A Comparative Study of Mobile Device and Terrestrial Laser Scanning-Based Scan-to-BIM Workflows

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Abstract – Scan-to-BIM procedures using terrestrial laser scanning (TLS) are accurate but require significant time and financial investment. This study evaluates a faster alternative utilizing mobile device-based LiDAR and a mobile application built on the Apple RoomPlan API. The research first assesses geometric reliability through point-cloud-to-BIM confidence indices, specifically Coverage, Distribution, and Distance. Additionally, it employs BIM-to-BIM matching metrics, including 3D-IoU and 3D-Compactness, to compare the mobile output against a TLS baseline in residential and office buildings. Results demonstrate that the mobile pipeline reduces total scan-to-BIM time from 3.5 min/m² to 0.1 min/m². Although the mobile application provides reliable room layouts with space 3D-IoU scores reaching 0.93, it exhibits limitations regarding wall thickness accuracy and positional drift. Consequently, based on these initial findings, this workflow shows potential for facility management and initial retrofit assessments where rapid data acquisition is prioritized over high geometric precision.

Keywords – Scan-to-BIM, Mobile LiDAR, TLS, Mobile Device, Geometric Accuracy

1 Introduction

Scan-to-BIM procedures are key to generate digital models containing geometry and core semantic information that support a range of applications. These BIM models support retrofit design, energy modelling, and facility management (including digital-twins or digital-logbooks).

Most scan-to-BIM workflows start from reality capture data, in which point clouds are the dominant representation used to capture the existing conditions as a reference geometry for creating parametric BIM objects. They provide high-resolution geometric information, and point clouds are usually generated using terrestrial laser scanning (TLS) and mobile laser scanning (MLS). TLS captures dense and accurate geometry. However, it requires multiple stations with subsequent data registration, which can slow down the data collection procedure. By contrast, handheld systems can be faster to deploy, yet their accuracy depends on the stability of tracking on the scene structure, which can lead to drift and misalignment based on the long scanning paths.

Recently, lidar sensors have become available on mobile devices, particularly on iPhone Pro and iPad Pro models. These devices are low-cost compared with professional scanners and easy to deploy for quick capture tasks [1]. Many studies have assessed the feasibility of lidar-integrated mobile devices for scan-to-BIM workflows by comparing output point clouds against TLS reference data [1][2][3][4]. They show that, while, like MLS, they can acquire data more rapidly than TLS and can achieve promising local precision in indoor settings. Beyond standalone indoor scans, some studies merge mobile lidar with other sensing sources, such as TLS, UAV lidar or photogrammetry, principally to improve completeness [5][6].

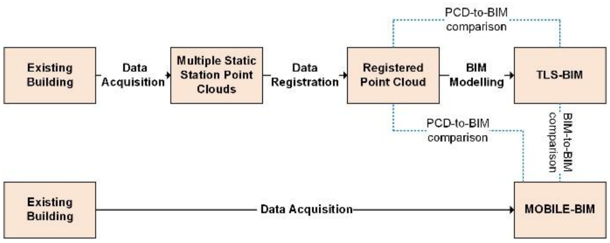


Figure 1. Framework of the proposed assessment method

However, regardless of whether the scan comes from TLS, MLS, or mobile device lidar, most workflows require post-processing followed by geometric and semantic modelling, hereafter BIM modelling. In these studies, the BIM model is typically reconstructed through manual or semi-manual/automated modelling.

It must be noted that, besides lidar depth sensing, mobile devices also provide RGB camera data, another modality containing useful information about the scene. This data can also be leveraged to detect and segment various elements in the scene, such as architectural elements (e.g., windows, doors) and furniture (e.g., tables, chairs) [7].

A key recent development in the use of mobile device lidar is Apple's RoomPlan [8]. Specifically, RoomPlan is an API that uses the device camera and lidar scanner to create parametric 3D room scans, including room dimensions and recognized furniture, producing a structured room representation rather than only raw points or a mesh. Several commercial apps use this type of pipeline, including Polycam [9], Magicplan [10] and Metaroom [11]. Even though many studies evaluate iOS lidar in terms of point cloud or mesh quality, few studies evaluate the full pipeline of RoomPlan using standardized and quantitative BIM-level metrics. Recently Mortazavi et al. [12] proposed an assessment system with criteria, a rating scheme, and utility value analysis to compare site-scanning methods for creating a BIM model, including Magicplan and Polycam against TLS and MLS. While this is valuable for tool selection, it mainly supports comparative scoring and does not report explicit geometric accuracy metrics for the produced models, such as deviation-to-ground-truth measures or systematic BIM-to-BIM overlap measures.

