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PERFORMANCE EVALUATION OF SMARTPHONE-BASED LIDAR FOR INDOOR 3D MODELLING APPLICATIONS

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Abstract. The increasing availability of smartphone-based LiDAR sensors is providing new opportunities for low-cost indoor three-dimensional (3D) modelling but the geometric accuracy remains a concern. Therefore, this study aims to evaluate the performance of iPhone LiDAR for indoor 3D modelling through a direct comparison with Terrestrial Laser Scanning (TLS) data acquired with a Leica BLK360. Point clouds were registered using the Iterative Closest Point (ICP) algorithm to produce registration residuals of 0.025–0.043 m. The quality of the point clouds was assessed using point density, surface roughness, and eigenvalue-derived curvature metrics. The iPhone LiDAR generated point densities of 485–610 points/m² which was substantially lower than the 2,485 points/m² for TLS and also exhibited higher surface roughness of 0.0116 compared to 0.0019 for TLS. Moreover, curvature values were also higher for iPhone LiDAR at 0.0878 than for 0.0321 for TLS which reflected a reduction in planar stability. Geometric accuracy analysis produced a paired dimensional RMSE of 0.182 m relative to the TLS reference. The Wilcoxon signed-rank test showed no statistically significant difference between the two datasets at the 95% confidence level.

Keywords: smartphone-based LiDAR, indoor mapping, 3D modelling, TLS, low-cost mapping, point cloud accuracy.

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1. Introduction

Three-Dimensional (3D) spatial modelling is currently a critical technology across multiple disciplines, including geomatics, architecture, construction, cultural heritage, and environmental monitoring. The capacity of the technology to capture and reconstruct complex structures in digital form provides invaluable insights for both academic studies and practical applications (Zhao et al., 2023; Buksa et al., 2025). The traditional solutions for high-fidelity 3D data acquisition have depended on Terrestrial Laser Scanning (TLS), which generates dense point clouds with sub-centimeter accuracy (Muralikrishnan, 2021; Shen et al., 2023). This method is constrained by operational challenges despite numerous advantages. For example, the

instruments are costly, heavy, and require skilled operators which makes the use impractical for rapid or resource-limited projects. These constraints have driven studies into more accessible alternatives with a specific focus on consumer-grade Light Detection and Ranging (LiDAR) systems integrated into smartphones and tablets (Çakir et al., 2021; Catharia et al., 2023).

The introduction of LiDAR sensors in the iPhone 12 Pro and iPad Pro models by Apple has increased the interest in evaluating the potential for 3D scanning. These devices use short-range time-of-flight LiDAR sensors which enable rapid scanning of indoor environments (Díaz-Vilaríño et al., 2022; Vacca, 2023). Previous studies such as Teo and Yang (2023) showed the ability of iPad LiDAR to achieve centimeter-level accuracy in indoor mapping tasks.

Comparative evaluations also produced promising but variable results. For example, Askar and Sternberg (2023) tested iPhone LiDAR for low-cost building documentation and reported reliable model reconstruction but with variability depending on the scanning applications. Abdel-Majeed et al. (2024) also confirmed that Apple LiDAR could approximate TLS accuracy for indoor spaces, but discrepancies increased with distance and surface complexity.

The studies on model quality added nuance to the results, and an example was the focus of Łabędź et al. (2022) on the validation of iPad Pro LiDAR against photogrammetry, with the report showing that surface models were generally accurate but limited by lighting and range. Costantino et al. (2022) also identified challenges in urban settings with a specific emphasis on reduced density and noise compared to TLS. These limitations show the need for careful workflow design when using smartphone LiDAR. More recently, systematic accuracy tests have become available and Janicka and Błaszczak-Bąk (2025) reported that the combination of smartphone LiDAR with optimized scanning strategies achieved a low Root Mean Square Errors (RMSE) of 0.012 m after registration against TLS. This reflects the potential of smartphones as low-cost instruments under controlled conditions.

Smartphone LiDAR has been tested in diverse domains beyond architectural applications. For example, Forkuo and Borz (2023) evaluated mobile LiDAR in forestry and Elias et al. (2025) applied the technology to log measurement with acceptable results. Grobler and Celano (2025) also used the iPhone LiDAR in agriculture for reconstructing fruit tree morphology and achieved accuracy suitable for field applications. For heritage documentation, Antón et al. (2025) applied smartphone LiDAR in archaeological and speleological modelling to show the importance for rapid data capture. However, a critical gap persisted with only a few studies observed to have conducted feature-based comparisons between smartphone LiDAR and TLS by evaluating metrics such as surface normals, curvature, and point density. Miller

et al. (2023) also examined the repeatability of smartphone LiDAR scans but the scope was limited to object-level models. Similarly, a heritage-oriented study by Llabani and Abazaj (2024) compared Personal Laser Scanning (PLS) with TLS but did not implement robust statistical validation.

