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Review

Unmanned aerial vehicle-based as-built surveys of buildings

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ABSTRACT

Camera-equipped Unmanned Aerial Vehicles (UAVs) are effective tools for as-built building surveys. Through a systematic literature review, we synthesized and categorized factors affecting the quality of UAV-based reconstructed scenes and their associated performance evaluation metrics (e.g., accuracy and time efficiency). Their interrelationships were analyzed by Social Network Analysis (SNA) to identify critical factors and their impacts. We further quantitatively evaluated these factors and metrics through controlled experiments with a camera-equipped UAV and a Terrestrial Laser Scanner for an institutional building. Various flight paths, photo overlaps, and distances to the building were tested to evaluate their impact on dimensional accuracy, time efficiency, and point cloud density. We demonstrated the trade-offs between the influential factors to provide insights into parameter selection. Additionally, a data requirements schema for UAV-based as-built 3D scene reconstruction was established toward standardization of data processing practices. This study could serve as a foundation for future research and applications of UAV-based photogrammetry for building surveys.

1. Introduction

Unmanned Aerial Vehicles (UAVs) have become increasingly popular in the Architecture, Engineering, and Construction (AEC) industry, with their utilization on project job sites nearly doubling from 20.7% in 2015 to 43% in 2020 [35,36]. UAVs have various applications throughout projects' life cycles, including land surveying, logistics tracking, on-site monitoring, and as-built surveys during the construction phase, as well as applications for maintenance, operation, and ultimately, demolition during the post-construction phase [49]. Among these applications, as-built building surveys are widely used for documenting building information, developing digital twins, and assessing and planning maintenance needs. Compared with conventional manual as-built surveys, three-dimensional (3D) scene reconstruction provides a more efficient and cost-effective solution with detailed visual information and measurements [42]. Although Terrestrial Laser Scanning (TLS) technology could largely reduce the surveying workload and generate a 3D building model with high efficiency and accuracy [70], the high cost of professional equipment limits its wider adoption. In contrast, UAV-based photogrammetry through image processing is an alternative for automated 3D as-built surveys with the benefits of time- and cost-efficiency. Compared with terrestrial measurement methods, a low-cost camera-equipped UAV system enables the collection of large amounts of building images from multiple views within a short time. These images can later be used for the reconstruction and survey of a 3D building model with access to detailed visual information and measurements [8,20,88].

With UAV-captured images and their camera position information, 3D reconstructed scenes or 2D orthophoto mosaics can be acquired through processing 2D image sets with triangulation and photogrammetric techniques such as Structure-from-Motion (SfM) [67]. To enhance the efficiency (e.g., time and cost) and performance (e.g., dimensional accuracy and point density) of the 3D reconstruction processes, previous research efforts have studied the impact of different data collection and processing features. These include flight design features, such as flight paths, flight timing, altitude, distance to the target, the total number of photos, and photo overlap percentages, as well as ground control points (GCPs) and rocessing software tools. They have shown wide ranges of variations, with the photo overlap percentages ranging from 35% to 95%, and the distance between UAV and building surface from 1 to 25 m for different building inspection applications [73]. However, existing studies have generally discussed overall

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factors or partially evaluated the influence of specific factors on the performance of UAV photogrammetry. There has been a lack of systematic synthesis of the reported factors and their impacts on performance across different studies. Therefore, this paper uses a systematic literature review and Social Network Analysis (SNA) to synthesize the influential factors, performance evaluation metrics, and their interrelationships for UAV-based as-built surveys for buildings. The experimental quantification of how these identified factors influence the quality of the reconstructed scenes was also carried out to reveal their quantitative relationship and build a foundation for the application of automated UAV-based building surveys. As such, with the aim of investigating these factors interrelationships, this study has sought to answer the following questions:

- What are the factors that impact the performance (i.e., accuracy-efficiency trade-off) of UAV-based photogrammetry for the reconstruction of 3D building models?
- What is the quantified impact of these factors on the quality of reconstructed models?

To answer these questions, we first identified the important factors and indicators for performance evaluation through a systematic literature review (SLR) and synthesis. For selected factors that were identified as important in previous literature, controlled experiments were conducted to quantify their accuracy-efficiency trade-off. Therefore, this study provides a comprehensive review of the influential factors and their quantified impact on the as-built survey process and outcome with a case study. The paper is organized into several sections: Section 2 provides an overall review of previous studies related to UAV applications in construction surveying and 3D reconstruction. Section 3 introduces the methodology of this study, which includes the SLR and the controlled experiments on a real-world building. Section 4 presents the results of the SLR, which identifies the critical influential factors, as well as metrics for performance evaluation. Section 5 discusses the case study including the selected influential factors and performance indicators, the controlled experiments, and the descriptive statistical analysis. Finally, Section 6 summarizes the key findings and limitations, and describes the future directions.

2. Background

2.1. Photogrammetry in the AEC industry

A photogrammetric survey entails mathematical modeling through central projection imaging techniques to locate object points in three dimensions and thus form 3D reconstructed scenes based on 2D images [54]. In the AEC applications, photogrammetry is typically referred to as close-range photogrammetry, where the camera is positioned within a range of 1 to 300 m from the target object [14]. The dimensions of the target object usually range from 0.5 to 200 m with an accuracy ranging from 0.1 mm to 1 cm [54]. In the AEC industry, photogrammetric surveys have been broadly applied in various stages of lifecycle management. For example, during the construction phase, photogrammetry can be utilized to generate consecutive as-built point clouds to monitor the progress of a construction project. By measuring and comparing the dimensions from the generated point clouds and the designed 4D building information model (4D-BIM), construction progress monitoring could be conducted with higher accuracy [80,89]. Photogrammetry has also been adopted in operational stages to model building facades for surveys and inspections [66,95].

There are a variety of factors that can influence the performance of photogrammetric surveys. Terrestrial photogrammetry, a subset of general photogrammetry, utilizes ground-based cameras and imaging techniques to capture data and measure the three-dimensional information of objects and environments [53]. It typically relies on specific sensing equipment and techniques tailored for ground-based data collection. Dai et al. [13,15] systematically reviewed the literature related to terrestrial photogrammetric modeling to identify influential factors, including camera-object distance, the number of photos, intersection angle, angle of incidence, and camera-related features (i.e., camera model, resolution, focal length, camera lens). While terrestrial photogrammetry has demonstrated significant potential for building surveys, its inherent limitations, notably the constrained field of view, hinder the surveying of geometric objects that are inaccessible, such as high-elevation building facades and roofs [75].

2.2. UAV applications in the AEC industry

With advances in UAV technologies, the application of cost-effective UAV camera systems could augment the data acquisition processes with improved accessibility and efficiency. This, in particular, enhances the capability for surveying and monitoring building structures at higher elevations expanding potential applications. In addition, UAVs can also be applied in indoor environments for applications such as monitoring construction sites, surveying, and information collection [38,48,57]. As revealed in previous studies, UAVs have found extensive applications across various stages of a building's life cycle. In the construction phase, UAVs can be used for detecting changes and deviations from planned structures [33]. Furthermore, in the post-construction phase, UAVs play a vital role in inspecting [43,81,85], measuring [31,81], and documenting the as-built model of construction projects [2]. In addition, recent studies have explored the utilization of multiple UAVs for the collection and analysis of large-scale data about multiple buildings, highlighting their potential for enhancing efficiency and precision in large-scale urban planning and development projects [10,28,50,97]. Several studies have reviewed the developments and applications of UAVs in the AEC industry. As shown in Table 1, we have compiled and summarized the main findings of these review studies. Most of these review papers introduced the application areas in the construction industry [5,8,16,59,102]. Some of them summarized the technologies, benefits, and challenges of applying UAVs in different fields [8,21,72,99,102]. Nevertheless, limited studies have compiled and investigated the influential factors in the UAV-based as-built 3D reconstruction of buildings [71,73].

Among all categories of UAV applications in the AEC industry, the focus of this study lies in the use of UAVs for as-built building surveys (i.e., 3D reconstructed models of buildings). Ham et al. [30] have compiled the related literature in this direction to summarize the workflow of UAV photogrammetry in building surveys as three major steps: (1) UAV-based data collection, (2) data processing to obtain actionable information (e.g., point clouds and reconstructed scenes or models), and (3) visualization, evaluation, and communication with practitioners in the project. These steps have been used in our study for the categorization of influential factors and evaluation metrics. Although the implementation of UAVs has greatly improved the application of photogrammetry for 3D building surveys and researchers have thoroughly reviewed and categorized these applications as reflected in Table 1, few studies have explored the influential factors that affect the outcome of the process in both qualitative and quantitative ways. In practical applications, while numerous case studies have demonstrated successful high-quality 3D scene reconstructions, there remains a gap in our collective understanding of how variations in individual influential factors affect the quality of building surveys across different levels of detail [15,71]. Despite some factors that are more or less similar in terrestrial photogrammetry (e.g., the distance between the camera and targets or the number of photos), UAV-based photogrammetric surveys have their unique features that need to be further investigated (e.g., flight path and flight height).

3. Research methodology

Our methodology was divided into two components: (1) a systematic

Table 1
Key review papers of UAV applications in the AEC industry.

References	Year	Main Findings
[8]	2014	• UAV hardware, software, control methodologies, and the latest related technologies. • Opportunities and challenges of applying UAV in 1) seismic risk assessment, 2) transportation, 3) disaster response, 4) construction management, 5) surveying and mapping, and 6) flood monitoring and assessment.
[30]	2016	• A review of UAV-driven research on automating construction monitoring and civil infrastructure condition assessment.
[19]	2017	• A value chain with stakeholders involved in UAV applications to outline the major trends of UAV usage in the industry. • Suggested four applications and gaps in the use of UAVs in 1) the design phase, 2) the construction phase, and 3) the exploitation phase in construction.
[57]	2017	• The potential applications for UAVs in indoor construction sites, their benefits, and challenges.
[86]	2017	• Summarized four categories of UAV use in the construction industry: 1) photography/videography, 2) surveying, 3) inspections, and 4) safety/security monitoring.
[60]	2017	• Characterized 9 applications and 10 issues reported in previous studies of applying UAVs in the construction industry
[73]	2018	• A historical timeline of UAV technology developments. • A standard procedure for operating a UAV for energy audit missions (documenting building performance, visualizing heat transfer using infrared imaging, and creating digital models).
[16]	2018	• Identified five Applications of UAV in the construction industry: 1) Project progress control, 2) Damage assessment, 3) Surveying, 4) Safety monitoring, 5) 3D modeling
[102]	2018	• Applications of UAVs in the industry: 1) building inspection, 2) damage assessment, 3) site surveying, 4) safety inspection, 5) progress monitoring, 6) building maintenance, and 7) other construction applications. • Benefits, types, onboard sensors, and control styles of UAVs in construction applications.
[5]	2019	• Categorization of UAV applications in the AEC domain: 1) infrastructure and structural inspection, 2) transportation, 3) cultural heritage monitoring, 4) city and urban planning, 5) progress monitoring, 6) post-disaster, 7) construction safety
[99]	2020	• Eight potential UAV application areas and three major challenges were identified. The challenges include 1) legal and regulatory requirements, 2) features and abilities of UAVs, and 3) qualities and capabilities of related software.
[21]	2020	• Four areas of applications of immersive technologies and two areas of applications of UAVs in the construction industry. For UAVs, the areas include 1) automated surveying, information management, and visualization, 2) construction inspection, monitoring, and safety management.
[100]	2021	• Two key components of applications of UAV aerial images for three-dimensional reconstruction: 1) image-based three-dimensional reconstruction technology, 2) UAV path planning technology.
[94]	2021	• Five main UAV application fields: 1) Mapping and 3D modeling, 2) Construction monitoring, 3) Structural damage detection, 4) Energy efficiency prospection, 5) Urban remote sensing.
[72]	2022	• Seven application areas of integrating UAV with Digital Twins: 1) progress monitoring, 2) historic building conservation, 3) information management, 4) construction safety, 5) construction education, 6) structural and infrastructure inspection, 7) transportation. Four technology trends: 1) automated progress monitoring, 2) automated UAV inspection planning, 3) real-time video streaming, 4) parametric model development of historic buildings
[65]	2023	• Five main dimensions of UAV application in the AEC industry: 1) inspections and mapping, 2) data processing and management, 3) safety and health management, 4) challenges and risks of drone use, 5) training aid for site personnel and students • Market review and comparison among different UAV types • Future directions of research: education, total quality management, safety risk related to drone use, human factors and their impact, regulatory interventions.
[59]	2023	• Two categories of UAV applications in construction management: 1) UAV uses including algorithms, applications, operations, framework, and training, 2) Construction uses including inspection, surveying, safety, and monitoring.

literature review and synthesis and (2) an experimental case study. To assess the underlying factors affecting the quality of the reconstructed scenes, we compiled the related articles and summarized the reported influential factors. These articles present field studies with quantified assessments of 3D scenes. In the next step, we analyzed these factors to develop a categorization for them. To explore the reflected relationships between different factors, we used the analytical method of Social Network Analysis (SNA) to measure the centrality degrees of the factors that appeared in the compiled articles. This method could be used to identify the co-occurrence frequency of different factors in previous studies and visualize their interrelationships [55].

