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Time-Benefit Analysis of Semiautomatic 3D Laser Scanning for BIM-based Facility Management

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ABSTRACT

Background and Aim: As-built data and knowledge of building structures are crucial for effective facility management (FM). Building Information Modeling (BIM) models offer the opportunity to integrate information from digital building models into FM systems, without information loss. Data acquisition methods include 3D modeling and point cloud-based 3D laser scanning. While modeling point clouds in BIM software manual can achieve precise results, the process is time-intensive. Semi-automated modeling that relies on AI-based software can contribute to as-built data acquisition and modeling with reduced time and personnel requirements, known as semi-automated. Therefore, this paper aims to investigate the efficiency and limitations of integrating AI with BIM for FM, comparing manual and semi-automatic modeling approaches.

Methodology: Manual modeling based on point clouds is conducted before a semi-automatic classification is performed. The generated data models are then quantitatively evaluated for the required time for each measurement size and qualitatively evaluated concerning the accuracy.

Results: The analysis illustrates that semi-automated modeling methods are particularly efficient for standardized and even historical buildings by a 65% faster data generation than manual building modeling. The results are proven by valid data.

Originality: The investigation compares manual and semi-automatic modeling approaches. Evaluating time requirements and qualitative criteria provides a practical framework for decision-makers.

Practical or Social Implications: The study offers insights for decision-makers in FM and related fields to make informed decision-making about modeling methods, contributing to process optimization by integrating modern technologies. Based on the results obtained, stakeholders receive a neutral approach backed up by valid key figures, providing a solid basis for future decisions in connection with data collection.

Type of paper – full technical paper.

Keywords: as-built data acquisition, AI-based building modeling FM, cost-benefit analysis, new technologies, 3D laser scanner

INTRODUCTION

Facility Management (FM) operates at the crossroads of several disciplines within the real estate sector, encompassing tasks in the infrastructural (such as catering, cleaning, or gardening), technical (such as repair and maintenance), and commercial sector (such as contract management or budgeting) (GEFMA e.V. Deutscher Verband für Facility Management, 2004). The execution of these tasks is referred to as facility services (FS). It requires various data to carry out and maintain the multidisciplinary activities of all building life cycle phases as part of its integrated processes (Gouda Mohamed et al., 2020;

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Wildenauer et al., 2022; Wills & Bartels, 2022). The demand for data in FM has become increasingly important in the era of digital transformation, where the real estate sector is undergoing a paradigm shift with essential roles played by the Internet of Things (IoT), Building Information Modeling (BIM), Building Automation Systems (BAS), and Artificial Intelligence (AI) (Atta & Talamo, 2020). Digitalization has become critical in enhancing operational efficiency and data-driven strategies, and BIM has become a crucial tool in the FM sector especially. By creating, storing, and exchanging data in a digital form, BIM represents buildings and elements, enabling a holistic view of their life cycle and a collaborative way of working (Boje et al., 2020). Moreover, building information models allow the transfer of semantic information from the model to selected building operation systems, such as Computer-Aided Facility Management (CAFM) systems, without information loss (Bender et al., 2018). Nevertheless, the use of BIM in FM is limited to less than 1 % of all new and existing buildings in the international context (GEFMA e.V. Deutscher Verband für Facility Management, 2019), whereby the advantages of BIM are most apparent during the planning and construction phases of new buildings.

In contrast, the existing built environment poses a challenge, with many as-built structures and data that are not yet available in digital form, requiring attention for effective FM processes. Even though a valid statement about non-digitalized existing areas in Germany (and consequently, lack of digitally available data) cannot be made due to a lack of data foundation, there are approximately 7.27 billion square meters of existing space (approximately 3.84 billion square meters of residential and 3.5 billion square meters of non-residential buildings) that are not (BIM-based) digitally planned and constructed, thus lacking a digital data basis (Hörner et al., 2022; Statistisches Bundesamt (Destatis), 2022). As mentioned above, a digital representation of building geometry and characteristics not only forms the initial basis for the digitization of buildings but also serves as a data foundation for execution plans and FM (Bartels, 2020).