The gap identified is significant because rigorous statistical analysis is required to validate the ability of smartphone LiDAR in serving as a practical alternative to TLS. The evaluations of RMSE, bias, and confidence intervals can establish the reliability of smartphone-based scans, specifically in indoor and confined environments where accuracy thresholds are critical. Therefore, this study aims to bridge the gap by systematically comparing iPhone LiDAR with TLS data under controlled indoor conditions. The focus is on evaluating point cloud features, reconstructing 3D models, and applying statistical tests to assess the differences. The expectation is to contribute towards the democratization of 3D scanning by expanding access to accurate spatial modelling with consumer-grade technology. Although previous studies demonstrated the feasibility of smartphone LiDAR for indoor mapping, most investigations focused primarily on dimensional accuracy or qualitative visualization. Comprehensive evaluations integrating geometric accuracy, feature-based point cloud metrics, statistical validation, and environmental robustness remain limited. Furthermore, few studies have systematically investigated the influence of lighting conditions, trajectory design, and sensor limitations on the reliability of smartphone LiDAR relative to professional TLS systems.

2. Method

2.1. Study area

The experiment was conducted in the Geomatics Engineering Laboratory, Laboratory Building 3, Institut Teknologi Sumatera (ITERA), Lampung, Indonesia as shown in Figure 1. The selected classroom measured approximately

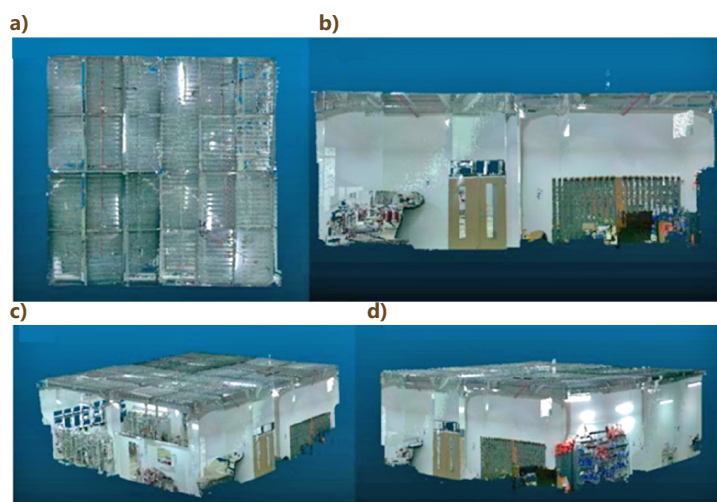


Figure 1. Multi-view visualization of the point cloud model including: a) top view; b) front view; c) left-side view; d) right-side view of the room

10 m × 8 m × 4 m and contained structural elements including walls, doors, and furniture. This setting was preferred because the space represented realistic indoor mapping conditions while remaining controlled to ensure comparability between datasets acquired using TLS and iPhone LiDAR. Figure 1a presents the top view, in which the roof structure is predominantly visible, while Figure 1b shows the front view. Figures 1c–1d present the left and right oblique perspectives.

The laboratory environment consisted of painted concrete walls, ceramic flooring, glass windows, wooden furniture, and metallic objects. The indoor space featured a partitioned, industrial-style layout with semi-open sections, exposed structural elements, and interconnected work areas. Under normal illumination conditions, lighting was supported by both artificial indoor lamps and natural daylight penetration through window ventilation openings. Additional experiments were also conducted in low-light conditions to evaluate sensor performance under reduced illumination. Two enclosed rooms without direct window access were included in the experiments; however, these areas still received sufficient illumination from indoor lighting systems and indirect sunlight penetration from adjacent spaces, allowing adequate visibility during scanning activities.

2.2. Materials, instruments, and data acquisition

The primary dataset consisted of point clouds acquired from the laboratory room and the instruments used were an iPhone 12 Pro Max equipped with an integrated LiDAR sensor and a Leica BLK360 TLS adopted as the reference system. Data were processed using an MSI GF66 laptop (8 GB RAM) while the software environment consisted of Cyclone Register 360 for TLS registration, Polycam Pro for iPhone LiDAR acquisition, and CloudCompare for point cloud analysis. TLS data were acquired using six scan stations to ensure complete coverage of the room and used as a reference dataset for comparison with point cloud data generated from the iPhone LiDAR. The survey for the TLS was conducted using six static scanning stations and the point clouds retrieved were registered using a cloud-to-cloud method which produced a registration error of 9.573 mm with an overall overlap of 37%. Meanwhile, the iPhone 12 Pro Max LiDAR data were collected using a walking-trajectory method with the operator walking along a path at 2–3 m spacing between passes. This acquisition protocol was designed to simulate practical workflows with TLS serving as a static and high-accuracy reference while iPhone LiDAR is the mobile and consumer-grade solution.

2.3. Data processing and registration

TLS point clouds were processed in Leica Cyclone Register 360 for filtering, alignment, and georeferencing into a local coordinate system. This Cyclone Register 360 is widely

used for TLS data preprocessing due to the robustness in scan registration and noise filtering (Abdel-Majeed et al., 2024; Batista et al., 2025). Meanwhile, iPhone LiDAR data were exported in LAS format using *Polycam Pro* and subsequently processed in *CloudCompare* which was the open-source platform commonly adopted for point cloud analysis and comparison (Girardeau-Montaut & Daniel, 2016; Janicka & Błaszczak-Bąk, 2025).

