A SEMI-AUTOMATED SCAN-TO-BIM APPROACH TO FIRE COMPARTMENTATION IN EXISTING BUILDINGS

Jorge Magalhães[1], Rafael Cabral[1], Jéssica Reis[2], Rui Gavina[2], José Aidos Rocha[3], Vaidotas Sarka[4], Tatjana Vilutiene[4], Ricardo Santos[1,5] and Diogo Ribeiro[1,5]
[1]iBuilt, Instituto Superior de Engenharia do Porto, Politécnico do Porto, Porto, Portugal
[2]VN2R-Engineering Innovation Consulting LDA, Porto, Portugal
[3]Exactusensu - Consultores Associados, Lda, Porto, Portugal
[4]Vilnius Gediminas Technical University, Faculty of Fundamental Sciences, Department of Engineering Graphics, Vilnius, Lithuania
[5]CONSTRUCT, Faculdade de Engenharia, Universidade do Porto, Porto, Portugal

Abstract

Fire safety compliance checks in existing buildings are often labor-intensive and prone to error, due to the lack of design data and the reliance on traditional inspection tools. This work proposes an alternative to conventional approaches through a semi-automated Scan-to-BIM methodology to create a BIM model directly from point cloud data. The methodology demonstrates robustness when applied to benchmark datasets. The results confirm the efficiency and accuracy of the methodology in developing early design and BIM models suited to support fire safety engineering and verification of compliance with fire safety regulations.

Introduction

According to the Portuguese National Emergency and Civil Protection Authority (ANEPC – Autoridade Nacionalk de Emergência e Proteção Civil) (Civil, 2024), 6,844 urban fires were confirmed, 603 of which occurred in unoccupied buildings of Portugal. Most of these buildings tend to be old and generally lack digital or even digitized geometrical information. These constraints create significant difficulties on the development of retrofitting projects, as building characteristics are typically obtained using traditional/manual methods that require excessive human intervention. One possible solution to overcome this challenge is the use of remote sensing methods, which enable the creation of point cloud data for generating *as is* geometric information (Oliveira et al., 2023, Ventura et al., 2026). For many building types, e.g. residential, office, or hotel, laser scanning is the standard, as it can accurately capture detailed reality with accurate dimensions in relatively straightforward field campaigns. The obtained raw data is the input for digital models' generation that can be further enriched to create BIM models and digital twins.

Fire safety is a critical aspect of building management, encompassing a comprehensive set of measures aimed at preventing and controlling fires Schönfelder et al. (2024). Among these measures, this work focuses on fire compartmentation requirements, in which a building is subdivided into compartments to isolated occupants and/or confine fire spread, thereby enhancing occupant safety. To address this issue, the present study proposes a semi-automated Scan-to-BIM methodology for generating BIM models promoting the implementation and assessment of fire compartmentation.

The Scan-to-BIM approach has become a prominent research topic in recent years. The scientific community has proposed several methods and alternatives to automate this process, though several approaches are still semi-automated and need manual intervention to identify structural elements (Zbirovský and Nežerka, 2025). The key step of this methodology is the contour extraction process. The point cloud contour extraction of a building seeks to obtain a clear description of the building's geometry, including aspects like shape, size, spatial positioning and internal layout. The existing building point cloud contour extraction methods mainly include image-based methods, geometric feature-based methods, and surface segmentation-based methods (Chen et al., 2025). Image-based methods consist of converting point cloud data into images for processing (Gao et al., 2024, Zbirovský and Nežerka, 2025). Geometric feature-based methods rely on extracting planes and line segments (Wang et al., 2022, Li et al., 2023), where the Random Sample Consensus (RANSAC) algorithm is the most used option for this end. Surface segmentation-based methods can be done by traditional point cloud segmentation strategies (edge detection, graph theory, clustering, hypervoxel) and Artificial Intelligence (AI) techniques (Chen et al., 2026, Mehranfar et al., 2024).

