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Review

From 3D point clouds to HBIM: Application of Artificial Intelligence in Cultural Heritage

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ABSTRACT

Interest in semantic segmentation of 3D point clouds using ML and DL has grown due to their key role in scene insight across a wide range of computer vision, robotics and remote sensing applications. In the domain of Cultural Heritage, 3D point clouds are increasingly used as the backbone for as-built BIM models becoming a conventional approach to design in the AEC industry. However, there's a research gap in this field regarding the interface between point cloud segmentation and the HBIM workflow: there are no consistent studies demonstrating the possibility of automating the construction of parametric historical features from the segmentation process results in terms of geometry and semantic labels. The current research intends to perform a systematic review of the current bibliography with the aim of offering a constructive synthesis that will provide as a springboard for the advancement of innovative strategies in the field of BIM and AI.

1. Introduction

Data acquisition by innovative technologies in the field of Cultural Heritage (CH) has proven to be widespread, due to the capacity to accurately digitise architectural features and artefacts, as well as develop information models helpful for analysis, simulation, and interpretation [1]. This allows for the integration of various layers of information to be linked between industry, community, researchers, and other building stakeholders in a flexible and timely way that traditional techniques could not demonstrate. Furthermore, the increasing complexity of buildings highlights the need for the AECO (Architectural, Engineering, Construction and Operations) sector to manage large amounts of data, for which digitisation is the current solution.

The emphasis on the broader role of Cultural Heritage in society is demonstrated by an explicit target for heritage, Target 11.4 [2], in the Sustainable Development Goals [3] that engages countries to make efforts to protect and safeguard the world's Cultural and Natural Heritage. In addition to this target, heritage is mentioned throughout the SDGs3 and in the UN's New Urban Agenda 2030, in paragraphs 124 and 125, which emphasise the safeguarding of a diverse range of tangible and intangible cultural and landscape assets, protecting them from the potential disruptive impacts of urban development [4]. The 2030 Agenda further promotes technological innovation applied to infrastructure, encouraging the field of research on the interaction between heritage conservation and digital technologies. Heritage preservation requires maintenance and conservation interventions involving multidisciplinary teams of experts such as architects, engineers, archaeologists and others, capable of producing parallel and heterogeneous data streams, often not directly integrated with each other. In response to the need to manage such diverse sources of information, research is moving towards the preparation of interdisciplinary databases that allow the documentation generated during the life cycle of the architectural artifact to be structured in order to adequately prepare future interventions.

Digital technologies play an increasingly central role in serving as a tool for holistic documentation of Cultural Heritage. In this framework, in recent years there has been a growing popularity of the BIM (Building Information Modelling) methodology, mainly due to the introduction of regulations and standards that impose or regulate its use. Several studies and researches on the application of BIM processes to Cultural Heritage (HBIM) have emphasised the significant challenges related with reconciling historical architecture's heterogeneity with the required discretization and standardisation suggested by parametric representation procedures: BIM's potential for documentation [5,6] pathology analysis [7], archaeological digitisation and archiving [8,9] scenario simulation, digital support for conservation plans [10], digital representation through augmented and virtual reality [11–13] and interoperability with GIS and CityGML [14,15]. Although HBIM is now a well-established practice, in the academic literature the ways in which content and libraries are created vary widely on a case-by-case basis [16–18]. This is due to the variety of historical architectural features,

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whose complexity requires highly distinct solutions suited to each specific situation. Furthermore, due to its sophisticated 3D modelling needs and a lack of standard references and strategic guidelines for semantic data [19], its use remains limited and is rarely adopted by facility/building managers in the Cultural Heritage field.

Responses to this issue started to be explored in the field of Computer Science. With the advent of Artificial Intelligence (AI) solutions [20–22] the need for automated and reliable methods to classify and 3D point clouds or meshes is becoming crucial. Several methodologies are based on the automatic classification and/or segmentation of architectural elements using Machine Learning (ML) and Deep Learning (DL) methods, enabling the development of algorithms capable of making decisions based on empirical training data, as a preliminary step for the HBIM process [1,23]. As a consequence, point clouds segmented into distinct architectural components (for example) with their identities and attributes can be obtained. But here is where the problem arises.