After identifying the characteristics of influencing factors and their interrelationships, a case study with controlled experiments on a university building was conducted to quantitatively evaluate the relationship between the identified important factors. The impact of three influencing factors (the flight path pattern, the distance between the UAV and the target, and the photo overlap percentage) was investigated by using three performance evaluation metrics including dimensional accuracy, point cloud density, and time efficiency. To this end, six mesh models of the reconstructed scenes with different settings were developed. Additionally, a terrestrial laser scanner-based (TLS-based) point cloud was also developed as the benchmark for performance evaluation. Benchmarking against the point clouds from laser scanners is a commonly used approach given the high accuracy of their resultant point clouds [4,25]. Based on the assessment of these models, we drew conclusions and discussed recommendations. Fig. 1 summarizes the methodology of our study. Details of each step have been presented in their corresponding results subsections.

4. Systematic literature review/synthesis

A Systematic Literature Review (SLR) was conducted to identify, select, and appraise the literature relevant to UAV-based photogrammetry for 3D as-built surveys. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [58], the SLR process was conducted as shown in the following steps.

4.1. Literature search strategies

We focused our search on articles with the subject matter at the intersection of UAVs, image-based 3D model reconstruction, and building assets. Considering that there are many alternative terms, the literature databases/libraries and various search keywords were used as follows:

- Literature database/libraries:
  - o American Society of Civil Engineers (ASCE) library.
  - o Institute of Electrical and Electronics Engineers (IEEE) Xplore.
  - o Web of Science (WoS).
  - o Engineering Village.

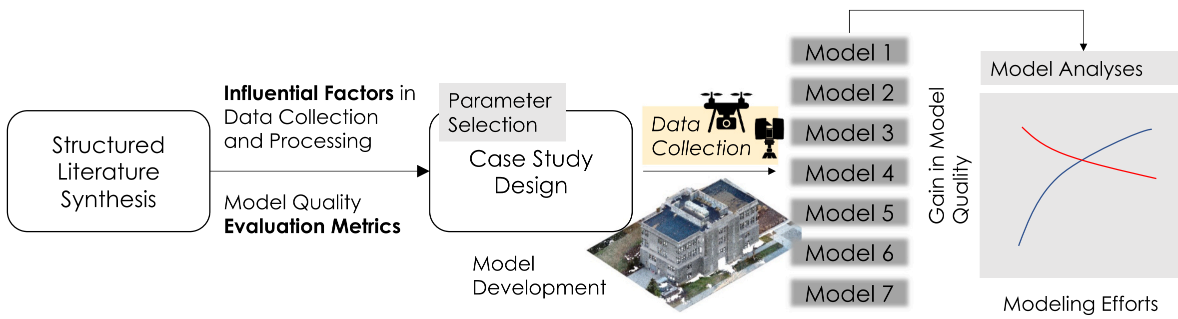

Fig. 1. The methodology of identifying the influential factors in developing 3D reconstructed scenes and their quantified impact.

- Since UAV systems and technologies are relatively new applications in the fields of buildings and construction, we concentrated on studies published in the past decade (2010–2023).
- Search terms
  - o Terms regarding UAV:
    - ▪ "UAV" OR "UAS" OR "drone" OR "unmanned aerial vehicle" OR "MAV";
  - o Terms regarding image-based 3D scene reconstruction:
    - ▪ "image" OR "photo" AND
    - ▪ "model reconstruction" OR "3D reconstruction" OR "photogrammetry";
  - o Terms regarding building assets:
    - ▪ "building" OR "architecture".

After the compilation, the studies were filtered by inclusion and exclusion criteria listed below:

- Inclusion criteria:
  - o include studies on real-world case studies or experimental practices
  - o include studies that present the complete process of UAV-based 3D scene reconstruction

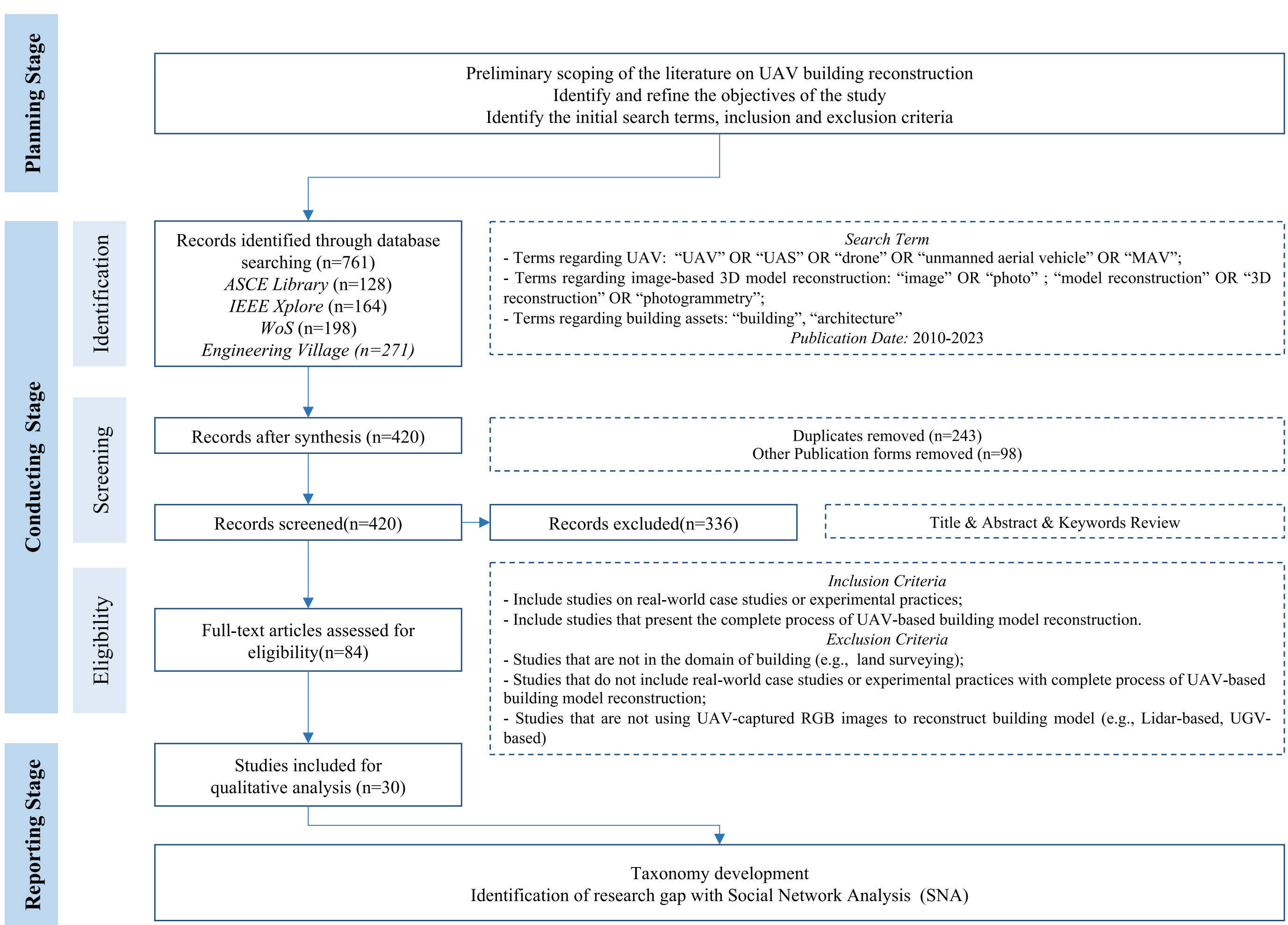

Fig. 2. Flowchart of the systematic literature review process (PRISMA flow diagram).

- Exclusion criteria:
  - o Studies that are not in the domain of buildings (e.g., land survey)
  - o Studies that do not include real-world case studies or experimental practices with a complete process of UAV-based 3D scene reconstruction
  - o Studies that are not using UAV-captured RGB images for photogrammetry (e.g., Lidar-based and UGV-based)

Fig. 2 illustrates the detailed procedure of the employed SLR using PRISMA guidelines. A total of 761 articles were identified through the aforementioned search strategy. These articles were then synthesized into 420 articles after removing duplicates and other publication forms (e.g., book chapters and articles in press). Then, the title, abstract, and keywords of 420 articles were further screened using the specified inclusion and exclusion criteria that resulted in the selection of 84 articles.

Table 2
Specification of the studies described in the selected articles related to UAV-based photogrammetric as-built surveys for buildings.

Reference	Year	Building Type	UAV & Camera Model (Resolution)	Mentioned Influential Factors	Mentioned Performance Evaluation Metrics
[34]	2010	Commercial Building	UAV: MD4–200 Camera: PENTAX Optio A40 (12MP)	Flight path, GCPs*, Photo overlap, Number of photos, Processing software	Number of points, Point cloud accuracy**, Time efficiency
[45]	2011	Commercial Building	UAV: (1) AscTec Falcon 8 (14MP), (2) swinglet CAM (12MP)	Flight path, Altitude, Photo Overlap, Number of photos, Processing software	Number of points
[26]	2012	School Building	UAV: FKC-1 Camera: Four-combined camera	GCPs, Photo overlap	Scale of mapping
[91]	2013	Cultural Heritage	UAV: DJI Phantom Camera: Canon A180 camera (16MP)	Flight path, GCPs, Processing software	No performance evaluation
[7]	2014	School Building	UAV: 3DR IRIS Quadcopter Camera: GoPro 3 (12MP)	Flight path, GCPs, Photo overlap	Dimensional accuracy
[25]	2014	School Building	UAV: Oben octocopter	Flight path, Altitude, GCPs, Photo overlap, Number of photos, Processing software	Point cloud accuracy
[18]	2014	Commercial Building	UAV: DJI Mavic Pro with a camera (12MP)	Flight path, Altitude, Distance, Photo overlap, Number of photos, Processing software	No performance evaluation
[12]	2015	School Building	UAV: AscTech Falcon octocopter Camera: Sony NEX-5 N	Number of photos, Processing software	Point cloud accuracy
[27]	2015	School Building	UAV: Asctec Falcon Camera: Camera with 10MP resolution	Processing software	Façade resolution in pixel
[29]	2015	Cultural Heritage	UAV: MD4–1000 Camera: Olympus PEN *E-* P2 (12MP)	Flight path, Distance, GCPs, Number of photos, Processing software	Point cloud accuracy
[98]	2015	Residential Building	UAV: DJI Phantom 2	Flight path, Altitude, Number of photos, Processing software	No performance evaluation
[93]	2015	Residential Building	VTOL (vertical take-off and landing) UAV	Number of photos, Processing software	Point cloud density
[4]	2016	Cultural Heritage	UAV: Mikrokopter Camera: Sony ILCE-5100 (24MP)	Flight path, Altitude, GCPs, Processing software	Point cloud accuracy, Number of points
[61]	2017	Cultural Heritage	UAV: (1) Sensefly Albris (2) DJI Phantom 3 Professional (38MP)	Distance, GCPs, Number of photos, Processing software	Point cloud accuracy
[92]	2017	Residential Building	UAV: FlyNovex Camera: Sony Alfa 6000 (24MP)	Flight path, Altitude, GCPs, Photo overlap, Number of photos, Processing software	Dimensional accuracy, Point cloud accuracy
[101]	2018	Stadium (school)	UAV: DJI F550 Camera: GoPro Hero 3 Plus	Flight path, Altitude, Number of photos, Processing software	Point cloud accuracy, Number of points, Time efficiency
[82]	2018	Cultural Heritage	UAV: DJI Phantom 4 (38MP)	Flight path, GCPs, Number of photos, Processing software, Point deviation	Point cloud accuracy
[44]	2019	Residential Building	UAV: DJI Mavic Pro 2 (12MP)	Flight path, Altitude, Distance, Number of photos, Processing software	Point cloud accuracy
[37]	2020	Cultural Heritage	UAV: DJI Inspire 1 Camera: Zenmuse X5R (16MP)	Altitude, Image shooting rate, Flight speed, Camera angle, Number of photos, Processing software,	Point cloud accuracy
[56]	2020	Cultural Heritage	UAV: DJI Matrice 600 Pro Camera: DJI Zenmuse X5 (16MP)	Flight path, GCPs, Altitude, Photo overlap, Number of photos, Processing software	Dimensional accuracy, Point cloud accuracy
[6]	2020	Cultural Heritage	UAV: DJI Phantom Pro 4 with camera (20MP); Corby Drone CX012 with camera (0.3MP)	GCPs, Altitude, Photo overlap, Number of photos, Processing software	Point cloud accuracy
[53]	2020	Cultural Heritage	UAV: DJI Mavic Pro Camera: FC 220 (12MP)	GCPs, Altitude, Distance, Number of photos, Processing software	Point cloud accuracy
[51]	2021	School Building	UAV: DJI Phantom Pro 4 with a camera (20MP)	Flight path, Distance, Photo overlap, Number of photos, Processing software	Dimensional accuracy
[77]	2021	School Building	UAV: DJI Mavic Pro with a camera (12MP)	Flight path, Altitude, Photo overlap, Processing software	Dimensional accuracy
[62]	2022	Public Building	UAV type not specified Camera: Model EP3 (12MP)	Flight altitude, Photo overlap, Number of photos, Processing software	Point cloud density, Point cloud accuracy
[32]	2022	School Building	UAV: DJI phantom 4 PRO with a camera (20MP)	Flight path, Altitude, Photo overlap, Number of photos, Processing software	Point cloud accuracy
[78]	2022	Stadium (public)	UAV: DJI Phantom 3 with a camera (12MP)	GCPs, Processing software	Dimensional accuracy
[87]	2022	School Building	UAV: Autel Evo Nano with a camera (48MP)	Flight path, Altitude, Camera angle, Number of photos, Processing software	Point cloud density
[79]	2023	Residential Building	UAV: DJI Phantom 4 Pro with a camera (20MP)	GCPs, Flight path, Altitude, Distance, Photo overlap, Number of photos, Processing software	Point cloud accuracy
[90]	2023	Cultural Heritage	UAV: DJI Matrice 300 RTK Camera: DJI Zenmuse P1 camera (45MP)	GCPs, Flight path, Altitude, Number of photos, Processing software	Point cloud accuracy

* GCP: Ground Control Points.
** Cloud-cloud distance based on the reference cloud (LiDAR).

