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Geometric parameter updating in digital twin of built assets: A systematic literature review

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ABSTRACT

The use of Digital Twin (DT) is becoming increasingly widespread in the construction industry. Considering that buildings are complex geometric structures that may change throughout their lifespan, it is essential to maintain up-to-date DT geometry. Despite its importance, the relationship between a building's physical geometry and its DT counterpart remains under-researched due to technical, financial, and practical challenges. This article aims to provide a comprehensive overview of current research on updating the geometry of DT in construction, identifying gaps and challenges for future research, with a focus on the life-cycle stages where updating the DT geometry is most relevant. Additionally, this paper examines the most used equipment and data collection methods, as well as the data processing and integration techniques used in DT. This study comprehensively reviews and analyses the DT concept, which involves the creation of a virtual model that accurately reflects the geometry of a physical object, and examines the DT concept from this perspective. Through a systematic literature review (SLR) and bibliographic analysis, this research examines various methods for updating the geometry of a DT. The methodology involved analyzing a final sample of 56 articles that met the inclusion and exclusion criteria. On the basis of the analysis, the study identifies six main directions that recent publications in this field have focused on. These directions highlight the main achievements and obstacles in the field and include the use of UAV/photogrammetry and laser scanning as data collection methods for building geometry, data visualization, updating the geometry of the virtual model in manufacturing, the application of DT in modular construction, and structural monitoring. Based on the SLR, this study has identified key areas that require further research and existing challenges in updating the geometry of the DT. Addressing these challenges will be critical to promoting the widespread adoption of DT in the construction industry. Therefore, the study highlights the importance of updating geometry data in the DT to improve the quality of the data and maximize the benefits of technology in the construction sector.

1. Introduction

The use of digital technology to manage built assets and the concept of Digital Twin (DT) are becoming increasingly popular in the construction industry. Previously, schematic representations of buildings or systems, such as Building Management Systems (BMS) or Lifecycle Information Management Systems (LIMS), were used for this purpose. However, DT now offers the advantage of both real-time data streams and geometrical representations of assets. Research on the potential benefits of using DT technology throughout the

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asset life cycle is growing rapidly as the number of publications on this topic in various fields, including construction, manufacturing, construction management, energy efficiency, safety management, and building sustainability, increases.

From the construction industry's point of view, the relationship between the physical geometry of a building and its corresponding DT remains understudied. This is due to several contributing factors, including the complexity of the building geometry, the stability of the building geometry after the construction stage, the cost and technical demands of updating the geometry information, and the challenges associated with accurately and completely integrating the building geometry into a DT. The geometry of buildings can be highly complex, making it difficult to accurately represent and integrate them into a DT. Furthermore, once a building has been constructed, its geometry typically remains unchanged unless it undergoes a renovation or reconstruction. This stability means that updates to the building's geometry information may be infrequent, making the investment in technology to provide such updates less attractive. However, when updates are necessary, the cost and technical demands of such updates can be significant. The requirements for accuracy and completeness of building geometry data are also high, as errors or omissions in these data can affect the performance and functionality of the DT. Finally, integrating building geometry data into a DT can be challenging, requiring significant processing power and expertise to ensure that the data are properly integrated and accurately represent the building in question. Ultimately, while the relationship between building geometry and DT remains understudied in the construction industry, this is due to a combination of technical, financial, and practical challenges that must be overcome to fully realize the potential of DT in this field. Considering all these challenges, it is critical to determine the criteria for updating the building's DT geometry, especially in cases where real-time updates are required. This will help to ensure that the DT accurately represents the building and that any updates to the building's geometry are performed in a timely and efficient manner.

Further investigation is needed in constant DT geometry updating to better understand.

- the key stages in a building's life cycle when geometry updates are necessary.
- the types of buildings and structures that require geometry updates.
- the most effective methods for collecting data, including the use of data collection equipment.
- methods for processing data and integrating it into the DT.

A comprehensive review of existing literature and bibliographic analysis can help to systematize existing knowledge and identify areas for future research. This will provide a comprehensive understanding of the current state of knowledge and will help focus efforts on addressing the gaps in the field. An overview of the study is provided in Fig. 1, which helps clarify the scope and focus. The paper is organized as follows: in Section 2, the study provides a general background, including definitions of key terms, concepts, and recent classifications in the field. Section 3 details the methodology of the systematic literature review and bibliographic analysis. Section 4 presents the results of the analysis of articles and highlights the main directions of research in the field. Finally, Section 5 concludes with a discussion of problematic issues and suggestions for future research, highlighting areas that require special attention.