As Tezel and Giritli (2023) highlight, there has been a notable emphasis on automatic methodologies of data generation such as two-dimensional (2D) imaging (Bhatla et al., 2012; Hong et al., 2020), photogrammetry (Braun & Borrmann, 2019; Xu & Stilla, 2021), or three-dimensional (3D) laser scanning (Hu et al., 2021). This trend departs from conventional approaches relying on visual inspection, and extensive manual data collection and document analysis. Among the various data types used in these advanced methods, 3D point clouds derived from laser scanning and multiview stereo vision have gained widespread acceptance and application across a variety of scenarios (Skrzypczak et al., 2022).

The manual process of converting raw data into usable data for FM is time-consuming and impractical, maily due to the subjectivity involved. Moreover, automated procedures can handle a substantial volume of data quickly, enhancing efficiency (Borisov et al., 2022). For instance, scan-to-BIM processes efficiently handle large volumes of data obtained from survey sources, including point clouds, by utilizing laser scanning or photogrammetry to capture data and then processing it through 3D modeling (Croce et al., 2023).

Various of software tools are available to support transforming point cloud data into BIM software, commonly known as semi-automatic modeling. While some software is independent of the manufacturer, others rely on the laser used for the scan process. Additionally, different software employs varying calculation methods, such as filtering, transformation, meshing, or classification (Gao et al., 2016). However, despite the advantages of semi-automatic processes in modeling point clouds in BIM, there is a lack of concrete evidence regarding time savings, and manufacturer specifications are often relied upon.

This study aims to investigate the efficiency and limitations of integrating an AI-supported model with BIM for facility management, comparing manual and semi-automatic modeling approaches. The paper is organized as follows: Section 2 provides information on different types of building modeling for facility

management. Section 3 presents a case study illustrating the various steps involved in the reconstruction approach (methodology). Section 4 presents and discusses the results, while Section 5 concludes the study and identifies potential areas for future development.

BIM-BASED DATA GENERATION FOR FM IN EXISTING BUILDINGS

Traditional methods for acquiring (geometric) as-built data involve using tools like laser distance meters, digital cameras, and measuring tapes. In this approach, dimensions of building components such as walls, windows, and doors are manually measured and recorded. The process is labor-intensive, time-consuming, and error-prone field surveying work (Anil et al., 2011; Klein et al., 2012). Furthermore, as data sets are typically interpreted manually, they must be electronically integrated into the project design and schedule (Akinci et al., 2006). In addition to the mentioned instruments, trained personnel is required, capable of working with modeling software such as Autodesk Revit.

An industry-used method is the scan-to-BIM-procedure that concentrates on converting available survey data, such as point clouds, into BIM (Rocha et al., 2020; Volk et al., 2014). Scan-to-BIM processes exists of three steps as shown in Figure 1.

Figure 1: Process of scan-to-BIM (source: created by authors)

In a first step, data become captured through laser scanners using point clouds or photogrammetry (Croce et al., 2023). Point cloud generation using a LIDAR (Light Detection and Ranging) or LADAR (Laser Detection and Ranging) sensor describes a contactless Time of Flight (TOF) measurement technique. Fundamentally, a distinction is made between the direct and indirect TOF methods. In direct TOF sensor measurement, the elapsed time between sending a light pulse, its reflection, and its return to the sensor is measured. The elapsed time and the distance between the object and the sensor are proportional, allowing for mathematical determination of the distance. In the indirect TOF measurement technique, distance is determined through the phase shift of the reflected and transmitted light. In the next step, the generated data become processed, which means that semantic descriptions for the objects within the unstructured point clouds are added (Rocha et al., 2020). Point clouds are an aggregation of individual measurement points, each receiving X, Y, and Z coordinates. This multitude of points within a vector space collectively forms a spatial structure known as a point cloud (Che et al., 2019). Last, the 3D modeling takes place (Croce et al., 2023). Depending on the available resources, the scan-to-BIM modeling can occur either manually or semi-automatically.