Most significant gap in knowledge concerning the interface between point cloud segmentation and BIM geometry development is presented: no studies show complete success in applying AI algorithms to automate the modelling of BIM historical features in terms of geometry and semantic labels as a subsequent step of the segmentation process. Normally, due to the geometrical complexity of historical features, this is a stage that must be completed manually taking a lot of time or solved with primitive geometries that do not represent the uniqueness of the historical artifact, rendering it an ineffective practise for use in Cultural Heritage field [24]. Thus, the difficulties of modelling existent artefacts in historic buildings with structural deformations and complex shapes remains an HBIM process weakness.

The major contribution of this research is a comprehensive review of the current state of the art in the application of AI for the automation of BIM modelling processes based on 3D point clouds. Research field is related to the application of advanced technologies in the field of Cultural Heritage. The following sections provides the methodological process performed in the literature review, then research goals and justification are introduced. A fourth section describes a first overview of semantic 3D point cloud segmentation and the initial assumptions of automation in BIM modelling. Finally, an analysis of the results and conclusions are presented.

2. Methods

As previously mentioned, the current research aims to provide a constructive analysis on the application of AI to convert 3D Point clouds in HBIM parametric objects related with Cultural Heritage (Fig. 1). In terms of characterization, this work is defined as a developmental review that provides new conceptualisations to a research community, research models, theories, frameworks or methodological approaches, giving directions for further improvements in the implementation of innovative strategies.

Following Templier and Pare's framework [25], six step were carried out: i) Formulating the problem, ii) Searching the Literature, iii) Screening for inclusion, iv) Assessing quality, v) Extracting data and vi) Analysing and synthesizing data (Table 1). A discussion of results and conclusions is presented in the final stage.

Table 1
Study selection by applying the Templier and Pare's framework.

Formulating the problem/initial research question	Is it possible to automate BIM modelling from point cloud (Scan to BIM) by applying artificial intelligence algorithms?		
Database	Web of Science, Scopus, Google Scholar		
	Number of analysed papers	Exclusion criteria	Number of excluded papers
Searching the Literature	102	Title, abstract, keywords Papers before 2010	48
Screening for inclusion	54	Duplicate papers	18
Assessing quality	36	Point cloud as a starting point	11
Extracting data	25	Case study application	15
Analysing and synthesizing	10	Not relating to research scope (e.g Does not use AI to geometric reconstruction)	–

The following were the general criteria for selecting papers:

- To illustrate the use of AI algorithms as a tool for 3D point cloud segmentation and classification in the framework of Cultural Heritage, which is already a well-developed field.
- Based on the abovementioned, apply AI algorithms to autonomously generate architectural geometry in the built environment.
- Including an illustrative case study rather than just a theoretical framework.

A systematic understanding of the different AI applications for the automatization of the Scan to BIM workflow is needed. The following research question was established to guide the research process: *Can BIM modelling of complex shapes belonging to the CH be automated from the point cloud by applying Artificial Intelligence algorithms?*

The main goal is to examine the current limitations and set some future research directions based on the reviewed documents and results from the first question. The research was carried out Web of Science (WoS), Scopus, and Google Scholar databases which, according to Mongeon and Paul-Hus [26], are the most used databases for studies in the areas of Natural Sciences and Engineering. It included studies published up to the first half of 2022, from the last ten years, justified by the great technological advances of the last decade. For each manuscript, preliminary relevance was determined by title and keywords resulting in a total of 102 articles. The occurrence of the keywords HBIM automation, H-BIM, AI Cultural Heritage, 3D Pointcloud, BIM complex shapes modelling, Heritage BIM, Building Information Modelling Artificial Intelligence is measured. Furthermore, all papers with a date earlier than 2010 were not taken into consideration. With these exclusion characters, the results were reduced to 54 manuscripts published after 2010.