The issue of updating the geometry of DT is not adequately covered for build assets. Although recent publications have addressed this topic, they only focus on specific aspects or processes related to working with virtual models or data processing and integration. This study aims to provide a more comprehensive and generalized perspective on the relationship between building geometry and its representation in DT for the construction industry. The general background for this research, outlined in Section 2, provides definitions of terms, DT concepts, classifications, etc., and it also emphasizes the significance of geometric parameters in the DT concept and their relation to the type of building and life cycle. Updating the virtual model to reflect changes in the physical object's geometry

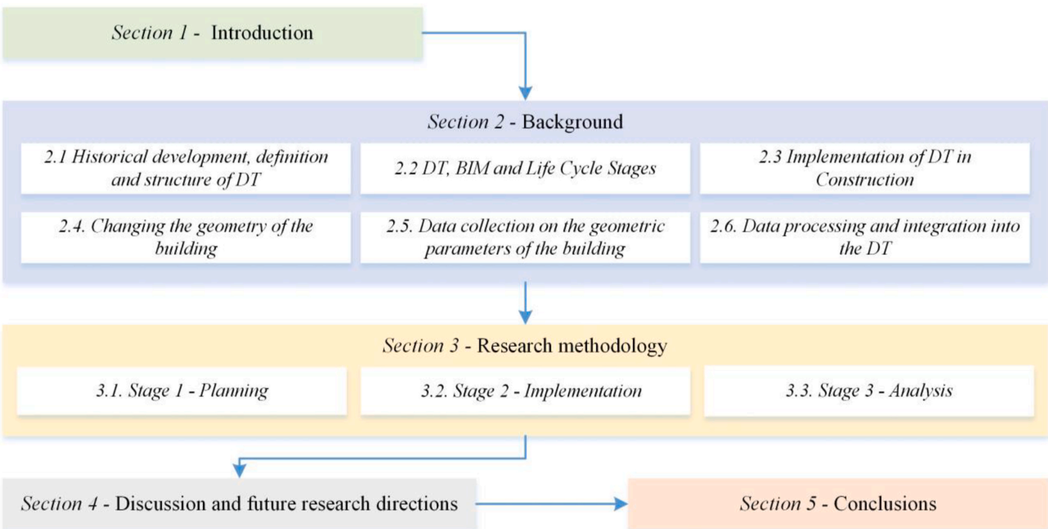

Fig. 1. The overall process and structure of the study.

is more extensively covered in other industries like industrial manufacturing, the automotive industry, etc. and these industries have standardized approaches in place. Therefore, it is worth considering the feasibility and practicality of using these standardized approaches to update the building geometry. Nevertheless, it is essential to acknowledge that building geometric parameters are more complex than the configurations of objects in these industries, such as the details of mechanisms or machines, which present unique challenges. Moreover, due to the swift advancement of technology for gathering data on building geometry (such as laser scanning, UAV/photogrammetry combination, sensors, etc.) and the subsequent processing and integration of these data, there is a pressing need to organize knowledge and pinpoint critical issues.

However, the limited number of studies and publications focused on updating the building's DT geometry, combined with the disparities and fragmentation across various fields, significantly restricts a comprehensive coverage of the topic. Furthermore, practical application is hampered by variations in data collection methods depending on the type of building, available equipment, and existing preliminary data, such as the availability of a BIM model, as well as the costs and qualifications of the personnel involved. These factors significantly impact the methods of further processing and data integration in DT, making it challenging to develop a unified geometry update process that can be broadly applied.

The study focused on three primary objectives.

- Examine the relationship between DT, BIM models, and the building life cycle, specifically in terms of updating the building geometry data. This examination will be based on publications from the past decade and aims to provide insight into when it is necessary to update building geometry data during its lifespan, based on available source data.
- Investigate the equipment and methods most widely used to collect, process, and integrate building geometry data in DT. The advantages, disadvantages, and possible challenges associated with each approach will be assessed. Additionally, practices for updating virtual model geometry in other fields will be considered with the aim of identifying possible adaptations for construction.
- Based on the analysis of the two previous goals, identify gaps and challenges in further research on updating DT geometry. These findings will inform a more detailed study aimed at better adapting DT to the needs of the construction industry.

The uniqueness of the study is its specific focus on the geometry of DT in the construction industry, as opposed to other industries where it is also applied. This paper attempts to develop a basis for a unified maintenance method for the geometry of a virtual model that can be widely applied in construction. The novelty of the research lies in identifying key problem areas based on the current state of affairs in the industry, with the aim of creating a practical and scalable method for updating the geometry of DT.