Manual scan-to-BIM process

General approaches of scan-to-BIM primarily involve manual processes, requiring visual recognition and manual tracing (evaluation) of building components from a point cloud (Croce et al., 2023). The process of evaluating point clouds is done manually by visually aligning point clouds with the building components within CAD software. Individual points within point clouds can also be used as anchor points to fix the orientation line of building elements, ensuring that the point cloud and building

component almost completely overlap in specific locations. The process is manual, as each anchor point of a building component is manually placed on the referenced point cloud. Distorted components in the existing structure must be accurately represented by the inserted 3D objects in the CAD software. The accuracy of the adaptation process of the 3D model to the referenced point cloud depends on the drafter and the predefined parameters that must be adhered to during modeling. As additional support for the alignment with the point cloud, the images captured by the 3D scanner can be used. The color and image data captured by the scanner can clarify any unclear technical relationships that cannot be derived from the point cloud. Several literature reviews, such as those by Volk et al. (2014), López et al. (2018), Logothetis et al. (2015), or Tang et al. (2010) prove that manual methods, while extensively established, result in time-consuming and labor-intensive processes. Responsible staff has to provide a manual identification, isolation, and reconstruction of each class of building elements, which requires time (Volk et al., 2014). Moreover, the process of manual modeling is subjective-oriented, as the result is based a) on the skills of the modeler and b) on the knowledge of the classification. Therefore, a risk of subjective decision-making within the classification exists (Xiong et al., 2013).

Semi-automatic scan-to-BIM process

In manual modeling, professionals typically remodel the individual points of a point cloud into components and classify them, which means that modeled building elements are assigned to a component class, such as walls, windows, or floors. The software partially classifies the point cloud imported into the CAD or BIM software in semi-automatic modeling. The term "semi" refers to the fact that the model is not entirely automatically created but that components must first be selected, and the software then provides a classification proposal. Core challenges in defining semi-automated methods lie in identifying and labeling data points on raw point clouds corresponding to specific building elements (e.g., windows, columns, walls, roofs) (Tang et al., 2010). Different strategies of semi-automatically scan-to-BIM process exist, such as primitive fitting methods, mesh-reconstruction methods, reconstruction by shape grammar and object libraries, or reconstruction by generative modeling (Croce et al., 2023). Primitive fitting methods use robust estimation of elementary parameters to fit basic geometries like planes, cylinders, and spheres to sets of points in the locations. Commercial solutions, such as “EdgeWise Building” by ClearEdge3D (clearedge3d.com) or “Scan-to-BIM Revit plug-in” by IMAGINiT Technologies (imaginit.com), utilize primitive fitting methods for semi-automatic recognition of walls, slabs, and pipes. Primarily applied in indoor environments (Jung et al., 2014; Previtali et al., 2014), these methods effectively detect building elements like floors and walls. However, shape extraction and BIM conversion are constrained to simple geometries with standardized dimensions, limiting their applicability to building structures with diverse forms and types (Macher et al., 2017).

Mesh-reconstruction methods involve reconstructing a mesh for each building component or group from the original point cloud using triangulation techniques. While 3D textured meshes can be converted into BIM objects, mesh manipulation, and geometric modification limitations exist, as the mesh models lack editability and parametric control (Yang et al., 2018).

Reconstruction via shape grammar and object libraries involves creating 3D libraries of architectural elements (families) to handle the complexity of materials and components in historic architecture (Baik, 2017).

Last, reconstruction by generative modeling involves guiding reconstruction through formalizing architectural knowledge, using visual programming languages (VPLs) to program geometric manipulations interactively. Tools like Grasshopper (for Rhino3D) and Dynamo (a Revit plug-in) are standard for new buildings, whereas VPL is less used for as-built buildings (Croce et al., 2023).

