2022	Infra.	TLS	DL	Multi	O&M
34	Pan et al. [82]	2022	Bldgs.	TLS	DL	Comm.	O&M
35	Ma et al. [83]	2022	Bldgs.	TLS	TML	Multi	O&M
36	Qiu et al. [31]	2022	Bldgs.	TLS	RB	Multi	O&M
37	Truong et al. [84]	2022	Bldgs.	TLS	RB	Comm.	Const.
38	Geyter et al. [85]	2022	Bldgs.	Multi	DL	Comm.	O&M
39	Perez et al. [86]	2021	Bldgs.	ED	DL	Multi	Const.
40	Kang et al. [41]	2020	Bldgs.	Multi	RB	Comm.	Const.
41	Andriasyan et al. [87]	2020	Bldgs.	TLS	RB	Multi	CHB
42	Ma et al. [88]	2024	Bldgs.	ED	DL	Comm.	O&M
43	Nieto-Julián et al. [89]	2024	Bldgs.	Multi	TML	Comm.	CHB
44	Cai et al. [90]	2024	Bldgs.	ED	DL	Comm.	Const.
45	Bosché et al. [91]	2015	Bldgs.	TLS	HA	Comm.	Const.
46	Barazzetti et al. [92]	2016	Infra.	TLS	HA	Multi	CHB
47	Laefer et al. [93]	2017	Bldgs.	TLS	TML	Comm.	O&M
48	Macher et al. [94]	2017	Bldgs.	TLS	RB	Multi	O&M
49	Adan et al. [95]	2018	Bldgs.	Multi	RB	Open	O&M
50	Wang et al. [96]	2018	Bldgs.	TLS	HA	Open	Const.
51	Wang et al. [14]	2019	Bldgs.	TLS	HA	Open	O&M
52	Capone et al. [97]	2019	Bldgs.	Multi	HA	Comm.	CHB
53	Mellado et al. [98]	2019	Bldgs.	Multi	HA	Multi	O&M
54	Rocha et al. [33]	2020	Bldgs.	Multi	HA	Multi	CHB
55	Pepe et al. [99]	2020	Infra.	TLS	HA	Multi	CHB
56	Croce et al. [100]	2021	Bldgs.	TLS	TML	Multi	CHB
57	Pepe et al. [99]	2021	Bldgs.	Multi	HA	Multi	CHB
58	Perez et al. [36]	2021	Bldgs.	TLS	TML	Comm.	O&M

Data acquisition method (DAM), software used, semantic enrichment methods, research scenarios, and applications were coded for each article. For instance, Mahmoud et al. [54] collected 3D point cloud data of indoor scenes using a mobile platform (Nav-Vis M6), performed down-sampling, and applied plane detection based on RANSAC to identify room boundary segments. They conducted semantic segmentation of the 3D point clouds using the RandLA-Net algorithm. The dataset utilized was S3DIS, and the Dynamo plug-in was integrated with Autodesk Revit software to implement the BIM parametric algorithm for automatic 3D model reconstruction, thus providing a technical basis for the application of smart cities and digital twins.

2.3 Bibliometric analysis

This paper uses bibliometric analysis to quantitatively analyze the structure and dynamics of current academic research, through keyword co-occurrence, and cluster-based topic analysis. These methods systematically reveal the research trends and hotspots within a specific field, providing researchers with a comprehensive perspective. The keywords in an article are a highly condensed summary of the research content. By drawing a knowledge domain map of the literature's keywords, the focus and potential development trajectory of current scan-to-BIM processes can be intuitively displayed. Cluster-based topic analysis can divide a large number of documents into several topic groups, helping researchers understand the main directions of the scan-to-BIM processes and their interrelationships, and facilitating the discovery of potential research gaps and future research trends.

Based on the literature collection in section 2.2, this review utilizes CiteSpace software to calculate the co-occurrence frequency among keywords, thereby obtaining the co-occurrence matrix and constructing the keyword co-occurrence network. The nodes in the network represent keywords, and the edges represent the co-occurrence relationship between these keywords, with the edge weights typically corresponding to the co-occurrence frequencies. Based on the keyword co-occurrence network map, K-means clustering is used to divide the keywords into several topics according to their co-occurrence relationships. This approach allows for the analysis of the characteristics of each theme, thereby revealing the foundational of current scan-to-BIM process and providing direction for future studies.

Through the above-mentioned bibliometric analysis, this review can provide theoretical guidance for AEC practitioners, clarify research topics, and enhance efficiency and effectiveness in practical work.

2.4 Technological analysis

Based on technological analysis, this paper explores the various technical methods and their applications involved in automated scan-to-BIM processes, which can reveal the current development and cutting-edge trends. Technological analysis can help researchers and practitioners understand the advantages and limitations of various technical approaches, providing a scientific basis for technology selection and optimization. We conduct a systematic technical analysis from the dimensions of research trends and data collection, data cleaning and down-sampling, semantic segmentation of scans, layout and registration, and BIM software.

Before data collection, equipment evaluation is essential to select appropriate equipment that meet the project requirements. The evaluation involves candidate scanning equipment's characteristics across multiple dimensions, such as scanning range, portability, as well as storage and processing costs. During data collection, data quality control on completeness, density, uniformity, and geometric accuracy has to be maintained [28]. Data cleaning and down-sampling can further enhance point data quality (e.g., better uniformity) and processing efficiency, which also save storage and processing costs. Methods such as statistical filtering, radius filtering, and conditional filtering are employed for data cleaning, while voxel grid, random, and uniform methods are used for data down-sampling. These techniques ensure the efficiency of subsequent model construction and analysis. Semantic segmentation of scans helps to identify and distinguish categories of 3D point clouds. Commonly used semantic segmentation methods include deep learning models such as convolutional neural networks (CNNs) and graph convolutional networks (GCNs). The operations of layout and registration are essential to match specific BIM objects. Analysis of BIM software can determine the suitable tools for the scan-to-BIM process, by assessing the functionality, compatibility, and user-friendliness of the software, we can ensure the efficiency and accuracy of data processing and BIM modeling.

Technical analysis provides the basis for the compilation of the best-practice guideline. Through these analyses, it is possible to ensure the selection of the appropriate technical solutions during the implementation of scan-to-BIM processes, thereby enhancing the efficiency and accuracy of data acquisition, processing, and modeling.

2.5 Compilation of the best-practice guideline

Constructing a standardized and adaptable set of best-practice guideline for automated scan-to-BIM, which can help solve the problem of technology fragmentation in the AEC industry, and improve automation efficiency. The development of compiling such a guide requires the division of steps, the necessity of each step, the target users, and the final deliverable format.

The first step in developing the guide is to conduct a needs analysis and scope definition. The purpose of this step is to identify pain points in the existing workflows, such as data acquisition method and software incompatibility issues in the automated scan-to-BIM process. Clear objectives and boundaries ensure that the development of the guide is well-targeted. The subsequent step involves literature review and benchmark analysis, which integrates mature methods from academic research and case studies to establish an evidence-based recommendation framework. This step can provide a foundation for drafting the guide. During the drafting phase, it is essential to translate consensus into actionable steps. Through actual project testing and iterative optimization of the guidelines, it is possible to identify and correct any deficiencies, ensuring the guide's feasibility and practicality.

The target users of the guide include project managers, software developers, and researchers. The final deliverable format of the guide should be an instruction document, which includes a decision tree for user selection and the necessary textual descriptions. Finally, the disclaimer of the guide is that the guidelines proposed in this review are only suggestions and need to be adjusted according to project constraints. The authors are not responsible for errors resulting from misuse or tool deficiencies, and users are required to independently verify compliance with local regulations.

3. Analytical results

Based on a systematic analysis of practical cases, this section employed Sankey diagram visualization and bibliometric methods. Building on this, the distribution characteristics of current automated Scan-to-BIM across different dimensions are revealed. By identifying a significant paradigm shift in the field from traditional rule-driven approaches to AI-driven approaches, this analysis provided an empirical basis for subsequent technical analysis and the development of practical guidelines.

3.1 Selection patterns of automated scan-to-BIM system

An overview of the 58 automated scan-to-BIM projects is presented in the form of a Sankey diagram in Fig. 2. The five main components of the conceptual model are shown from left to right, namely, scene, data acquisition method, semantic segmentation of scans, BIM software, and construction digital transformation (CDT) stage.

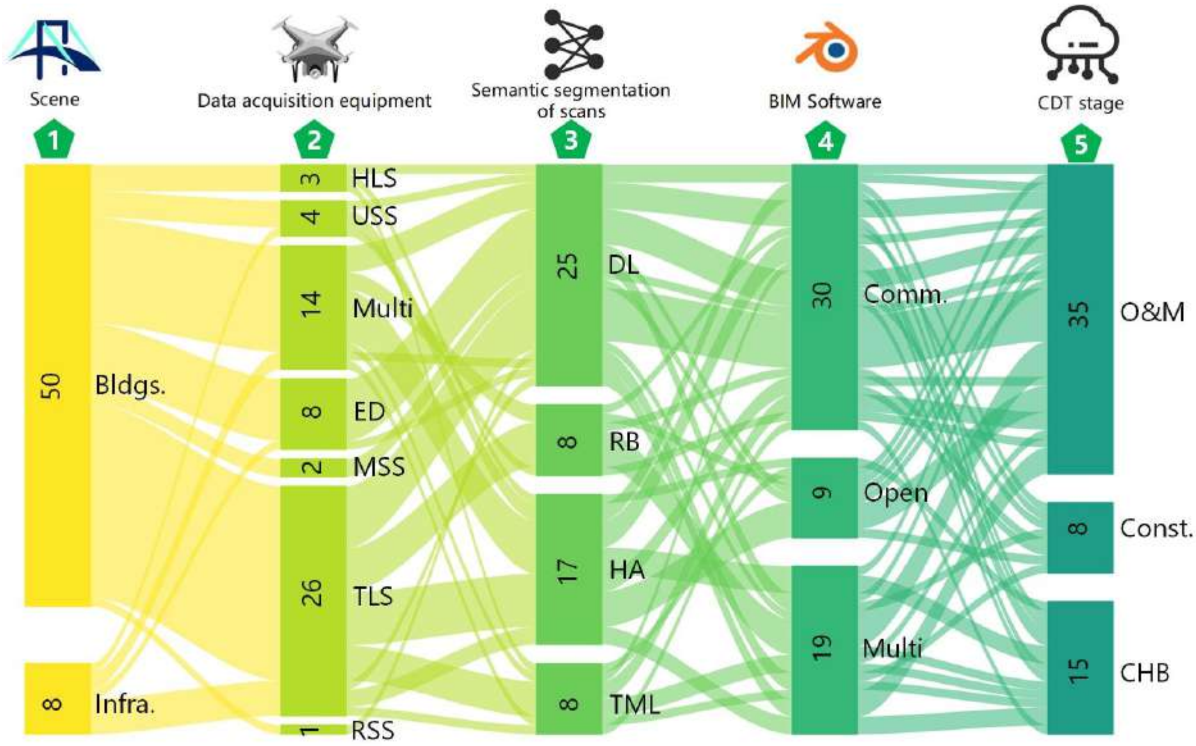

Fig. 2. Sankey chart of automated scan-to-BIM.

In the Sankey chart diagram, the size of the rectangle indicates the number of cases involving different labels, and the curved "flow" between components represent the frequency of co-occurrence in the 58 cases. Analysis of Table 2 and Fig. 2 reveals that the selection mode of the automated scan-to-BIM system can be summarized as follows:

(1) The current scan-to-BIM case scenarios are mainly (50 out of 58) focused on the exterior or interior structure of buildings. Since there are often differences between the design model and the as-build BIM, by capturing detailed geometric information of indoor MEP [79, 81] and air-conditioning and mechanical ventilation (ACMV) [42], it can better support the operation and management of buildings. Scan-to-BIM technology in the infrastructure field is mainly used for digital modeling and management of large structures such as bridges [63, 101] and tunnels [47]. Some infrastructure, such as the Toppoli Bridge [102], also belongs to the category of historical buildings. Based on scan-to-BIM, not only the geometric information of the building is preserved, but also detailed data such as materials, structure and decoration can be included, providing a scientific basis for restoration and maintenance work [25, 71, 103, 104].