After conducting a full-text review of these articles, we extracted a subset of 30 articles that introduced factors used in their UAV-based photogrammetry, and were thus used for the detailed quantitative analysis.

4.2. Literature analysis

The details of the selected 30 articles are listed in Table 2, which summarizes the specifications of each study including the target building type, equipment setup, and reported factors in their experimental design. As shown in this table, previous studies have discussed various influential factors for different scenes. We used these reported factors in developing a qualitative categorization and a quantitative relationship analysis in the following sections.

4.2.1. Categorization of influential factors

The process of using UAVs for photogrammetric building surveys mainly includes the equipment setup (e.g., UAV type, camera resolution, etc.), planning of in-flight data collection, and post-flight processing of collected imagery data [23,73]. Upon review of the articles in Table 2, we clustered the parameters of interest that were discussed in each article. The parameters were respectively categorized into (1) influential factors in the process of 3D scene reconstruction and (2) performance evaluation metrics. Fig. 3 illustrates the mapping of all the parameters of interest. The influential factors can be further grouped into factors related to data collection versus data processing steps. The performance evaluation metrics could be associated with accuracy, time efficiency, and point cloud characteristics. Table 3 shows the range of influential factors reported in the previous studies. These ranges were identified across multiple papers as individual studies have not specified the effective ranges. In the following subsections, further details are presented.

4.2.1.1. Data collection. In the UAV-based data collection processes, multiple factors need to be configured before take-offs, such as the equipment setup and the flight path design. These factors must be set considering the constraints imposed by the UAVs and their cameras, battery life, surveying conditions, and legal regulations [52]. In terms of hardware settings, it can be seen from Table 3, that DJI UAVs are commonly used multirotor UAVs in photogrammetry. Although, in the literature, there is no clear reported linkage between the resolution or the type of the UAV-attached camera and the quality of the reconstructed scenes, a study in terrestrial photogrammetry indicated that the average error is reduced by 0.83 cm (11.2%) per 1 MP resolution increase [15], which can be a reference to the effect of the camera resolution for UAV-based photogrammetry as well.

Flight Design: The influential factors in designing a flight include image capturing configurations, camera position, and ground control points. In the image-capturing configurations, the flight path pattern is the most fundamental setting. There are three commonly used patterns for flight path design in building surveys, which are Strip Path [4,34,92], Polygon Path [18,25,44,91,98], and Circle Path [7,45] patterns. As shown in Fig. 4, the strip path pattern means flying a UAV in strips with a zig-zag pattern across the area of interest [24,46,79]. The strip path could be further divided into horizontal (Fig. 4. a) and vertical (Fig. 4. b) paths. Polygon path patterns (Fig. 4. c) set waypoints surrounding the survey target, and the shape of the close-loop generated from the path varies according to the shape of the building envelope, which in most cases are rectangular or polygon shapes [7,18,98]. The circle path pattern (Fig. 4. d) is similar to the polygon pattern because both patterns collect data surrounding the target, with just the shape of the path being different [4,11].

Some studies have combined both the strip path and the polygon path, creating a camera network to capture all angles of buildings [29,82,101]. For example, in the study by Grenzdörffer et al. [29], the authors combined the strip path pattern and the circle path pattern to acquire images from a network of more dense camera positions for a cultural heritage monument's main structure. A similar approach was also adopted by Tran et al., in which a combination of strip and circle path patterns was adopted for the data collection of a school building [87]. Apart from manual flight path design, previous studies have also explored various methods for automatic flight path planning. Tan et al. addressed the UAV coverage path planning problem by employing a genetic algorithm (GA) to minimize the UAV flight length while ensuring a comprehensive and high-quality image data collection [84]. They also introduced a "global-local" adaptive inspection method integrating BIM and wide-angle camera technology for dynamic UAV flight path adjustment, enhancing efficiency, precision, and cost-effectiveness

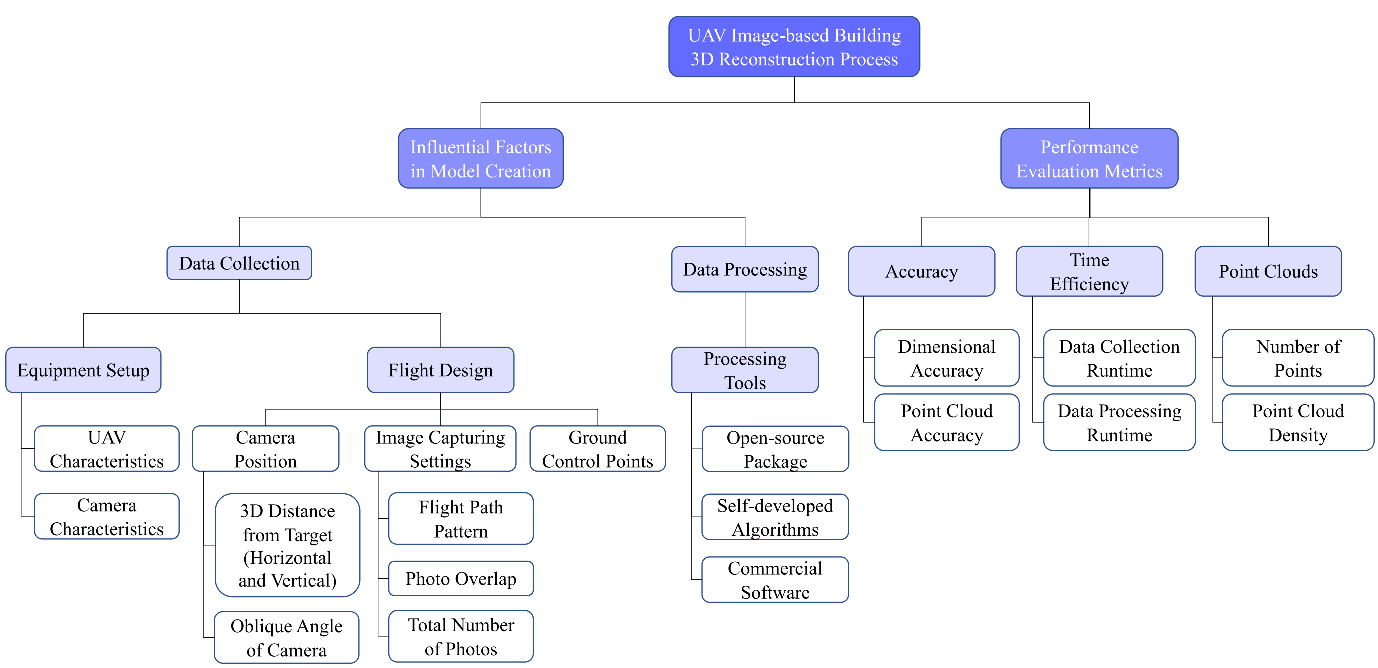

Fig. 3. Categorization of factors and evaluation metrics in UAV-based photogrammetric as-built survey for buildings.

Table 3
Range of influential factors for 3D scene reconstruction from previous literature.

Categorization	Factors		Cases from Literature
Data Collection	Equipment Setup	UAV Characteristics	DJI series products (Inspire, Mavic [18,44,53,77], Phantom [6,32,78,82,91], Matrice [90])
			MD4 series [29,34]
			AscTech Falcon [12,27,45]
			FlyNovex [92]
			Autel Evo Nano [87]
		Camera Characteristics	Different Cameras with resolutions from 10Mp [27] to 48 MP [87]
	Flight Design	Flight Path Pattern	Polygon Pattern [18,25,44,51,77,91,98]
			Circle Pattern [7,45]
			Strip Pattern [4,34,92]
			Mixed Pattern [29,82,87,101]
		Photo Overlap	40%–50% [7]
			60%–80% [25,45]
			70%–80% [18,56]
			86% [34]
		Total Number of Photos	Varying from 27 [18] to 2755 [61]
		3D Distance from Target	Horizontal: 5 m [44] – 100 m [18]
			Vertical: 20 m [4] – 100 m [18]
		Oblique Angle of Camera	Varying from 15° to 45° [4,17,87,92]
		Ground Control Points	Varying from 4 [92] to 117 [29]
Data Processing	Software Applications	Open-source Packages	PMVS [45]
			Bundler [12]
			MicMac [4,61]
		Self-developed Algorithm/Tools	Visual SfM [34]
			MAVMAP [27]
			Interactive SfM [12]
		Commercial Tools	Agisoft Photoscan (now Metashape) [4,17,25,29,53,56,61,79,82,92,98]
			Pix4D [4,6,17,37,44,45,61,62,78,79,92,93]
			Recap Photo [18]
			3Df Zephyr [4]
			SURE [4,29]
			PhotoModeler [34,61,92]
			Drone Deploy [18]

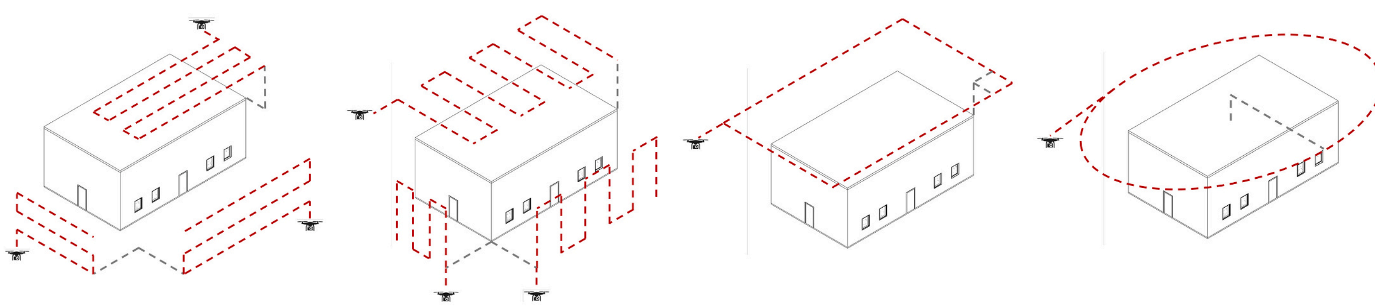

Fig. 4. Typical pre-flight path planning (a. Strip Pattern (horizontal), b. Strip Pattern (vertical), c. Polygon Pattern, d. Circle Pattern).

[85]. In addition to single-UAV flight path planning, previous studies have also investigated a multi-UAV path planning approach for efficient 3D reconstruction of post-disaster buildings, balancing flight distance and time while avoiding obstacles [63].

Flight planning also includes planning the photo overlaps for robust data collection and the efficiency of the post-flight processing [73]. Photo overlap percentages were reported in ranges from 40% to about 90% [7,34] (Table 3). We did not find a benchmark study of this factor while it has a significant connection with the flight path pattern, and all previous studies have set specific photo overlap percentages for each survey target. The number of overlapping photos has already been identified as a critical factor in terrestrial photogrammetric modeling [15]. However, the total number of photos in the 3D reconstruction of buildings can considerably vary depending on the building type, survey objectives, and level of detail requirements. For example, Djimantoro and Suhardjanto [18] successfully transformed only 27 images into a reconstructed scene of a commercial project for urban planning, while Murtiyoso, et al. [61] used 2755 images for information documentation of a historical building. For this reason, instead of the total number of photos, the photo overlap percentages would be a more suitable factor for establishing standards in future studies.