Automated (fully) modeling is not considered in this paper, as this method is still a challenge in the literature and has yet to be sufficiently scientifically tested (Jäkel et al., 2023). Reasons for this include the lack of publicly available training data sets of heterogeneous building elements and components that cover a variety of inventory scenarios (Schlenger et al., 2023).

RESEARCH METHODOLOGY

The integration of 3D laser scanners with AI-driven software in the real estate sector necessitates a thorough examination of their time-effectiveness. This evaluation is crucial for making informed decisions regarding optimal FM practices. The primary goal of this study is to assess the potential improvement in modeling efforts through the practical application of semi-automated classification in the modeling of as-built models using software. The methodological approach employed in this study is outlined in Figure 2.

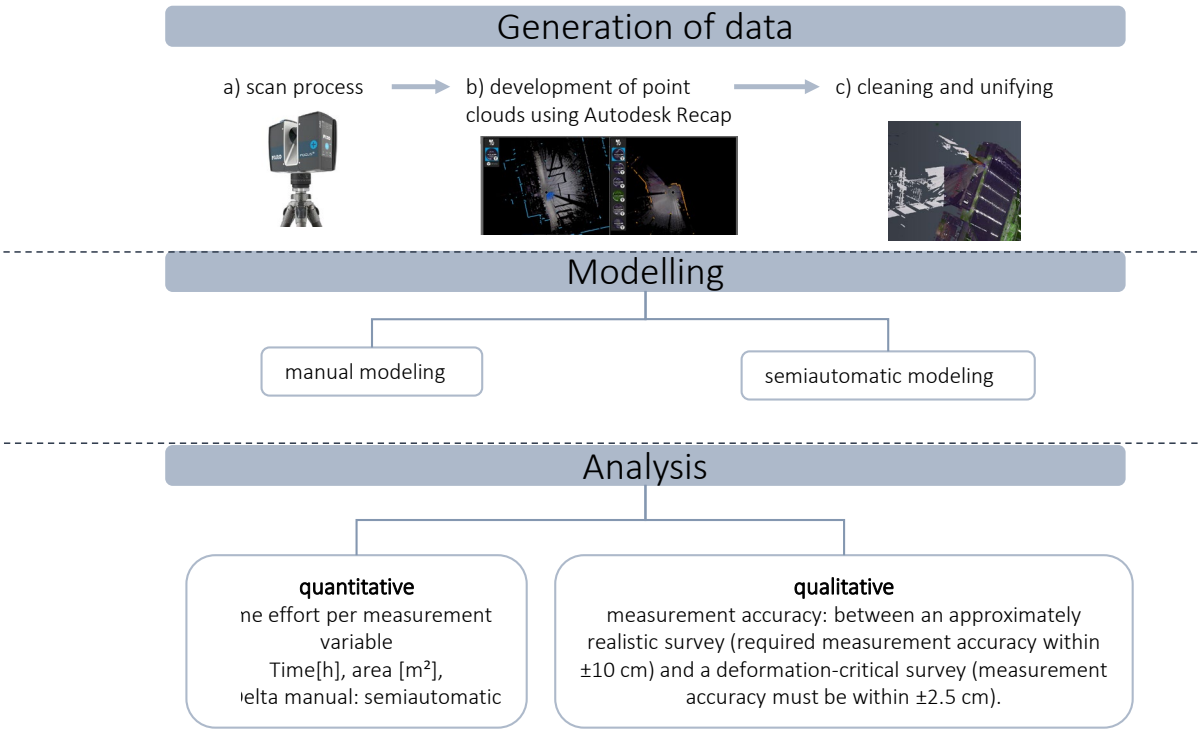

Figure 2: Methodical approach (source: created by authors)