Apart from the on-site collection of 3D point clouds, commonly used established datasets include Stanford Large-Scale 3D Indoor Spaces (S3DIS) [89] and ModelNet40 [105]. The S3DIS dataset is a large-scale 3D indoor space dataset created by Stanford

University. This dataset comprises 3D scan data collected from six different buildings, covering various indoor scenes such as offices, conference rooms, and hallways. ModelNet40 is a widely-used 3D CAD model dataset created by Princeton University, which contains 3D object models from 40 different categories.

(2) Terrestrial laser scanning (TLS) is the most prevalent method for 3D point cloud acquisition, featuring in nearly half (26 out of 58) of the cases. TLS is usually mounted on a tripod, and is favored for its high accuracy and density. Common models include the Leica RTC360 [31, 66] and the Faro Focus3D S120 [62, 67]. Handheld laser scanning (HLS) is lightweight and easy to carry, allow operators to directly hold the equipment for scanning [42]. Mobile scanning systems (MSS), installed on vehicles, ships, or other mobile platforms, can continuously collect 3D point cloud data while moving [27]. In addition, based on drones [26, 61, 62] or robots [76], through pre-programmed paths or autonomous navigation functions, can perform 3D laser scanning tasks in special scenarios. The drone- and robot-borne methods are particularly suited for rapid scanning of large areas, as well as hard-to-reach or hazardous locations.

However, LiDAR point cloud acquisition of small, openings or glass objects faces inherent limitations. Limited spatial resolution of lasers, particularly for distant objects, results in incomplete capture of small objects like fire sprinklers; Transparent and reflective surfaces can cause laser signal loss or scattering, and leads to voids or noises in the point cloud, respectively. Utilizing multiple data acquisition equipment or methods can mitigate these constraints by reducing coverage gaps and measurement errors in the literature. The inclusion of high-definition imagery, for example, can enhance the semantic richness of 3D datasets for accurate object classification, material identification, and comprehensive interpretation of complex environments [66].

(3) Nearly 43.1% (25 out of 58) of the cases use deep learning-based methods to achieve semantic segmentation of 3D point clouds. Existing semantic segmentation algorithms based on deep learning can be generally divided into the following categories: (i) Point convolutional network. PointNet [53] is one of the earliest deep learning models used for point cloud classification and segmentation. It achieves classification by learning global and local features of point clouds [83]. PointNet++ [106] introduces a hierarchical structure on this basis, further improving the segmentation effect [68, 76]. (ii) Voxel-based methods divide the point cloud into voxel grids and then perform convolution operations on each voxel [73, 74], with models like VoxNet [107] and 3D U-Net [32, 108]. (ii) Graph-based

methods treat point clouds as graph structures and use graph neural networks (GNNs) to capture the relationship between points, with models such as GAPointNet [109] and Graph-CNNs [30].

(4) Commercial BIM software usually provides more comprehensive functions and professional technical support, while open-source software has higher flexibility and customizability. Autodesk ReCap and Revit are two commercial software that are currently widely used. Autodesk ReCap [62, 67] is mainly used for pre-processing of point cloud data, such as data cleaning, noise reduction, and preliminary geometric reconstruction. Autodesk Revit [41, 85] is a BIM software widely used in the AEC industry. It supports full-process management from design to construction to operation and maintenance. Its main functions include 3D geometric mapping and object-based modeling. Some software needs to be used in conjunction with specific models of 3D point cloud acquisition equipment, such as Trimble RealWorks [61], which supports full-process management from data acquisition to final model generation. In addition, Blender's open-source characteristics and active community support make it a highly customizable and extensible tool suitable for projects that require flexible processing and innovative solutions.

(5) As-built BIM is an essential digital asset supporting the operation and maintenance (O&M) of buildings, enhancing information management across various stages of the building lifecycle, particularly in facility management and space management [36, 69]. Scan-to-BIM is an effective method for obtaining as-built BIM, enabling construction quality monitoring, reducing human errors, and accelerating project delivery during the construction (const.) phase [41, 86]. The digital twin based on scan-to-BIM can also reduce material waste and rework, saving both costs and time. For newly constructed buildings, such as indoor scenes of university buildings, evaluating the geometric uncertainty of the created BIM model supports operational and maintenance management of building projects, especially in civil engineering fields that require high precision [73]. For aging concrete buildings, the purpose of scan-to-BIM is to improve safety inspection processes, supporting efficient maintenance decision-making [60]. In the conservation of historical buildings (CHB), scan-to-BIM is utilized to record and analyze, connecting different databases to support the preservation, management, and restoration of cultural heritage [99, 100, 110].

3.2 Keyword co-occurrence and cluster analysis

Keywords provide a concise overview of an article’s research content. In this review, we visualize a knowledge domain map of literature keywords to highlight current research focuses and potential future directions. As shown in Fig. 3, a collaborative analysis of keywords was implemented, which clearly illustrates the research dynamics of the automated scan-to-BIM processes. In this Figure, the importance of keywords is reflected by the font size. The larger the font, the higher the frequency of the keyword. The strength of the association between keywords is represented by the thickness of the connecting line. The thicker the line, the closer the relationship between the keywords.

As illustrated in Fig. 3, scan-to-BIM is integrally linked to established domains such as 3D point cloud processing, semantic segmentation, and building information modeling for construction. Moreover, it demonstrates substantial interactions with emerging technologies, including advanced laser scanning and 3D reconstruction. In particular, "culture heritage" and "facility management" reflect the application potential of scan-to-BIM processes in engineering. Additionally, Fig. 3 reveals a dense cluster centered on "point cloud," underscoring the high importance of this topic in the relevant literature. These keywords form the core concept and technical application of 3D point cloud data in scan-to-BIM processes, enabling the automatic detection and extraction of architectural elements through high-precision data acquisition and processing. The above analysis indicates that scan-to-BIM serves a bridge connecting the physical world and the digital world. Future research should explore the use of advanced artificial intelligence methods to optimize scan-to-BIM processes. Concurrently, emphasis should be placed on interdisciplinary collaboration to foster the deep integration of theory and practice.

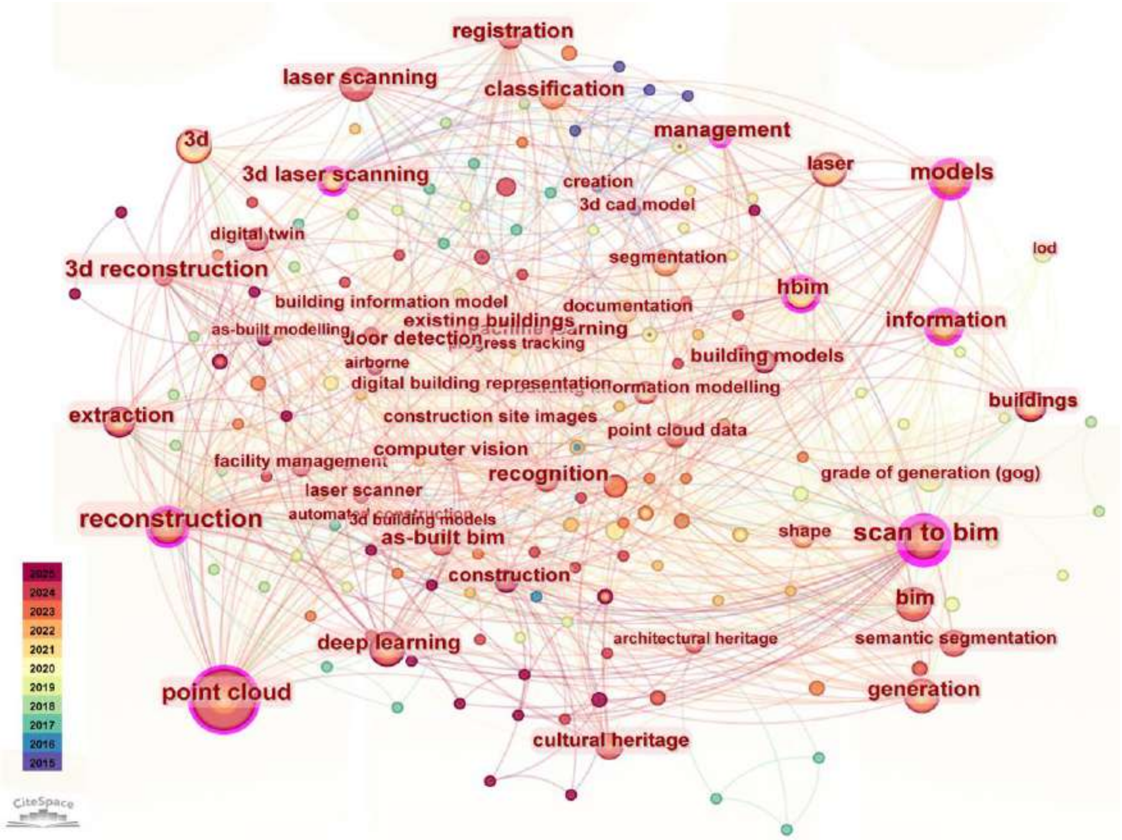

Fig. 3. Co-occurrence network mapping of keywords.

By performing cluster-based topic analysis on the literature, the association of hidden characteristic topics can be revealed in different literature, which is crucial for conducting a systematic review. The cluster topic analysis was performed using the log-likelihood ratio (LLR) algorithm in CiteSpace software, with the results presented in Fig. 4. Each group is marked with a unique color code. By exploring these different clusters or topics, the objective is to identify the research hotspots and challenges encountered by automated scan-to-BIM processes.

The largest cluster (labeled as "#0") is centered around "point clouds," this cluster is connected to several other clusters such as "terrestrial laser scanning", "3D semantic segmentation", "classification", "progress tracking", "quality assessment". These clusters represent different aspects of the scan-to-BIM processes, including data acquisition, processing, analysis, and management. The cluster "scan to BIM" (#6) serves as a key node in the network, and it is associated with various other keywords such as "architectural heritage", "facilities management", "quality", and "reverse engineering". The network visualization provides insights into key topics and trends in research on automated scan-to-BIM processes, highlighting areas that require further investigation to address challenges and advance the technology.

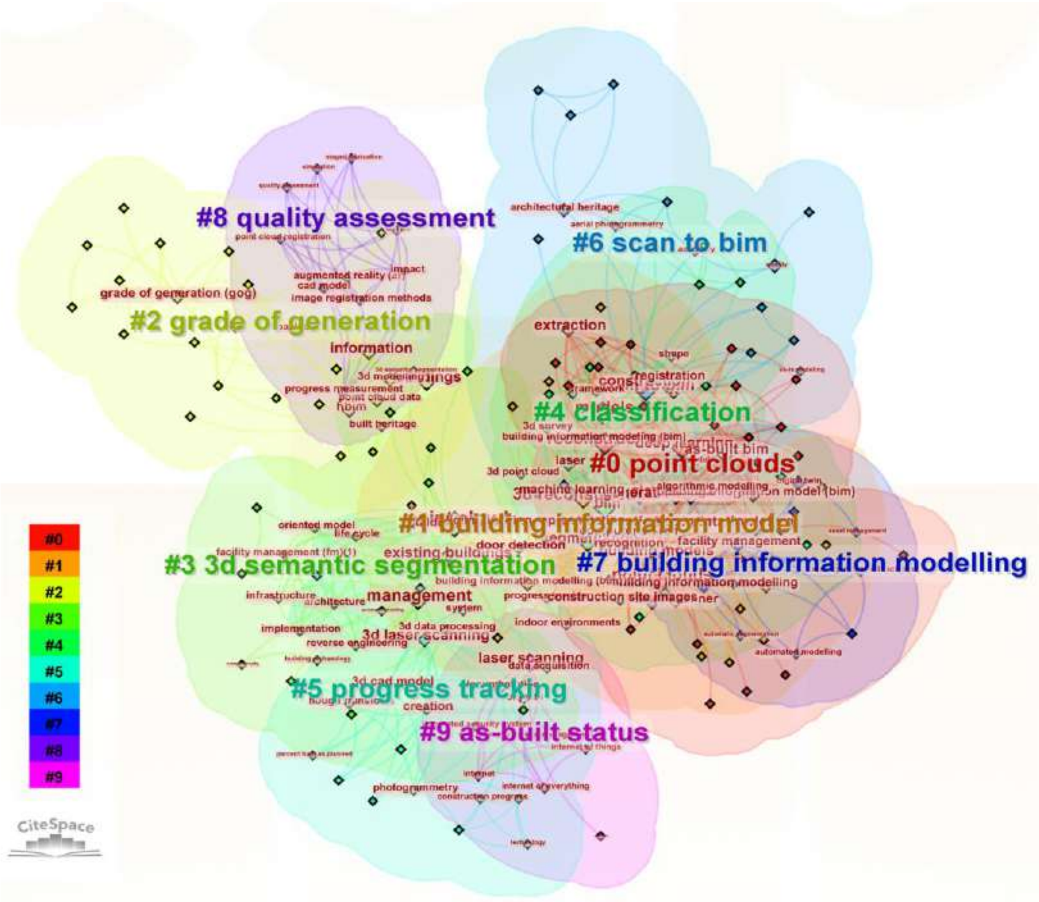

Fig. 4. Cluster-based topic distribution.