To address this gap, this study proposes an assessment of a smartphone-based scan-to-BIM application built using the RoomPlan API, focusing on the full pipeline from on-device capture to BIM model output. For evaluation, we adopt quantitative, geometry-focused metrics at two levels. First, we use point-cloud-to-BIM confidence indices to assess matching reliability by integrating Coverage, Distribution, and Distance measures [13]. Second, we use BIM-to-BIM matching metrics based on 3D-IoU and 3D-Compactness to compare the outputted BIM model against a reference BIM model, following the benchmark design of Liu et al. [14]. By combining these evaluation layers, the study aims to clarify the challenges and opportunities of fast scan-to-BIM for future research and practice, especially for reliable as-built modelling.

2 Method

This section outlines the method employed for the assessment of a smartphone-based scan-to-BIM workflow, as summarised in Figure 1.

2.1 TLS-based BIM Modelling

The traditional scan-to-BIM methodology utilises TLS to establish an accurate geometric baseline of the existing environment. As illustrated in Figure 1, the workflow follows a sequential, multi-stage process to transform physical space into a digital representation.

Reality capture is performed using a static, multi-station laser scanning approach. The scanner is strategically positioned at various locations throughout the building to ensure comprehensive coverage and minimise data gaps caused by occlusion shadows. Following the acquisition, the individual point clouds from each station are registered into a single coordinate system. This stage results in a high-density unified point cloud that serves as the precise geometric reference of the as-built conditions. Finally, the registered point cloud is used as a spatial reference for manual BIM modelling. During this phase, semantic BIM objects are created by interpreting the point cloud data to represent the building's geometry and components accurately. The resulting manually-created model serves as a validation reference (TLS-BIM) against which the automated outputs of the mobile workflow are quantitatively measured.

2.2 Mobile-app-based BIM Modelling

The mobile-app-based method focuses on the creation of automated BIM models using an app that deploys the RoomPlan API on a mobile device. Unlike the traditional workflow above, this procedure employs a continuous and integrated real-time data acquisition and processing process, which depends on the selected app. RoomPlan API was released by Apple in 2022 for generating a parametric 3D floor plan of an indoor environment using mobile scanning. The capture is performed using iPhone or iPad devices equipped with an RGB camera and a lidar scanner. The API simultaneously conducts real-time scanning and device pose tracking, also known as Simultaneous Localization and Mapping (SLAM). During scanning, RoomPlan combines RGB-D frames and associated camera poses to create semantic point clouds. Then, by using learning-based estimators, the framework creates walls, openings, doors, windows, and furniture objects.

Indoor environment reconstruction is composed of two parts: 3D room layout estimation and 3D object (e.g., furniture) detection. Room layout estimation detects walls, floors, ceilings, openings, doors, and windows in real time. Walls are first predicted as 2D lines in bird's-eye view and then extruded into 3D surfaces based on the distance between the detected floor and ceiling. All spaces bounded by walls, ceiling, and floor are also additionally defined. Doors and windows are detected using multimodal (RGB and lidar) data, and projected into 3D using projection information and camera position. The 3D object detection pipeline recognizes 14 object categories, in addition to windows and doors. These are furniture objects and include: tables, chairs, cabinets, fridges, etc. The object detection combines a local and global detector. Local detector is operating during scanning on a seen camera view, and a global detector is working after scanning on the full reconstructed scene to fuse results (which is particularly necessary for larger items). All detected objects are then associated with the space within which they have been detected.

The output of the API is thus not only geometric, but also includes semantics, including object types and some object relationships (relationships of walls, ceilings, doors, and furniture with spaces). The results of indoor capturing can be exported in Universal Scene Description (USD) formats. Some apps also map the information into IFC. As previously mentioned, there are various apps in the market that leverage this API, including Polycam [9], Magicplan [10] and Metaroom [11].