Step 1: Generation of data

The initial preparatory step divided the data generation process into three sub-steps. The Faro Laser Scanner Focus 3D S was utilized to create point clouds. During an automated scanning step sequence, the scanner captures measurement points with a 300° vertical field of view and a 360° horizontal field of view. The scanner is equipped with a built-in optical emitter and a deflecting unit that can orient itself in any direction through a two-axis rotation. The scanner captures both black-and-white and color scans. Color scans capture exterior and facade scan points with an outer 4x recording profile. In contrast, black-and-white scans are used to conduct interior and confined space scans using the inner 4x profile. Scanning was conducted on 12 buildings in the Middle Hesse region of Germany, characterized as historical or existing structures built as half-timbered buildings. It is acknowledged that deformations in historical properties are inherent in the region of Middle Hesse, presenting novel challenges for surveying endeavors. This research extends beyond examining conventional warehouses or model

homes typical of new construction. Instead, the focus lies on the assessment of urban properties currently vacant, which harbor considerable potential for conversion into valuable residential spaces.
In the next step, point clouds were developed by processing the scanned data using Autodesk ReCap® registration software. The software merges the individual scan positions to generate a structured point cloud with interconnected panoramic views. The point-to-point (P2P) distance of individual scans in Recap was set to 6mm by default. The scaling process involves automatic distance detection by the laser scanner, with a 1:1 scaling factor applied in Recap. Any ambiguity surrounding this process requires clarification. The data were consolidated and cleaned in the third substep to optimize the computational resources during processing and analysis. During the capture process, insignificant points and errors described as "ghosts" are identified alongside important distance points to the object and neighboring structures. Ghosts result from laser reflection off reflective surfaces, such as mirrors, glass, reflective coatings, and smooth surfaces, such as metals. Although ghosts can be reduced with matte sprays, they remain unavoidable in an efficient workflow. The Autodesk ReCap® functions select and remove specific point cloud areas in a three-dimensional space.
Additionally, all points outside a small radius extending from the eaves of the buildings are removed, and mobile objects, such as people or cars, are excluded. The third step involves unifying. "Unifying" refers to the removal of point duplicates from the point cloud. This step reduces the data mass, points, and relative relationships between the individual scan positions. A single scan without duplicates was created from numerous individual scan positions connected through relative relationships and point or distance overlaps. It is important to note that this step is irreversible and occurs after processing.

Step 2: Modeling

The modeling process is divided into two sub-steps after generating the required data as a point cloud. In the first step, manual modeling is performed. Manual evaluation of point clouds is primarily conducted by visually aligning the point cloud imported into the CAD program with the utilized components. The individual points of the point cloud can also serve as anchor points to fix the orientation line of a component. This way, the point cloud and component coverage can be ensured at specific locations. Adapting a 3D model to a reference point cloud is performed manually. Each anchor point of a component is manually placed onto the point cloud, and the deformed components in the existing structure must be accurately represented by inserting 3D objects into CAD software. The images captured by the 3D scanner can further enhance alignment with the point cloud. The color and image data captured by the 3D scanner may clarify any unclear constructional relationships that cannot be deduced from the point cloud alone.
The generated point clouds were modeled in the second step using software to identify the efficiency of semi-automatic modeling compared to manual modeling, which involves the execution, compilation, and processing of the scan data, facilitated by software tools such as Recap. Subsequently, in Revit, the ability to filter point clouds by classes (layers) was utilized, and particular objects, such as walls, were automatically placed based on predefined criteria. According to the manufacturer, the software is an AI-based tool that accelerates scan-to-BIM by directly assigning BIM attributes to the point cloud of objects. The manufacturer promises time savings of 50%. The AI used in the software recognizes pipes and their fittings, trusses, stairways, furniture, walls, windows, doors, ceilings, and floors from point clouds. A specific manufacturer was deliberately not named to ensure a completely neutral and reliable database.

Step 3: Analysis

While conducting steps one and two, a quantitative and qualitative evaluation of the generated data models occurs. Therefore, the time taken for the scans and the manual and semi-automatic modeling processes were recorded, including all relevant time components, such as data preparation and modeling (quantitative analysis). The time hours are calculated per person; e.g., if five individuals work for one hour each, five hours are recorded. Two individuals were involved in these calculations. For qualitative analysis, the models generated in the semi-automated process were analyzed concerning the quality and usability for further use in FM by considering the measurement accuracy. Tolerances are defined between +-2.5 cm and +-10 cm, aligning with Level of Detail 100 and LOD 200. Finally, the data were compared.