3.3 Research trends

In recent years, research on Scan-to-BIM has exhibited concurrent trends of diversification and intelligent development. A comprehensive analysis reveals a steady increase in the number of related publications, as illustrated in Fig. 5. The focus of research has evolved from an early reliance on terrestrial laser scanning [67-69] to a broader adoption of various methods, including handheld laser scanning [42] and mobile scanning systems [27], in order to meet the requirements of different application scenarios in terms of accuracy, efficiency and accessibility. In particular, advances in unmanned aerial vehicle and robotic technologies [76] have led to significant breakthroughs in acquisition of point clouds within high-risk environments. To address the storage and processing burdens associated with high-density point clouds, data cleaning and down-sampling techniques have been continuously refined [111], encompassing statistical filtering, radius filtering, and conditional filtering, as well as voxel grid, random, and uniform down-sampling, with the aim of improving both data quality and processing efficiency [114].

In the stages of semantic and instance segmentation, deep learning approaches have significantly improved accuracy in complex scenes [118]; however, challenges remain in environments with high density and occlusions. In terms of building layout reconstruction and component matching, research has progressively shifted from traditional geometric feature extraction toward deep learning-based methods [127, 128], incorporating 3D feature learning networks into matching and registration processes to enhance robustness. Regarding software support, developments included the seamless integration between Autodesk ReCap and Revit to the flexible plugin ecosystems of open-source platforms such as Blender, which reflected an increasing demand for cross-platform and cross-format data exchange and collaborative modeling [62, 67]. Overall, the Scan-to-BIM domain is rapidly progressing toward multi-source data fusion, higher levels of automation, and intelligent processing. The dual driving forces of hardware diversification and algorithmic intelligence continue to expand its application potential in the management of the entire lifecycle of buildings.

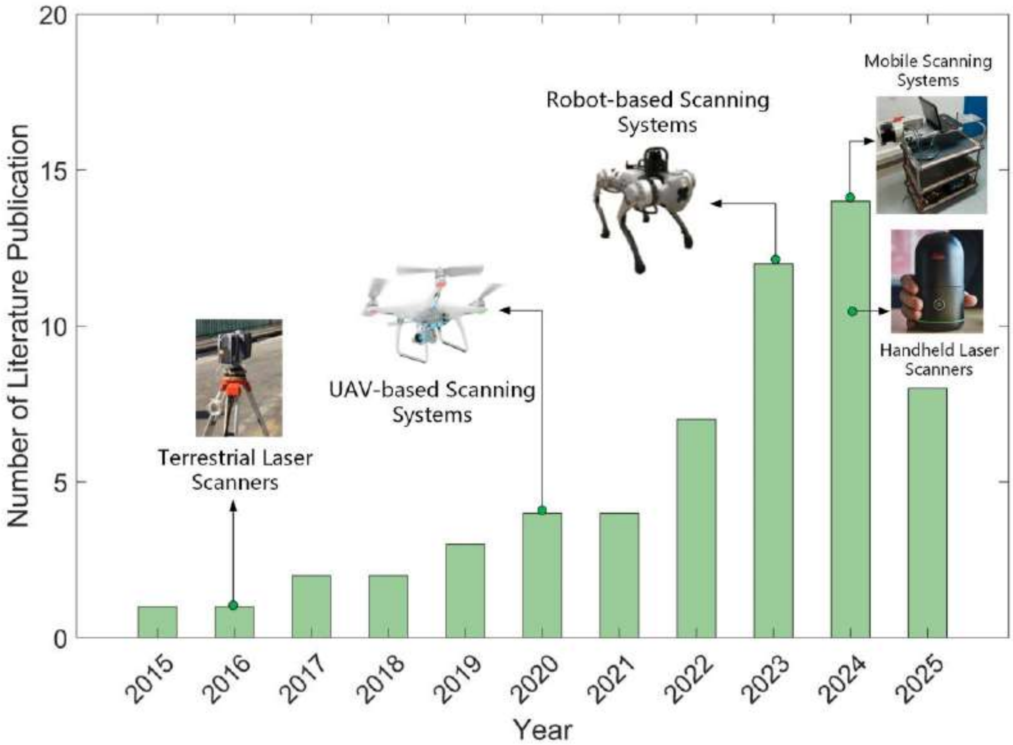

Fig. 5. Research trends and data acquisition equipment, Jan. 2015-Aug. 2025.

Therefore, systematically summarizing the guiding principles of Scan-to-BIM is essential for coordinating diversified equipment selection, optimizing data processing workflows, and improving the accuracy of semantic segmentation and model generation. Guidelines for adopting Scan-to-BIM processes can serve as standardized references for practice amid rapid technological advancement, thereby facilitating the transition of industry applications from experimental research toward large-scale, engineering-oriented implementation.

4. Technological analysis and guidelines

Building on the preceding systematic literature review and case analyses, this section undertook the technical exploration and formulates practice-oriented guidelines. A multi-dimensional technical analysis enables an evaluation of the applicability of current research. By integrating different construction stages, a clearly structured four-step implementation framework is proposed, which aims to provide AEC practitioners with comprehensive decision support spanning from technology selection to practical implementation.

4.1 Technological analysis results

The technical analysis provided an in-depth review of the core stages within the automated Scan-to-BIM pipeline, covering five areas: data acquisition hardware, data cleansing and down-sampling, semantic segmentation of scans, layout estimation and registration, and widely used software tools.

4.1.1 Data acquisition equipment

The initial step in implementing a scan-to-BIM system is to select appropriate equipment for acquiring 3D point cloud of the real world. This involves evaluating various scanning methods and factors such as accuracy, scanning range, portability, and cost to determine which technology that suits the project's requirements.

Terrestrial laser scanning (TLS) provides high measurement accuracy and resolution, and are particularly suitable for scenarios where detailed documentation of the interior and exterior structures of buildings is required [67-69]. Such equipment are usually fixed in one position and rotate to obtain 3D point cloud data of the surrounding environment. Despite their accuracy advantages, TLS equipment has some drawbacks, including lengthy setup times and complex data processing requirements. Additionally, they are non-portable and relatively expensive. Handheld laser scanning (HLS) is renowned for its portability and flexibility, making it suitable for scanning of small-scale spaces [42]. However, the accuracy of handheld equipment can be constrained by the stability of the operator's hand, and may not be practical for scanning large areas. From a cost perspective, HLS equipment is economical for smaller projects with limited budgets.

Mobile scanning systems (MSS) integrate vehicles with laser scanning technology to collect large amounts of 3D point cloud data while in motion, making MSS ideal for scanning urban infrastructure, roads, and outdoor spaces [27]. MSS is highly efficient and offers wide coverage area, but is also costly. UAV-based scanning systems (USS) are particularly suitable for areas that are difficult to access or present hazardous conditions [26]. USS can scan large areas of terrain and buildings from high altitudes, providing comprehensive data coverage while being portable. However, their performance is significantly impacted by weather conditions. Robotic scanning systems (RSS) utilize automated robots equipped with laser scanning equipment, which can navigate along a predefined path and complete scanning tasks [76]. RSS are suitable for hazardous environments or tasks that require repeated scanning, such as inspections of the internal structures of nuclear power plants. Robotic systems can provide stable data collection and minimize human error, but the initial investment cost is high and professional technical support may be required. Based on this analysis, the selection of data acquisition equipment should align with specific project scenarios and constraints at different construction stages, as summarized in Fig. 6. The figure illustrates the correlations and decision-making between equipment selection, construction stages (CDT), and specific scenarios, including factors such as access difficulty, hazard level, and environment type (e.g., infrastructure, buildings).

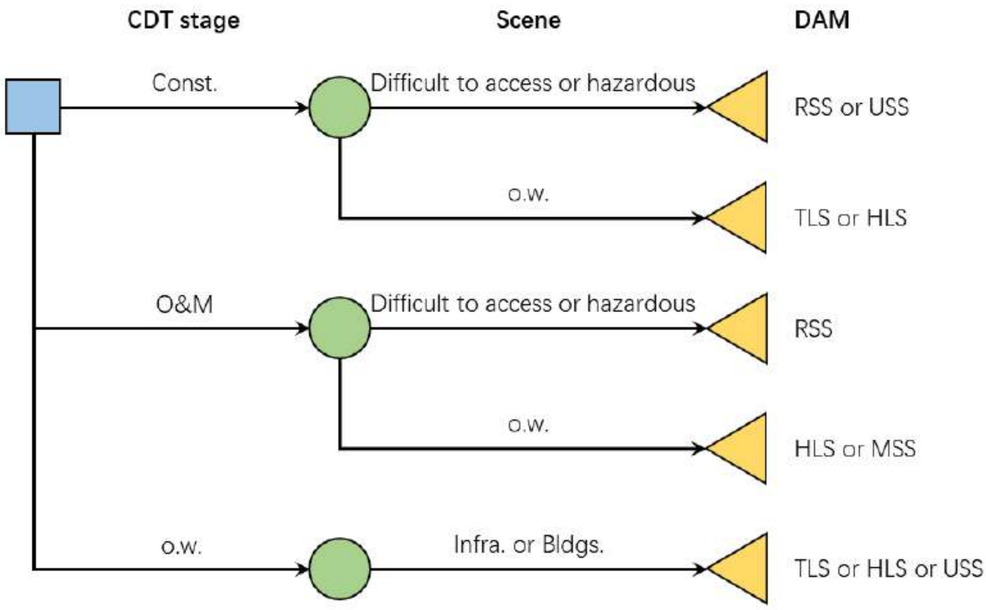

Fig. 6. Decision tree for DAM selection.

4.1.2 Data cleaning and down-sampling

The inherent complexity of raw 3D point clouds induces computational burdens throughout storage and processing pipelines, consequently compromising the integrity of downstream processes ranging from reconstruction to the generation of topologically consistent. Within the field of scan-to-BIM processes, effective data cleaning and down-sampling methods are crucial for enhancing data quality and processing efficiency [30, 32].

The presence of noise points and outliers can adversely affect the accuracy of subsequent data processing and modeling [111]. Common data cleaning methods include statistical filtering, radius filtering, and conditional filtering. Statistical filtering identifies and removes noise points by calculating the local density of point cloud data [112], radius filtering determines and removes outliers based on the neighborhood radius of each point in the point cloud [113], and conditional filtering selects data points that meet the requirements according to preset conditions [114].