To maintain consistency and data integrity during the acquisition process, the following best-practice procedures were followed during scanning:All doors and windows within the scan area were closed.Curtains and blinds remained open to ensure visibility of windows. Scanning was performed using a slow vertical oscillation (up and down movement) to capture ceilings, walls, and floor slabs. A maximum scanning distance of 5 meters from the device to the surface was maintained.Scanning was performed during maximum daylight conditions.The device camera remained open and active from start to end of the scanning.

2.3 Evaluation Criteria

To assess the proposed scan-to-BIM pipeline, an evaluation is conducted at two levels. The point cloud (PCD)-to-BIM evaluation measures how well the BIM elements created using the mobile app match the TLS PCD, and the BIM-to-BIM evaluation compares the mobile app-based BIM model against the BIM model manually created from the TLS PCD. The scope of this evaluation is limited to assessing the geometric fidelity and spatial placement of the core architectural elements

2.3.1 PCD-to-BIM Comparison

Before comparing the TLS PCD to the mobile-app BIM model, they must be aligned in the same coordinate system. We have done this using the 4-Plane Congruent Sets (4-PlCS) method [15] (see implementation at https://github.com/CyberbuildLab/4PlCS). The algorithm extracts planar patches from both the input point clouds and the BIM model. It randomly searches for bases of four planes where three are not pair-wise parallel and the fourth is not co-planar. To handle potential matching failures and reject outliers, the algorithm replaces standard RANSAC with a custom two-step support evaluation method. It first assesses centroid support by checking if the centroids of the point cloud patchs project inside the matched model patches. It then evaluates plane support by calculating the percentage of all remaining point cloud planar patches that support the transformation. Finally, it groups similar transformations and presents a ranked list of the most likely alignments for the user to quickly verify and select the correct one. While this semi-automated approach improves efficiency, manual alignment remains an alternative that does not affect subsequent analyses of this study

Then, for PCD-to-BIM comparison, we adopt the framework of confidence indices proposed by Ersöz and Bosché [13] (see implementation at https://github.com/CyberbuildLab/pcd-bim-matching-confidence).This framework evaluates matching reliability by computing an overall Confidence Index (I-confidence) per BIM element. This is achieved by integrating Coverage (I-coverage), Distribution (I-distribution), and Distance (I-distance) indices, which assess how well scan points align with visible BIM surfaces..Detailed mathematical definitions and algorithmic procedures for these indices are thoroughly described in [13].

2.3.2 BIM-to-BIM Comparison

To assess the geometric similarity between the MOBILE-BIM and TLS-BIM models, we employ the model-to-model evaluation metrics introduced by Liu et al. [14] (see implementation at https://github.com/CyberbuildLab/bim-bim-matching). This approach utilizes two complementary metrics: 3D-IoU and 3D-Compactness. 3D-IoU measures the spatial alignment and Boolean volume overlap between strictly matched semantic classes in the Ground Truth and estimated models. Meanwhile, 3D-Compactness penalizes many-to-many geometric mappings to evaluate whether the reconstructions align in a clean, one-to-one correspondence (highlighting over-segmentation or over-merging). Detailed definitions and the underlying computation logic for these volumetric metrics are provided in [14].

3 Experiments, Results, and Discussion

3.1 Test Environments

To evaluate the mobile device-based scan-to-BIM mobile-app pipeline, we conducted a comparative study across two distinct building typologies representing varying levels of geometric and semantic complexity. The residential case (RES) consists of a single-storey residential unit characterized by medium clutter with an area of approximately 50 m^2. This environment features standard furniture and opaque partition walls, representing a controlled baseline for occlusion. In contrast, the office case (OFF) involves a two-storey university facility characterised by high levels of clutter. The corresponding dataset is split into the first floor (OFF1) and the second floor (OFF2), both with an area of approximately 150 m^2.

3.2 TLS Workflow

To establish a GT baseline, we employed a Leica BLK360 terrestrial laser scanner. The scanner was positioned at multiple stations throughout each room and corridor to capture overlapping point clouds, which were then registered into a unified, high-density point cloud to serve as the precise reference of existing conditions. Using this registered point cloud as an underlay, BIM models were then manually created in Autodesk Revit (Figure 2) and then exported in IFC format. To ensure consistency and eliminate operator variability, the modelling was performed by a single BIM professional with over five years of specialized scan-to-BIM experience. The modelling scope was defined at a Level of Development (LOD) 300, focusing specifically on the elements (walls, floors, doors and windows) necessary for a direct comparative analysis with the mobile application's output.The TLS point cloud and resulting TLS BIM model jointly represent the reference GT.