The TLS and smartphone datasets were coordinated using the Iterative Closest Point (ICP) algorithm which minimized the point-to-plane residuals and was particularly suitable for dense 3D point clouds with planar structures (Yuan et al., 2025; Zhu et al., 2025). The objective function is expressed as follows:

$$\min_{R,t} \sum_{i=1}^N \left(n_i^\top (Rp_i + t - q_i) \right)^2, \quad (1)$$

where, R and t represent the rigid body rotation and translation, p_i is a source point, q_i is the corresponding reference point, and n_i is the surface normal at q_i . Registration quality was quantified using the residual Root-Mean-Square Error (RMSE) which the standard indicator of alignment accuracy in TLS–iPhone comparisons (Teo & Yang, 2023; Kovanič et al., 2025):

$$RMSE_{reg} = \sqrt{\frac{1}{N} \sum_{i=1}^N r_i^2}. \quad (2)$$

2.4. Point cloud accuracy assessment

Point cloud quality was evaluated using density, surface normals, curvature, and roughness which collectively captured both geometric structure and local surface fidelity (Weinmann et al., 2015; Janicka & Błaszczak-Bąk, 2025). The calculation of the point density was achieved using the following equation:

$$\rho = \frac{N_{pts}}{A}, \quad (3)$$

where, N_{pts} is the number of points within a grid cell of area A . Another important observation is that density is a critical parameter influencing surface completeness and reconstruction quality particularly for consumer-grade LiDAR systems (Luetzenburg et al., 2021; Kovanič et al., 2025). Moreover, surface normals were estimated using *Principal Component Analysis (PCA)* of local neighborhoods where the eigenvector corresponding to the smallest eigenvalue represented the normal direction (Zhou et al., 2023; Lyu et al., 2024). The curvature was also computed using the eigenvalue-based surface variation as follows:

$$\kappa = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}. \quad (4)$$

The method is widely applied to characterize surface smoothness and structural complexity in point clouds (Milenković et al., 2018; Sadaoui et al., 2025). Furthermore, surface roughness was defined as the Root-Mean-Square

(RMS) deviation of points from a best-fit local plane to provide a quantitative measure of noise and surface irregularity (Mokroš et al., 2021). The combination of the metrics enabled a detailed assessment of spatial fidelity beyond simple dimensional accuracy.

2.5. Statistical validation

The statistical significance of measurement deviations was evaluated using a paired statistical analysis because both TLS and iPhone LiDAR observed the same objects under identical acquisition conditions. The use of paired statistical tests is recommended when comparing two measurement systems that observe the same samples (Montgomery, 2017; Miller et al., 2023). The statistical evaluation employed 15 independent paired measurements, comprising the minimum 12 samples recommended in SNI 8202:2019 for accuracy assessment in relatively small, controlled survey environments, with three additional samples included to improve spatial representation of different geometric features and reduce localized geometric bias in the comparative analysis. Furthermore, the number of measurement points was constrained by the limited spatial extent of the indoor laboratory and the availability of geometrically stable reference features suitable for paired observations. Prior to hypothesis testing, the normality of paired differences was evaluated using the Shapiro–Wilk test, which indicated that the data were not normally distributed ($p < 0.05$). Therefore, a non-parametric Wilcoxon signed-rank test was additionally employed to ensure robustness of the comparative analysis, particularly for small sample observations and non-normally distributed datasets. In addition to hypothesis testing, RMSE was reported as a complementary indicator of geometric accuracy, providing a comprehensive and statistically robust evaluation framework (Teo & Yang, 2023; Janicka & Błaszczak-Bąk, 2025).

2.6. Technical evaluation

The quantitative validation was supported with the testing of the iPhone LiDAR sensor under challenging conditions including low-light scanning, noise assessment on planar walls, and evaluation of missing data near complex geometries. The experiments were conducted to identify practical limitations of smartphone LiDAR in real-world scenarios. The assessment of the conditions strengthens the novelty of this study because few previous efforts have systematically evaluated the technical limits of consumer-grade LiDAR relative to TLS benchmarks.

3. Results and discussion

3.1. Registration accuracy

The comparison of the registration process between the iPhone LiDAR and TLS BLK360 datasets produced residual RMSE values ranging from 0.025 m to 0.043 m. This showed that the consumer-grade sensor produced sufficiently close alignment with TLS data for room-scale mod-

elling but could not achieve a millimeter-level accuracy. The visual inspection of the registered datasets in CloudCompare reflected consistent overlap across principal wall planes but slight discrepancies were observed along furniture edges and window corners. These localized misalignments reflected the lower density and higher noise levels of iPhone LiDAR, which affected fine structural detail. However, the ICP algorithm effectively minimized overall error to show the geometric coherence of the smartphone dataset at the macro level. A previous study by Askar and Sternberg (2023) reported similar ICP performance with deviations of approximately 0.02–0.05 m to confirm the comparability of the present results. In both cases, the error levels were considered acceptable for visualization and preliminary documentation. The trend shows that smartphone LiDAR cannot replace TLS in engineering-grade surveying but is considered a reliable tool for registering indoor datasets at a practical level. The novelty of this study is the systematic quantification of the deviations in a controlled laboratory environment to provide reproducible evidence of the registration performance of consumer LiDAR.