For the camera position, researchers have investigated the relative locations of UAVs during data collection, which is represented by the altitude (vertical distance) and the distance (horizontal distance) between UAVs and the respective target surfaces. Adopting the presentation style of summarizing the cases of UAV applications by Rakha and Gorodetsky [73], Fig. 5 demonstrated various vertical and horizontal distances between UAVs and the target from the collected articles. Based on our observations, the altitude varies from 6 m to 100 m depending on the target buildings. The distance may also be adjusted according to the data collection objectives. The distance between the camera and the object determines the ground sampling distance (GSD), which is the distance between the centers of two adjacent pixels in an image. The building surveys with requirements for higher levels of detail need low GSD and shorter distances between the UAV and the target. For building inspection or damage detection, the typical distance has been found to

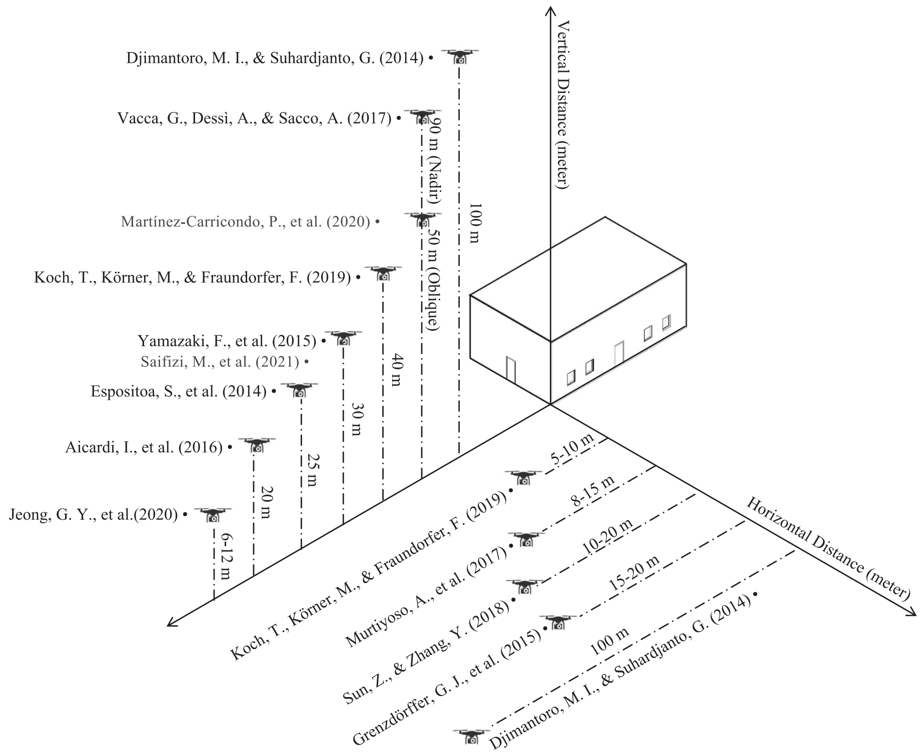

Fig. 5. The vertical and horizontal distance between UAVs and the building targets in the compiled literature.

be smaller between 1 and 5 m [9,83]. For example, the distance between camera and the target can be between 2 and 5 m in the assessment of post-disaster areas (e.g., post-earthquake building evaluation) [1,47], or less than 1 m in the detection of façade cracks [22]. For 3D reconstruction of buildings, larger distances have been reported, typically more than 10 m, e.g. between 15 and 20 m in the reconstruction of cultural heritages [29]. The oblique angle of the camera is normally set at 45 degrees [4,92], but the specific angle should be determined by other factors, such as 3D distances (horizontal and vertical distances) between the UAV and the target [4]. One previous study has identified that a combination of UAV images taken at 30° and 90° angles is optimal for generating a sufficient number of matching points with high precision [68].

The last factor in data collection is Ground Control Points (GCPs), which are used to guide the flight of the UAVs in covering the areas of interest. The setting of GCPs is for geo-referencing in data collection and data processing. Agüera-Vega, et al. [3] demonstrated the influence of the number of GCPs on the accuracy of UAV-based products through field studies and stated that both the horizontal and vertical accuracy increases with the increasing number of GCPs. A previous study has identified that the number and the distribution of the GCPs can significantly affect the computational cost and the quality of the reconstructed point cloud model [79]. Nevertheless, similar to the number of photos, the settings of GCPs and the number of GCPs can vary across different buildings, so it may not be suitable to set the number of GCPs as a benchmark feature to be applied for general applications.

The influential factors in data collection may be cross-correlated and thus sometimes the modification of one factor would affect the other factors. For example, the change of photo overlap would affect the total number of photos and the time effiency related to the data collection amd processing. Previous studies have not explored the influence of changing these factors with the consideration of cross-correlation, which is what we have investigated in our case study. Details of the findings will follow in the case study section.

4.2.1.2. Processing methods and tools. The processing of UAV-collected data is a critical step in building surveys. As indicated in Fig. 3 and Table 3, the processing methods and tools in previous studies can be divided into three groups: 1) self-developed algorithms/tools, 2) open-source packages, and 3) commercial tools. Some studies have focused on developing algorithmic frameworks to create 3D reconstructed scenes. The Scale Invariant Feature Transform (SIFT) for feature matching and interactive Structure from Motion (SfM) techniques for image transformation [12,64] are among the core algorithmic components for this purpose. Others utilized open-source packages like PMVS [45], Bundler [12], and MicMac [4,61] for image processing. However, most of the previous studies have utilized well-established commercial software applications, such as Agisoft Photoscan (now Metashape), Pix4D, or 3Df Zephyr for data processing. It can be seen from Table 3 that Agisoft Photoscan and Pix4D are the two most frequently used commercial tools in the compiled articles.

Some studies have further compared these commercial tools to identify the ones with better performance. As presented in Table 4, previous studies [4,17,61,79,92] have investigated the accuracy of UAV-based building surveys by adjusting critical factors such as data processing software. By comparing the point clouds generated from terrestrial laser scanner (TLS) and the point clouds generated from UAV images using different data processing software tools, they proved that all of the tested software tools could produce building point clouds with high quality (less than 0.05 m difference between TLS and image-based point clouds). Based on these comparisons, Agisoft Photoscan and Pix4D have been shown to have better overall model accuracy among the commonly used commercial tools [17,79].

4.2.2. Categorization of performance evaluation metrics

For performance evaluation metrics, accuracy, time efficiency, and point cloud characteristics (as shown in Table 5) have been commonly used in previous studies. To evaluate the quality of 3D reconstructed scenes, measurements of these as-built scenes need to be compared with actual real-world data. Accuracy reflects the reliability of photogrammetric measurements in applications. As shown in Table 5, many studies utilized comparisons of point clouds obtained from the image-based

Table 4
Performance evaluation of UAV-based photogrammetric image processing by different commercial software tools in previous literature.

Performance Evaluation	Commercial Tools									
	Agisoft Photo Scan	Pix4D	3D Zephyr	MicMac	SURE	Context Capture	Photo Modeler	Visual SfM	3Dsurvey	Ref.
Point cloud mean difference compared with TLS data (mm)	3	4	5	6	25	4	–	5	–	[4]
	0	2	–	2	–	–	4	–	–	[61]
	8	5	–	–	–	–	–	–	–	[92]
Maximum dimensional difference compared with TLS data (m)	0.01	0.03	–	–	–	–	–	–	0.06	[17]

Table 5
Performance evaluation metrics for UAV-based photogrammetric 3D scene reconstruction in previous literature.

Categorization	Evaluation Factor	References
Accuracy	• Point cloud (image) to point cloud (TLS) comparison (point cloud accuracy)	[4,7,12,17,25,29,34,53,56,61,79,82,92,101]
	• Dimensional accuracy	[7,17,37,78,79,92]
Time Efficiency	• Data collection runtime	[101]
	• Data processing runtime	[12,34,101]
Point Clouds	• Number of points in the model	[4,25,27,29,34,45,92,101]
	• Point cloud density	[44,62,92]

models and the point clouds generated from Terrestrial Laser Scanning (TLS) (as the ground truth data). For example, Aicardi et al. [4] evaluated the quality of point clouds by calculating the minimal, maximal, and average point distances and compared them with TLS-based point clouds. Some studies have also used dimensional accuracy as an evaluation metric. Vacca et al. [92] evaluated the dimensional accuracy of models by comparing the measurements of key dimensions between UAV-based and TLS-based point clouds. Time efficiency is also a performance indicator for UAV photogrammetric surveys. The on-site data collection duration and the post-flight model processing time should be recorded as the reference for evaluation of the time efficiency [15]. As an example, Zheng et al. [101] have demonstrated that the usage of multiple UAVs can dramatically decrease the data collection time from 42 min to 15 min. Another factor that can affect the time efficiency is the control of the UAV during on-site data collection. Compared with manual-flying control, autonomous control with pre-programmed routes is much faster and more efficient. As the third group of metrics, the total number of points in a model and the density of the point clouds have been also considered for performance evaluation. A denser point cloud could provide information with a higher level of detail [25].

4.3. Interrelationships between factors

To analyze the interrelationships between the above-mentioned parameters (influential factors in 3D scene reconstruction and performance evaluation metrics), as noted, we utilized the Social Network Analysis (SNA) method. SNA enables the analysis and visualization of interrelationships between multiple entities in a network using graph theory [55]. For each reviewed article (case) in the selected pool from Table 2, the terms, associated with our parameters of interest, that appeared in each article were counted, while the non-existing terms were set to zero. A two-mode (bi-partite) network, which quantifies the occurrence of each parameter in each paper, was generated. The two-mode network can then be transformed into a one-mode network for the studied parameters to quantify the co-occurrence frequency among all parameters. The heatmap shown in Fig. 6 presents the calculated probability of the co-occurrence for each set of two factors in the network. The values in each cell represent the frequency of co-occurrence of two factors in the reviewed literature. The higher the value, the higher the co-occurrence frequency of the two factors in previous studies.

The parameters co-occurrence matrix was used to measure the centrality of each parameter (factor) using the software Netminer [76]. As shown in Fig. 7, the size of each node in the SNA network represents the degree of centrality of each factor, which identifies the most important or influential factors. It can be observed that the most influential factors during the data collection phase (blue nodes) show very high degrees of centrality, especially the factors representing equipment setup configurations such as flight path, and the total number of photos. For post-flight data processing factors (green nodes), commercial software tools were most commonly used. Performance evaluation metrics (red nodes) of accuracy and point cloud quality were broadly investigated to evaluate the performance of 3D model reconstruction. Meanwhile, the thickness of each link in the SNA network represents the frequency of co-occurrence of two correlated factors in the reviewed literature. The thicker the link, the higher the frequency of co-occurrence between the two factors. The equipment setup, flight path, distance, number of photos, and commercial software/tools are the important factors that have been frequently mentioned when studying the accuracy performance of the reconstructed models. For the point cloud quality, equipment setup, flight path, distance, number of GCPs, and the number of photos were mostly related. However, time efficiency was seldom mentioned in the collected studies because it was seldom used in evaluations. Based on the SNA analysis, it can be concluded that the equipment setup, flight path patterns, the 3D (horizontal and vertical) distance between the UAV and the target, the overlap between photos, the number of photos, and the choice of the data processing commercial software may play a critical role in the quality of the 3D reconstructed as-built scenes.

The majority of the selected studies have investigated the 3D scene reconstruction with specific pre-flight settings and performance evaluation metrics, which makes it difficult to evaluate the impact of the influential factor ranges on the outcome. Although we sought to quantify the impact of influential factors on performance indicators using the selected literature, the numeric patterns for each parameter (e.g., photo overlap percentages, photo numbers, and distances) are difficult to be synthesized and analyzed. For this reason, in Section 5 we designed a case study to investigate the impact of three identified important factors (i.e., flight path pattern, the distance between the UAV and the target, and photo overlap) on three frequently used performance measurements including dimensional accuracy, time efficiency, and point cloud quality.