3.3 Mobile device-based Scan-to-BIM Workflow

After the TLS data collection, the same environments were captured using a lidar-enabled iPad Pro 13-inch (M4) running iPADOS Version 18.1.1. Metaroom version 7.2.1 app, built on the RoomPlan API, was used for modelling [11]. The scanning protocol presented in Section 2.2 was strictly followed to ensure data consistency. While the residential unit was captured in a single continuous session, the complex two-storey office required a segmented approach. Initial attempts to scan both floors in a continuous sequence revealed a limitation in the device's vertical localization ability, where the algorithm struggled to maintain accurate floor-to-floor height consistency during the transition via the staircase, resulting in vertical misalignment (demonstrated in Figure 4a). Consequently, to ensure geometric integrity, we adopted a strategy where each floor is scanned and analysed separately.

Unlike the TLS workflow, no post-acquisition registration or modelling is required; the application performed real-time semantic segmentation, instantly generating and extruding 3D components (walls, doors, windows) into a parametric model immediately upon scan completion. Then, BIM models were exported from the app in IFC format.

3.4 PCD-to-BIM Geometric Confidence Analysis

We first computed the confidence indices of the generated BIM models against the TLS data using the PCD-to-BIM confidence indices. The confidence indices provide a granular view of how well the BIM geometries align with the reality capture data.

Following the method established by Ersöz and Bosché, wall elements were selected as the primary reference for evaluating the confidence indices due to their significant prevalence and geometric diversity within the datasets, and grouped as interior and exterior walls. The results are tabulated in Table 1 and Table 2. Note that the I-confidence reported in these tables is calculated by simply multiplying the I-coverage, I-distribution, and I-distance indices.

The main observation is that MOBILE-BIM models have lower values for all indices in all three cases (Table 1). This highlights the geometric deviation inherent in the mobile device tracking and reconstruction process, which spatial data patterns suggest is primarily driven by SLAM drift. As the device is moved, the real-time tracking over longer trajectories or within texture-poor scenes accumulates small errors, resulting in a cumulative SLAM drift (positional shift). Consequently, while individual wall segments are all detected successfully, their relative placement within the global coordinate system deviates from the GT. This in turn results in fewer TLS points being matched to the MOBILE-BIM elements (which is limited to 5 cm) which results in the observed lower index values.

Exterior Wall Challenges: Table 2 reveals significantly lower confidence scores for exterior walls across both TLS and MOBILE models (e.g., I-confidence ranging from 0.05 to 0.18). This is because scanning was performed indoors, so that the exterior faces of these walls were not scanned. Furthermore, a noteworthy observation in Table 2 is that the MOBILE-BIM appears to demonstrate higher confidence indices for exterior walls compared to the TLS-BIM. This is in fact misleading and is due to chance. Indeed, due to the global positional drift in the mobile workflow, the external faces of the MOBILE-BIM exterior walls were often positioned wrongly (Figure 3) in a way that they ended up residing close and were matched to the available point cloud of the interior wall surface to calculate the indices. The true confidence index values for those walls should have instead been lower than for the TLS-BIM.