Regarding the inclusion step, after filtering out repeated articles, the

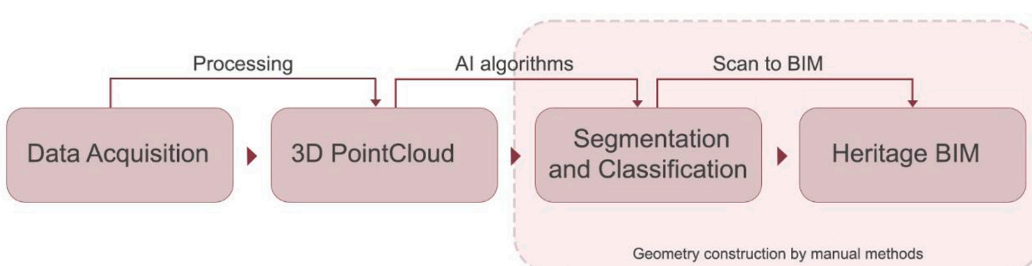

Fig. 1. Scan to BIM workflow highlighting the phase that will be further explored in the literature review.

papers were read in their entirety, and checked to see if they met the inclusion criteria or fit any exclusion criteria, leaving only those that would form part of the review. These articles were classified into groups according to their contribution to this review. A total of only 18 repeated papers were found and therefore discarded.

Assessing quality includes guidelines associated with evaluating the rigor of the included papers: articles that did not present a real case study were not considered. The results must have a strong basis for possible application to other situations. If individual studies included in a review contain methodological shortcomings or invalid results due to systematic errors, then these studies could distort the results of the entire review and introduce potential distortion into the conclusions [27]. Extracting data involves the collection and extraction of applicable information from each case study; therefore, all papers were read in their entirety. An important criterion was that the papers should use the scan to BIM workflow as a starting point. Consequently, papers that did not include the application of point clouds as a BIM basis were discarded.

By analysing and synthesizing, all papers that did not use Artificial Intelligence for geometric reconstruction were discarded, as they were far from the initial research question. On the other hand, it was found that these cases were quite geometrically accurate but using manual construction methods would take a lot of time and resources. Finally, 10 papers were selected: for these documents a matrix was made, organised by publication date, author, journal, technologies, and reference LOD (Level of Development) in order to synthesise and organise the information.

As an initial statement, to avoid ambiguities, BIM needs the characterization of the LOD for the information within the model. The Level of Development is a level of graphic and semantic information that can be achieved for each target set by following the protocol of the minimum information content and the reliability of graphical content and information [28]. Because HBIM models should represent an “as-built” or “as-is” condition, providing a higher degree of completeness by a geometric survey, finalised and updated with all the necessary information for management and maintenance and aiming at a certain level of automation in semantic enrichment and analysis, the LOD in restoration projects should not be lower than LOD 500. To achieve a detailed and realistic “as-built” model, the graphical representation of historic buildings for restoration should not be smaller than scale 1:100 [24]. The goal is for digitally modelled architectural and archaeological features to have the closest geometric resemblance to genuine artefacts, preserving their particular geometric uniqueness.

3. Goals and justification

Considering the strategic nature of BIM as an innovation tool, exploring its specificities and innovative parameterisation concepts, the question is why this application is not consolidated and what gaps need to be filled for an effective application in the field of Cultural Heritage. On the other hand, with the advent of AI solutions, the need for automated and reliable methods to classify point clouds or 3D meshes that act as the basis for HBIM modelling is becoming increasingly important. On these bases, the present research analyses the scientific literature under the premise of generating a solid background bridging the gap between BIM modelling and AI. The study’s significance in the architectural field and future potential are centred on laying the foundation for developing a workflow to automate the HBIM geometric modelling process from the 3D point cloud.

To this aim, a systematic review of the literature of the last ten years was carried out, focusing on two fundamental pillars: first, the segmentation and classification of 3D point clouds by applying AI algorithms as a general staring point (Section 4.1); and second, the application of AI to automate the BIM modelling process from the 3D point cloud (Section 4.2). It should be noted that the research will focus on the second part already mentioned.

4. State of art: preliminary assumptions

Present section depicts the state of the art in the field of Scan to BIM automation. The classification and segmentation of point clouds using AI is described in the first introductory subsection. Subsequently, several semi-automated BIM geometric modelling solutions that the market offers in the domain of CH are outlined as a starting point for the current research.