2. Background

Advancements in virtual modelling and improved data collection have made DT possible in construction. DT involves creating a digital representation of a physical object that accurately captures its features and adapts to changes in its environment for optimal performance. This technology enables the tracking and management of physical objects through a digital model, including real-time monitoring and simulation-based forecasting to predict and plan behavior and future states. The DT architecture is complex, incorporating a physical object, a virtual model, and a network of sensors or devices for interaction and communication. Despite its potential benefits, full implementation of DT in construction is challenging due to the complex nature of building structures and processes, as well as the participation of multiple stakeholders and unpredictable factors. DT is not a novel concept and is already widely used in industries such as aerospace, industrial manufacturing, robotics, automotive, wind engineering, telecommunications, healthcare, and others that use object prototyping to improve outcomes.

2.1. Historical development, the definition of the concept and structure of DT

The concept of twinning a physical object was first introduced during the 1960s as part of NASA's Apollo Project. The aim was to create two identical vehicles, one in space and the other on Earth, to mirror each other. However, due to limited digital technology at the time, only a physical prototype system was developed. The term “Digital Twin” was later coined by Grieves in 2002–2003 and applied to the field of Product Lifecycle Management (PLM). Over the next few years, the concept has evolved and gained widespread adoption, especially in the industrial sectors. In 2010, NASA formalized the definition of DT and began using it as a key technology in 2012, followed by the US Air Force.

Tao et al. (2019) divide the period 2003-present into three stages, each influenced by advances in information technologies that support DT [1].

- Formation stage (since 2003) - The DT concept was first introduced.
- Incubation stage (since 2011) – DT began to gain momentum and was adopted in other industries, particularly in aircraft structural life forecasting.
- Growth stage (since 2014) – The publication of the first white paper on DT marked its transition from a theoretical idea to being applied in various practical ways across a multitude of fields.

With the introduction of DT as part of Siemens' Industry 4.0 concept in 2016, the exploration of its potential has increased, including in the construction sector.

The definition of DT varies across industries and has evolved over time with advances in technology. The first general definition of DT was provided by Grieves et al., in 2014, which defined it as a virtual digital representation equivalent to a physical product [2]. In

2020, Liu et al. defined DT as a digital entity that reflects the behavior and updates of a physical entity [3]. In construction, there is no standardized definition of DT, and discussions on the subject continue.

DT can have a three-dimensional or a five-dimensional structure. The latter is more adaptable in construction, as it categorizes all the variables involved in the process more specifically [1]. The creation of DT in construction requires careful attention to three key elements: the physical object, the virtual model, and the connections between them. The virtual model can serve multiple purposes, such as monitoring building state, analysis, simulation, forecasting, etc. The level of detail of the physical representation and the virtual model requirements may differ depending on the purpose of DT's implementation. The development of DT in various fields was based on key concepts, including modelling and simulation, data integration from diverse sources and formats, collaboration among stakeholders through defined data access protocols, and purpose-driven services such as monitoring, prediction, and real-time physical object management [1]. These concepts shape the complexity and detail requirements of DT. Fig. 2 shows the main components of DT and the connections between them based on the five-dimensional structure of DT. Generally, a five-dimensional structure of DT can be described by the formula [17,18]:

$$M_{DT} = (PE, VM, Ss, DD, CN) \tag{1}$$

Where M_{DT} is a complex DT, *PE* is a physical entity, *VM* is a virtual model, *Ss* are services, *DD* are DT data, and *CN* are connections. It is worth noting that the connections between the components of DT should be two-way. At the same time, "input" connections, i.e. those capable of affecting a physical object, are difficult to provide for the building, so they are optional or can only be used for certain systems.

From a construction industry perspective, DT implementation can be viewed as a way to achieve specific benefits, referred to as "Ss components" (services). This approach involves dividing the components into separate parts: expected results and main beneficiaries. To optimize problem areas and processes, it is crucial to identify participants/executives, process data, and potential implementation challenges. Maintaining the accuracy of the DT geometry is a key component of the Ss system and the ultimate desired outcome. The virtual model should accurately reflect the physical object, including its geometric parameters.

Fuller et al. (2020) classify three levels of a potential system that lead to DT misunderstandings based on the connections between physical objects and virtual models [5], as shown in Fig. 3. In manual data flow, the virtual model is only a digital copy and does not reflect changes made to the physical object. Digital shadow features semi-automatic data flow, where some data from the physical object updates the virtual model automatically, while other data must be manually entered. However, the virtual model cannot directly influence the physical object. In DT, the data flow is fully automated and operates in both directions.