Down-sampling is first designed to control the volume and increase uniformity of point cloud data, while it well preserves the geometry, thereby enhancing data processing and storage efficiency [115]. Common down-sampling methods encompass voxel grid down-sampling, random down-sampling, and uniform down-sampling. Voxel grid down-sampling reduces the amount of data by partitioning the point cloud into fixed-size 3D grids and retaining a representative point within each grid [84]. Random down-sampling involves the random selection of a subset of points from the point cloud, making it suitable for scenarios with lower accuracy requirements [116]. Uniform down-sampling selects data points at regular intervals and is employed for point clouds characterized by large volumes and uniform distribution [117].

4.1.3 Semantic segmentation of scans

Semantic segmentation establishes a comprehensive partitioning of scenes at the semantic level by assigning category labels (such as wall, floor, ceiling, etc.) to each point cloud. Instance segmentation extends this capability by precisely delineating and distinguishing different object instances (such as different chairs or different tables) that share identical semantic classifications. In recent years, the rapid advancement of deep learning has led to the prominence of semantic segmentation based on convolutional neural networks (CNNs), graph convolutional networks (GCNs), and other deep learning models. Notable examples include models such as PointNet [53], PointNet++ [106], and PointCNN [118]. Additionally, deep learning methods based on multi-view representations have also demonstrated substantial progress in enhancing the performance of point cloud semantic segmentation.

Instance segmentation is more complex than semantic segmentation because it not only needs to identify the category of points, but also needs to distinguish different instances in the same category. Currently, there are two main types of instance segmentation methods: grouping-based methods and detection-based methods. Grouping-based methods, such as similarity group proposal network (SGPN) [119] and generative shape proposal network (GSPN) [120], group points of the same instance together by learning the relationship between points; while detection-based methods, such as 3D semantic instance segmentation (3D-SIS) [121] and VoteNet [122], first detect the bounding box of the instance, and then perform instance-level point cloud segmentation. PointGroup [123] and PointRCNN [124] significantly improve the accuracy and robustness of segmentation by introducing attention mechanism and multi-stage detection strategy. Although these methods improve the accuracy of instance segmentation to a certain extent, there are still challenges when dealing with dense, complex, severely occluded, and dynamic scenes.

4.1.4 Layout and registration

The reconstruction of general AEs focuses on extracting and reconstructing the main structure and layout of the building, such as walls, floors, and ceilings, from 3D point cloud data. The matching and registration of detailed BIM objects refine this process to specific building components, such as doors, windows, pipes, and furniture. The accuracy and efficiency of these two steps directly impact the quality and utility of the final BIM model.

In terms of general AEs layout reconstruction, traditional methods usually rely on the extraction and rule matching of geometric features, such as plane detection algorithms, line segment detection, and surface fitting techniques to identify and reconstruct basic elements such as walls, floors, and ceilings [125, 126]. These methods perform well when dealing with simple and regular building structures, but often have limited performance when faced with complex and irregular building layouts. In recent years, layout reconstruction methods based on deep learning have gradually emerged, such as using convolutional neural networks (CNNs) and generative adversarial networks (GANs) to automatically extract and reconstruct architectural elements [127, 128]. These methods have shown great potential in dealing with complex scenes and improving reconstruction accuracy.

Matching and registration of detailed BIM objects refers to matching specific building components in point cloud data with predefined BIM object libraries and accurately registering them to their actual locations. Traditional matching and registration methods mainly include feature-based matching, such as SIFT [129], SURF [130], etc., and optimization-based registration, such as ICP [131], GICP [132]. These methods are more effective when dealing with simple objects, but the matching accuracy and efficiency will be affected when faced with occlusion, noise and complex backgrounds. In order to solve these problems, matching and registration methods based on deep learning have emerged in recent years, such as using 3D convolutional neural networks and point cloud feature learning networks to automatically extract and match high-dimensional features, thereby improving the accuracy and robustness of registration [133].

4.1.5 Software

This paper reviews several commonly used software and explores their applications and advantages in the scan-to-BIM processes, as shown in the Fig. 7. Autodesk ReCap is mainly used for data preprocessing of point cloud data, such as data cleaning, noise reduction, and preliminary geometry reconstruction [62, 67]. It can be seamlessly integrated with Autodesk Revit, allowing users to use the processed point cloud data directly in Revit for detailed BIM modeling. Revit has powerful parametric modeling capabilities, can efficiently create and edit building information models, and supports export in multiple formats, such as IFC and RVT, which facilitates data exchange and collaboration with other BIM software [41, 85].

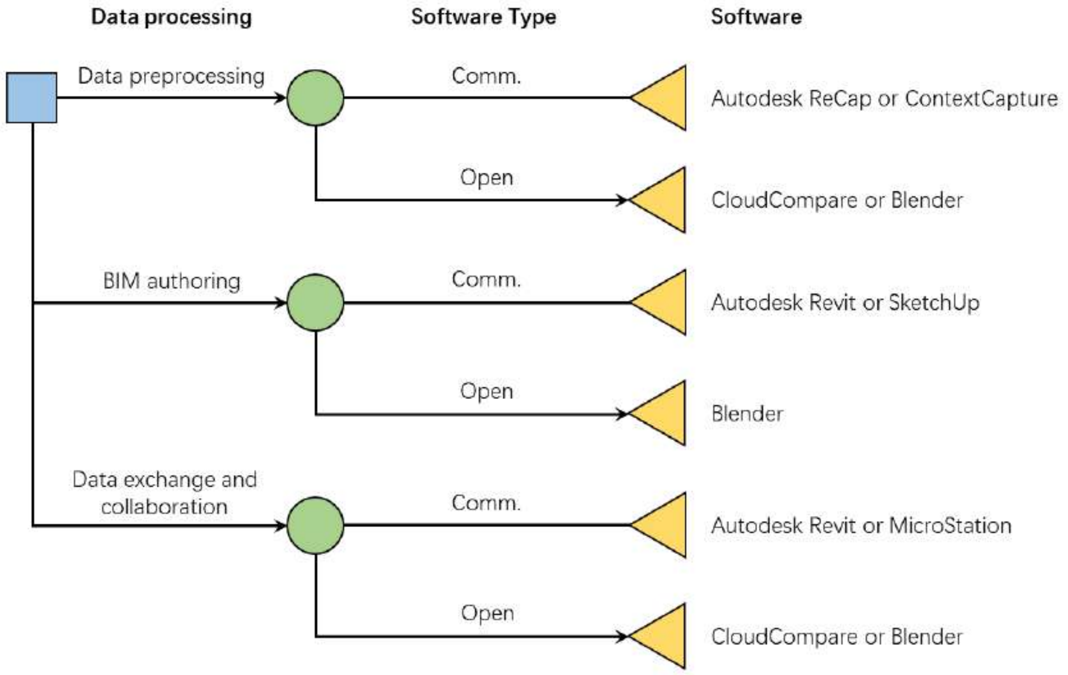

Fig. 7. Decision tree for software selection.

Blender is an open-source 3D modeling and rendering software with powerful modeling, animation, rendering, and visual effects capabilities [63, 134]. Although Blender was not originally designed for building information modeling, its flexible plug-in system and powerful Python script support enable it to adapt to various point cloud data processing and BIM authoring needs. Blender's point cloud processing plug-ins, such as BlenderGIS and Point Cloud Visualizer, can help users import, visualize, and process point cloud data.

Through compatible plug-ins with other BIM software, Blender can export files in multiple formats, such as OBJ, FBX, and IFC, which facilitates data exchange and collaboration with other BIM software.

Bentley Systems' ContextCapture and MicroStation are also commonly used 3D reconstruction software. ContextCapture generates high-precision 3D models through photogrammetry technology, which is suitable for data processing of large-scale and complex building scenes [27, 74]. The created model can be imported into MicroStation for further BIM modeling and editing. MicroStation has powerful 3D modeling and data management capabilities, supports the import and export of multiple file formats, such as DGN and IFC, and is suitable for the data exchange and collaboration needs of complex engineering projects. Trimble's RealWorks [61] provides a variety of point cloud processing functions, such as point cloud stitching, cleaning, and classification, and can efficiently process large-scale point cloud data. SketchUp is widely popular among users for its easy-to-use interface and powerful modeling functions. Through plug-ins, SketchUp can exchange data with other BIM software, such as exporting to IFC file format.

4.2 Guidelines for adopting scan-to-BIM processes

Based on the preceding analysis and the 58 cases examined in this review, we have summarized the guidelines for automated scan-to-BIM processes, which are organized into four key steps as shown in Fig. 8.

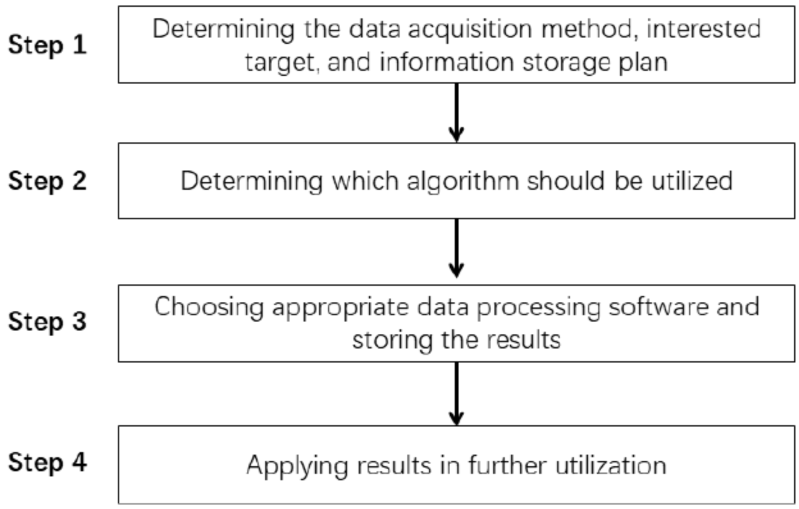

Fig. 8. Four-step guidelines for choosing appropriate scan-to-BIM processes.

Step 1: The first step is determining the data acquisition method. The implementation of the automated scan-to-BIM process requires the selection of appropriate equipment to acquire 3D point cloud data from the real world. In the construction stage, some scenes are difficult to access or hazardous, so robotic scanning systems or UAV-based scanning systems can be appropriate. Robotic scanning systems is suitable for dangerous environments or tasks that require repeated scanning, and robotic scanning systems can navigate along a predefined path [76]. UAV-based scanning can scan large areas of terrain and buildings from high altitudes [26], but is greatly affected by weather conditions.

During the O&M stage, robotic scanning systems is suitable for difficult-to-access or dangerous scenarios, otherwise (noted as “o.w.”) handheld laser scanner or mobile scanning systems can be selected. Handheld laser scanners are known for its portability and flexibility, and is suitable for scanning small-scale spaces [42]. Mobile scanning systems can collect large amounts of 3D point cloud data while on the move, making it ideal for scanning urban infrastructure, roads, and a wide range of outdoor spaces [27]. For the remaining stages, such as CHB, it can be selected between terrestrial laser scanners, handheld laser scanners, or UAV-based scanning systems, to ensure efficient and accurate data collection. TLS provide high measurement accuracy and resolution, and are particularly suitable for scenarios that require detailed recording of the internal and external structures of buildings [67-69]. However, terrestrial laser scanners lack portability and require extended data collection times.

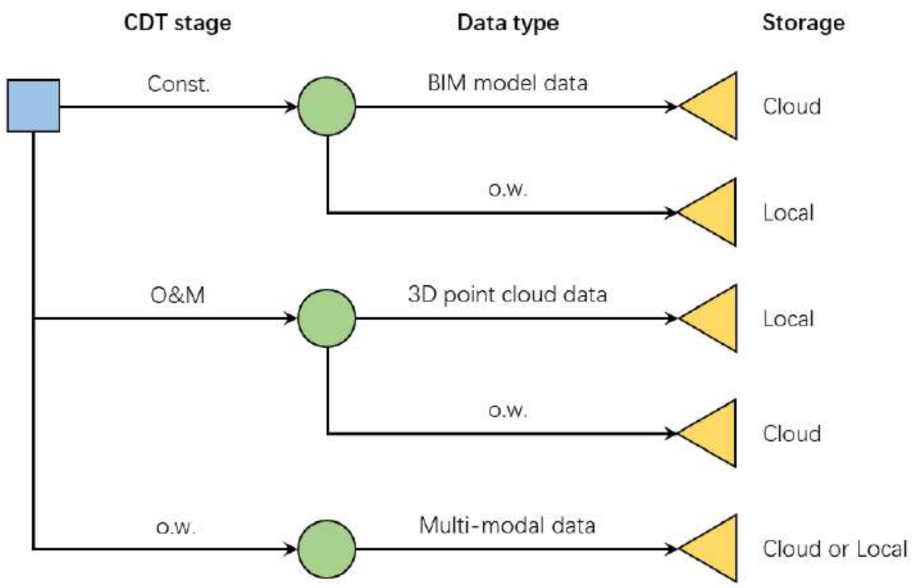

Fig. 9. Decision tree for data storage selection.