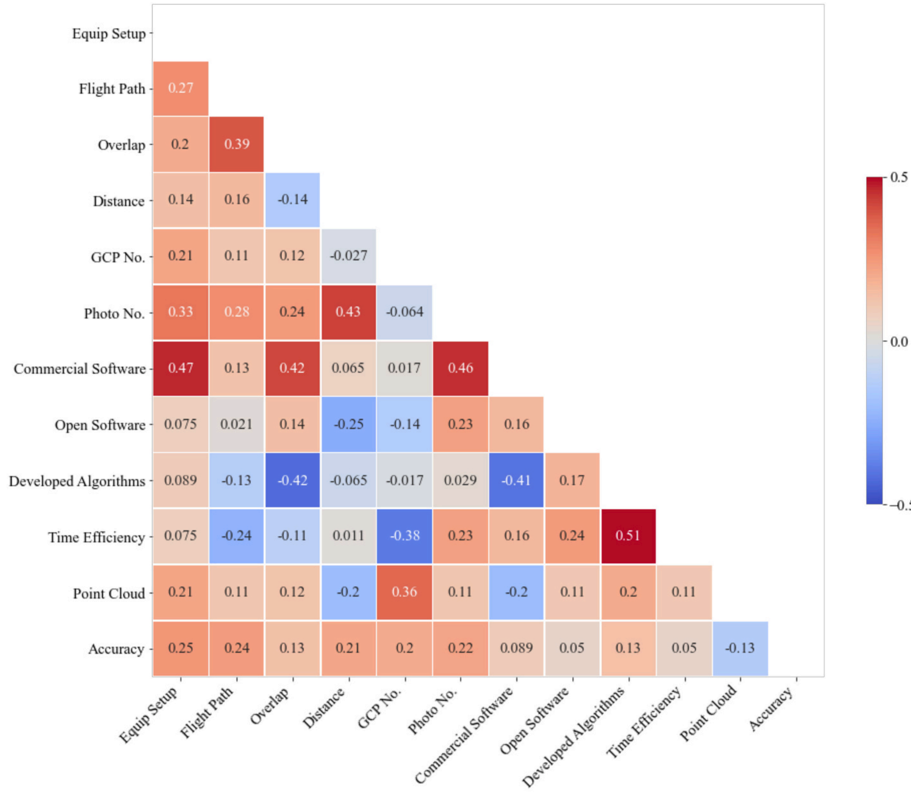

Fig. 6. The heatmap of the co-appearance probability of the identified factors in the compiled literature.

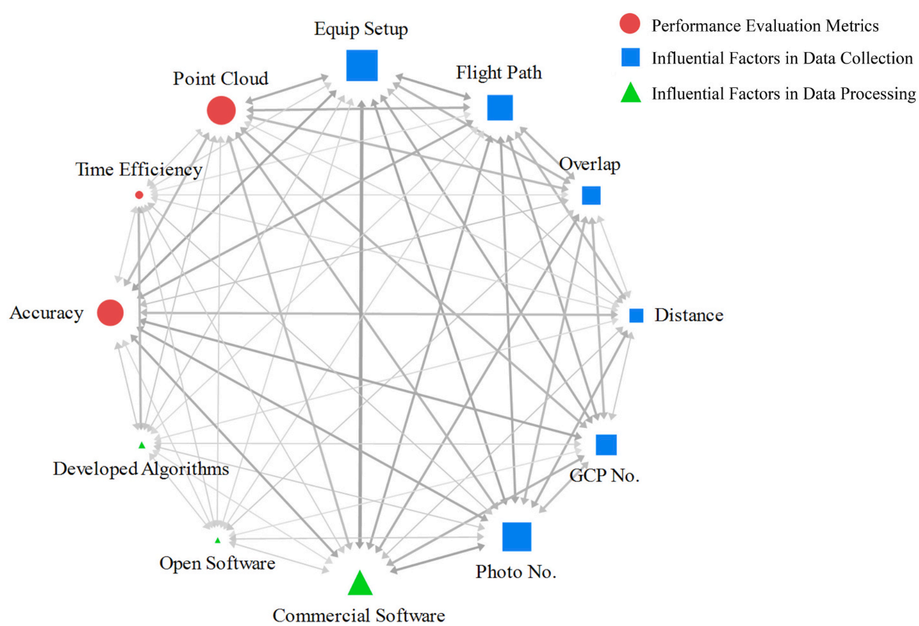

Fig. 7. Degree centrality of and potential interrelationships between different identified parameters.

5. Case study

5.1. Design of experiment for factor assessment study

For the case study of factor assessment, we selected a mixed-use building on Virginia Tech's campus as the target object. The building has a regular cuboid shape, and the overall dimensions of the building are 37 m × 17.5 m × 20 m (length x width x height). For equipment setup, considering their wide application in academic research and the market penetration of DJI products, we chose a DJI Mavic Mini drone equipped with a 12 MP camera for our experiments. The comparison of different camera resolutions was not conducted in this case study as previous studies have already identified the influence of camera resolution on the photogrammetry outcome [15]. Several data-processing software tools have also been utilized in previous studies [4]. Through a comparison of reported quality from various software solutions in the literature (shown in Table 4), Agisoft Photoscan (now Metashape) was selected for processing. We collected the data on cloudy days with an overcast sky and wind speed in the range of 3–6 km/h to mitigate the effects of interfering environmental factors. The following ranges of factors were used in our data collection:

- *Flight path:* we set three flight path types for the building survey, consisting of a horizontal strip path pattern, a polygon path pattern, and a circle path pattern (Fig. 8. a-d, e, and f.)
- *Horizontal distance:* A close distance of 15 m and a long distance of 30 m were used (Fig. 8. a, d). For polygon and circle path patterns, the distance values were higher (at 30–50 m).
- *Vertical distance:* The altitude of flight paths above the top of the building was set as 30 m, which was 10 m above the roof of the building.
- *Photo overlap percentages:* 80%, 60%, and 40% were used (Fig. 8. a, b, c).

Apart from using the collected UAV-based data for 3D reconstruction, a terrestrial laser scanner (TLS) was also utilized to create point clouds of the building as a baseline for performance evaluations. Previous studies have broadly utilized TLS-based point clouds and models as the benchmark for model evaluation [4,61,92], and it has been universally acknowledged that laser scanners can be used to rapidly collect data with high accuracy. A FARO Focus laser scanner was utilized with the predefined scan profiles of "Outdoor HDR", the resolution of 1/8, and the quality of "4×". The accompanied FARO SCENE software was used for laser scanner data processing. Three stations on each side of the building (12 stations in total) were set for laser scanning (Fig. 9), and the model performance was evaluated following the same criteria for the UAV-based models.

Upon developing the 3D as-built point clouds, the large-scale building dimensions (i.e., building length, width, and height) and selected detailed dimensions (e.g., the width of a window, the height of a door) were measured and compared with the dimensions of as-built drawings of the building (ground truth data). Errors and error rates were calculated to measure the dimensional accuracy. To evaluate the point cloud quality, the number of points in the entire point cloud and the number of points on different surfaces were measured. During the data collection and post-processing, the time needed for data collection and processing was recorded for time efficiency comparisons.

5.2. Findings from the case study

During flight planning, we utilized UgCS, which is a commercial software tool with various UAV toolsets for land surveying and industrial inspections. In consideration of safety issues such as avoiding surrounding buildings and pedestrians, we identified reference points for the building and then collected data with manual control. Therefore, while we set the photo overlap as a fixed value in the design, the actual photo overlap may vary by ±5% around the set values as shown in Table 6. Following data collection, we developed 3D reconstructed scenes in the form of point clouds and built mesh models of the building with Agisoft Photoscan software. In the remainder of the text, we also refer to these as-built scenes as models.

As shown in Table 6, seven 3D models with different factor configurations were built to compare the influence of various factors. Fig. 10 shows the oblique view of these models. These visualizations show clear quality differences between the models. Among all cases, six proper models were developed, while for model c (Fig. 10.c) the images were not properly aligned to successfully form the complete building mesh model. For model c, 60 photos were collected as the original setting, while only 33 of them were properly aligned by the software despite different rounds of data collection. Additionally, as the laser scanner only collected terrestrial data, the top surface was not modeled in the TLS-based model (Fig. 10. g) compared with other UAV-based models with sufficient information on the building's top surface. Apart from that, there are also other differences among these seven models. Further quantitative comparisons have been discussed in the following subsections.

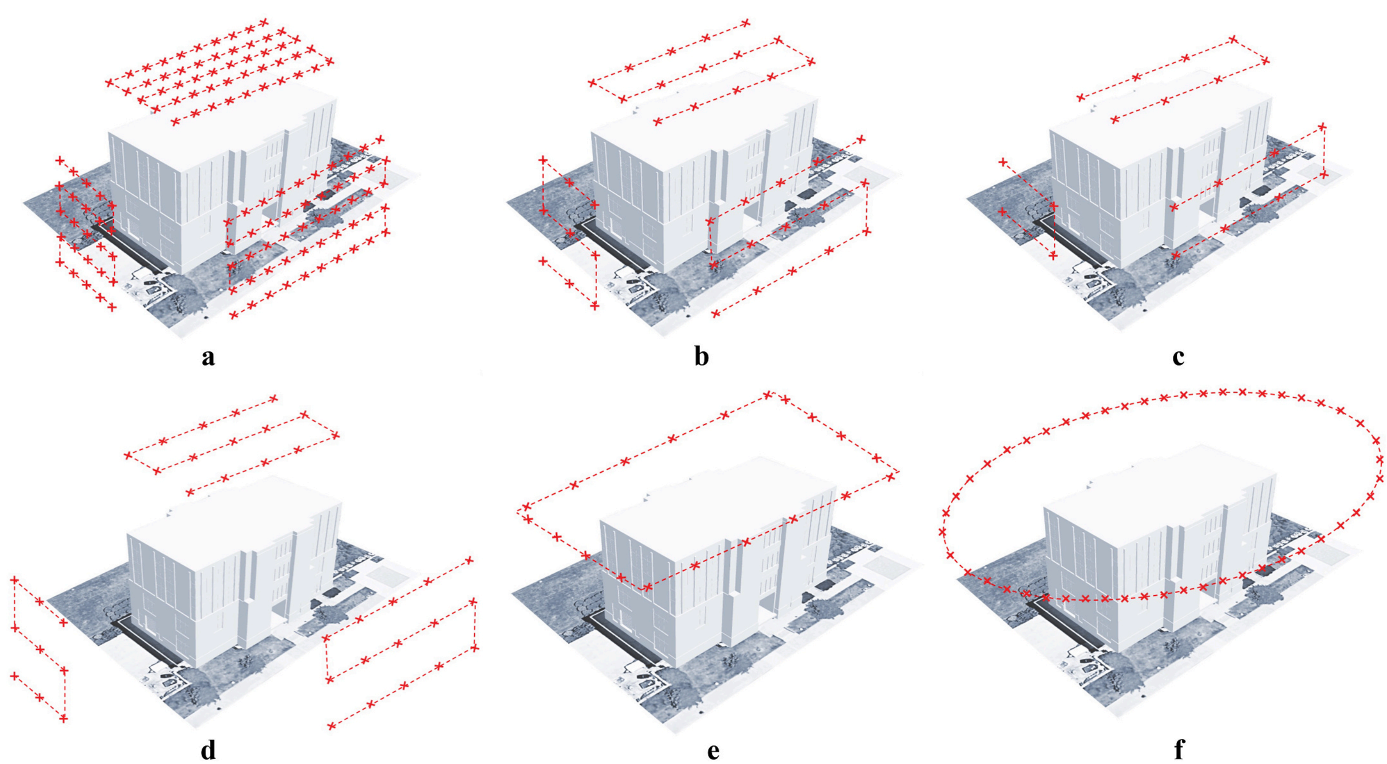

Fig. 8. Pre-flight path planning for the case study building (a. Strip Pattern (80% photo overlap), b. Strip Pattern (60% photo overlap), c. Strip Pattern (40% photo overlap), d. Strip Pattern (30 m), e. Polygon Pattern, f. Circle Pattern).

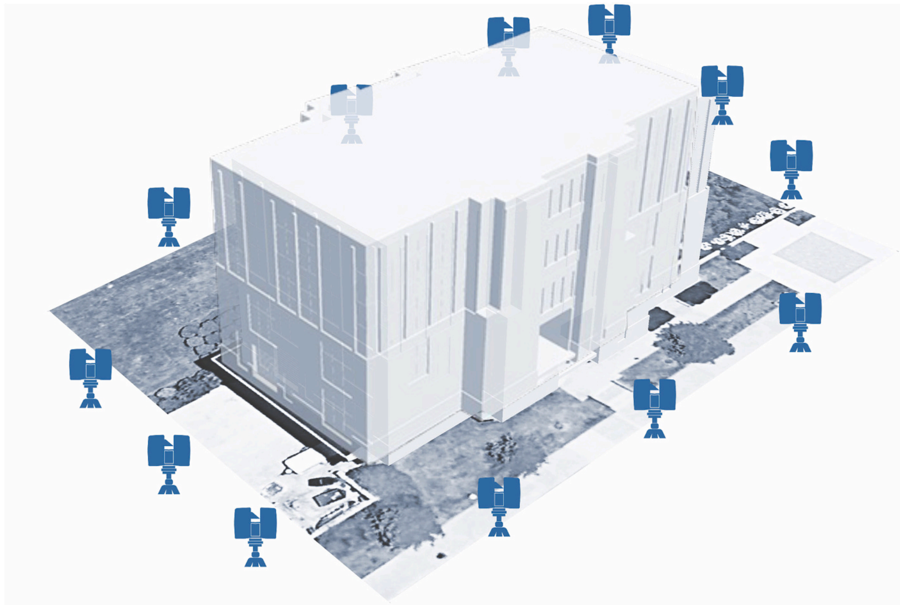

Fig. 9. Terrestrial laser scanner data collection stations (12 stations in total).

Table 6
Seven 3D as-built reconstructed scenes and their mesh models with various factor settings.