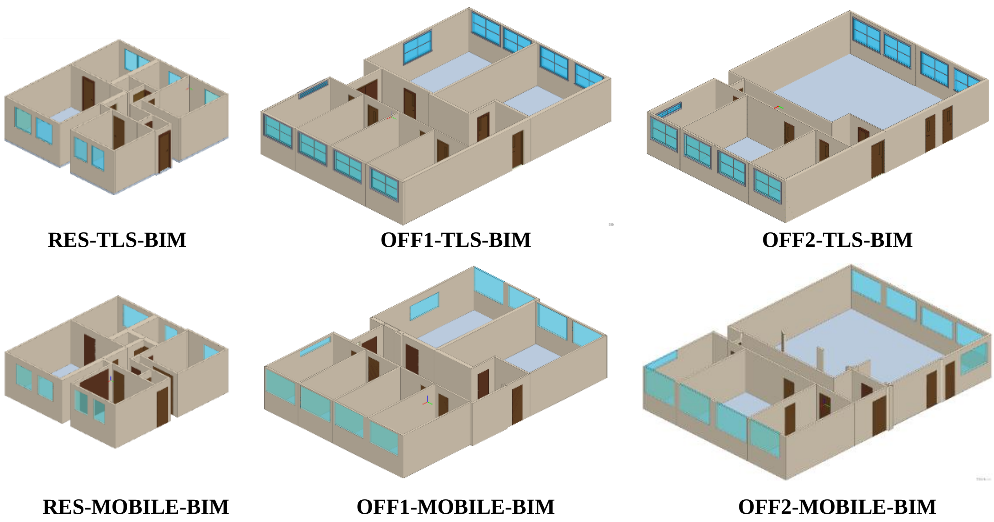


Figure 2. TLS, BIM models created via the TLS and mobile app-based workflow

3.5 BIM-to-BIM Geometric Comparison

We evaluate the BIM model's geometric fidelity using the 3D-IoU and 3D-Compactness indices. A comparative analysis of 3D-IoU and total area difference across the datasets reveals a critical distinction between volumetric precision and quantitative estimation.

Table 1. PCD-to-BIM confidence indices for interior walls

BIM Models	I-cov	I-distri	I-dista	I-confi
RES TLS	0.64	0.70	0.74	0.36
RES MOBILE	0.55	0.63	0.57	0.24
OFF1 TLS	0.71	0.94	0.64	0.44
OFF1 MOBILE	0.50	0.84	0.45	0.20
OFF2 TLS	0.71	0.91	0.67	0.45
OFF2 MOBILE	0.42	0.67	0.47	0.18

Table 2. PCD-to-BIM confidence indices for exterior walls

BIM Models	I-cov	I-distri	I-dista	I-confi
RES TLS	0.36	0.36	0.76	0.10
RES MOBILE	0.48	0.70	0.50	0.18
OFF1 TLS	0.29	0.48	0.55	0.08
OFF1 MOBILE	0.40	0.66	0.49	0.15
OFF2 TLS	0.24	0.42	0.49	0.05
OFF2 MOBILE	0.36	0.54	0.47	0.13

For both residential and office buildings the results were tabulated in Table 3 to Table 5. The total areas presented in the tables are calculated based on specific geometric projections. For vertical components, windows, doors, and walls, the areas are calculated using the projection of the 3D geometry onto their respective wall planes. The areas for space elements are determined by projecting the volumes onto the horizontal (Z) plane, which represents the net floor area.

Walls: Across all three datasets, for the wall elements, the mobile app achieved relatively low m3D-IoU scores, ranging from 0.20 (Office Floor 1) to 0.32 (Residential). Such low IoU values typically indicate issues with wall thickness and positional shift. However, the area difference remains remarkably low. For instance, in the Office Floor 1 dataset (Table 4), the predicted wall area (243.18 m^2) is nearly identical to the ground truth (242.87 m^2), with a difference of only 0.31 m^2. This highlights that the mobile application is highly effective at capturing the existence and length of walls (hence the accurate total area) but struggles with the precise placement and thickness (hence the low 3D-IoU).

Furthermore, as illustrated in Figure 4b, the app misinterprets square columns as short, isolated wall segments rather than distinct column elements, because the API does not have the capability to specifically detect columns. This error directly contributes to lower 3D-Compactness scores for walls, as the one-to-one correspondence between the TLS-BIM wall and the MOBILE-BIM geometry is broken by these false-positive wall segments.

Spaces: In contrast, the room spaces demonstrate better performance, with m3D-IoU scores reaching 0.90-0.93 and 1.00 for compactness in the office datasets. This confirms that the primary strength of the mobile app-based approach lies in room layout estimation. The app successfully generates watertight, logically correct room volumes and topology, making it highly reliable for space management where room boundaries and connectivity are more critical than the precise thickness of the partitioning walls. Top views of the space elements are shown in Figure 3.

Doors: In the residential dataset (Table 3), door elements exhibit a significant difference between directional compactness scores. The TLS-to-MOB score is high (0.88), indicating that the app successfully detected most existing doors. However, the MOB-to-TLS score is notably lower (0.64), and the predicted door area (20.36 m^2) exceeds the reference TLS model (13.34 m^2). This indicates a high rate of false positives (redundancy). Indeed, the mobile app misinterpreted other wall features (e.g., storage) as doors, as shown in Figure 4c. This suggests that while the app has high recall (finds real doors), its precision is compromised by environmental clutter and class similarities.