4.1. Point cloud segmentation and semantic classification in Cultural Heritage

In the field of CH, the classification and semantic segmentation associated with ML and DL techniques can help to recognise historical architectural elements, at an appropriate level of detail, and thus speed up the process of reconstructing geometries in the BIM environment. Cultural assets, and especially archaeological assets, are in fact characterised by more complex geometries, highly variable even within the same class and only describable at a high level of detail, so making the application of AI strategies to this domain much more complicated.

Several solutions for the classification of architectural 2D images have been presented in the literature. These include the detection of stone pavement patterns as a result of applying CNN to photogrammetric images acquired by UAV [29]; K-means algorithms for classification in architectural masonry [30]; GAN’s neural network implemented to semantic classification in different facades acquired by aerial photogrammetry [31]; Mo.Se. (Mosaic Segmentation), an algorithm that exploits DL and image segmentation techniques, was developed to be implemented in archaeological sites [32].

Currently research is focusing on automated processes for segmentation and classification of point clouds or 3D meshes, which can speed up the study of a landmark by combining heterogeneous information and relevant features that characterise and describe the item under study. The use of DGCNN (Dynamic Graph Convolutional Neural Network) was implemented by adding significant features, such as normal and colour, to generate multi-scene datasets [33]; the Self-OrganizingMap (SOM) algorithm was applied via the Neural Network Clustering App to improve the accuracy of point clouds generated from UAV images in the temples of Paestum [34]; furthermore, in the archaeological domain AI was applied to identify and map the building functions and materials of Heritage structures at different scales of representation [35]. Also, an automatic reconstruction method of multi-level indoor spaces with unique models, including inter-room and inter-floor connections from point cloud and trajectory was studied by Lim et al. [36].

Studies discussed above are an overview of the various issues that arise in the field of Cultural Heritage. The identification of specific categories is much more complicated as for the same case study several classes can be identified based upon different purposes. Shape and colour are not always linked to a specific semantic class and objects belonging to the same class can have completely different shapes as well as complex geometries [37,38]. To date, there are still no published datasets that focus on tangible CH in a level of detail that shows all three-dimensional attributes of the asset [37]. Only available databases of annotated heritage are 2D images that exclusively refer to building facades, such as the Facades dataset of the Ecole Centrale Paris (ECP) [39], eTRIM [40], and the CMP Facade Database. The ArCH dataset [37], is a preliminary attempt to reorder and archive multiple sets of annotated 3D point clouds to provide large datasets of CH object formation.

4.2. From semantic point cloud towards HBIM modelling

Development of an ‘as built’ BIM model involves measuring the geometry and appearance of an existing asset and transforming these parameters into a high-level, semantically rich representation.

Unfortunately, in the Cultural asset's digitalization process, the Scan to BIM workflow currently remains a time-consuming and erroneous manual process. Manual methods involve the reconstruction of objects on the point cloud through visual recognition and subsequent manual tracing of geometries. These methods were first introduced by Murphy et al. [41], followed by Barazzetti et al. 2016 [42], Wang et al. 2019 [43], Yang et al., 2019 [44] are now widespread and widely established. Therefore, the study by Tommasi et al. [45] brings together various software packages on the market for reverse engineering in BIM applied to historical elements, while Pocobelli et al. [46] integrated the organised moisture data into spreadsheets and associated them with the development of parametric objects using Dynamo.

As confirmed by the extensive available literature, such reverse engineering processes require a considerable investment of time and resources [47] since the state of art in the creation of As-Built BIMs is fundamentally a manual process. In addition to the fact that they require the presence of an experienced operator who has followed the survey and has expertise in processing point clouds and is therefore able to quickly identify, isolate and then manually reconstruct each class of elements. Such manual procedures, besides being time-consuming and cumbersome, can lead to overly subjective choices.

The automation of the scan-to-BIM process is therefore a very active area of research in line with the built environment. To manually model a building from point clouds, one can use the point clouds as a visual support (usually in a top view), or sections can be generated. Manual modelling causes some errors, as the modelling is obtained from 2D views or is limited to specific locations. Several studies have applied AI algorithms to rebuilding NURBS from 3D meshes, but they are only concerned with surface reconstruction. Zheliazkova et al. 2015 [48] presented an algorithmic-based approach to NURBS reconstruction from 3D mesh aiming to automate the process of data elaboration and achieve accurate results with minimum effort by implementing a reconstruction process where arbitrary modelling operations are avoided and replaced by algorithms able to compute automatically large amount of geometric data. Antón et al. 2018 [49] provides a new automated method for improving the accuracy of historical building information models, but it comes directly from closed meshes from segmented and managed TLS point clouds, utilising NURBS as a non-optimal technique to create closed polysurfaces.