RESULTS

The total gross floor area of the 12 scanned buildings was 3,495m², with the smallest building covering 140 m² and the largest building spanning 800m². The scanned data volume amounts to a total of 74.15 GB. Processing the data in Autodesk Recap into point clouds increased the data volume to 202.6 GB. The scanning effort for all buildings was 129.5 hours, with individual buildings requiring between seven and 28.5 hours, reflecting the heterogeneity of objects, construction states, and accessibility. Figure 3 shows two outward scan views of one of the buildings, with the left view yet to be classified and the right view already classified.

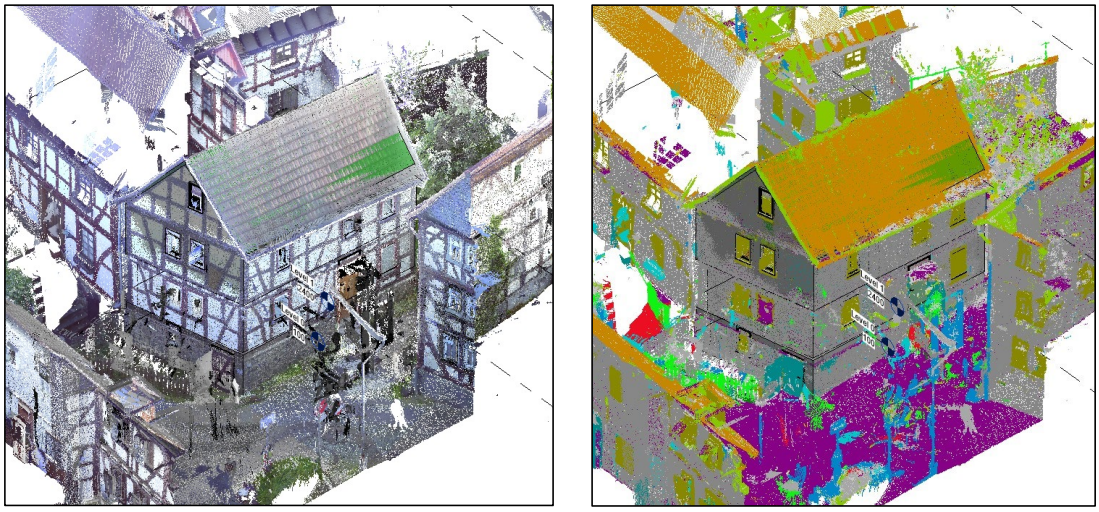

Figure 3: Exterior views – unclassified and classified scan views of building (source: created by authors)

Point clouds were imported into Autodesk Revit for manual modeling and subsequently modeled iteratively, starting with different levels, walls, stairs, windows, doors, and furniture. The manual modeling efforts for scanned buildings varied across different constructions, reflecting the diversity of objects, construction states, and accessibility. The time spent on manual modeling ranged from 15 hours for a building with a construction area of 150 m² to 95 hours for a larger building covering 800 m². On average, the manual modeling effort was approximately 103.7 m²/h. All buildings' total manual modeling effort amounted to 413.5 hours, covering a gross floor area of 3,495 m².

The semi-automatic modeling process involved selecting different objects within the point clouds of the buildings, which were then classified by the software. The effort required for semi-automatic modeling varied, taking nine hours for a building with a construction area of 150 m² and approximately 61 hours for a building that covers 800m². The total semi-automatic modeling effort was approximately 252.85 hours. Despite the software's occasional incorrect suggestions, building components such as windows,

walls, ceilings, furniture, and stairs were easily classified in the interior. Figure 4 provides a visual representation of the semi-automatic modeling process, illustrating the work within the software and an example of incorrect classification.