Fig. 9. shows the decision tree for data storage selection at various CDT stages. During the construction stage, the primary data to be processed is BIM model, which are typically stored in the cloud to facilitate collaboration and access. In the O&M stage, the data to be

managed are predominantly 3D point cloud data, which are large and needs to be accessed quickly, so local storage is usually selected. For other works, the data handled are multi-modal, including images, videos, and sensor data, which require flexible storage solutions to meet the diverse needs of different projects.

Step 2: The next step involves selecting suitable algorithms for data processing. The detailed data processing workflow includes data cleaning and down-sampling, semantic segmentation of scans, and layout and registration, as discussed in detail in Sections 4.1.2–4.1.4. Raw 3D point cloud data often contains noise, outliers, and redundant information, which not only increases the costs of data storage and processing, but also negative impacts on subsequent model construction and analysis. Therefore, applying effective data cleaning and down-sampling during the scan-to-BIM process is essential for ensuring data quality and processing efficiency [30, 32].

The automation of scan-to-BIM is closely associated with semantic enrichment. Semantic segmentation aims to classify each point into a specific category (e.g., walls or windows), while instance segmentation further distinguishes between different instances within the same category (e.g., different chairs). The rapid advancement of deep learning techniques in recent years has facilitated the widespread adoption of semantic segmentation methods utilizing deep learning models, such as CNNs [53, 106] and GCNs [30]. Retrieval-augmented generation (RAG)-based segmentation has emerged as a promising approach, leveraging external knowledge retrieval to enhance segmentation performance [134, 135].

Traditional layout and registration methods rely on the extraction of geometric features for rule-based matching. Examples include plane detection algorithms, line segment identification, and surface fitting techniques [125, 126]. In recent years, deep learning-based layout methods have gradually emerged, for instance, application of GANs to automatically extract and reconstruct architectural elements [127, 128]. Registration refers to matching specific building components in the point cloud data with predefined BIM object libraries. Commonly algorithms for registration include ICP [131] and SIFT [129]. These advancements contribute to increased precision and efficiency in Scan-to-BIM processes.

Step 3: The third step involves selecting appropriate data processing software and storing the results. During the data preprocessing stage, commonly used commercial software includes Autodesk ReCap and ContextCapture, while frequently utilized open-source software comprises CloudCompare and Blender. These software tools are primarily employed for point cloud data cleaning, noise reduction, and preliminary geometric reconstruction [62, 67].

In the BIM modeling stage, commonly used commercial software includes Autodesk Revit and SketchUp. These software packages possess parametric modeling capabilities, which allow for the efficient creation and editing of BIM. They also support exporting in multiple formats, facilitating collaboration with other BIM software [41, 85]. Additionally, the open-source software Blender is equipped with modeling and rendering capabilities. It can adapt to various point cloud data processing and BIM modeling requirements through its flexible plugin system and robust support from Python scripting [63, 136].

Step 4: The final step involves applying the results for further utilization. During the construction phase, Scan-to-BIM is suitable for scenarios such as verification and deformation monitoring [41, 86]. In the O&M phase, digital twin technology based on Scan-to-BIM can reduce material waste and rework, thereby saving costs and time. In the field of infrastructure, Scan-to-BIM is primarily used for the digital modeling and management of large structures such as bridges [63, 101] and tunnels [47]. For infrastructure like bridges, researchers have proposed an integrated Scan-to-BIM-to-Sim framework to support structural performance analysis and evaluation [137]. In addition, point cloud completion techniques are being explored to further improve the integrity and precision of model reconstruction [138]. In the context of historic building preservation, Scan-to-BIM is employed for documentation and analysis. By integrating various databases, it supports the conservation, management, and restoration of cultural heritage [52, 99, 110]. At the stage of building demolition, the coupling of Scan-to-BIM data and robotics enables the automated sequencing of reinforced concrete structure disassembly, thereby supporting the sustainable reuse of components [139].

5. Conclusion

BIM is a crucial digital asset for enhancing the digitization level of AEC, and automated scan-to-BIM offer an effective system of obtaining as-built BIM. This paper summaries a conceptual model to demonstrate the current status and development trajectory of automated scan-to-BIM processes, based on the systematic analysis of 58 real cases. Terrestrial laser scanning is identified as the most prevalent method for collecting 3D point clouds, and there is a growing trend towards the use of deep learning-based methods for the semantic segmentation of 3D point clouds. However, point cloud data quality remains a significant bottleneck in practice, particularly in complex, occluded, and dynamic environments. The generalizability of deep learning across different architectural styles and construction environments needs further validations. Commercial software offers comprehensive functions and professional technical support, whereas open-source software provides flexibility and customizability. Automated scan-to-BIM serves not only as a bridge connecting the physical and digital worlds but also as a significant driving force for the development and application of construction management.

Guidelines has been developed to assist future practitioners in selecting and implementing appropriate automated scan-to-BIM processes, thereby maximizing their capabilities in AEC. The guidelines encompass four main steps: (1) Determining the data acquisition equipment, interested target, and information storage plan; (2) Determining which algorithm should be utilized; (3) Choosing appropriate data processing software and storing the results; and (4) Applying results in further utilization. These steps have been demonstrated to be effective in actual applications in construction projects.

Future research is recommended to focus on five key directions as follows. (1) More infrastructure scenes can be included in the applications of Scan-to-BIM. For large-scale infrastructure, it would be beneficial to enhance 3D point clouds with satellite or terrestrial Interferometric Synthetic Aperture Radar (InSAR) sensing to enable millimeter-accurate structural health analysis for bridges, tunnels, and dams. (2) Multi-source sensing data fusion can enable novel scan-to-BIM applications. For example, high-definition imagery can supplement 3D point cloud for small building elements, such as fire sprinklers, while ground-penetrating radar can detect subsurface concrete details. Open accessible benchmark datasets can boost the reproducibility and trustworthiness of scan-to-BIM research findings to impact the industry. (3) In semantic segmentation, emerging generative AI methods may open new opportunities for 3D point cloud segmentation in several ways, e.g., improving the automated data cleaning of incomplete or noisy 3D points of openings and glass and retrieval-augmented generation (RAG) segmentation. (4) For BIM ecosystems, a diversification of BIM authoring and analytic tools, e.g., OpenBIM and localized BIM beyond existing mainstream platforms, can better align with local technical standards and cultural-economic contexts, for BIM resilience in a dynamic world. (5) Researchers are suggested to push the boundaries of CDT in applying novel simulation and reasoning for responding to global climate shocks and extreme weathers to buildings and infrastructure, and in energy efficiency in operational stage of buildings for lower carbon footprints.

This paper addresses a significant knowledge gap in the application of automated scan-to-BIM, by reviewing the status quo of technological areas, active development trends, practical guidelines, and future directions. The applicability of the automated scan-to-BIM guidelines is recommended in a broader range of construction scenarios, particularly infrastructure projects. From a long-term perspective, automated scan-to-BIM is not a one-off task, but a promising knowledge base for digital transformation and value cocreations in off-site construction, operations and maintenance, and demolition stages.

Acknowledgments

The work presented in this study was supported by the Hong Kong Innovation and Technology Commission (ITC) (No. ITP/004/23LP) and the Hong Kong Research Grants Council (No. 17201325).

CRediT author statement

Ke YOU: Conceptualization, Methodology, Software, Formal Analysis, Data Curation Writing – Original Draft, and Visualization.

Ke CHEN: Conceptualization, Methodology, and Supervision.

Fan XUE: Conceptualization, Methodology, Writing – Review & Editing, Supervision, and Funding Acquisition

All authors have approved the submitted version and agree to be personally accountable for their contribution

GenAI declaration

This work was reviewed and edited for grammatical accuracy using university-hosted GenAI tools. After using this tool, the authors reviewed and edited the content selectively and took full responsibility for the publication's content. The viewpoints and ideas expressed herein are solely those of the human authors.

References

[1] A.E. Ikudayisi, A.P.C. Chan, A. Darko, Y.M.D. Adedeji. Integrated practices in the Architecture, Engineering, and Construction industry: Current scope and pathway towards Industry 5.0. Journal of Building Engineering. 2023, 73, pp. 21, https://doi.org/10.1016/j.jobe.2023.106788

[2] B. Becerik-Gerber, K. Kensek. Building Information Modeling in Architecture, Engineering, and Construction: Emerging Research Directions and Trends. Journal of Professional Issues in Engineering Education and Practice. 2010, 136, (3), pp. 139-147, https://doi.org/10.1061/(asce)ei.1943-5541.0000023

[3] A.O. Olanipekun, M. Sutrisna. Facilitating Digital Transformation in Construction-A Systematic Review of the Current State of the Art. Frontiers in Built Environment. 2021, 7, pp. 21, https://doi.org/10.3389/fbuil.2021.660758

[4] F. Xue, L.P.F. Wu, W.S. Lu. Semantic enrichment of building and city information models: A ten-year review. Advanced Engineering Informatics. 2021, 47, pp. 11, https://doi.org/10.1016/j.aei.2020.101245

[5] S.A. Adekunle, C.O. Aigbavboa, O. Ejohwomu, E.A. Adekunle, W.D. Thwala. Digital transformation in the construction industry: a bibliometric review. Journal of Engineering Design and Technology. 2021, pp. 29, https://doi.org/10.1108/jedt-08-2021-0442

[6] V. Patraucean, I. Armeni, M. Nahangi, J.M. Yeung, I. Brilakis, C. Haas. State of research in automatic as-built modelling. Advanced Engineering Informatics. 2015, 29, (2), pp. 162-171, https://doi.org/10.1016/j.aei.2015.01.001

[7] K. Abu Awwad, A. Shibani, M. Ghostin. Exploring the critical success factors influencing BIM level 2 implementation in the UK construction industry: the case of SMEs. International Journal of Construction Management. 2022, 22, (10), pp. 1894-1901, https://doi.org/10.1080/15623599.2020.1744213

[8] D.W.M. Chan, T.O. Olawumi, A.M.L. Ho. Perceived benefits of and barriers to Building Information Modelling (BIM) implementation in construction: The case of Hong Kong. Journal of Building Engineering. 2019, 25, pp. 10, https://doi.org/10.1016/j.jobe.2019.100764

[9] L. Tang, G. Chan, C. Chen, Z. Zhang, Y. Zheng, X. Yi, A. Mok, D. Mak. CIC BIM Adoption Survey 2020—Public-Facing Report. Construction Industry Council: Hong Kong, China. 2021

[10] A. Akcamete, B. Akinci, J.H. Garrett. Potential utilization of building information models for planning maintenance activities. In: Proceedings of the international conference on computing in civil and building engineering, 2010 pp. 151-157

[11] C. Gourguechon, H. Macher, T. Landes. AUTOMATION OF AS-BUILT BIM CREATION FROM POINT CLOUD: AN OVERVIEW OF RESEARCH WORKS FOCUSED ON INDOOR ENVIRONMENT. In: 24th ISPRS Congress on Imaging Today, Foreseeing Tomorrow, 2022 pp. 193-200, https://doi.org/10.5194/isprs-archives-XLIII-B2-2022-193-2022