The method provided by Barazzetti et al. 2016 [42] involves the use NURBS curves and surfaces to generate 3D parametric objects of various structural components. The original NURBS surface is conserved, and a dynamic representation is achieved based on the entire object (including semantics and attributes). Andriasyan et al. 2020 [50] make progress in the automated translation of point cloud data into a parametric model by defining forms using mathematical functions in the Rhino+Grasshopper-ArchiCAD software combination. As a consequence, editable mesh parametric objects with information and an identity label are produced (ID). In terms of morph objects, these elements have no geometric constraints and are designed to avoid the import of particular forms from other programmes. Unfortunately, the process remains semi-automatic. Moyano et al. 2021 [51] expresses the need to demonstrate that semantic segmentation can provide a representative sample point set to mesh and then generate parametric BIM objects by applying CANUPO plug-in. However, BIM geometry modelling remains a semi-automated process.

On these bases, preliminary semi-automatic tools have been developed to avoid potential errors. Dedicated point cloud processing software such as Realworks (Trimble), CloudCompare (EDF R&D) or 3D Reshaper (Technodigit) offer tools to create geometric primitives or meshes directly from 3D data. Unfortunately, this modelling does not generate objects that can be directly integrated into BIM software such as Revit (Autodesk), ArchiCAD (Graphisoft) or Tekla Structures (Trimble). A conversion phase is required, which often involves several software packages and can cause data interoperability problems. For this reason, semi-automatic software (e.g., EdgeWise, ClearEdge3D [52]) or plugins integrated into BIM software (e.g., Cloudworkx for Revit, ImaginIT [53] and AsBuilt, FARO [54]) have been developed specifically for the scan-to-BIM process. In these software packages, structural elements are adapted to point clouds from the information provided by the user. A disadvantage of these plugins is that they only handle definition by one surface, which means that one side of a wall must be depended on to represent the full volume, unless a mass wall is fitted from each surface and a Boolean function is used to blend the two solids correctly.

Nevertheless, the successfully application of IA in BIM Cultural Heritage is confined to monitoring activities [55], diagnosis [24], sustainability applications [56–58] data management [45], rule checking [59,60] and to improve the quality of the clash detection process [61,62] leaving the field of geometric reconstruction partially unsolved. Currently challenges in the CH and informatics field is to design an algorithm capable of representing the link between the point set obtained from data acquisition techniques and converting it into a surface shape, whether triangles or any other BIM surface. Despite improvements in geometric design, semi-automation continues to be a challenging operation that requires a huge amount of software and professionals skilled in mathematics and computer science. A comprehensive solution is required.

5. Results: findings from the analysis

The previous section provides an overview of point cloud segmentation and classification applications in Cultural Heritage field. Additionally, various semi-automated BIM geometric modelling tools on the market were highlighted as a starting point towards IA investigation. Current section conducts a detailed analysis of the 10 papers identified as potential applications of IA in the field of HBIM geometric reconstruction.

In order to establish an initial statement, it should be highlighted that a large number of research studies have utilized the Manhattan World (MW) workflow [63], which is valid for many interior scenes containing man-made architectural structures. The MW approach assumes that most man-made structures can be approximated by planar surfaces that are parallel to one of the three principal planes of a common orthogonal coordinate system [64]. Evidently, this statement provides a huge issue when talking about CH, as generalising difficulties and taking orthogonality of walls for granted is a conceptual mistake.

Further lines of research demonstrate the reverse process, i.e., how to create by CNN algorithms, 3D point clouds with internal semantic labels based on existing BIM models [65]. Furthermore, an approach for the automatic generation of construction models in IFC BIM format from unstructured point clouds was generated using a RANSAC (Random Sample Consensus) iterative algorithm [66]. Unfortunately, in the applied case study the algorithm is not suitable for complex geometries: it reconstructs columns and beams as walls with extremely large doors. Thomson and J. Boehm (2015) [67] use similar criteria to automate the identification of geometric objects from point clouds and vice versa, concentrating on classic geometries such as walls, exporting the results in .IFC extension.