Windows: Across all datasets, windows achieved very low 3D-IoU scores. This poor volumetric performance is a direct effect of the misplacement particularly observed for exterior walls. Since most windows are hosted on exterior walls, which suffer from positional shifts due to global drift, the generated windows inherit these spatial offsets. Consequently, even if a window is correctly sized, its 3D volume does not intersect correctly with the TLS-BIM, resulting in a low, even zero IoU score. Despite the positional failure, the area difference remains relatively stable, which implies that the detection logic (fusion of camera and lidar) successfully identifies the presence and dimensions of the openings. The failure is therefore not one of recognition, but of spatial dependency: the openings are correctly seen but placed in incorrectly modelled exterior walls (inadequate thickness).

3.6 Comparison of Workflow Efficiency

Table 6 illustrates the comparative analysis of workflow efficiency of TLS and mobile app workflows. The total time spent decreased from 20 hours for the TLS workflow to 32 minutes for the mobile app-based workflow. When normalized by floor area, this represents an efficiency improvement from 3.5 min/m² to 0.1 min/m².

All steps of the TLS workflow are time consuming. While acquisition required 4 hours (necessitated by the logistics of static setups, target placement, and repositioning to minimize occlusion), point cloud registration took 6 hours, and manual BIM modelling took 10 hours. This 10-hour duration reflects the efficiency of an experienced professional generating a tightly scoped LOD 300 architectural model. This baseline time could vary depending on operator proficiency or if higher LODs were required. In contrast, the mobile app conducts data acquisition, registration and modelling jointly in real-time. In particular, the mobility of the devices means that interior environments consisting of many rooms and occlusions can be visited very fast.

Table 3. Residential House BIM-to-BIM metrics

	m3D-IoU	3D-Comp (TLS-to-MOB)	3D-Comp (MOB-to-TLS)	m3D-Comp	TLS El. Count	MOB El. Count	TLS Total Area (m^2)	MOB Total Area (m^2)
Doors	0.34	0.88	0.64	0.76	8	11	13.34	20.36
Walls	0.32	0.60	0.61	0.61	29	31	143.19	145.86
Windows	0.05	0.25	0.29	0.27	8	7	9.14	8.57
Room spaces	0.84	1.00	1.00	1.00	8	8	49.48	47.04

Table 4. Office Building Floor 1 BIM-to-BIM metrics

	m3D-IoU	3D-Comp (TLS-to-MOB)	3D-Comp (MOB-to-TLS)	m3D-Comp	TLS El. Count	MOB El. Count	TLS Total Area (m^2)	MOB Total Area (m^2)
Doors	0.40	1.00	1.00	1.00	8	8	15.65	13.58
Walls	0.20	0.46	0.42	0.44	20	38	242.87	243.18
Windows	0.03	0.10	0.10	0.10	10	10	22.00	25.08
Room spaces	0.90	1.00	1.00	1.00	7	7	143.96	134.96

Table 5. Office Building Floor 2 BIM-to-BIM metrics

	m3D-IoU	3D-Comp (TLS-to-MOB)	3D-Comp (MOB-to-TLS)	m3D-Comp	TLS El. Count	MOB El. Count	TLS Total Area (m^2)	MOB Total Area (m^2)
Doors	0.32	0.88	0.78	0.83	8	9	13.34	13.95
Walls	0.26	0.57	0.48	0.53	22	29	209.36	209.97
Windows	0.00	0.00	0.00	0.00	9	10	21.40	26.32
Room spaces	0.93	1.00	1.00	1.00	5	5	148.16	140.40

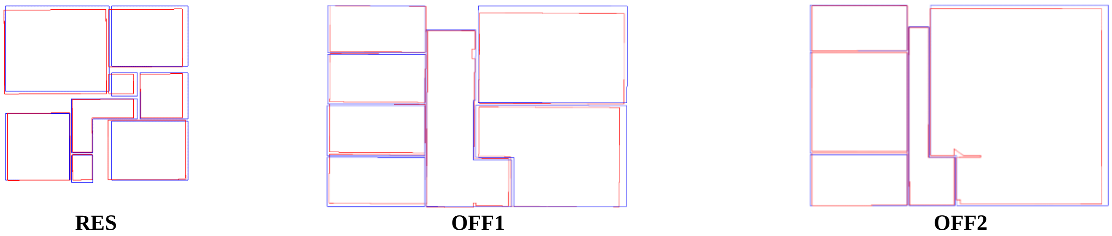


Figure 3. Room space comparison (Blue color: TLS-based BIM , Red color: Mobile-based BIM)

In conclusion, while the TLS workflow prioritises geometric precision at the cost of time, the Mobile device-based Scan-to-BIM prioritises immediacy and semantic readiness, suggesting it could be a suitable option for applications where accuracy is not so important (e.g., retrofit assessment, facility management).