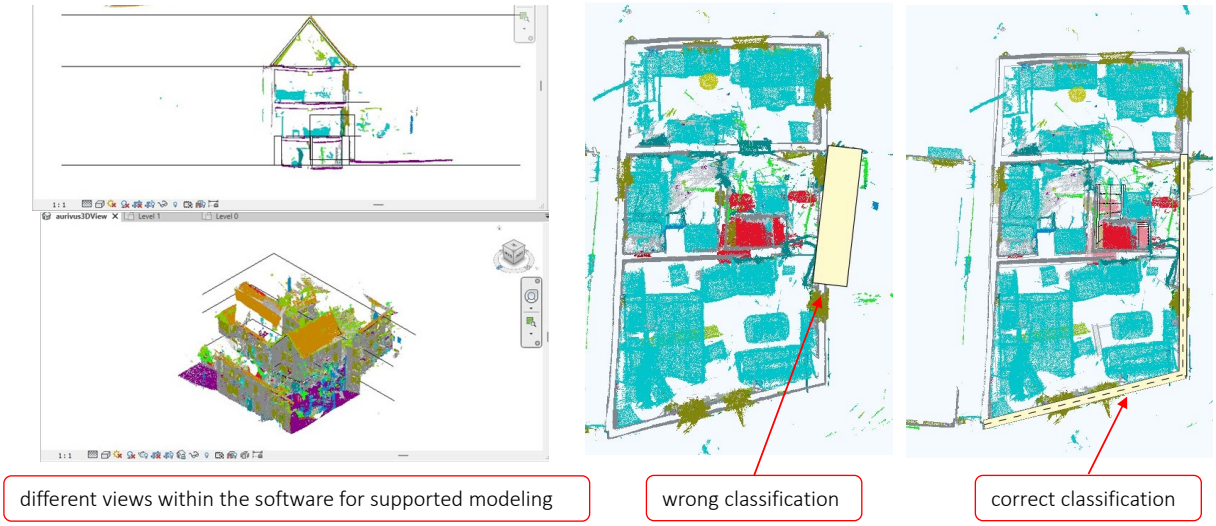

Figure 4: Semi-automatic modeling process and classification error example (source: created by authors)

Regarding the quality of semi-automatic modeling, it can be stated that the measurement data exhibits an accuracy of ± 3.8 cm, falling between an approximately realistic survey (required measurement accuracy within ±10 cm) and a deformation-critical survey (measurement and representation accuracy must be within ±2.5 cm).

The results of the comparison analysis are summarized in Table 1, which shows the key metrics for each scanning session. The data volume is presented in gigabytes (GB) for each relevant category, including scans and Recap project files. Additionally, the scan and manual efforts are provided in hours for a comprehensive overview of the resources invested in each scanning session.

Table 1: Data generation and time efforts comparison for Scan-to-BIM process

	Data generation					Time efforts						
	Object ID	Scans	Data Volumes		Time	manual			semiautomatic		comparison	
	Serial-ID	scan-positions	scans [GB]	Recap Project [GB]	scan effort [h]	manual effort [h]	gross floor area	m²/h manual	semi-automatic effort [h]	m²/h semi-automatic	Δ Delta manual:semi-automatic	semiautomatic /manual [%]
Project	P-9	80	6	15.1	15	45	370	8.22	26.625	13.897	-5.674	169.01%
	P-2	138	8.2	25.4	8	36	470	13.06	20.882	22.508	-9.452	172.40%
	P-5	68	7.7	21.2	17	54	350	6.48	32.841	10.658	-4.176	164.43%
	P-6	212	17.9	47.2	28.5	95	800	8.42	61.720	12.962	-4.541	153.92%
	P-7	82	5.1	13.2	9	22.5	186	8.27	13.313	13.972	-5.705	169.01%
	P-A	62	5	11.3	7	25	250	10.00	15.250	16.393	-6.393	163.93%
	P-B	56	3.3	9.2	8	30	200	6.67	17.750	11.268	-4.601	169.01%
	P-C	66	2.8	10.9	5	19.5	140	7.18	12.000	11.667	-4.487	162.50%
	P-D	96	3.8	15.3	6	18.5	197	10.65	11.250	17.511	-6.862	164.44%
	P-13	75	5.9	19	11	23	200	8.70	14.284	14.002	-5.306	161.02%
	P-E	36	2.45	5.8	7	15	150	10.00	9.000	16.667	-6.667	166.67%
	P-4	40	6	9	8	30	182	6.07	17.936	10.147	-4.080	167.26%
Σ			**74.15**	**202.6**	**130**	**413.5**	**3495**		**252.8502**		**-67.94595775**	**165.30%**