3.2. Point density and completeness

Point cloud density was defined as the number of points generated within a unit area during scanning. For this analysis, point cloud samples were extracted from a $1 \times 2 \text{ m}^2$ area which served as the basis for evaluating and comparing the density produced by both sensing systems. The TLS BLK360 generated an average point density of 2,485 points/ m^2 in Figure 2b while the iPhone LiDAR produced only 485–610 points/ m^2 in Figure 2a across flat surfaces.

The fivefold difference showed the hardware limitation of smartphone LiDAR particularly in larger rooms where the maximum range of $\sim 5 \text{ m}$ led to incomplete surface coverage. Lower density inevitably reduced the detail and produced gaps on flat surfaces and irregular sampling near corners. The dataset showed that sparse coverage was most pronounced along the ceiling and at distances greater than 4 m from the sensor. Despite the reduced density, iPhone LiDAR data successfully captured the major geometry of the room to reflect the suitability for rapid documentation. Comparable density gaps were reported by Kovanič et al. (2025) that smartphone LiDAR consistently produced sparser point clouds than TLS specifically for long-range scans. Janicka and Błaszczak-Bąk (2025) further confirmed that acquisition strategies such as trajectory planning and overlap strongly affected the density results. Under controlled conditions, the density of smartphone LiDAR is sufficient for coarse modelling while acknowledging the limitations in fine architectural applications. The precise quantification of the density difference allows this study to provide more straightforward guidelines on when and how smartphone LiDAR can be adopted in practice.

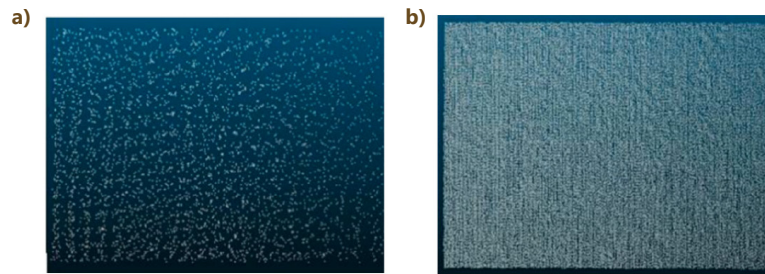


Figure 2. Point cloud density of: a) iPhone; b) TLS

3.3. Surface roughness and noise

Surface roughness and noise were implicitly characterized using eigenvalue-based feature-extraction parameters. The analyses of curvature based on Figure 3a–3b and normal orientation in Figure 4 with a specific focus on surface variation, planarity, and eigen-entropy. As shown in Figures 3a–3b, the surface-variation values derived from the iPhone LiDAR point cloud exhibited greater variability than those obtained from TLS. Similar patterns were observed in the planarity results presented in Figures 3c–3d, as well as in the eigen-entropy distributions shown in Figures 3e–3f. These results indicate higher local surface roughness and noise in the iPhone LiDAR data, particularly on planar surfaces. This behavior is consistent with the lower point density of the iPhone LiDAR data relative to TLS, which reduces the stability of local eigenvalue estimation. However, the statistical test showed that the mean values of all evaluated feature-extraction parameters for the iPhone LiDAR and TLS point clouds were not significantly different at the 95% confidence level.

Figure 3 shows that, based on analysis of the represented point-cloud subsets, the surface roughness of the iPhone LiDAR point cloud is 0.0116, approximately six times the 0.0019 recorded for TLS. This reflects substantially higher noise and reduced planar stability in consumer-grade LiDAR data. Under low-light conditions, the roughness increased to approximately 0.020 which confirmed high sensitivity of iPhone LiDAR to environmental illumination. Furthermore, the eigen-entropy results in Figures 3e–3f indicate greater local geometric disorder in the iPhone LiDAR data than in the TLS data. This degradation affected the planar stability and also increased deviations in edge features. Previous studies by Mokroš et al. (2021) and Janicka and Błaszczak-Bąk (2025) documented similar trend by reporting higher variability in mobile LiDAR under non-ideal lighting conditions. This result contributes to existing literature by quantifying roughness changes in controlled indoor experiments by showing the influence of doubling noise in dim conditions. The quantification is very important because the focus is on a specific operational constraint that is required to be considered when applying smartphone LiDAR in practice. TLS performance remained stable across lighting scenarios but the smartphone sensor showed significant variability. The results emphasized the importance of accounting for environmental conditions during acquisition and reflected the

robustness insufficiency of consumer-grade LiDAR for all indoor mapping contexts.