The transition toward full BIM adoption begins with the conversion of these models into the Industry Foundation Classes (IFC) standard, where building elements are explicitly classified into semantic entities and can be further enriched with structured parameters and properties. Zbirovský and Nežerka (2025) developed an open-source Scan-to-BIM tool, named Cloud2BIM, that automates the conversion of large-scale point clouds into BIM models in the IFC format. More recently, Chen et al. (2026) developed a framework that combines deep learning-based semantic segmentation with unsupervised clustering to generate models in IFC from point cloud data. This step is particularly relevant in the fire-safety domain, where Scan-to-BIM workflows are often limited to geometric reconstruction. Converting reconstructed models into IFC enables fire-safety engineers to systematically augment *as is* models with domain-specific information, such as the fire resistance classes of construction elements and the fire reaction classes of linings the fire reaction classes of linings, supporting analysis, compliance verification, and decision-making processes.

Based on these findings and considering the diversity of building typologies, the automated generation of BIM models from existing buildings continues to be a prominent research topic and remains a challenging task. Moreover, point cloud data acquisition in buildings that are still in service often results in increased noise levels and incomplete geometric information, which can adversely affect the robustness of Scan-to-BIM frameworks. In the fire safety domain, the availability of BIM models for existing buildings can significantly enhance fire safety analyses, particularly in the assessment of compartmentation, where retrofit interventions may alter the original geometric layout.

The present work proposes a semi-automated Scan-to-BIM approach suitable for retrofit projects. The resulting digital models provide a semantic volumetric representation of the building structure at schematic design level, corresponding to a Level of Development (LOD) 200 (American Institute of Architects and buildingSMART International), and are intended to support decision-making processes related to fire compartmentation requirements. The conversion of point cloud data into BIM is evaluated using the IFC format, with a specific focus on the entities IFCSpace, IFCWall, and IFCSlab.

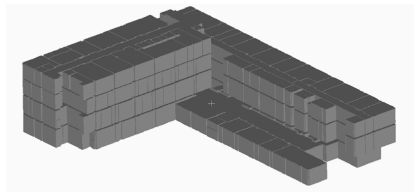
Proposed Methodology

The methodology is structured by four main steps, as shown on Figure 1. The step-by-step explanation will be illustrated by its implementation on a synthetic dataset composed of a part of Vilnius Gediminas Technical University (VILNIUS TECH). This data is characterized as an early design BIM model similar to indoor point clouds of empty buildings. The development was based on Python algorithms and applicable to multi-level Manhattan-world structures (Mehranfar et al., 2024).

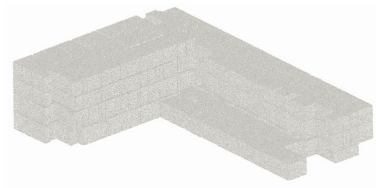
Point cloud acquisition and registration

Point cloud acquisition and registration is characterized by transferring information from the real world into an available digital format. Terrestrial laser scanning (TLS) is typically the most suitable method for acquiring indoor point clouds. Normally, this procedure is performed in the proprietary software of the scanner brand used.

In the case of synthetic data, acquisition is performed through mesh disassociation, where a 3D model is converted into a point cloud based on a specified point density or number of points. Figure 2 presents the case study that supports the results of the application of the proposed framework.



a)



b)

Figure 2. VILNIUS TECH: a) Early design BIM model; b) point cloud.

Point cloud processing

Point cloud processing begins with a global reorientation of the dataset based on the clustering of estimated surface normal vectors. Surface normals were computed using a KD-tree–based hybrid neighborhood search, combining k-nearest neighbor (KNN) and radius-based criteria. Subsequently, the estimated absolute normal vectors were grouped using the k-means clustering algorithm.
The resulting clusters represent dominant surface orientations within the point cloud and are used to infer a consistent global orientation of the dataset. This procedure guarantees that the point cloud is centered and aligned with the orthogonal axis, which prevents aleatory