Wang et al. (2015) [68] proposed a method for automatic building geometry extraction from unorganized point clouds collected from a 3D laser scanner with the aim to convert the extracted data into a .gbXML format that can be imported into the energy simulation tools. Existing residential buildings or small commercial buildings are mainly studied. A semi-automatic approach [69], is proposed for the 3D reconstruction of existing buildings from point clouds classified and exported in .OBJ format: the open-source parametric 3D CAD modeller FreeCAD was used to generate a file in .IFC. Although, the case studies always dealt with simple geometries such as apartment buildings or office buildings. Tang et al. 2022 [70] proposed an automatic algorithm to reconstruct an indoor BIM model from RGB-D or LiDAR point cloud and obtaining a 3D model with some loss in geometric accuracy, especially for the curved structure, which may be caused by an inaccurate plane fitting process. The method is not yet able to reconstruct furniture, such as tables and chairs, even though they can be labelled by Deep Learning classification. A recent research group [71] has been developed an algorithm called *ABM-indoor,* that sequentially performs the automated segmentation of a point cloud and the creation of corresponding 3D surfaces of buildings. Yang et al. 2019 [64], on the other hand, distinguish themselves in the geometric reconstruction process by include curves in addition to straight lines. The experimental findings showed that the suggested technique is well suited for indoor modelling of multi-room situations with curved walls, laying the first foundations out of the parameters of orthogonality and perpendicularity.

All previous research deal with case studies involving office buildings or residential typologies. As main principle they assume vertical walls, cells are generally created by the intersection of 2D lines corresponding to the projection of wall faces on a horizontal plane. For those starting from flat segments rather than 2D lines, robust estimators or least squares-based algorithms are used to fit them.

Table 2 summarises the main aspects of the 10 articles analysed from 2015 to 2022 inclusive. An important parameter to highlight was the main tools/algorithms that the research put into practice to carry out the process: RANSAC (Random Sample Consensus) [76] algorithm for the detection of geometric shapes in point clouds was predominant. RANSAC is capable of interpreting/smoothing data containing a significant percentage of gross errors and is thus ideally suited for applications in automated image analysis where interpretation is based on the data provided by error-prone feature detectors [76]. Nevertheless, the application of these algorithms is not always within the capabilities of conventional BIM operators. This is due to the software's usability, which requires mathematical processes; secondly, not all point cloud files are legitimate because they may or may not be structured. Most segmentation algorithms operate with structured or LiDAR information.

Regarding the geometric quality, the models obtained remain at a low Level of Development (LOD), not exceeding LOD 100. Furthermore, related to the research topic, it should be noted that the applications were carried out in practical cases of simple broad geometries using parameters and algorithms based on orthogonality and perpendicularity of the cells: this represents a weakness in the idea of applying these parameters to historical heritage, as this is composed of geometries that present a notable level of degradation in their materiality.

The selected studies in this review include publications from 5 different journals. Table 3 lists the journals that have contributed two or more relevant papers to this research database. Automation in Construction has contributed the most to this domain, with a contribution of four papers. Other highly relevant journals include Remote Sensing with two relevant articles, while Applied Sciences count with another two and Sensors had only one. The rest of the papers are peer reviewed conference proceedings.

Table 3
Top Journals in BIM Artificial Intelligence applications.

Journal Name	Number of Papers
Automation in Construction	5
Remote sensing	1
Applied sciences	2
Sensors	1
IASS Annual Symposia. International Association for Shell and Spatial Structure	1

6. Discussion: outstanding issues in Cultural Heritage

Based on the previous bibliographic research, there is a gap in the automation of BIM modelling linked to complex geometries related to Cultural Heritage. The case studies evaluated contain relatively regular geometries have not undergone degradation or deformation processes over time, allowing the application of AI algorithms to the semantic categorization of 3D clouds as well as geometric reconstruction feasible. No case studies efficiently applied to CH can be found in the present literature review.