3.4. Curvature and normal orientation

The analyses of curvature based on Figures 3a–3b and normal orientation in Figure 4 showed distinct differences between the TLS and iPhone LiDAR datasets. The TLS curvature was shown in Figures 4a–4b indices remained close to 0.0321 (avg) to show planar stability of the captured surfaces. Meanwhile, iPhone LiDAR had 0.0878 (avg) which reflected deviations even on surfaces expected to be flat.

The surface normal vectors in Figures 4a–4b derived from the iPhone LiDAR deviated by 0.2177 which was 72% of the ratio from the TLS reference normals. These deviations suggested that consumer-grade LiDAR struggled to maintain surface orientation stability.

The trend was consistent with the observation of Askar and Sternberg (2023) that angular instabilities were identified in iPhone LiDAR scans as well as the emphasis of Teo and Yang (2023) on the influence of trajectory and motion on surface orientation. In practice, the deviations possibly do not have significant effect on general visualization or indoor navigation but limit applications in deformation monitoring or structural health assessment. The novelty added is by systematically quantifying the deviations within a controlled laboratory setting. The evidence confirmed that TLS ensured high stability of surface features but smartphone LiDAR should be used cautiously in applications requiring precise orientation measurements. The results contribute to more nuanced deployment strategies for consumer-grade sensors by identifying the limitations.

3.5. Dimensional accuracy

Dimensional analysis showed that iPhone LiDAR overestimated measurements compared to TLS references with the signed differences ranged from -0.104 m to 0.580 m, while the absolute deviations ranged from 0.003 m to 0.580 m. This systematic bias showed that smartphone LiDAR tended to scale dimensions slightly larger than reality. The modesty but consistency and predictability of the deviations showed the possibility of adopting calibration factors for the correction. A previous study by Elias et al. (2025) also identified overestimation biases in smartphone LiDAR measurements to reinforce the reliability of the results. The systematic overestimation observed in the iPhone LiDAR