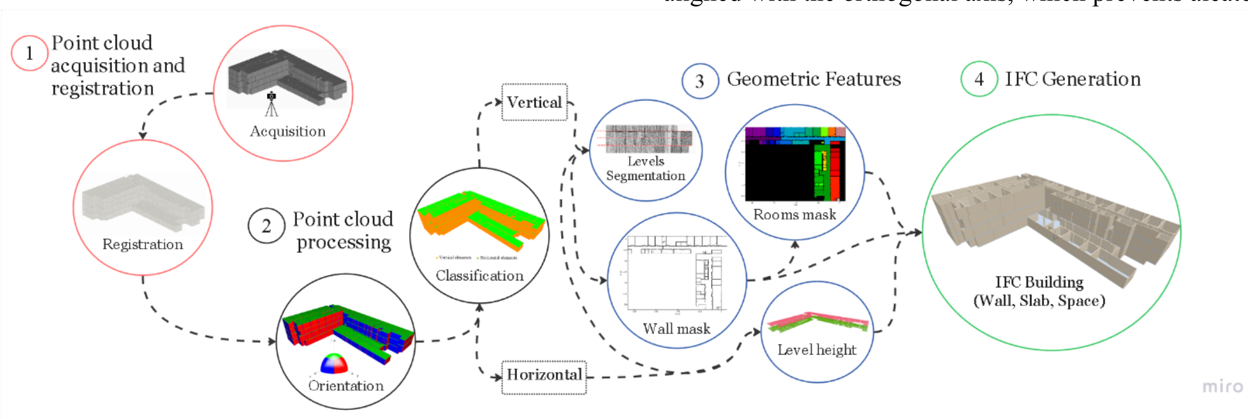


Figure 1. Flowchart of proposed methodology

position of the data in 3D space facilitating subsequent steps. The aligned point cloud is subjected to a second normal estimation stage to enable geometric classification into vertical and horizontal elements, as illustrated in Figure 3. After classification, a statistical outlier removal filter and a voxel downsampling is applied to clean each point cloud and eliminate spurious points.

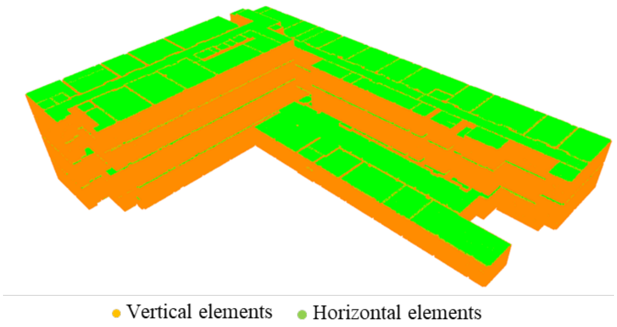


Figure 3. Point cloud classification.

Geometric Features

To automatically identify building storey levels, a height-based segmentation is performed using the vertical-point subset of the point cloud. Local minimum of a smoothed density function are used as cut elevations by two consecutive height intervals. After determining the set of level boundaries, each input point cloud class (e.g., vertical, horizontal) is segmented per level. On real point clouds, the quantity of noise can hinder the acquisition of entire contours of the existing rooms. On this work, the contour extraction for synthetic data is acquired from a z section of the vertical point cloud. Further ahead, on the Experimental analysis and discussion section, this extraction will be presented in more detail.

The point cloud contour extracted is given by:

$$\mathcal{P} = \{(x_k, y_k, z_k)\}_{k=1}^{N} \tag{1}$$

Where (x_k, y_k, z_k) represent the coordinate points of the point cloud contour then transformed into a 2D occupancy grid by discretizing the horizontal spatial domain into square cells of fixed resolution r. Each point projected onto the horizontal plane, and the grid cell c_{ij} is considered occupied (wall) if the number of projected points falling inside the cell (p_i) exceeds a predefined threshold τ:

$$c_{ij} = \begin{cases} 1, if\ p_{ij} \geq \tau \\ 0, otherwise \end{cases} \tag{2}$$

This procedure yields a binary wall mask that is robust to noise and suitable for image-based operations. These operations ensure that wall regions form coherent, topologically closed boundaries suitable for spatial reasoning. From the refined wall mask, a complementary free-space mask is obtained by logical inversion. To distinguish interior spaces from the exterior environment, a border-seeded flood fill is applied. This step guarantees that only enclosed regions bounded by walls are considered as candidate interior spaces. Therefore, a vectorization stage is applied to transform room masks into polygonal room boundaries (Figure 4), which can subsequently be extruded into 3D solids and IFCSpace.