According to Madni et al. (2019), there are four levels of maturity of DT, each with a different definition [7].

- Pre-Digital Twin: A virtual representation of a future physical object during the design phase.
- Digital Twin: A virtual model of a physical object that displays its properties and manages data.
- Adaptive Digital Twin: A virtual model that displays real-time properties and manages the data of a physical object.
- Intelligent Digital Twin: A virtual model that displays real-time properties, manages data, and predicts behavior using mathematical models and machine learning.

The classification of DT systems proposed by Fuller et al. (2020) and Madni et al. (2019) provides valuable information on the potential of DT in the construction industry. Fuller et al. (2020) classify DT based on the connections between physical objects and virtual models into three levels: manual data flow, semi-automatic data flow, and fully automated data flow. On the other hand, Madni et al. (2019) describe four levels of DT maturity, starting from predigital twin to intelligent digital twin, each with an increasing capability to manage and display real-time properties and predict the behavior of physical objects. This classification highlights the importance of understanding the different levels of DT systems and their potential applications.

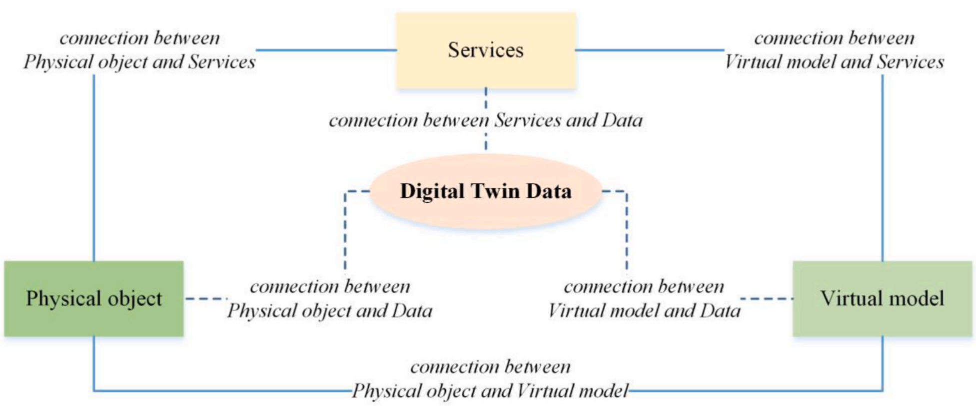

Fig. 2. Five-dimensional structure of DT [4].

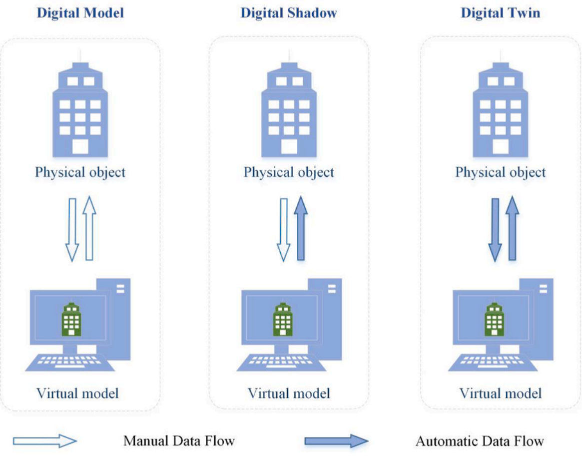

Fig. 3. Schematic representation of the differences between the digital model, the digital shadow, and the digital twin [5,6].

2.2. DT, BIM, and life cycle stages

Additionally, the construction industry has a close connection between Building Information Modelling (BIM) and DT, often being used interchangeably, as BIM serves as a virtual representation of the building. However, it is important to understand the distinctions between the two. To clarify, it is useful to look at the five common stages of a building's life cycle: planning, design, construction, operation, and demolition. These stages may have further subdivisions based on the type of building, construction technology, regional norms, and regulations. Fig. 4 illustrates the relationship between BIM, DT, and the building's life cycle. The figure shows that BIM is used during the planning, design, construction, and operation stages, while DT is used during the construction, operation,