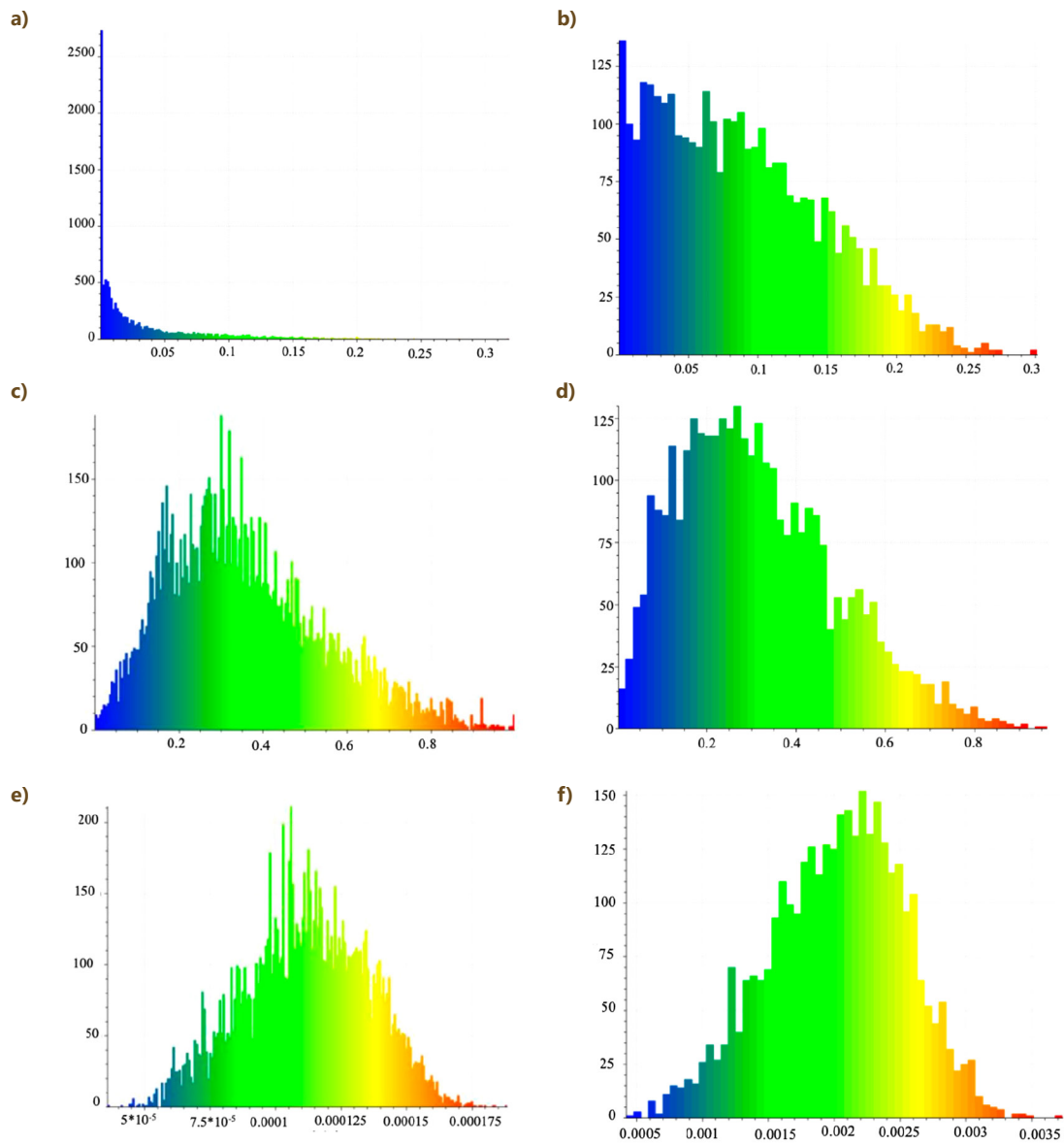


Figure 3. Geometric features of: a) TLS; b) iPhone surface variation; c) TLS; d) iPhone planarity; e) TLS; f) iPhone eigen-entropy

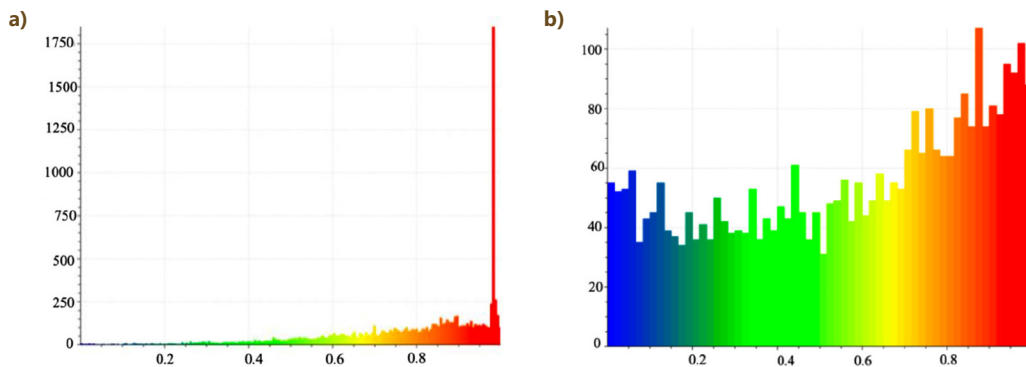


Figure 4. Normal orientation of: a) TLS; b) iPhone

dataset may be attributed to accumulated SLAM trajectory drift, lower sampling density, interpolation within depth estimation algorithms, and instability in surface reconstruction over low-texture or reflective surfaces. The reproducibility of the errors across trials ensured confidence in achieving correction through calibration. The deviations exceeded TLS precision but remained within acceptable margins for visualization, architectural planning, and educational contexts. The novelty of this study is related to the documentation and framing of the systematic bias as a potential strength. The trend was identified from the predictable error that could be mitigated through calibration rather than random noise considered harder to control. This insight enhances the practical applicability of iPhone LiDAR in geospatial workflows.

3.6. Statistical significance of deviations

Statistical test showed subtle differences between TLS and iPhone LiDAR datasets. The trend was observed from the absence of substantial differences in room dimensions for relative accuracy at the 95% confidence level which confirmed the reliability of iPhone LiDAR for gross architectural measurements. The statistical significance of dimensional deviations between TLS and iPhone LiDAR measurements was evaluated using paired observations obtained from identical indoor features. A total of 15 independent paired measurements were used in the analysis, comprising the minimum 12 samples recommended in SNI 8202:2019 for spatial accuracy assessment in relatively small and controlled environments, with three additional samples added to better represent various geometric features, such as wall segments, openings, and vertical elements. The number of observations was also constrained by the limited spatial extent of the indoor laboratory and the availability of geometrically stable reference objects suitable for paired comparison.

Prior to statistical testing, the normality of paired differences was evaluated using the Shapiro–Wilk test. The results indicated that the paired differences were not normally distributed ($p < 0.05$), primarily due to several large deviations in vertical and corner-related measurements. Therefore, a non-parametric Wilcoxon signed-rank test was additionally employed to ensure robustness of the comparative analysis for the relatively small sample size and non-normal data distribution. Table 1 presents the dimensional differences between the TLS and iPhone LiDAR observations. The results show that most measurements exhibited relatively small deviations, with differences generally remaining below 0.10 m, although several larger discrepancies were observed in specific features such as elongated wall sections and vertical dimensions. The largest deviation reached 0.580 m, indicating that certain geometries were more sensitive to smartphone LiDAR instability and reconstruction uncertainty.