[12] A. Alsuhaibani, J. Rojas, C. Leffel, J.W. Ma, F. Leite. LivingBIM Dataset: As-Designed and As-Built Dataset for an Academic Building Including BIM 3D Models, Point Clouds, and Panoramic Images. In: ASCE International Conference on Computing in Civil Engineering (I3CE), 2023 pp. 672-679

[13] J. Xu, L.Y. Ding, P.E.D. Love. Digital reproduction of historical building ornamental components: From 3D scanning to 3D printing. Automation in Construction. 2017, 76, pp. 85-96, https://doi.org/10.1016/j.autcon.2017.01.010

[14] Q. Wang, J.J. Guo, M.K. Kim. An Application Oriented Scan-to-BIM Framework. Remote Sensing. 2019, 11, (3), pp. 27, https://doi.org/10.3390/rs11030365

[15] A. Ursini, A. Grazzini, F. Matrone, M. Zerbinatti. From scan-to-BIM to a structural finite elements model of built heritage for dynamic simulation. Automation in Construction. 2022, 142, pp. 13, https://doi.org/10.1016/j.autcon.2022.104518

[16] I. Skrzypczak, G. Oleniacz, A. Lesniak, K. Zima, M. Mrówczynska, J.K. Kazak. Scan-to-BIM method in construction: assessment of the 3D buildings model accuracy in terms inventory measurements. Building Research and Information. 2022, 50, (8), pp. 859-880, https://doi.org/10.1080/09613218.2021.2011703

[17] M.C.P. Sing, Y.Y.L. Sophie, K.H.C. Chan, H.J. Liu, R. Humphrey. Scan-to-BIM technique in building maintenance projects: practicing quantity take-off. International Journal of Building Pathology and Adaptation. 2022, pp. 13, https://doi.org/10.1108/ijbpa-06-2022-0097

[18] Y. Xie, M.X. Teo, S.Y. Li, L.H. Huang, N.Y. Liang, Y.Y. Cai. As-built BIM reconstruction of piping systems using smartphone videogrammetry and terrestrial laser scanning. Automation in Construction. 2023, 156, pp. 21, https://doi.org/10.1016/j.autcon.2023.105120

[19] L. Yang, J.C.P. Cheng, Q. Wang. Semi-automated generation of parametric BIM for steel structures based on terrestrial laser scanning data. Automation in Construction. 2020, 112, pp. 17, https://doi.org/10.1016/j.autcon.2019.103037

[20] Y.J. Cheng, W.G. Qiu, D.Y. Duan. Automatic creation of as-is building information model from single-track railway tunnel point clouds. Automation in Construction. 2019, 106, pp. 16, https://doi.org/10.1016/j.autcon.2019.102911

[21] J. Park, J. Kim, D. Lee, K. Jeong, J. Lee, H. Kim, T. Hong. Deep Learning-Based Automation of

Scan-to-BIM with Modeling Objects from Occluded Point Clouds. Journal of Management in Engineering. 2022, 38, (4), pp. 11, https://doi.org/10.1061/(asce)me.1943-5479.0001055
[22] M. Intignano, S.A. Biancardo, C. Oreto, N. Viscione, R. Veropalumbo, F. Russo, G. Ausiello, G. Dell'Acqua. A Scan-to-BIM Methodology Applied to Stone Pavements in Archaeological Sites. Heritage. 2021, 4, (4), pp. 3032-3049, https://doi.org/10.3390/heritage4040169
[23] F. Banfi, C. Stanga, R. Brumana. A Digital Workflow for Built Heritage: From SCAN-to-BIM Process to the VR-Tour of the Basilica of Sant'Ambrogio in Milan. In: 7th European-Mediterranean International Conference (EuroMed), 2018 pp. 334-343, https://doi.org/10.1007/978-3-030-01762-0_28
[24] M.G. Angelini, V. Baiocchi, D. Costantino, F. Garzia. SCAN TO BIM FOR 3D RECONSTRUCTION OF THE PAPAL BASILICA OF SAINT FRANCIS IN ASSISI IN ITALY. In: 1st International Conference on Geomatics and Restoration - Conservation of Cultural Heritage in the Digital Era, 2017 pp. 47-54, https://doi.org/10.5194/isprs-archives-XLII-5-W1-47-2017
[25] J. Werbrouck, P. Pauwels, M. Bonduel, J. Beetz, W. Bekers. Scan-to-graph: Semantic enrichment of existing building geometry. Automation in Construction. 2020, 119, pp. 15, https://doi.org/10.1016/j.autcon.2020.103286
[26] T.W. Kang. Scan to BIM Mapping Process Description for Building Representation in 3D GIS. Applied Sciences-Basel. 2023, 13, (17), pp. 16, https://doi.org/10.3390/app13179986
[27] M.H. Ibrahimkhil, X.S. Shen, K. Barati, C.C. Wang. Dynamic Progress Monitoring of Masonry Construction through Mobile SLAM Mapping and As-Built Modeling. Buildings. 2023, 13, (4), pp. 15, https://doi.org/10.3390/buildings13040930
[28] Q. Wang, J.J. Li, X.Y. Tang, X.C. Zhang. How data quality affects model quality in scan-to-BIM: A case study of MEP scenes. Automation in Construction. 2022, 144, pp. 14, https://doi.org/10.1016/j.autcon.2022.104598
[29] E. Valero, F. Bosché, M. Bueno. LASER SCANNING FOR BIM. Journal of Information Technology in Construction. 2022, 27, pp. 486-495, https://doi.org/10.36680/j.itcon.2022.023
[30] Y.X. Zhang, M. Rabbat, Ieee. A GRAPH-CNN FOR 3D POINT CLOUD CLASSIFICATION. In: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018 pp. 6279-6283
[31] Q. Qiu, M.J. Wang, J.J. Guo, Z.W. Liu, Q. Wang. An adaptive down-sampling method of laser scan data for scan-to-BIM. Automation in Construction. 2022, 135, pp. 16, https://doi.org/10.1016/j.autcon.2022.104135
[32] M. Kellner, B. Stahl, A. Reiterer. Reconstructing Geometrical Models of Indoor Environments Based on Point Clouds. Remote Sensing. 2023, 15, (18), pp. 21, https://doi.org/10.3390/rs15184421
[33] G. Rocha, L. Mateus, J. Fernández, V. Ferreira. A Scan-to-BIM Methodology Applied to Heritage Buildings. Heritage. 2020, 3, (1), pp. 47-65, https://doi.org/10.3390/heritage3010004
[34] E. Acosta, F. Spettu, F. Fiorillo. A PROCEDURE TO IMPORT A COMPLEX GEOMETRY MODEL OF A HERITAGE BUILDING INTO BIM FOR ADVANCED ARCHITECTURAL REPRESENTATIONS. In: 9th International Workshop on 3D-ARCH 3D Virtual Reconstruction and Visualization of Complex Architectures, 2022 pp. 9-16, https://doi.org/10.5194/isprs-archives-XLVI-2-W1-2022-9-2022
[35] W.G. Zhao, Y.Y. Yan, C.L. Yang, J.N. Ye, X. Yang, K.Z. Huang, Ieee. Divide and Conquer: 3D Point Cloud Instance Segmentation With Point-Wise Binarization. In: IEEE/CVF International Conference on Computer Vision (ICCV), 2023 pp. 562-571, https://doi.org/10.1109/iccv51070.2023.00058
[36] Y. Perez-Perez, M. Golparvar-Fard, K. El-Rayes. Segmentation of point clouds via joint semantic and geometric features for 3D modeling of the built environment. Automation in Construction. 2021, 125, pp. 19, https://doi.org/10.1016/j.autcon.2021.103584
[37] C. Morbidoni, R. Pierdicca, M. Paolanti, R. Quattrini, R. Mammoli. Learning from Synthetic Point Cloud Data for Historical Buildings Semantic Segmentation. Acm Journal on Computing and Cultural Heritage. 2020, 13, (4), pp. 16, https://doi.org/10.1145/3409262
[38] M. Nahangi, C.T. Haas. Automated 3D compliance checking in pipe spool fabrication. Advanced Engineering Informatics. 2014, 28, (4), pp. 360-369, https://doi.org/10.1016/j.aei.2014.04.001
[39] R. Schnabel, R. Wahl, R. Klein. Efficient RANSAC for point-cloud shape detection. Computer Graphics Forum. 2007, 26, (2), pp. 214-226, https://doi.org/10.1111/j.1467-8659.2007.01016.x
[40] F.C.D. Tsai. GEOMETRIC HASHING WITH LINE FEATURES. Pattern Recognition. 1994, 27,

(3), pp. 377-389, https://doi.org/10.1016/0031-3203(94)90115-5
[41] T. Kang, S. Patil, K. Kang, D. Koo, J. Kim. Rule-Based Scan-to-BIM Mapping Pipeline in the Plumbing System. Applied Sciences-Basel. 2020, 10, (21), pp. 18, https://doi.org/10.3390/app10217422
[42] X.Y. Chen, Y.J. Pan, V.J.L. Gan, K. Yan. 3D reconstruction of semantic-rich digital twins for ACMV monitoring and anomaly detection via scan-to-BIM and time-series data integration. Developments in the Built Environment. 2024, 19, pp. 18, https://doi.org/10.1016/j.dibe.2024.100503
[43] B. Quintana, S.A. Prieto, A. Adán, F. Bosché. Door detection in 3D coloured point clouds of indoor environments. Automation in Construction. 2018, 85, pp. 146-166, https://doi.org/10.1016/j.autcon.2017.10.016
[44] X.H. Xiong, A. Adan, B. Akinci, D. Huber. Automatic creation of semantically rich 3D building models from laser scanner data. Automation in Construction. 2013, 31, pp. 325-337, https://doi.org/10.1016/j.autcon.2012.10.006
[45] J. Schult, F. Engelmann, A. Hermans, O. Litany, S.Y. Tang, B. Leibe, Ieee. Mask3D: Mask Transformer for 3D Semantic Instance Segmentation. In: IEEE International Conference on Robotics and Automation (ICRA), 2023 pp. 8216-8223, https://doi.org/10.1109/icra48891.2023.10160590
[46] Y.Q. Dong, Y.H. Li, M.L. Hou. The Point Cloud Semantic Segmentation Method for the Ming and Qing Dynasties' Official-Style Architecture Roof Considering the Construction Regulations. Isprs International Journal of Geo-Information. 2022, 11, (4), pp. 20, https://doi.org/10.3390/ijgi11040214
[47] J. Park, B.K. Kim, J.S. Lee, M. Yoo, I.W. Lee, Y.M. Ryu. Automated semantic segmentation of 3D point clouds of railway tunnel using deep learning. In: ITA-AITES World Tunnel Congress (WTC) / 49th General Assembly of the International-Tunnelling-and-Underground-Space-Association (ITA-AITES), 2023 pp. 2844-2852, https://doi.org/10.1201/9781003348030-343
[48] R. Volk, J. Stengel, F. Schultmann. Building Information Modeling (BIM) for existing buildings - literature review and future needs. Automation in Construction. 2014, 38, pp. 109-127, https://doi.org/10.1016/j.autcon.2013.10.023
[49] R. Rashdi, J. Martínez-Sánchez, P. Arias, Z.Y. Qiu. Scanning Technologies to Building Information Modelling: A Review. Infrastructures. 2022, 7, (4), pp. 29, https://doi.org/10.3390/infrastructures7040049
[50] M. Bassier, M. Vergauwen. Unsupervised reconstruction of Building Information Modeling wall objects from point cloud data. Automation in Construction. 2020, 120, pp. 21, https://doi.org/10.1016/j.autcon.2020.103338
[51] J.W. Ma. Exploring the Feasibility of Deep Learning-Based Boundary Extraction for Scan-To-BIM: A Case Study Analysis. In: Annual Conference of the Canadian-Society-for-Civil-Engineering (CSCE), 2023 pp. 167-179, https://doi.org/10.1007/978-3-031-61499-6_13
[52] M. Buldo, L. Agustín-Hernández, C. Verdoscia, R. Tavolare. A SCAN-TO-BIM WORKFLOW PROPOSAL FOR CULTURAL HERITAGE. AUTOMATIC POINT CLOUD SEGMENTATION AND PARAMETRIC-ADAPTIVE MODELLING OF VAULTED SYSTEMS. In: 29th CIPA Symposium on Documenting, Understanding, Preserving Cultural Heritage - Humanities and Digital Technologies for Shaping the Future, 2023 pp. 333-340, https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-333-2023
[53] C.R. Qi, H. Su, K.C. Mo, L.J. Guibas, Ieee. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. In: 30th IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2017 pp. 77-85, https://doi.org/10.1109/cvpr.2017.16
[54] M. Mahmoud, W. Chen, Y. Yang, Y.X. Li. Automated BIM generation for large-scale indoor complex environments based on deep learning. Automation in Construction. 2024, 162, pp. 25, https://doi.org/10.1016/j.autcon.2024.105376
[55] M. Mahmoud, Z.B. Zhao, W. Chen, M. Adham, Y.X. Li. Automated Scan-to-BIM: A deep learning-based framework for indoor environments with complex furniture elements. Journal of Building Engineering. 2025, 106, pp. 20, https://doi.org/10.1016/j.jobe.2025.112596
[56] L.C. Luo, C.S. Cheng, W. Mobley, A. Novoselac, K. Lieberknecht, F. Leite. Scenario Generation for Built Environment Decision Support under Uncertainty: Case Studies of Airflow Modeling and Climate-Resilient Infrastructure System Design. Journal of Computing in Civil Engineering. 2025, 39, (4), pp. 18, https://doi.org/10.1061/jccee5.Cpeng-6253