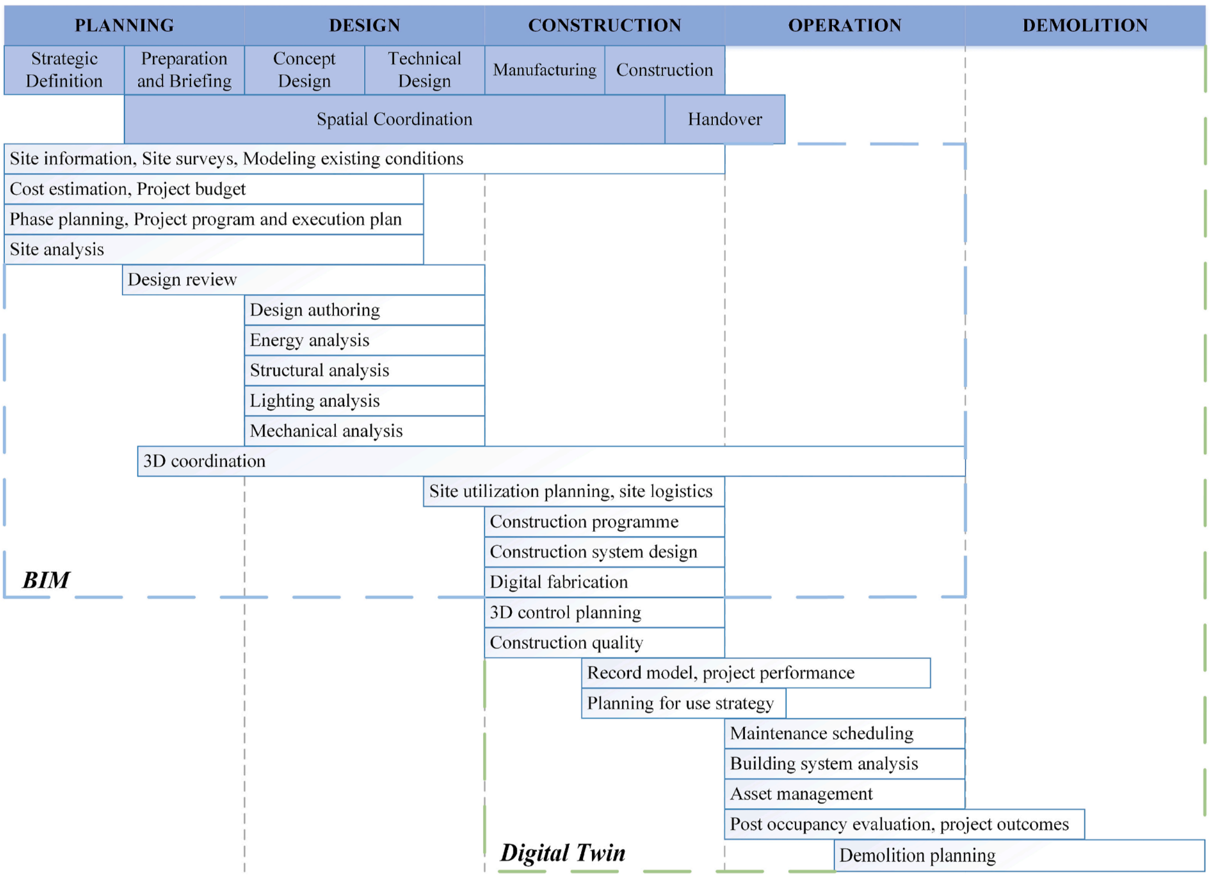

Fig. 4. Relationship between BIM, DT, and life-cycle stages.

and demolition phases. Therefore, there are overlapping stages where the BIM model can be updated to the DT level, known as "as-built" BIM to DT.

BIM and DT both utilize virtual representations of a building, but DT is a step further. DT is a cyber-physical system that integrates a model of the physical object and has real-time access to the object. Unlike "as-built" BIM which only reflects changes made to the "as-designed" BIM, DT connects to the physical object through sensors and devices to monitor the building's state in real time. Deng et al. (2021) suggested a 5-level ladder taxonomy to illustrate the evolution of BIM to DT [8].

- Level 1 - BIM: A static 3D virtual model that improves communication and provides information throughout the building's life cycle.
- Level 2 - BIM-supported simulation: Use of BIM and additional data for simulations, such as construction process, energy performance, and thermal environment evaluation.
- Level 3 - BIM with Sensors: Combining a digital building model with real-time sensor data to monitor construction, energy performance, indoor environment, and hazards.
- Level 4 - BIM with Artificial Intelligence (AI): Incorporating the Internet of Things (IoT) into digital building models to make real-time predictions and manage building systems.
- Level 5 - DT: A complex DT system capable of collecting, processing, monitoring, and controlling building information in real time.