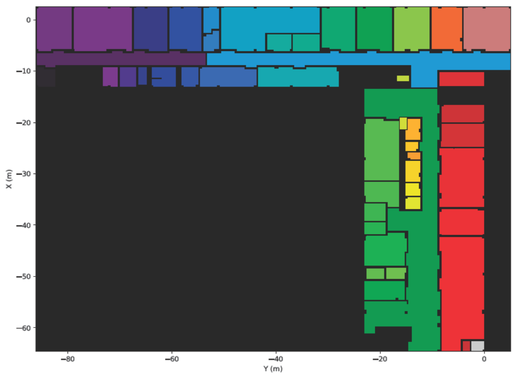


Figure 4. Room mask.

The binary regions are vectorized into metric polygons by enumerating boundary edges of occupied cells and colinear vertices are removed to yield simplified orthogonal loops. Ultimately, to mitigate corner gaps caused by discretization and later wall thickening, segments connected at junction endpoints are extended by half the nominal wall thickness, improving closure when generating IFCWall.

For level height, the RANSAC algorithm is applied on the horizontal point cloud to characterize the level. These geometric features are used to set the height of IFCSpace and to generate IFCSlabs.

IFCBuilding generation

The IFC generation was implemented using the ifcopenshell library. This stage instantiates a schema-compliant IFC4 spatial hierarchy (IfcProject–IfcSite–IfcBuilding–IfcBuildingStorey). For each storey, elements are positioned through hierarchical IfcLocalPlacement, ensuring consistent coordinate handling. The reconstructed 2D room boundaries are converted into IfcPolyline-based closed profiles and extruded along the +Z direction to form IfcSpace solids with a fixed height extracted from horizontal point cloud classification. Wall and slab elements are generated analogously by extruding closed profiles into IfcWall and IfcSlab solids; slabs are placed with a negative Z-offset so that their top surface coincides with the storey elevation, except on the first floor. As a result, a structured and information-rich IFC model is created, enabling BIM-based analysis, as can be observed in Figure 5.

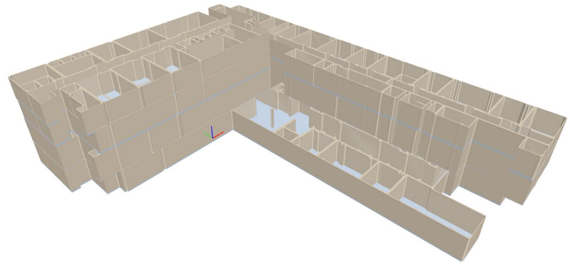


Figure 5. BIM model generated

Experimental analysis and discussion

This section presents the application of the proposed methodology to three public TLS datasets. The input point cloud, the resulting early design model and BIM model,