Models	Flight Path	Photo Overlap	Horizontal Distance (meters)	Number of Photos
a (Strip – 80% -15)	Strip Pattern	80% (75%–85%)	15	240
b (Strip – 60% -15)	Strip Pattern	60% (55%–65%)	15	115
c (Strip – 40% -15)	Strip Pattern	40% (35%–45%)	15	60 (33 aligned)
d (Strip – 80% -30)	Strip Pattern	80% (75%–85%)	30	82
e (Polygon – 80%)	Polygon Pattern	80% (75%–85%)	20–30	60
f (Circle – 80%)	Circle Pattern	80% (75%–85%)	40–50	82
g (Laser Scanner)	N/A	N/A	15	N/A

5.2.1. *Accuracy analysis*

We imported the reconstructed 3D models from Photoscan into Autodesk Revit to measure the dimensions of the 3D scenes. For each model, we collected six major dimensions such as the length, width, and height of the building (Fig. 11. a), and extracted six detailed dimensions, such as the width and height from a window on the east side wall and a door of the main entrance in the building (Fig. 11. b). These measurements of the reconstructed 3D models were then compared with the ground truth dimensions to evaluate the accuracy of the reconstructed 3D models. The accuracy analysis was conducted by calculating the average absolute error, average error rate, and standard deviation of these measurements.

Table 7 presents the results of the dimensional accuracy assessments. Note that all values in the table are mean values of the related items. The average absolute errors and error rates are the mean values calculated from the absolute errors and error rates of measured dimensions, respectively. The observations from Table 7 have been summarized below and the error rate comparison has been presented in Fig. 12.

As shown in Fig. 12, the strip path pattern (Table 7. a) demonstrates superior performance compared with the polygon path (Table 7. e) and the circle path (Table 7. f) patterns, particularly in measuring detailed dimensions, where the average error rate of all four strip path models is around 1%, while the average error rate of the other two path types (polygon and circle) are as high as 6%. As expected, the decrease in the photo overlap leads to a decrease in dimensional accuracy. When assessing all dimensions, the error, and the standard deviation gradually increase as the photo overlap decreases from 80% to 40% (Table 7. a, b, and c). Compared with the model generated from the laser scanner (Table 7. g), UAV-based models exhibit a considerably higher standard deviation of the measured absolute errors. In Fig. 12, when considering the error rate, the small gap between the UAV-based (strip pattern with 80% photo overlap) model and the TLS-based model indicates the high accuracy that the UAV-based models can reach.

Table 7 also shows that the impact of the change in photo overlap on the major dimensions is larger than its impact on detailed dimensions. By comparing the variations between 80% and 40% photo overlaps, we can see that the increase in the error rates of the detailed dimensions is smaller than the increase of error rates in major dimensions as the photo overlap decreases. The effect of changing the distance between the UAV and the building facade is relatively less considerable than that of the photo overlap. When comparing the impact of distance and photo overlap, the increase of error rate between the model with a 15-m (Table 7. a) distance and the model with a 30-m distance (Table 7. d) (0.08%) is less than the difference between model built with 80% photo overlap (Table 7. a) and the model built with 60% photo overlap (Table 7. b) (0.15%).

5.2.2. *Point clouds (model) quality analysis*

Based on performance evaluations reported in previous studies [4,18,24,58], we defined the total number of points in the reconstructed scenes and the density of points as reference metrics for quality assessments. To calculate point cloud density, we segmented the point cloud into three surfaces (South, West, and Top) and two detailed components (a Window and Entrance Door) as presented in Table 8. The point cloud density was calculated based on the number of points in the related facades. The density of the top surface is higher than the others since the top surface also includes components, such as building systems and parapet walls. The point cloud density of the windows and doors (containing large portions of glass) is generally lower than the other parts of the building surfaces (containing concrete or steel material).

As presented in Table 8 and Fig. 13, with the same photo overlap (80%), the number of points in the scenes from strip patterns (Table 8. a)

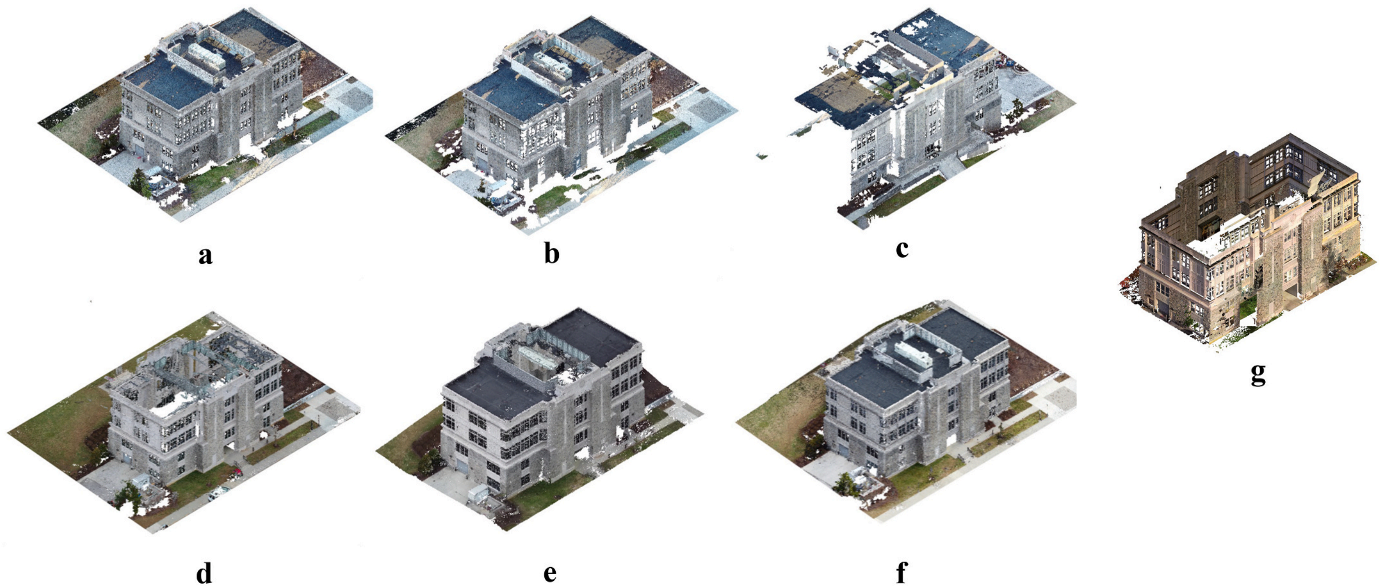

Fig. 10. 3D as-built scenes (i.e., mesh models) reconstructed based on different flight paths (a. Strip Pattern (80% photo overlap), b. Strip Pattern (60% photo overlap), c. Strip Pattern (40% photo overlap), d. Strip Pattern (30 m), e. Polygon Pattern, f. Circle Pattern, g. Terrestrial Laser Scanner).

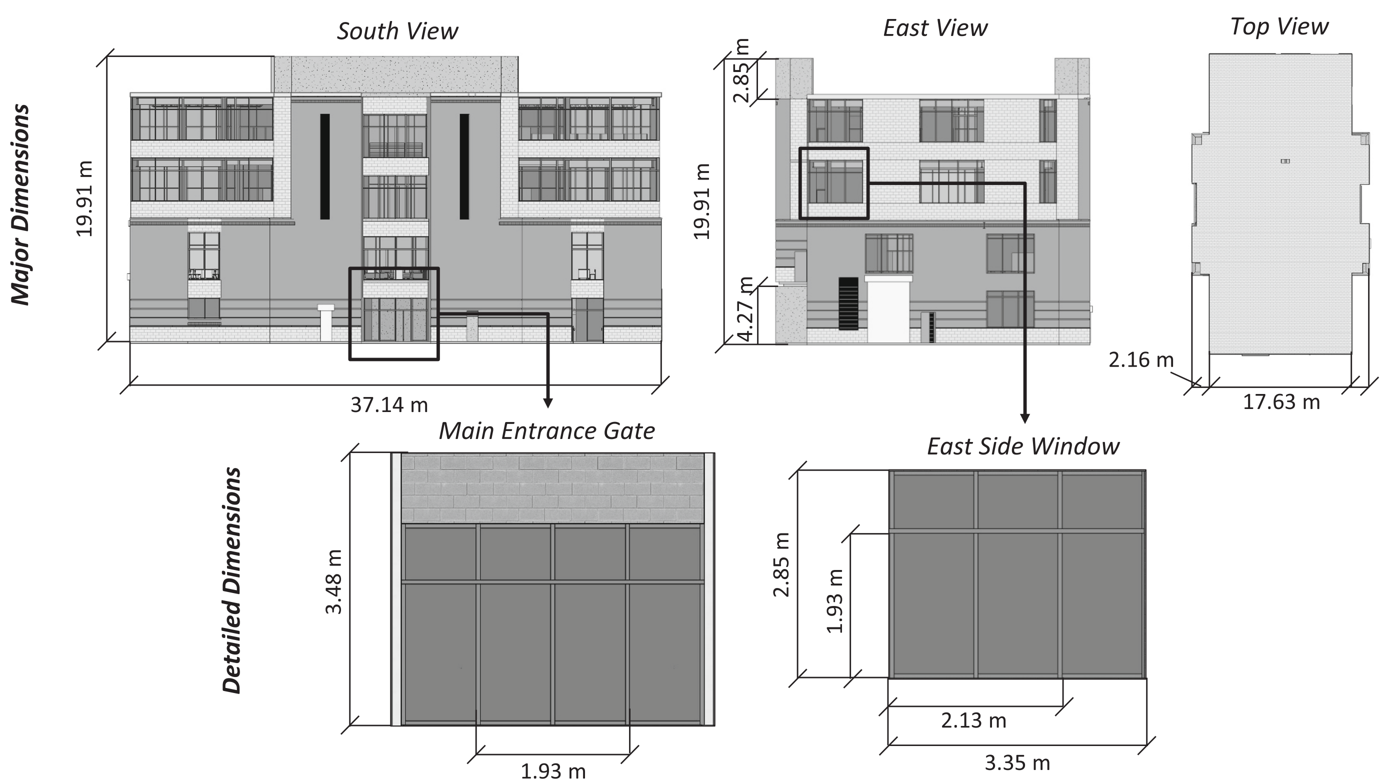

Fig. 11. Dimension references of the case study building (Major Dimensions and Detail Dimensions) from a 3D model of the building - the dimensions reflect the actual as-built dimensions of the building.

is larger than the number of points in those from polygon patterns (Table 8. e) and the circle pattern (Table 8. f). The number of points in the point cloud decreases as the photo overlap percentage decreases or the distance between UAVs and the building facade increases (Table 8. a-c). Nevertheless, in contrast to the dimensional accuracy, the impact of changing the object distance is larger than changing photo overlap percentages when it comes to point cloud density. The decrease in point cloud density between a reconstructed scene from images taken at a 15-m distance (Table 8. a) and at a 30-m distance (Table 8. d) is much larger than the decrease of point cloud density between an as-built scene from 80% photo overlap (Table 8. a) and from 60% photo overlap (Table 8. b). The low point cloud density of the circle pattern (taken at 40–50 m from the building facade) could also be an indicator of the significant impact the distance has on the point cloud density. For non-strip patterns, larger distances are required so that the whole surface of a facade can be captured, which is also a reason for the drop in the point cloud

Table 7
Comparison of dimensional accuracy for different reconstructed scenes and their mesh models.

Model	All Dimensions			Major Dimensions			Detailed Dimensions		
	Abs. Error (cm)	Error Rate	STD	Abs. Error (cm)	Error Rate	STD	Abs. Error (cm)	Error Rate	STD
a (Strip – 80% -15)	6.15	0.72%	26.57	11.00	1.0%	34.06	1.27	0.45%	5.41
b (Strip – 60% -15)	8.99	0.87%	36.75	15.24	0.68%	48.44	2.74	1.05%	5.16
c (Strip – 40% -15)	17.65	1.48%	71.40	30.48	1.76%	85.85	2.29	1.13%	5.74
d (Strip – 80% -30)	4.70	0.80%	13.08	7.62	0.95%	14.83	1.80	0.65%	5.03
e (Polygon – 80%)	50.80	6.12%	165.28	84.25	6.08%	202.31	17.35	6.15%	43.08
f (Circle – 80%)	14.53	3.07%	42.37	12.19	1.03%	17.27	17.48	5.63%	65.28
g (Laser Scanner)	3.25	0.5%	4.05	6.00	0.9%	4.05	0.5	0.1%	1.22

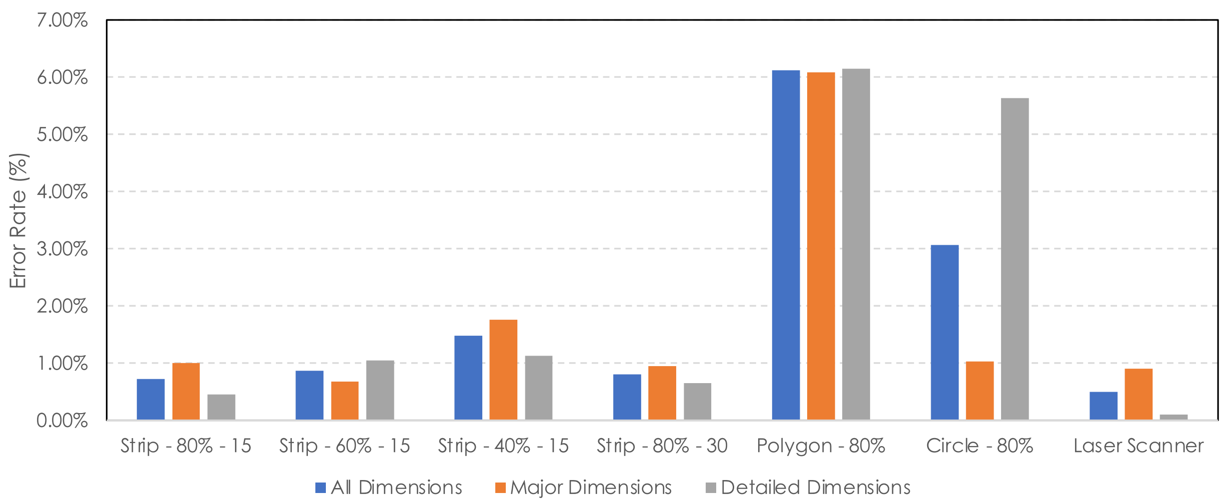

Fig. 12. Comparison of the error rates for different reconstructed scenes and their mesh models.