Table 6. Total time required for Residential and Office Building

Workflow Stage	TLS-based	Mobile device-based
Data Acquisition	4 hr	32 min
Data Processing	6 hr	
Modelling	10 hr	
Total	20 hr (3.5 min/m^2)	32 min (0.1 min/m^2)

4 Conclusion

This study presented a quantitative assessment of a mobile app-based Scan-to-BIM workflow utilising a mobile app that uses lidar & RGB camera for data acquisition. The results were benchmarked against TLS scan data and BIM models generated from them. By applying PCD-to-BIM and BIM-to-BIM matching metrics across residential and office environments, we have assessed the capabilities and current limitations of this pipeline.

The major finding of this research is the improvement in workflow efficiency. The mobile app-based pipeline demonstrated a reduction in total production time of 97%.

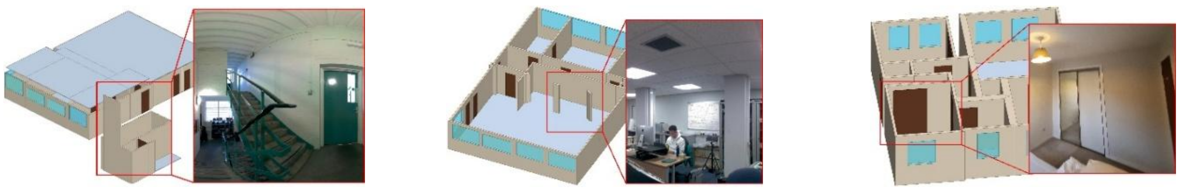
Despite the observed issues with wall thickness and positioning precision, the high 3D-IoU scores for room space elements confirm that the generated watertight room volumes are accurate. Moreover, the minimal area differences observed for windows and walls indicate that the system is effective at identifying the existence and gross dimensions of building elements.

This makes the workflow uniquely suited for applications where room layouts and asset counts are prioritized over highly accurate geometric fidelity. The mobile app-based solution is also significantly cheaper.

However, this automation introduces geometric trade-offs that must be considered. A primary technical constraint identified in this study is the inaccuracy of wall thickness estimation. The system often struggles to determine actual wall thickness due to factors such as accumulated SLAM drift, frequently reverting to default thicknesses or misinterpreting the distance between finished surfaces. Future research utilizing independent, high-precision localization tracking (e.g., via ground control points) is recommended to quantitatively decouple sensor depth noise from algorithmic SLAM drift. As errors in wall thickness aggregate, the relative positioning of adjacent rooms shifts away from the ground-truth global coordinates. For practitioners, this implies that while the model is reliable for floor area calculations and interior finish schedules, it may require manual adjustment where exact wall-thicknesses are critical.

Another observed challenge is operational scalability. The current API operates on real-time processing with significant memory constraints, which typically limits accurate single-session captures to areas of approximately 15m x 15m; larger floor plans often force a scan completion to preserve data integrity. Furthermore, as evidenced by the vertical misalignment observed in the continuous scanning test, the lack of robust loop closure for vertical transitions yields significant elevation and rotational drifts between floors.

This study evaluates geometric fidelity by utilizing the mobile pipeline's semantic classifications to establish valid, class-strict correspondences between the ground truth and estimated models. Consequently, semantic errors inherently penalize the geometric evaluation; for instance, misidentifying columns as walls creates unmatched false positives that directly lower compactness scores. Building on this integrated approach, future research can incorporate dedicated semantic metrics, such as precision, recall, and confusion matrices, to quantify the system's ability to categorize complex indoor components alongside its geometric reconstruction.



(a) (b) (c)

Figure 4. Misalignments and misclassifications (a) Two-storey scanning test with the app yielded misalignments (b) Misclassified columns as walls in the OFF2 dataset (c) Storage detected as doors in the residential dataset

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