[57] H. Elsharkawi, E. Elbeltagi, M.S. Eid, W. Alattyih, H. Wefki. Construction Payment Automation Through Scan-to-BIM and Blockchain-Enabled Smart Contract. Buildings. 2025, 15, (2), pp. 28, https://doi.org/10.3390/buildings15020213
[58] J. Patil, M. Kalantari. Automatic Scan-to-BIM-The Impact of Semantic Segmentation Accuracy. Buildings. 2025, 15, (7), pp. 30, https://doi.org/10.3390/buildings15071126
[59] Y.D. Liu, H. Huang, G. Gao, Z.Y. Ke, S.T. Li, M. Gu. Dataset and benchmark for as-built BIM reconstruction from real-world point cloud. Automation in Construction. 2025, 173, pp. 21, https://doi.org/10.1016/j.autcon.2025.106096
[60] S. Kang, S. Kim, S. Kim. Improvement of the defect inspection process of deteriorated buildings with scan to BIM and image-based automatic defect classification. Journal of Building Engineering. 2025, 99, pp. 13, https://doi.org/10.1016/j.jobe.2024.111601
[61] K. Cho, H. Park, C. Kim, T. Kim. Toward sustainable urban energy solutions: Introducing F NeCESSCity framework for energy-saving smart city configuration. Sustainable Cities and Society. 2024, 113, pp. 13, https://doi.org/10.1016/j.scs.2024.105674
[62] G. Rocha, L. Mateus. Using Dynamo for Automatic Reconstruction of BIM Elements from Point Clouds. Applied Sciences-Basel. 2024, 14, (10), pp. 41, https://doi.org/10.3390/app14104078
[63] L. Yang, Y.C. Lin, H.B. Cai, A. Habib. From Scans to Parametric BIM: An Enhanced Framework Using Synthetic Data Augmentation and Parametric Modeling for Highway Bridges. Journal of Computing in Civil Engineering. 2024, 38, (3), pp. 17, https://doi.org/10.1061/jccee5.Cpeng-5640
[64] X. Pan, Q. Lin, S.Y. Ye, L. Li, L. Guo, B. Harmon. Deep learning based approaches from semantic point clouds to semantic BIM models for heritage digital twin. Heritage Science. 2024, 12, (1), pp. 17, https://doi.org/10.1186/s40494-024-01179-4
[65] M. Pepe, A.R. Garofalo, D. Costantino, F.F. Tana, D. Palumbo, V.S. Alfio, E. Spacone. From Point Cloud to BIM: A New Method Based on Efficient Point Cloud Simplification by Geometric Feature Analysis and Building Parametric Objects in Rhinoceros/Grasshopper Software. Remote Sensing. 2024, 16, (9), pp. 18, https://doi.org/10.3390/rs16091630
[66] B.Y. Wang, Z.Y. Chen, M.K. Li, Q. Wang, C. Yin, J.C.P. Cheng. Omni-Scan2BIM: A ready-to-use Scan2BIM approach based on vision foundation models for MEP scenes. Automation in Construction. 2024, 162, pp. 18, https://doi.org/10.1016/j.autcon.2024.105384
[67] G. Rocha, L. Mateus, V. Ferreira. Historical Heritage Maintenance via Scan-to-BIM Approaches: A Case Study of the Lisbon Agricultural Exhibition Pavilion. Isprs International Journal of Geo-Information. 2024, 13, (2), pp. 23, https://doi.org/10.3390/ijgi13020054
[68] A.A. Birkeland, M. Udnaes. Semi-automated dataset creation for semantic and instance segmentation of industrial point clouds. Computers in Industry. 2024, 155, pp. 11, https://doi.org/10.1016/j.compind.2023.104064
[69] H.M. Zhu, M.Q. Huang, Q.B. Zhang. TunGPR: Enhancing data-driven maintenance for tunnel linings through synthetic datasets, deep learning and BIM. Tunnelling and Underground Space Technology. 2024, 145, pp. 17, https://doi.org/10.1016/j.tust.2023.105568
[70] S. Kim, H. Kim, J.W. Lee, T. Hong, K. Jeong. An Integrated Assessment Framework of Economic, Environmental, and Human Health Impacts Using Scan-to-BIM and Life-Cycle Assessment in Existing Buildings. Journal of Management in Engineering. 2023, 39, (5), pp. 12, https://doi.org/10.1061/jmenea.Meeng-5600
[71] C. Stanga, F. Banfi, S. Roascio. Enhancing Building Archaeology: Drawing, UAV Photogrammetry and Scan-to-BIM-to-VR Process of Ancient Roman Ruins. Drones. 2023, 7, (8), pp. 27, https://doi.org/10.3390/drones7080521
[72] I. Aftab, K. Kapitány, T. Lovas. Automating Scan to BIM Operations Using Grasshopper. Periodica Polytechnica-Civil Engineering. 2023, pp. 6, https://doi.org/10.3311/PPci.22390
[73] M. Jarzabek-Rychard, H.G. Maas. Modeling of 3D geometry uncertainty in Scan-to-BIM automatic indoor reconstruction. Automation in Construction. 2023, 154, pp. 12, https://doi.org/10.1016/j.autcon.2023.105002
[74] N. Abreu, R. Souza, A. Pinto, A. Matos, M. Pires. Labelled Indoor Point Cloud Dataset for BIM Related Applications. Data. 2023, 8, (6), pp. 19, https://doi.org/10.3390/data8060101
[75] J. Martens, J. Blankenbach. VOX2BIM+-A Fast and Robust Approach for Automated Indoor Point Cloud Segmentation and Building Model Generation. Pfg-Journal of Photogrammetry Remote Sensing and Geoinformation Science. 2023, 91, (4), pp. 273-294, https://doi.org/10.1007/s41064-023-00243-1
[76] D. Hu, V.J.L. Gan, C. Yin. Robot-assisted mobile scanning for automated 3D reconstruction and

point cloud semantic segmentation of building interiors. Automation in Construction. 2023, 152, pp. 21, https://doi.org/10.1016/j.autcon.2023.104949

[77] S. Kim, K. Jeong, T. Hong, J. Lee, J. Lee. Deep Learning-Based Automated Generation of Material Data with Object-Space Relationships for Scan to BIM. Journal of Management in Engineering. 2023, 39, (3), pp. 13, https://doi.org/10.1061/jmenea.Meeng-5143

[78] V. Croce, G. Caroti, A. Piemonte, L. De Luca, P. Véron. H-BIM and Artificial Intelligence: Classification of Architectural Heritage for Semi-Automatic Scan-to-BIM Reconstruction. Sensors. 2023, 23, (5), pp. 30, https://doi.org/10.3390/s23052497

[79] Y. Xie, S.Y. Li, T.R. Liu, Y.Y. Cai. As-built BIM reconstruction of piping systems using PipeNet. Automation in Construction. 2023, 147, pp. 19, https://doi.org/10.1016/j.autcon.2022.104735

[80] D. Campagnolo, E. Camuffo, U. Michieli, P. Borin, S. Milani, A. Giordano, Ieee. FULLY AUTOMATED SCAN-TO-BIM VIA POINT CLOUD INSTANCE SEGMENTATION. In: 30th IEEE International Conference on Image Processing (ICIP), 2023 pp. 291-295, https://doi.org/10.1109/icip49359.2023.10222064

[81] B.Y. Wang, Q. Wang, J.C.P. Cheng, C. Yin. Object verification based on deep learning point feature comparison for scan-to-BIM. Automation in Construction. 2022, 142, pp. 15, https://doi.org/10.1016/j.autcon.2022.104515

[82] Y.D. Pan, A. Braun, I. Brilakis. Enriching geometric digital twins of buildings with small objects by fusing laser scanning and AI-based image recognition. Automation in Construction. 2022, 140, pp. 19, https://doi.org/10.1016/j.autcon.2022.104375

[83] J.W. Ma, F. Leite. Performance boosting of conventional deep learning-based semantic segmentation leveraging unsupervised clustering. Automation in Construction. 2022, 136, pp. 14, https://doi.org/10.1016/j.autcon.2022.104167

[84] L. Truong-Hong, R. Lindenbergh. Extracting structural components of concrete buildings from laser scanning point clouds from construction sites. Advanced Engineering Informatics. 2022, 51, pp. 20, https://doi.org/10.1016/j.aei.2021.101490

[85] S. De Geyter, M. Bassier, M. Vergauwen. AUTOMATED TRAINING DATA CREATION FOR SEMANTIC SEGMENTATION OF 3D POINT CLOUDS. In: ISPRS WG V/7 Conference on Measurement, Visualisation and Processing in BIM for Design and Construction Management II, 2022 pp. 59-67, https://doi.org/10.5194/isprs-archives-XLVI-5-W1-2022-59-2022

[86] Y. Perez-Perez, M. Golparvar-Fard, K. El-Rayes. Scan2BIM-NET: Deep Learning Method for Segmentation of Point Clouds for Scan-to-BIM. Journal of Construction Engineering and Management. 2021, 147, (9), pp. 14, https://doi.org/10.1061/(asce)co.1943-7862.0002132

[87] M. Andriasyan, J. Moyano, J.E. Nieto-Julián, D. Antón. From Point Cloud Data to Building Information Modelling: An Automatic Parametric Workflow for Heritage. Remote Sensing. 2020, 12, (7), pp. 22, https://doi.org/10.3390/rs12071094

[88] J.W. Ma, J. Jung, F. Leite. Deep Learning-Based Scan-to-BIM Automation and Object Scope Expansion Using a Low-Cost 3D Scan Data. Journal of Computing in Civil Engineering. 2024, 38, (6), pp. 17, https://doi.org/10.1061/jccee5.Cpeng-5751

[89] E. Nieto-Julián, S. Bruno, J. Moyano. An Efficient Process for the Management of the Deterioration and Conservation of Architectural Heritage: The HBIM Project of the Duomo of Molfetta (Italy). Remote Sensing. 2024, 16, (23), pp. 33, https://doi.org/10.3390/rs16234542

[90] W.L. Cai, D.Q. Hua, S.H. Li, S.W. Xue, Z. Xu. 3D reconstruction of building interiors based on scan-to-BIM and generative design for as-built building. Engineering Construction and Architectural Management. 2024, pp. 21, https://doi.org/10.1108/ecam-07-2024-0984

[91] F. Bosché, M. Ahmed, Y. Turkan, C.T. Haas, R. Haas. The value of integrating Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The case of cylindrical MEP components. Automation in Construction. 2015, 49, pp. 201-213, https://doi.org/10.1016/j.autcon.2014.05.014