Table 8
Comparison of point cloud characteristics in different reconstructed scenes.

Model	Number of Points in the Whole Model	Point Cloud Density (pts/m^2)				
		South Facade	West Facade	Top Surface	Window	Door
a (Strip – 80% -15)	117,074,368	26,198	26,909	40,061	23,279	15,220
b (Strip – 60% -15)	83,803,128	22,414	21,511	33,049	20,545	12,722
c (Strip – 40% -15)	27,296,209	10,208	1262	12,522	8687	5083
d (Strip – 80% -30)	51,037,110	8149	7797	12,641	7479	5820
e (Polygon – 80%)	42,487,232	7264	6354	3153	6478	5456
f (Circle – 80%)	12,338,180	473	521	693	642	318
g (Laser Scanner)	50,024,868	19,758	5995	N/A	4810	8318

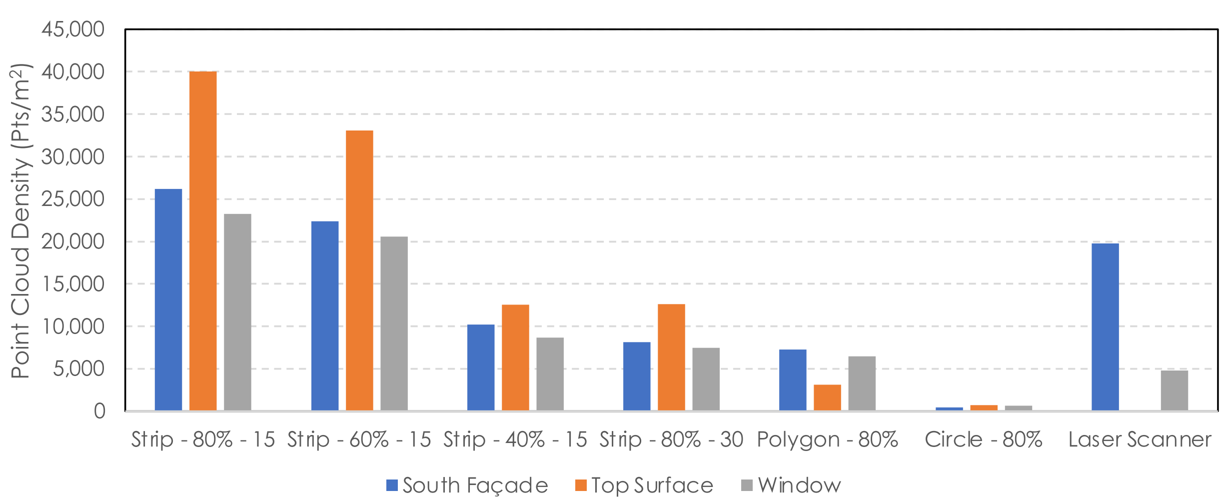

Fig. 13. Comparison of point cloud density for selected surfaces across different reconstructed scenes.

density.

The TLS-based point cloud (Table 8. g) did not include information on the building's top surface, resulting in a lower number of points. Also, the point cloud density was not the best TLS-based point cloud attribute given that we did not use the highest resolution and quality settings, due to the consideration of time efficiency, which will be further discussed in the next section. The differences in the point cloud quality are apparent in Fig. 14–16, which show comparisons of the South facade and the main entrance of the case study building. It can be seen from the figures that point cloud density is reflected in the quality of the mesh models and the level of detail. In Fig. 15 a, b, c, and Fig. 16, we can still see the incised building name and the basic frame of the building entrance door, while in Fig. 15 d, e, and f, this information is mostly lost.

5.2.3. *Time efficiency analysis*

We recorded the elapsed times for both data collection and data processing to analyze the time efficiency of the 3D scene reconstruction process. Table 9 presents the results, which show that the data processing time accounts for a major portion of the overall processing time. While hardware characteristics such as differences in graphics processing units (GPU) can also impact processing time, we focused solely on the impact of pre-flight design factors on time efficiency. The data processing was conducted on the same device with a Core i7 processor and 16 GB of RAM to avoid the impact of hardware differences.

The results presented in Table 9 indicate that the total processing time for strip patterns is much higher than that for circle and polygon patterns. The model from the strip pattern with 40% photo overlap is an outlier case, as the model was not properly aligned in the 3D reconstruction process. Generally, it can be observed that as the photo overlap decreases or the distance increases, the data processing time decreases. One of the major reasons for the difference is the number of photos that need to be aligned. The mesh model from the strip pattern with 80% photo overlap covers 240 photos in total, and the data processing time (49.8 h) is much longer than the data processing time of any of the other mesh models, which only cover 60–115 photos. In the case of terrestrial laser scanning, most of the time was spent on data collection. A single scan can take up to 2 h when using the highest resolution and quality settings. However, with 12 scanning stations and the practical requirements in real-world scenarios, we used the FARO's predefined scan profile of “Outdoor HDR” that limited the time of each full scan to 15 min. Compared with laser scanning, UAV-based data collection takes considerably less time to finish, but this may come at the cost of longer data processing time and reduced model performance, which will be discussed in the next section.

5.2.4. *Trade-off between as-built reconstructed scene quality and time efficiency*

The case study results suggest that the 3D scene reconstructed by images collected using the strip path pattern outperforms polygon and circle path patterns in terms of dimensional accuracy and point cloud density. However, better model performances also require more post-processing time because larger photo overlaps result in greater numbers of photos. Changing the distance between the UAV and the target building has a limited impact on the dimensional accuracy but a considerable effect on the point cloud density. On the contrary, the photo overlap percentage plays a crucial role in model performances. When the photo overlap was set to 40%, photos of some surfaces could not be properly aligned in this case study, and the 3D scene could not be properly formed. As the photo overlap percentage increases, it leads to higher dimensional accuracy and point cloud density, but this also results in an increase in total post-processing time. As such, there is a trade-off between the quality of the reconstructed scene (dimensional accuracy, point cloud density) and the time efficiency (total time) as illustrated in Fig. 17.

As shown in Fig. 17, for photo overlap percentages below 60%, increasing the percentage considerably affects the quality of 3D reconstructed scenes, with a relatively high variation rate for both dimensional accuracy and point cloud density. The decrease in error rate and increase in point cloud density change dramatically when moving from 40% to 60% overlaps. However, once the photo overlap percentage goes above 60%, the rate of improvement in the quality drops considerably. The photo overlap percentage of around 60% (50%–60%) acts as a watershed of allocative efficiency in this case study experiment. It is efficient to increase the photo overlap when it is under 60%, while the efficiency cost of processing will be higher than the benefits of model improvement when the overlap percentage is above 60%. Nevertheless, it is worth noting that the observed allocative efficiency point could be a feature of this case study. For generalization, more applied cases with different influential factors and various building types need to be investigated in future studies.

5.2.5. *Other influential factors*

In addition to the flight design factors discussed earlier, we identified two other factors that may affect the performance of UAV-based 3D

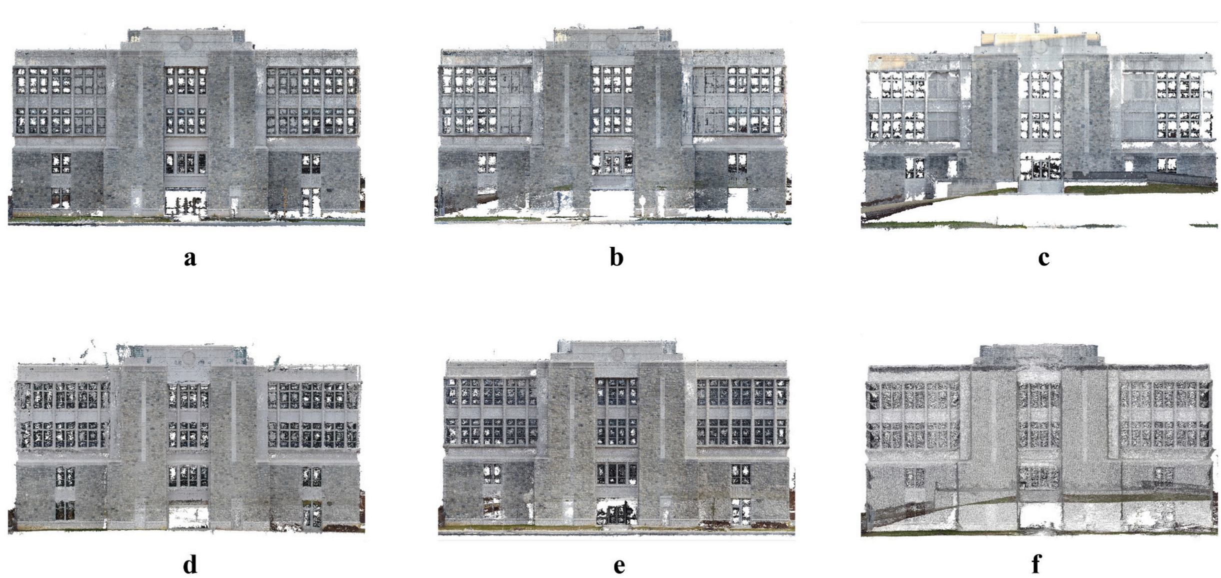

Fig. 14. Point cloud of the South facade of the case study building (a. Strip Pattern (80% photo overlap), b. Strip Pattern (60% photo overlap), c. Strip Pattern (40% photo overlap), d. Strip Pattern (30 m), e. Polygon Pattern, f. Circle Pattern).

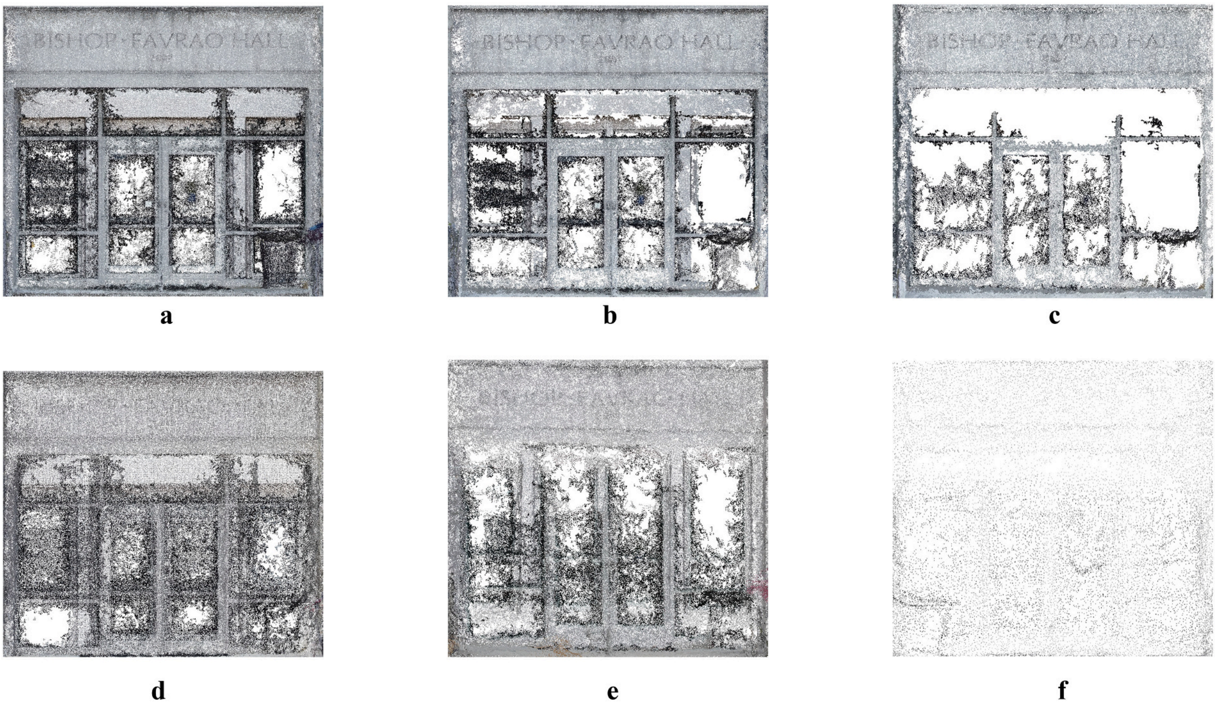

Fig. 15. Point cloud of the main entrance door of the case study building (a. Strip Pattern (80% photo overlap), b. Strip Pattern (60% photo overlap), c. Strip Pattern (40% photo overlap), d. Strip Pattern (30 m), e. Polygon Pattern, f. Circle Pattern).