Opoku et al. (2021) described the main differences between BIM and DT in terms of their application throughout the stages of the life cycle of a construction project [9]. During the design stage, BIM is mainly used, though some detailed drawings based on the BIM model may also be created during the construction stage. Moreover, the use of sensors and monitoring equipment during construction can influence design decisions. The construction stage is where DT is utilized to track progress, resource and material planning, production management, and quality control, making it crucial for modular construction and process safety. Although DT is used in construction, its implementation is limited in many case studies. In the operation and maintenance stage, DT improves facility management, maintenance, monitoring, logistics, and energy simulation. This allows facility managers to make informed decisions about building operations, performance, and energy consumption optimization. For example, managers can analyze "what if" scenarios to enhance occupant comfort and reduce energy waste. Studies show that both real-time and historical building occupancy data have significant value for building management. The application of DT in the demolition and recovery phase is currently underexplored, with only a limited number of case studies examining its practical applications, such as using augmented reality (AR) and virtual reality (VR) to create an interactive virtual model of destroyed historical buildings.

Building facilities differ in their usage (e.g., residential, commercial, infrastructure), age (new, existing, historic, etc.), and ownership (private, state, communal, etc.), leading to varying needs among stakeholders when implementing DT [10]. Currently, DT is used mainly for large and complex structures. For new buildings or those under construction, the DT can be derived from the BIM with regular updates. However, existing buildings may have a DT in place during their operation, but the information may be scattered or inadequate, often in the form of 2D drawings or paper records. According to Volk et al. (2014), to overcome this, there are three main methods to create a DT for an existing building: using laser scanning and photogrammetry to create a 3D model, converting an existing 3D model to include semantic information, or automatically converting 2D drawings to a 3D model [10]. The general process of creating a DT for an existing building and its relationship to the geometry update process is shown in Fig. 5. Depending on whether or not there is an existing BIM model of the building, the process of creating a DT will vary. However, the essential stages of updating the building's geometry remain the same. DT requires high precision and accuracy in the data used to construct it to ensure effective im-

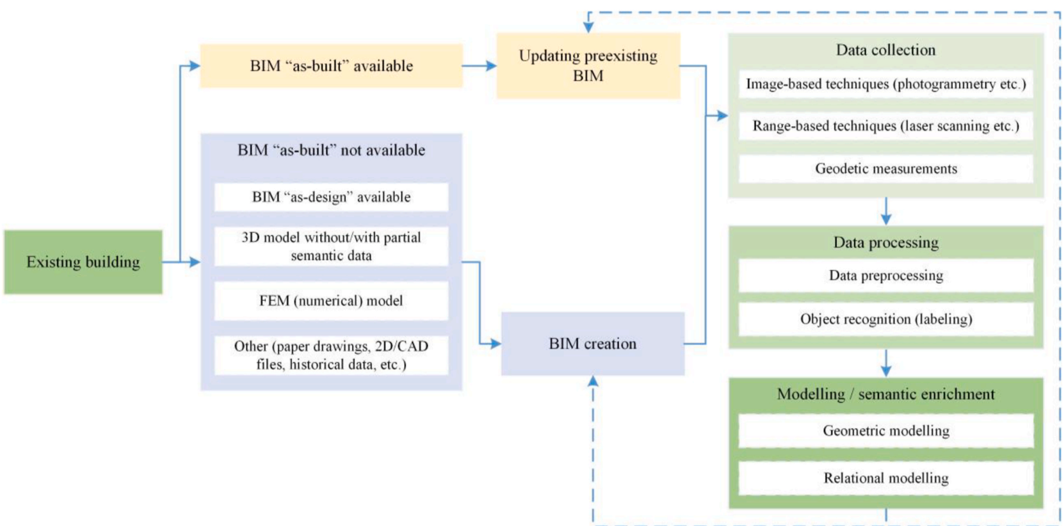

Fig. 5. Process of creating and updating the DT geometry for existing buildings.

plementation. The Level of Detail (LOD) is a measure of the amount of information contained in the DT and is often related to the level of development, rated on a scale from LOD 100 to LOD 500 [10]. For existing buildings, a LOD of 300 is commonly used.

Mandi et al. (2019) have identified several key features that differentiate DT from other systems and BIM as well. These include.

- Comprehensive representation of the physical object, including its characteristics, changes over time, management, and historical data such as repairs, modifications, and reconstructions.
- Use of historical data to monitor the current state of the object, simulate and predict future changes.
- Potential for remote control of specific building systems, enhancing versatility and functionality.
- Integration of IoT and AI technologies with the virtual object model, expanding DT capabilities and enabling more robust analysis and decision-making.