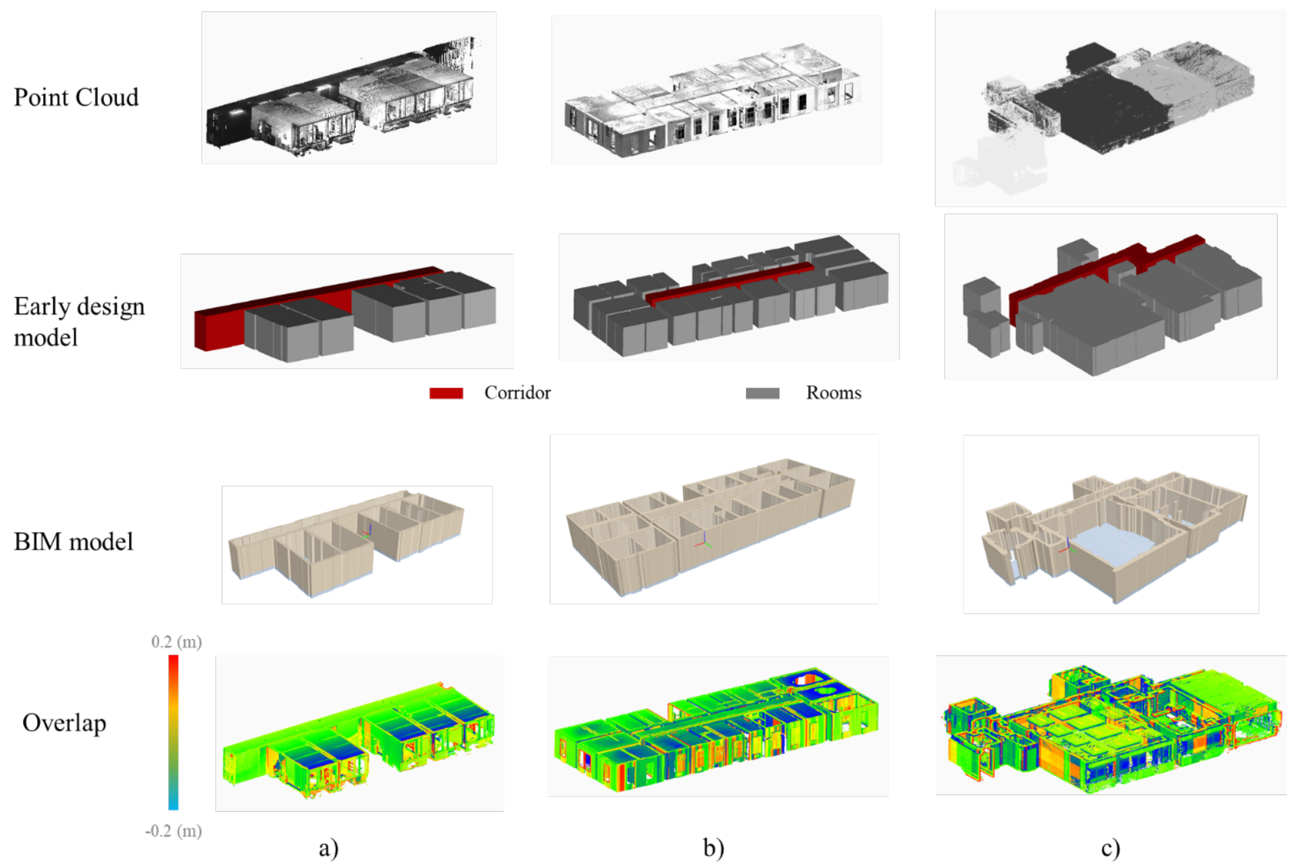


Figure 6. Experimental analysis of proposed methodology on real point clouds: a) University of Zurich (room3); b) Kladno railways station and c) University of Melbourne.

as well as the corresponding overlap results are shown in Figure 6.

For this type of data, the noise level of the point cloud has a significant impact on the contour extraction stage and consequently on the final result. To account for the diversity of building geometries, several trials were conducted to obtain contours that are both as clean and as complete as possible. In addition to vertical and horizontal surfaces, an inclined point cloud was extracted from the normal-based classification, comprising points whose unit normal vectors fall outside the predefined angular thresholds used to distinguish vertical and horizontal elements. This subset mainly represents transitional regions between horizontal and vertical surfaces and can reveal space-level separations.

Regarding the results obtained from the public datasets, the case studies of the University of Zurich (University of Zurich) (Figure 6a) and Kladno station (Urban, 2024) (Figure 6b) presents a good accuracy across most elements, achieving a mean distance of 0.059 m and 0.048 m, respectively. Nevertheless, variations in ceiling heights are visible. When the methodology was applied to a more complex dataset, such as the University of Melbourne case (Khoshelham et al., 2017) (Figure 6c), a reduction in performance was observed by a mean distance of 0.136 m. This dataset exhibits a higher noise level and includes a room that is not fully orthogonal, revealing limitations of the current approach. These results highlight the need for additional filtering of the extracted segments and for the generation of cleaner and smoother wall masks.