Fig. 16. Details of the terrestrial laser scanner-based Point cloud (Left: south façade; Right: main entrance door).

Table 9
Time elapsed for processing images to 3D reconstructed scenes and their mesh models.

Model	Data Collection (h)	Data Processing (h)	Total Time (h)
a (Strip – 80% -15)	0.8	49.8	50.7
b (Strip – 60% -15)	0.4	17.2	17.6
c (Strip – 40% -15)	0.2	1.3	1.5
d (Strip – 80% -30)	0.3	7.5	7.9
e (Polygon – 80%)	0.2	3.3	3.5
f (Circle – 80%)	0.2	2.3	2.4
g (Laser Scanner)	3.5	1	4.5

reconstruction in the case study trial tests. These factors are weather conditions during data collection and the collection of data from the intersection between two surfaces of the target building. Weather conditions can considerably impact the quality of the collected data. Data collection on a sunny day can lead to data processing errors. The reflection of sunlight from glass surfaces, the shadows cast by the sunlight, and the illumination differences can be sources of errors. The influence of lighting and weather conditions on UAV photogrammetry has also been reported in previous literature, in which they also collect data during an overcast period to avoid the negative effect of the changing illumination [76]. Therefore, it is recommended to collect data on cloudy days with an overcast sky. Collecting data from the point of convergence between two distinct building surfaces, such as the south facade and the roof, can pose a challenge due to a misalignment. This misalignment can, in turn, lead to the failure of image matching during the data processing stage. To circumvent these challenges, it is recommended to incorporate a strategic flight path plan that includes coverage of the interface regions where two surfaces meet. In the planning of the UAV's flight path, it is important to ensure that the UAV camera is oriented at a 45-degree angle along each edge, thereby ensuring unobstructed visibility of both adjoining building surfaces. Employing this approach in data collection can markedly mitigate the occurrence of image misalignment issues during data processing and thereby enhance the overall quality of the resulting 3D model.

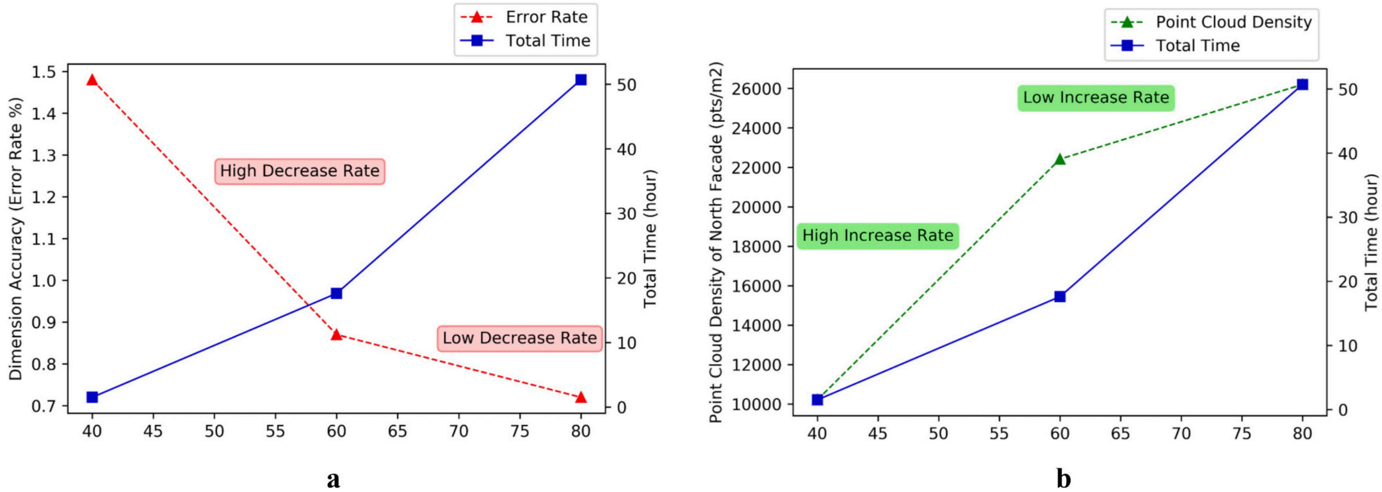

Fig. 17. Comparison of the 3D model reconstruction performance for different photo overlap percentage using strip pattern for flight path: a. Dimensional accuracy vs. Total time, b. Point cloud density vs. Total time).

6. Discussion

6.1. Data Schema for building survey based on UAV-based photogrammetry

As we evaluated the selected literature, it was observed that these studies did not uniformly specify the detailed information on influential factors as identified in this article. This could pose a challenge in synthesizing the information across multiple studies to draw generalized conclusions. Accordingly, we propose a generalizable data schema that could be adopted in future studies and practices in the field of UAV-based photogrammetry. In this way, the findings in individual studies can be analyzed and compared across studies. We have presented the data requirements for such a schema in Table 10. If future researchers or industry practitioners include these data items in reporting their findings, a larger-scale meta-analysis and comparative assessment of modeling performance could be facilitated, contributing to the development of standardized procedures for UAV-based photogrammetry data collection and processing for buildings' as-built surveys.

As shown in the proposed data schema, various factors can affect the UAV-based 3D as-built scene reconstruction, including survey target shapes and dimensions, data collection-related features, and data processing methods. Different evaluation criteria and point cloud measurements should also be considered. In previous studies, researchers attempted to achieve the optimal performance quality of the reconstructed models in their case studies. However, different objectives and levels of detail for different applications may require different configurations to improve time efficiency. While some studies have investigated the impact of specific factors on the model performance individually, few have investigated the collective effect of these factors. Although we conducted a case study to investigate the trade-off between different factors and reconstructed model quality, several limitations still exist that require further investigation in future studies.

6.2. Limitations and future studies

In this study, a detailed factor assessment was conducted through a systematic literature review and a case study field evaluation. While the outcome of this endeavor offers valuable insights, there are inherent limitations of the case study conducted in this research. First, our case study was restricted in scope, assessing a limited subset of influential factors with relatively modest variations. The selection of photo overlap percentages (40%, 60%, 80%) and the two selected fixed UAV-to-building distances (15 m and 30 m) presents an opportunity for more comprehensive and diversified experimentation. Given the computing-intensive nature of the analyses, it is challenging to compile an extensive repository of sample data, encompassing diverse factor combinations, distinct building typologies, and a broad array of architectural forms. Deploying cloud computing resources, a future avenue of research could involve a broader spectrum of factors, including additional photo overlap percentages, broader variations in the number of photos, investigated distances, altitudes, and ground control points (GCPs), as well as comparisons between different processing software solutions, and utilized hardware specifications. Additionally, the inclusion of various building types, sizes, and real-world applications can help expand the foundation developed in this study.

Furthermore, while terrestrial laser scanning served as the ground truth data source for comparison in this study, comparison against alternative means of data collection, such as terrestrial robots (e.g., agile mobile robots [39]), remains to be explored [96]. Future investigations may encompass a more extensive examination of the disparities between 3D as-built reconstructions derived from UAV-based photos and those gathered by alternative data collection methods, such as alternative ground-based methods. Future studies should also examine the synergistic potential of integrating UAV and terrestrial photogrammetry or laser scanning data to enhance model accuracy [41,74,90]. Empirical studies have proposed frameworks for operating mobile robots equipped with laser scanning systems in cluttered outdoor environments with the aid of UAVs [40,69], and developed methods to automatically register the 3D point clouds collected both from UAVs and tresterial robots [68]. Such integrated approaches hold promise in pushing the boundaries of precision in building surveys and construction analysis.

7. Conclusion

The practices of UAV-based as-built scene reconstruction have achieved significant advancements, primarily focusing on optimizing the quality of image-based 3D reconstructed scenes. However, in the literature, there exists a gap in the systematic identification and analysis of critical factors in UAV-based photogrammetry that could have a significant impact on performance. Therefore, in this study, we presented a comprehensive factor assessment using a systematic literature review, through which a categorization of relevant parameters was developed for the three phases of scene reconstruction: (1) flight design for data collection, (2) data processing, and (3) performance evaluation. Through social network analysis and frequency assessment in the selected literature, we identified the most influential factors to be flight path patterns, the distance between the UAV and the target building,

Table 10
Data requirements for a data schema in UAV-based 3D as-built scene reconstruction.

Section	Factor	Data/Information
Survey Target	Target Information	• Target Type (e.g., residential building, commercial building, or cultural heritage) • Target general information (including (1) shape: cuboid, tower, ring shape, L shape, etc.; (2) number of floors; (3) surrounding context (e.g., obstacles)) • Target dimensions (length, width, height)
Data Collection	Equipment Setup	• UAV type and make • UAV specifications (flight duration time, flight speed, and whether they support autopilot or not) • Attached camera type and make • Attached camera specifications (specifically camera resolution)
	Flight Design	• Flight path (strip pattern, polygon pattern, circle pattern, or mixed pattern) • Camera positions (including (1) distance between the camera and the target; (2) altitude of the camera; (3) oblique angle of the camera) • Image overlap percentage (from 0% to 100%) • Ground control points specification (whether GCPs were set or not; the number of GCPs; positions of the GCPs) • Number of images that were planned to be collected
	Spatial and Temporal Information	• Climate condition at the time of data collection (e.g., sunlight condition: sunny sky or overcast sky; wind speed) • Data collection duration
Data Processing (Model Building)	Processing software information	• The type, name, and version of the data processing tools/software (commercial product, open-source package, or self-developed system)
	Model building information	• Number of aligned images in creating the point cloud/ model • Elapsed time for data processing
Performance Evaluation	Evaluation Criteria	• Accuracy evaluation type (dimensional accuracy or point cloud to point cloud (TLS) deviation) • Model accuracy metrics (e.g., mean dimension errors, mean point distance from TLS point cloud)
	Point Cloud	• Number of points in the model • Point cloud density specifications (e.g., point cloud density of specific facade)

and photo overlap percentages. Subsequently, we conducted an in-depth case study to quantitively analyze the trade-off between these factors and their impact on the quality of the reconstructed scenes. Performance evaluations revealed that the strip pattern flight path results in higher-quality point clouds when compared to polygon and circle patterns. The distance between the UAV and the target building has a more profound influence on point cloud density compared to the dimensional accuracy. Among all factors examined, photo overlap percentages emerged as the primary driver of 3D scene reconstruction performance. We identified a trade-off between the point cloud quality and time efficiency, where a photo overlap percentage of about 60% can be the tipping point of allocative efficiency in the case study experiment. For detailed building elements, a strip pattern with a close-range (about 15 m) data collection process resulted in high point cloud density and dimensional accuracy. The comparisons between UAV-based models and terrestrial laser scanner-based models revealed that UAV-based photogrammetry (using a strip pattern with 80% photo overlap) can considerably reduce data collection time while achieving equivalent model quality compared to laser scanning.

This study contributes by systematically identifying and quantitatively analyzing factors and metrics in UAV-based photogrammetry, expanding practical knowledge for as-built building surveys. The findings could offer guidance for efficient and precise as-built building surveys with standardized procedures, which in turn could benefit industry practices and future research in this area. Moreover, future studies can leverage the presented categorization and suggested data requirement schema to move towards standardized procedures that could balance the trade-off between data collection and processing efforts and the reconstructed scene quality. Additionally, the findings could contribute to the automation (with pre-set factors and survey objectives) of larger-scale UAV-based photogrammetry workflows that could in turn support the creation of digital twins at different scales.

Declaration of generative AI in the writing process

During the preparation of this work, the authors used ChatGPT in order to refine and polish parts of the text. After using this tool/service, the authors reviewed and edited the content as needed, and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Tianzhi He: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing – original draft. **Kaiwen Chen:** Investigation, Methodology, Writing – original draft, Writing – review & editing. **Farrokh Jazizadeh:** Conceptualization, Investigation, Resources, Supervision, Writing – original draft, Writing – review & editing. **Georg Reichard:** Resources, Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

The data cannot be shared.

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