Table 1. The paired measurement differences between TLS and iPhone Lidar datasets

No.	Sample size		Difference (m)
	iPhone (m)	TLS (m)	
1	4.479	4.486	0.007
2	11.75	11.983	0.233
3	11.67	11.952	0.282
4	11.265	11.845	0.58
5	1.631	1.688	0.057
6	4.465	4.461	−0.004
7	5.678	5.697	0.019
8	5.572	5.523	−0.049
9	5.667	5.563	−0.104
10	5.615	5.603	−0.012
11	2.084	2.087	0.003
12	4.502	4.573	0.071
13	2.425	2.403	−0.022
14	4.529	4.487	−0.042
15	2.079	2.051	−0.028

The Wilcoxon signed-rank statistical evaluation showed that no statistically significant difference existed between TLS and iPhone LiDAR measurements at the 95% confidence level ($p > 0.05$). These findings indicate that smartphone LiDAR was capable of producing relatively consistent dimensional measurements for general indoor mapping applications despite exhibiting systematic bias and reduced geometric stability compared to TLS. The paired dimensional RMSE calculated from the measurements relative to the TLS reference was 0.182 m. Table 2 summarizes the comparative statistical evaluation between the two datasets. Although several measurements showed larger deviations, most observations remained within acceptable ranges for visualization, rapid documentation, and preliminary indoor modelling applications. However, the results also confirmed that TLS maintained superior stability and consistency, particularly for vertical structures, corners, and small-scale geometric details.

Table 2. Comparative statistical evaluation between iPhone LiDAR and TLS

Statistical Parameter	Value
Number of paired observations	15
Shapiro-Wilk test p-value	0.00063
Distribution characteristic	Non-normal distribution
Wilcoxon test statistic (W)	48.000
Wilcoxon test p-value	0.524
Confidence level	95%
Statistical decision	No significant difference

Table 2 confirmed that there was no statistically significant overall difference between the iPhone LiDAR and TLS measurements. This showed that smartphone LiDAR performed better on larger planar features than on vertical or

small-scale features. Similar observations were made by Miller et al. (2023) who reported higher errors in vertical dimensions during mobile LiDAR acquisition. The adoption of both descriptive metrics and inferential statistics allowed this study to provide a more robust evaluation than previous efforts which often depended solely on descriptive comparisons. The novelty is methodological through the combination of quantitative measures with significance tests to produce more profound insights into feature-dependent biases. The trend emphasizes the importance of customizing smartphone LiDAR adoption to specific measurement needs to ensure reliability in suitable contexts while recognizing the limitations. The observed deviations were primarily attributed to lower point density, SLAM trajectory drift, limited sensor range, and reduced stability of surface reconstruction in the smartphone LiDAR dataset. These factors affected the quality of point cloud generation, particularly in complex geometries and narrow indoor features. Nevertheless, the statistical results demonstrate that smartphone LiDAR still holds considerable potential as a low-cost, portable alternative for indoor spatial documentation, where centimeter-level accuracy is sufficient.

3.7. Low-light performance

The study's results show that iPhone LiDAR exhibits severe performance degradation in low-light conditions, often failing to generate a 3D point cloud as shown in Figure 5. The low-light experiments showed that ambient illumination plays a critical role in determining the performance of smartphone-based LiDAR sensors. Under reduced lighting conditions, the iPhone LiDAR exhibited a substantial degradation in point cloud quality, while the TLS reference remained largely unaffected. Quantitatively, point density generated by the iPhone LiDAR roughness increased by approximately 72% under low-light conditions relative to normal lighting conditions resulting in incomplete surface coverage, particularly in corners, narrow spaces, and areas distant from the sensor. In contrast, the TLS point density and spatial completeness showed no discernible variation, confirming the illumination-independence of professional laser scanners.

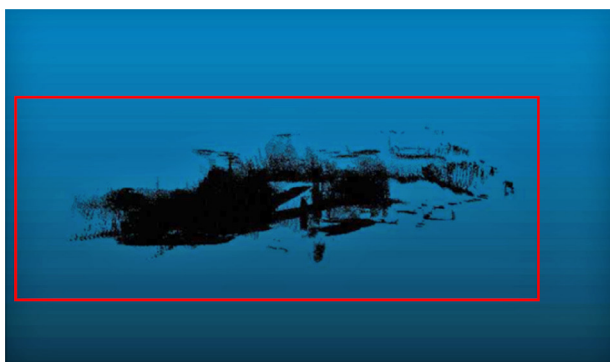


Figure 5. iPhone LiDAR point cloud under low-light conditions

Figure 5 shows emitted laser pulses do not return to the sensor under low-light or no-light conditions due to the absorption by dark surfaces and this prevents accurate distance measurement and surface reconstruction. Meanwhile, TLS maintained consistent density and roughness across illumination conditions. Surface quality metrics further showed the sensitivity of iPhone LiDAR to low-light environments as observed in the increase in roughness from 0.0116 m under normal illumination to approximately 0.020 m in low-light conditions which represented nearly a twofold rise in noise. This elevated roughness manifested as scattered points and irregular planar surfaces which directly affected curvature and normal stability. The degradation was attributed to reduced laser returns and to a lower reliability of the depth estimation pipeline for the sensor when interacting with dark or low-reflectance surfaces. The results were consistent with the report of Zolli and Marconi (2025) on instability in smartphone LiDAR under twilight conditions extended by the quantification of the effect in a controlled laboratory.