Contour extraction is therefore identified as the most critical stage of the entire process and remains the focus of ongoing research, with the objective of developing a method capable of handling a wider range of building typologies.

For the fire compartmentation evaluation, the early design model was manually modified to differentiate corridor spaces from rooms. This initial semantic distinction establishes the foundation for subsequent enrichment of the BIM model, particularly enabling the association of corridor-adjacent walls with fire-rated elements and supporting the definition of evacuation routes.

The proposed methodology ensures scalability and interoperability by transitioning from manual classification to a fully automated space classification framework, which builds on both property-based and relationship-based modeling strategies within the IFC schema.

At the property level, individual spaces (IfcSpace) may be enriched through dedicated property sets, such as Pset_SpaceCommon and Object Type, which explicitly encode whether a space is classified as a private room or a circulation area. This approach ensures compatibility with common BIM authoring and analysis tools while enabling straightforward querying and filtering operations. Complementarily, a higher-level semantic grouping can be established through the use of IfcSpatialZone entities, allowing spaces to be aggregated into functional zones. This relationship-based structuring enhances the model’s capacity to support fire safety analyses, including compartmentation logic, evacuation route modelling, and accessibility assessments, while preserving flexibility for multi-criteria classifications.

The transition towards automated classification is supported by a topology-driven strategy based on spatial adjacency. In this context, each space identified in the room mask (Figure 4) will be evaluated according to its connectivity with neighbouring spaces, derived from shared boundaries. Spaces exhibiting a number of adjacent connections above a predefined threshold will be interpreted as circulation elements (e.g., corridors or transitional zones), whereas spaces with limited connectivity are classified as enclosed functional units (e.g., rooms or offices). This graph-based interpretation of the spatial structure aligns with the inherent relational nature of the IFC schema and enables the derivation of higher-level semantic information from purely geometric and topological inputs. Furthermore, such an approach supports extensibility towards more advanced classification criteria, including geometric properties, accessibility patterns, or integration with external ontologies and classification systems.

Conclusions

The lack of architectural designs, detailed floor plans and 3D models for older buildings is a significant challenge in Portugal. To address this problem, this work presents a semi-automated scan-to-BIM methodology designed to support fire safety analysis in retrofitting projects.

The proposed methodology was first developed and described using a synthetic dataset and was subsequently validated on three different real-world point clouds from benchmark datasets. The results demonstrate the methodology's sensitivity when applied to noisy data, where the generated BIM models may contain irregularities. Nevertheless, validation across multiple datasets highlights the framework's primary advantage: its robustness and adaptability to diverse real-world conditions.

Conducted within the scope of the FireBIM project, this work provides a foundational contribution to fire safety analysis, specifically in assessing compartmentation within existing buildings. Furthermore, the resulting early-design model can be utilized to assist in planning fire safety evacuation routes, such as checking evacuation distances, width of exits and stairways, and determining the number of exits based on the capacity of the building's premises.

Future work will focus on developing more robust strategies for extracting accurate spatial contours from dense and noisy point clouds. This step is identified as critical to the entire workflow, as incomplete contours prevent the generation of successful BIM models. Moreover, an automated approach for BIM model enrichment will be incorporated, aimed at ensuring compliance with evacuation and compartmentation requirements. Additionally, the automated characterization of key building elements, such as stairs, doors, and openings, will be investigated to support connectivity modelling and fire safety analysis.

Acknowledgments

This work has been funded by the NORTE 2030 Programme through the European Regional Development Fund (ERDF), under project FireBIM, reference NORTE2030-FEDER-00358400. Also, this work was supported by: UID/04708/2025 and https://doi.org/10.54499/UID/04708/2025, of the CONSTRUCT - Instituto de I&D em Estruturas e Construções - funded by Fundação para a Ciência e a Tecnologia, I.P./ MECI, through the national funds.