As can be seen from the table, the required times for semi-automatic modeling were lower than those for manual modeling. The time savings range between four hours (project P-4) and 9.5 hours (project P-2), depending on the size and complexity of the buildings. The average savings amount to approximately 65.3%.

DISCUSSION OF THE RESULTS

The productivity rates, calculated in terms of square meters processed per hour, reveal striking differences between manual and semi-automatic methodologies. For instance, project P-2 demonstrated a 172.40% efficiency increase when employing semi-automatic techniques, underlining the potential for significant time savings. Despite variations in project characteristics, the overall trend indicates a consistent advantage in favor of semi-automatic methods. The average efficiency rate for semi-automatic processes is 165.30%, showcasing the potential for streamlining scan-to-BIM workflows. The delta values underscore the difference between manual and semi-automatic efforts. The ratio between semi-automatic and manual efficiencies further accentuates performance disparities.

The software manufacturer mentioned that semi-automatic modeling makes 50% of the time savings possible. The study shows that semi-automatic classification modeling enables modeling of 60 % to 70% more square meters per unit of time. However, the nuanced interplay of project-specific factors may contribute to occasional instances in which manual methods exhibit comparable or superior performance. It is essential to understand that while AI saves time using semi-automatic modeling software, it is not the only factor. The time saved is also due to the simplified process for the modeler, who benefits from the automatic component classification. The subjective factors mentioned at the beginning of this paper, which influence modeling, remain present even in the case of semi-automatic modeling by executing personnel. Moreover, it should be noted that the buildings in this study did not involve sensitive data, so no special requirements were placed on the data security of the software used. However, protecting sensitive project data and intellectual property must be considered when using semi-automated modeling software from FM stakeholders, which includes compliance with data protection regulations and implementing robust security measures.

CONCLUSION

This study explores the intersection of FM and digital transformation by integrating AI with BIM for efficient scan-to-BIM processes. The study assesses the potential improvements and limitations of AI-driven BIM in FM by comparing manual and semi-automatic modeling approaches. Because there are extensive volumes of non-digitally documented as-built areas, artificial intelligence methods for data capture are viable solutions. While the literature often emphasizes the qualitative aspects of data generation techniques, the industry frequently mentions potential time savings that still need to be validated scientifically. This study implemented a three-stage potential savings process to provide a substantiated estimation of the actual time saved through semi-automatic modeling methods (incorporating AI in their software). The existing buildings were first scanned, followed by manual and semi-automatic modeling. Qualitative analysis revealed that applying semi-automatic modeling methods saves time, enabling the modeling of approximately 65% more square meters per hour. Furthermore, the semi-automatic approach meets the qualitative requirements of the FM. The semi-automatic modeling approach provides a simplified and time-resource-saving method for stakeholders in FM to capture existing data.

However, semi-automatic modeling represents only an initial milestone. Future research should focus on enabling fully automated modeling using training datasets and machine learning. In the case of non-standardized structures and historical buildings, many training datasets may be necessary for this purpose.

Furthermore, the modeled data consisted only of geometric information. In BIM models, details regarding building elements, known as Property Sets, must still be manually supplemented. This study has limitations in that it only examines purely geometric data capture without addressing the assignment of properties to individual building elements. The next step should investigate the amount

of additional time required to assign properties to the modeled building elements. Moreover, this study aimed to examine the time components of manual and semi-automatic modeling. Monetary aspects, such as the costs of software or personnel, were not considered in this analysis, but this should be examined in detail in an additional case study.

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