2.3. Implementation of DT in the construction industry

The implementation of DT in the construction industry can present significant challenges, but also has the potential to bring numerous benefits. Brilakis et al. (2019) identified key advantages of DT in construction, such as automated construction monitoring, improved resource planning, enhanced safety monitoring, work quality assessment, optimized buildings and equipment, and more [11]. To fully realize these benefits, it is necessary to integrate advanced technologies, including big data, AI, IoT, and cloud-based technologies, into the process [12]. Opoku et al. (2022) further investigated the main drivers of DT in the construction industry [13]. These drivers include real-time data visualization and control, optimized construction processes, improved environmental monitoring, safety risk management, improved energy management, improved design process and decision-making, more sustainable project design, reduced construction cost, predictive maintenance, real-world asset management, improved materials selection, logistics monitoring and simulation, automation, smart services, and improved project performance. To provide a deeper understanding of these drivers, they can be categorized into four groups. Concept-oriented, Operational success, Production-driven, and Preservation-driven. This categorization provides valuable insights into the specific areas of focus for implementing DT in the construction industry, as well as a better understanding of the purpose behind such implementations.

Implementing DT is becoming a priority for an increasing number of companies in the construction industry. The process involves six key steps to ensure the successful integration and optimization of DT into the company's operations [12,14].

- Clarifying goals and starting data: this step involves understanding the DT purpose of the implementation and the data that are available at the start of the process. It is important to have a clear understanding of the desired outcome so that the implementation process can be tailored to achieve these goals.
- Defining implementation parameters: during this step, parameters that will guide the implementation process are defined. This includes the scope of the project, budget, timeline, and any other relevant factors that may impact the success of the implementation.
- Developing a test version: although this step is optional, it can be beneficial to test and evaluate the DT implementation in a controlled environment, for example, for some particular processes in a company. This allows for any issues or challenges to be addressed before the full-scale implementation begins.
- Expanding to other building components: the DT implementation process should be extended to other building systems and components to ensure complete coverage. This will help optimize the performance of the building and ensure that all relevant data are captured and analyzed.
- Including stakeholders: scaling DT should involve the participation of other stakeholders, such as building managers, occupants, and service providers. This will ensure that a comprehensive and collaborative approach is taken, leading to a more successful implementation.
- Monitoring and evaluation: the final step involves monitoring and evaluating the results of the DT implementation to confirm that the objectives have been met and to identify areas for improvement. This feedback loop is critical to refine and optimize the DT implementation for future applications.

The adoption of digital technology in construction is still relatively low compared to other industries, with a digitization rate of 1.4% compared to 4.6% in the Information and Communication Technology industry [12]. However, it should be noted that industries differ greatly in their processes, making it more challenging to achieve the same level of digitization in construction due to its complex nature with numerous participants, variables, and external factors. Additionally, there is a lack of standardization in the implementation of DT and digitizing processes in construction, reflecting the unique nature of each project.

Each building project and construction process is unique and there is no one-size-fits-all solution for the successful implementation of digital technologies. It is crucial to assess each project's problem areas and processes and optimize them using the current technology. According to Sacks et al. (2020), three essential elements are required for construction technology innovation [15]: a real process in the industry that requires optimization; the application of new technology that meets specific requirements; a feasible virtual model. By starting with small optimization within the project and gradually moving toward more complex automation, the construction industry can achieve the most comprehensive and effective implementation of DT. This approach demands a thorough analysis of even the simplest processes and operations and the potential for further optimization.

The study by Bosch-Sijtsema et al. (2021) identified a hype factor related to the "knowledge of technology/actual use of technology", which describes the level of adoption of digital technologies for the Architecture, Engineering, and Construction (AEC) sector [16]. It has been determined that digital technologies in AEC belong to the Experimentation cluster, meaning they are mainly used in pilot projects, but have not yet been widely adopted. However, experts surveyed in the study showed a willingness to invest in these technologies in the next 5 years, with the main technologies being BIM (70%), AI/ML (42%), 3D scanning (38%), sensors (37%), robots and automation (34%) and DT (32%) [16]. This highlights the importance and demand for research in the field to improve understanding of technology and its potential applications in the real world.

2.4. Changing the geometry of the building during the life cycle

According to Brilakis et al. (2019), a DT is a digital replica of a physical built asset [11]. The information included in a DT must match the purpose for which it was created and must be updated regularly to accurately reflect the physical object. The core geometry of most built assets can remain unchanged for extended periods of time, but it is important to understand when updates to the geometry data are necessary.