[92] L. Barazzetti, F. Banfi, R. Brumana, M. Previtali, F. Roncoroni. BIM FROM LASER SCANS... NOT JUST FOR BUILDINGS: NURBS-BASED PARAMETRIC MODELING OF A MEDIEVAL BRIDGE. In: 23rd ISPRS Congress, 2016 pp. 51-56, https://doi.org/10.5194/isprsannals-III-5-51-2016

[93] D.F. Laefer, L. Truong-Hong. Toward automatic generation of 3D steel structures for building information modelling. Automation in Construction. 2017, 74, pp. 66-77, https://doi.org/10.1016/j.autcon.2016.11.011

[94] H. Macher, T. Landes, P. Grussenmeyer. From Point Clouds to Building Information Models: 3D

Semi-Automatic Reconstruction of Indoors of Existing Buildings. Applied Sciences-Basel. 2017, 7, (10), pp. 30, https://doi.org/10.3390/app7101030

[95] A. Adán, B. Quintana, S.A. Prieto, F. Bosché. Scan-to-BIM for 'secondary' building components. Advanced Engineering Informatics. 2018, 37, pp. 119-138, https://doi.org/10.1016/j.aei.2018.05.001

[96] Q. Wang, H. Sohn, J.C.P. Cheng. Automatic As-Built BIM Creation of Precast Concrete Bridge Deck Panels Using Laser Scan Data. Journal of Computing in Civil Engineering. 2018, 32, (3), pp. 17, https://doi.org/10.1061/(asce)cp.1943-5487.0000754

[97] M. Capone, E. Lanzara. SCAN-TO-BIM vs 3D IDEAL MODEL HBIM: PARAMETRIC TOOLS TO STUDY DOMES GEOMETRY. In: 8th International Workshop on 3D Virtual Reconstruction and Visualization of Complex Architectures (3D-ARCH), 2019 pp. 219-226, https://doi.org/10.5194/isprs-archives-XLII-2-W9-219-2019

[98] F. Mellado, P.F. Wong, K. Amano, C. Johnson, E.C.W. Lou. Digitisation of existing buildings to support building assessment schemes: viability of automated sustainability-led design scan-to-BIM process. Architectural Engineering and Design Management. 2020, 16, (2), pp. 84-99, https://doi.org/10.1080/17452007.2019.1674126

[99] M. Pepe, D. Costantino, A.R. Garofalo. An Efficient Pipeline to Obtain 3D Model for HBIM and Structural Analysis Purposes from 3D Point Clouds. Applied Sciences-Basel. 2020, 10, (4), pp. 19, https://doi.org/10.3390/app10041235

[100] V. Croce, G. Caroti, L. De Luca, K. Jacquot, A. Piemonte, P. Véron. From the Semantic Point Cloud to Heritage-Building Information Modeling: A Semiautomatic Approach Exploiting Machine Learning. Remote Sensing. 2021, 13, (3), pp. 34, https://doi.org/10.3390/rs13030461

[101] Y. Schatz, B. Domer. Semi-automated creation of IFC bridge models from point clouds for maintenance applications. Frontiers in Built Environment. 2024, 10, pp. 18, https://doi.org/10.3389/fbuil.2024.1375873

[102] A. Aglietti, C. Biagini, A. Bongini, P. Ottobri. HISTORIC BRIDGES MONITORING THROUGH SENSOR DATA MANAGEMENT WITH BIM METHODOLOGIES. In: 29th CIPA Symposium on Documenting, Understanding, Preserving Cultural Heritage - Humanities and Digital Technologies for Shaping the Future, 2023 pp. 33-41, https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-33-2023

[103] M. Aricò, M. Lo Brutto, A. Maltese. A Scan-to-BIM Approach for the Management of Two Arab-Norman Churches in Palermo (Italy). Heritage. 2023, 6, (2), pp. 1622-1644, https://doi.org/10.3390/heritage6020087

[104] R. Angeloni, C. Mariotti, L. Petetta, L. Coppetta. ENABLING SCAN-TO-BIM WORKFLOW FOR HERITAGE CONSERVATION AND MANAGEMENT PROCESS. In: 29th CIPA Symposium on Documenting, Understanding, Preserving Cultural Heritage - Humanities and Digital Technologies for Shaping the Future, 2023 pp. 79-86, https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-79-2023

[105] Z.R. Wu, S.R. Song, A. Khosla, F. Yu, L.G. Zhang, X.O. Tang, J.X. Xiao, Ieee. 3D ShapeNets: A Deep Representation for Volumetric Shapes. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015 pp. 1912-1920

[106] C.R. Qi, L. Yi, H. Su, L.J. Guibas. PointNet plus plus : Deep Hierarchical Feature Learning on Point Sets in a Metric Space. In: 31st Annual Conference on Neural Information Processing Systems (NIPS), 2017

[107] D. Maturana, S. Scherer, Ieee. VoxNet: A 3D Convolutional Neural Network for Real-Time Object Recognition. In: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2015 pp. 922-928

[108] Ö. Çiçek, A. Abdulkadir, S.S. Lienkamp, T. Brox, O. Ronneberger. 3D U-Net: learning dense volumetric segmentation from sparse annotation. In: Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19, 2016 pp. 424-432

[109] C. Chen, L.Z. Fragonara, A. Tsourdos. GAPointNet: Graph attention based point neural network for exploiting local feature of point cloud. Neurocomputing. 2021, 438, pp. 122-132

[110] M. Pepe, D. Costantino, V.S. Alfio, A.G. Restuccia, N.M. Papalino. Scan to BIM for the digital management and representation in 3D GIS environment of cultural heritage site. Journal of Cultural Heritage. 2021, 50, pp. 115-125, https://doi.org/10.1016/j.culher.2021.05.006

[111] Y. Li, H. Sheng. A single-stage point cloud cleaning network for outlier removal and denoising.

Pattern Recognition. 2023, 138, pp. 109366
[112] A. Yerokhin, V. Semenets, A. Nechyporenko, O. Turuta, A. Babii. F-transform 3D point cloud filtering algorithm. In: 2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP), 2018 pp. 524-527
[113] P. Szutor, M. Zichar. Fast Radius Outlier Filter Variant for Large Point Clouds. Data. 2023, 8, (10), pp. 149
[114] X. Li, Z. Gao, X. Chen, S. Sun, J. Liu. Research on estimation method of geometric features of structured negative obstacle based on single-frame 3d laser point cloud. Information. 2021, 12, (6), pp. 235
[115] T. Huang, J. Chen, J. Zhang, Y. Liu, J. Liang. Fast Point Cloud Sampling Network. Pattern Recognition Letters. 2022, 164, pp. 216-223
[116] E. Nezhadarya, E. Taghavi, R. Razani, B. Liu, J. Luo. Adaptive hierarchical down-sampling for point cloud classification. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020 pp. 12956-12964
[117] L. Yu, X. Li, C.-W. Fu, D. Cohen-Or, P.-A. Heng. Pu-net: Point cloud upsampling network. In: Proceedings of the IEEE conference on computer vision and pattern recognition, 2018 pp. 2790-2799
[118] Y. Li, R. Bu, M. Sun, W. Wu, X. Di, B. Chen. PointCNN: Convolution on x-transformed points. Advances in neural information processing systems. 2018, 31
[119] W.Y. Wang, R. Yu, Q.G. Huang, U. Neumann, Ieee. SGPN: Similarity Group Proposal Network for 3D Point Cloud Instance Segmentation. In: 31st IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2018 pp. 2569-2578, https://doi.org/10.1109/cvpr.2018.00272
[120] L. Yi, W. Zhao, H. Wang, M. Sung, L.J. Guibas. Gspn: Generative shape proposal network for 3d instance segmentation in point cloud. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019 pp. 3947-3956
[121] J. Hou, A. Dai, M. Nießner. 3d-sis: 3d semantic instance segmentation of rgb-d scans. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019 pp. 4421-4430
[122] Z. Ding, X. Han, M. Niethammer. Votenet: A deep learning label fusion method for multi-atlas segmentation. In: Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part III 22, 2019 pp. 202-210
[123] L. Jiang, H.S. Zhao, S.S. Shi, S. Liu, C. Fu, J.Y. Jia, Ieee. PointGroup: Dual-Set Point Grouping for 3D Instance Segmentation. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020 pp. 4866-4875, https://doi.org/10.1109/cvpr42600.2020.00492
[124] S. Shi, X. Wang, H. Li. Pointrcnn: 3d object proposal generation and detection from point cloud. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019 pp. 770-779
[125] Z. Kang, J. Yang, Z. Yang, S. Cheng. A review of techniques for 3d reconstruction of indoor environments. Isprs International Journal of Geo-Information. 2020, 9, (5), pp. 330
[126] F. Gherardini, F. Leali. A framework for 3D pattern analysis and reconstruction of Persian architectural elements. Nexus Network Journal. 2016, 18, pp. 133-167
[127] C. Zou, A. Colburn, Q. Shan, D. Hoiem. Layoutnet: Reconstructing the 3d room layout from a single rgb image. In: Proceedings of the IEEE conference on computer vision and pattern recognition, 2018 pp. 2051-2059
[128] L. Wang, X. Zhou, J. Liu, G. Cheng. Automated layout generation from sites to flats using GAN and transfer learning. Automation in Construction. 2024, 166, pp. 105668
[129] K. Şekeroğlu, Ö.M. Soysal. Comparison of SIFT, Bi-SIFT, and Tri-SIFT and their frequency spectrum analysis. Machine Vision and Applications. 2017, 28, pp. 875-902
[130] E. Oyallon, J. Rabin. An analysis of the SURF method. Image Processing On Line. 2015, 5, pp. 176-218
[131] S. Rusinkiewicz, M. Levoy. Efficient variants of the ICP algorithm. In: Proceedings third international conference on 3-D digital imaging and modeling, 2001 pp. 145-152
[132] K. Koide, M. Yokozuka, S. Oishi, A. Banno. Voxelized GICP for fast and accurate 3D point cloud registration. In: 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021 pp. 11054-11059
[133] Z. Gojcic, C. Zhou, J.D. Wegner, A. Wieser. The perfect match: 3d point cloud matching with

smoothed densities. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019 pp. 5545-5554

[134] A. Li, Z. Zhu, & M. Wei. GenPC: Zero-shot Point Cloud Completion via 3D Generative Priors. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2025, pp. 1308-1318. https://doi.org/10.1109/CVPR52734.2025.00130

[135] Z. Qi, Y. Fang, Z. Sun, X. Wu, T. Wu, J. Wang, et al., GPT4Point++: Advancing Unified Point-Language Understanding and Generation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2025, pp.1-16, https://doi.org/10.1109/TPAMI.2025.3597938

[136] P.A. Escudero. Scan-to-HBIM: automated transformation of point clouds into 3D BIM models for the digitization and preservation of historic buildings. Vitruvio-International Journal of Architectural Technology and Sustainability. 2023, 8, (2), pp. 52-63. https://doi.org/10.4995/vitruvio-ijats.2023.20413

[137] Y. Fang, S. A. Mitoulis, D. Boddice, J. Yu, & J. Ninic. Scan-to-BIM-to-Sim: Automated reconstruction of digital and simulation models from point clouds with applications on bridges. Results in Engineering, 2025, 25, pp. 104289. https://doi.org/10.1016/j.rineng.2025.104289

[138] T. Yang, Y. Zou , E. del Rey Castillo, L. Hou, & J. Zhong. Enhancing Scan-to-BIM for reinforced concrete bridges using point cloud completion techniques. Automation in Construction, 2026, 181, pp. 106606. https://doi.org/10.1016/j.autcon.2025.106606

[139] K. Ostapska, R. Hingorani, W. Tecław, F. Kaufmann, K. Gradeci, & P. Rüther. Automated robotic deconstruction sequence planning from scan-to-BIM data for reinforced concrete structure reuse. Automation in Construction, 2025, 180, 106548. https://doi.org/10.1016/j.autcon.2025.106548