The presence of missing data is part of the most critical limitations in iPhone LiDAR point cloud datasets. This was observed from the fact that the smartphone-based LiDAR data exhibited substantial gaps particularly in corners, narrow passages, and regions located beyond approximately 4 m from the sensor. The trend was different from the TLS reference which provided approximately complete surface coverage. The missing areas were due to the fragmented point clouds and incomplete surface representations which compromised the integrity of the reconstructed 3D models. Those identified in corners and reflective surfaces further showed the limitations of the sensor in non-ideal environments as presented in Figure 6.

The results in Figure 5 showed that smartphone LiDAR was not yet sufficiently robust for professional workflows requiring reliability across diverse conditions. However, the novelty of this study is in providing reproducible, quantified evidence of the effects of lighting on indoor performance. The practical perspective showed that the missing data significantly reduced the reliability of smartphone LiDAR for applications requiring complete spatial representation such as precise architectural documentation or deformation analysis. Meanwhile, the gaps could be tolerable for rapid indoor mapping and visualization tasks when supplemented with optimized scanning trajectories or additional lighting. The results generally showed that missing data were a fundamental limitation of consumer-grade LiDAR and reinforced the need for careful acquisition planning and complementary sensing methods where possible.

3.8. Implications

The results confirmed that iPhone LiDAR could not replace TLS for high-precision surveying but served as a practical alternative for rapid and low-cost indoor mapping. The novelty is in the integrated framework designed by combining registration analysis, feature-based metrics, dimen-



Figure 6. Void areas in the 3D point cloud model (Red Box)

sional validation, statistical significance tests, and low-light evaluation. Previous efforts often examined only one or two of these aspects but the current study systematically addressed all in a controlled environment. The observed dimensional deviations observed suggests that calibration can improve the reliability of smartphone LiDAR and echoes the calls for correction models in recent literature (Batista et al., 2025). Moreover, the sensitivity to lighting emphasizes the importance of workflow adaptation such as optimizing trajectories or integrating supplementary illumination. The results show potential for smartphone LiDAR beyond indoor mapping with a focus on education, asset documentation, and augmented reality where centimeter-level accuracy is sufficient. The framing of consumer-grade LiDAR as a complementary tool rather than a competitor to TLS allows the contribution of this study to a balanced perspective in the growing body of geospatial literature. Future study is expected to explore sensor fusion methods that integrate smartphone LiDAR with photogrammetry or inertial sensors to overcome density and completeness limitations.

4. Conclusions

In conclusion, this study systematically compared the performance of the iPhone LiDAR sensor with TLS under controlled indoor conditions. The results showed that TLS consistently outperformed smartphone LiDAR in terms of point density, surface roughness, curvature stability, and dimensional accuracy. However, the iPhone LiDAR produced geometrically coherent point clouds, with a paired dimensional RMSE of 0.182 m relative to TLS and a maximum observed deviation of 0.580 m. The Wilcoxon signed-rank test indicated no statistically significant difference between the paired dimensional measurements at the 95% confidence level. These results show that smartphone LiDAR can capture the general geometry of indoor environments, although TLS provides greater stability for precise dimensional and fine-scale applications. Smartphone LiDAR exhibited an approximately 72% increase in surface roughness under low light conditions, indicating greater point dispersion and noise, reduced planar stability, and lower surface reconstruction quality. The novelty of this study was in the development of an integrated evalu-

ation framework that measured geometric accuracy and also assessed feature-based metrics, statistical significance, and technical resilience under varying conditions. This multi-dimensional assessment was different from previous studies that often examined individual aspects in isolation. Furthermore, the quantification of predictable biases and systematic evaluation of sensor performance in low-light environments allowed the contribution of this study to new insights into both the strengths and weaknesses of consumer-grade LiDAR for indoor geomatics applications.

The limitations identified include the reliance on a single smartphone model (iPhone 12 Pro Max) and testing in a single laboratory environment with the possibility of producing different results across devices, scanning applications, and real-world contexts. The restricted range of ~5 m and lighting sensitivity also limited applicability in larger or outdoor spaces. The quality of smartphone LiDAR acquisition is strongly influenced by operator movement consistency, scanning trajectory design, overlap strategy, and the internal processing algorithms implemented within proprietary applications such as Polycam. However, the predictable error behavior observed in this study allowed calibration-based correction models and workflow optimizations that could expand the usability of smartphone LiDAR in professional practice. From a practical standpoint, smartphone LiDAR was unable to replace TLS for high-precision surveying but served as a low-cost, portable, and user-friendly complement in specific scenarios such as architectural visualization, rapid indoor mapping, educational exercises, and augmented reality applications. This showed that the role was not as a competitor to TLS but a democratizing tool for 3D data acquisition in contexts where centimeter-level accuracy was sufficient. Future studies should explore multi-sensor fusion methods that combined smartphone LiDAR with photogrammetry, inertial systems, or RTK solutions, and develop calibration strategies to correct systematic bias.

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