References

American Institute of Architects and Buildingsmart International. Level of Development (LOD) Specification [Online]. Available: https://bimforum.org/resource/lod-level-of-development-lod-specification/ [Accessed 2026].

Chen, T., Wang, H., Li, D., Liu, J., Liu, P., Wu, Z., Xu, C. & Zhang, M. (2026). An automated framework for converting point cloud data to building information modeling with segmentation and refinement. Engineering Applications of Artificial Intelligence, 163, 112915, https://doi.org/10.1016/j.engappai.2025.112915

Chen, X., Mao, J., Zhao, B., Tao, W., Qin, M. & Wu, C. (2025). Building contour extraction from hypervoxel growth point cloud surface neighborhood azimuth geometric features. Journal of Building Engineering, 101, 111914, https://doi.org/10.1016/j.jobe.2025.111914

Civil, A. N. D. E. E. P. (2024). Anuário ANEPC [Online]. Available: https://prociv.gov.pt/pt/documentacao/anuario-de-seguranca-contra-incendio-em-edificios-2024/ [Accessed 2026].

Gao, X., Yang, R., Chen, X., Tan, J., Liu, Y., Wang, Z., Tan, J. & Liu, H. (2024). A New Framework for Generating Indoor 3D Digital Models from Point Clouds. 16, 3462,

Khoshelham, K., Díaz Vilariño, L., Peter, M., Kang, Z. & Acharya, D. (2017). THE ISPRS BENCHMARK ON INDOOR MODELLING [Online]. Copernicus Publications. Available: https://isprs-archives.copernicus.org/articles/XLII-2-W7/367/2017/ [Accessed XLII-2/W7].

Li, F., Shi, W., Tu, Y. & Zhang, H. (2023). Automated methods for indoor point cloud preprocessing: Coordinate frame reorientation and building exterior removal. Journal of Building Engineering, 76, 107270, https://doi.org/10.1016/j.jobe.2023.107270

Mehranfar, M., Braun, A. & Borrmann, A. (2024). From dense point clouds to semantic digital models: End-to-end AI-based automation procedure for Manhattan-world structures. Automation in Construction, 162, 105392, https://doi.org/10.1016/j.autcon.2024.105392

Oliveira, R., Ribeiro, D., Oliveira, P. & Gavina, R. (2023). Laser Scanner in Construction Quality Control of Steel Industrial Buildings. 28, 04023055, doi:10.1061/PPSCFX.SCENG-1389

Schönfelder, P., Aziz, A., Bosché, F. & König, M. (2024). Enriching BIM models with fire safety equipment using keypoint-based symbol detection in escape plans. Automation in Construction, 162, 105382, https://doi.org/10.1016/j.autcon.2024.105382

University of Zurich. VMML, ETH Zurich Office3 Point Cloud Dataset [Online]. Available: https://www.ifi.uzh.ch/en/vmml/research/datasets.html [Accessed 2026].

Urban, R. (2024). Cloud2BIM benchmark point cloud dataset [Online]. Available: https://zenodo.org/records/14221915 [Accessed 2026].

Ventura, J., Magalhães, J., Jorge, T., Oliveira, P., Santos, R., Cabral, R., Araújo, L., Moreira, R. F., Oliveira, R. & Ribeiro, D. (2026). Geometric Monitoring of Steel Structures Using Terrestrial Laser Scanning and Deep Learning. 26, 831,

Wang, Q., Zhu, Z., Chen, R., Xia, W. & Yan, C. (2022). Building Floorplan Reconstruction Based on Integer Linear Programming. 14, 4675,

Zbirovský, S. & Nežerka, V. (2025). Open-source automatic pipeline for efficient conversion of large-scale point clouds to IFC format. Automation in Construction, 177, 106303, https://doi.org/10.1016/j.autcon.2025.106303