Algorithms and methodologies used to automatically generate BIM geometric features from a 3D point cloud are based on principles such as orthogonality and perpendicularity. Properties that are difficult, if not impossible, to find due to the natural processes of transformation and loss of matter of architectural materials caused by natural or external events. Furthermore, since point clouds are irregular geometric structures with a high variability of density, are unordered, and are invariant to transformations and permutations, looking to exploit them in the BIM domain with ML/DL approaches is still a challenge, and it becomes even more difficult when it comes to datasets oriented towards digital Cultural Heritage.

With this framework, future research goals involve developing a workflow capable of automating the modelling of HBIM geometries related to Cultural Heritage, adopting previously segmented and classified 3D point clouds as a starting point. In contrast to traditional BIM case studies, standard libraries of items, architectural features, and masonry configuration are far more difficult to build in historical scenarios. Buildings are frequently visible at the foundation level; the surface is frequently irregular in walls and roofs, and geometry due to degradation processes presents only remaining visible forms of an uncertain structure. This is crucial to facilitate the manual processes of architectural rendering and documentation as it is becoming a systematic, time-consuming task. Dissemination and training in the new approaches will be relevant as it concerns a platform accessible to all regular BIM operators, offering an intuitive interface and supporting training material.

Table 2
Case studies identified in the systematic review ordered by chronological data.

Automatized Scan to BIM Workflow						
Author	Year	Country	Main Tools utilized	LOD	Format output	Building typology
[67]	2015	U. K	RANSAC	100	.IFC	Office
[68]	2015	USA, Korea	Region Growing Segmentation [72] + Boundary Detection [73]	100	.gbXML	Single house
[66]	2016	Denmark	RANSAC	100	.IFC	Office
[69]	2017	France	RANSAC + MLESAC + FreeCAD	100	.OBJ/.IFC	Office
[63]	2018	Spain	RANSAC+ Rhino	100	.GML/.IFC	Office
[64]	2019	China	RANSAC+ Markov Random Field (MRF)	100	.IFC	Office
[74]	2020	Belgium	RANSAC+ Rhino	200	.IFC	Multi-story building
[71]	2021	Spain	RANSAC + ABM-indoor	300	.IFC	Parking
[75]	2021	China	MSAC + DBSCAN+ RANSAC + Dynamo	100	.IFC/.RVT	MEP components
[70]	2022	China	RANSAC + PCA + MRF	100	.IFC	Office

7. Conclusions

The present paper explores a systematic literature review of the automatic scan-to-BIM approaches in which point-cloud segmentation is the first step: until today, there are many studies in which point clouds are used for the recognition and reconstruction of geometries related to BIM models. However, these methods try to be applied to digital Cultural Heritage but do not fully exploit Machine and Deep Learning strategies.

The use of AI in BIM Cultural Heritage is confined to monitoring activities, diagnosis, sustainability applications, data management, rule checking, and improving the quality of the clash detection process, with the field of autonomous geometric reconstruction remaining unsolved.

Current BIM representation and data exchange formats assume idealized geometries that are rarely seen in real facilities. Walls are not exactly planar, and corners are rarely precisely orthogonal, so using cell segmentation would not be considered optimal. Furthermore, the imperfect nature of sensing data for as-built BIMs leads to other representation needs that are outside of the current capabilities of BIM formats, including representation of occluded regions and information about model uncertainty. The aim is that both architectural and archaeological elements modelled on digital platforms should represent the greatest geometric similarity to real objects, essentially to preserve their characteristic geometric uniqueness, it is therefore necessary to develop new strategies related to the interoperability of accurate modelling systems, and especially those related to Cultural Heritage.

Most of the time spent on building information management is implemented in the modelling phase, therefore it is necessary to find innovative approaches to architectural representation or extensions to existing ones to fill these capacity gaps, especially in the field of Cultural Heritage. This integration of BIM and automation is required because incremental and accurate knowledge by investigation of tangible and performance parameters is the main objective of stakeholders in conservation and restoration projects, representing the strong assumption for non-invasive interventions to ensure the valorisation of Cultural Heritage.

Declaration of Competing Interest

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

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