There are two approaches to determine when to update the geometry data of a building. The first approach is based on *the life cycle of the building*. At the construction stage, geometry changes are dynamic and there is often no two-way communication between the virtual model and the physical object. At this stage, the main focus is on creating an "as-built" model that accurately reflects any deviations from the design plan. During the operational stage, changes to the geometry of the building typically occur due to renovations, damage from natural or man-made disasters, or deformation processes resulting from aging, changes in geological or hydrological conditions, technological impacts of new construction, etc. The second approach is based on *the type of building*. Buildings that require constant or periodic updates to their geometry data can be categorized as those with a high risk of deformations (such as heritage buildings, old structures, buildings located in seismically active zones, etc.), those with high occupant density (such as airports, train stations, shopping malls, etc.), and those subjected to significant variable short-term loads (such as bridges, oil platforms, skyscrapers, industrial buildings, etc.).

It is crucial to keep in mind that a building's geometry changes over its lifespan. During the initial stages of planning, a life cycle approach should be applied to anticipate future challenges and needs, preventing the following issues [17,19].

- The design stage's geometric model may not be updated, leading to incorrect and unreliable data.
- The model may not consider future operational requirements, limiting its future use and making data integration more difficult.
- Building geometry data is usually static, whereas real-time data is dynamic and demands distinct processing techniques, leading to complications in their integration.

Updates to geometric data in real time may not be necessary for all buildings, but they are crucial to ensuring safe operation in some cases. The decision to update should be made based on a cost-benefit analysis. It is important to note that the expediency of updating the data on geometric parameters should be considered on a case-by-case basis.

2.5. Data collection on the geometric parameters of the building

The selection of methods and equipment to collect data on the geometric parameters of a building should be carefully considered based on several factors. These factors include the complexity of the building's form, the required accuracy and completeness of the data, the cost and availability of equipment, and the time required for preparation, data collection, and processing. In the context of a DT, laser scanning and photogrammetry are commonly used technologies for existing buildings. However, to achieve the highest level of data completeness, a combination of technologies, such as geodetic measurements using total stations, sensors, and Global Positioning System (GPS) equipment, can also be employed.

Brilakis et al. (2019) have categorized the technologies used in DT into two groups [11].

- General technologies that aim to collect and display data, including 3D scanning.
- Technologies that are designed for specific use cases, such as the use of a mobile phone, manual devices, current and newly created databases, and data collected from sensors.

When updating the geometry of a building in DT, several critical considerations must be taken into account [11].

- The geometric representation of the digital model should have desirable characteristics such as being lightweight, scalable, stable, and capable of being easily exchanged and used across multiple platforms.
- Information availability can be hindered by occlusions, which result in the missing information.
- Visualization and simulation of complex information must be effective and easy to interpret.

When developing a DT, it is crucial to first establish its purpose. Then, for this purpose, the level of detail and accuracy of the geometric model must be determined and the equipment and methods to collect the necessary geometric data should be selected. The requirements for updating the building's DT geometry will vary for each case. Previously, it was noted that the most used methods for collecting building geometry data (UAV/photogrammetry, laser scanning, total station measurement, GPS measurement, sensors such as clinometers and accelerometers) can be evaluated using the following criteria: accuracy, real-time data updating capability, suitability for indoor use, dependence on reflective surfaces, and the level of human involvement required, as listed in Table 1.

For accurate updating of the building geometry data, a combination of methods is often recommended. For instance, the exterior of a building can be modelled using UAV/photogrammetric techniques, while indoor work can be done with laser scanning as seen in the construction of the Turin Exhibition Centre's interior [20]. Other techniques like SLAM-based (Simultaneous Localization and Mapping) hybrid systems and close-range digital photogrammetry were also used. Another example is the real-time monitoring of Burj Khalifa in Dubai, where GPS measurements, high-precision total station measurements, and sensors were combined [21,22].

Table 1
Comparison of the main data collection tools for updating building geometry.

	UAV/photogrammetry	Laser scanning	Total station	GPS	Sensors (clinometers/ accelerometers)
Accuracy	±20 mm [20,33–35]	±2 mm (Faro Focus 3D) [33,36]	0.6 mm + 1 ppm/0.5" (Leica Nova TS 60)	±10–20 mm [37]	±0.5" [21]
Real-time update	–	–	–	+	+
The possibility of use in the indoor environment	In general, UAVs are not used indoors, except for specific models	Can be used indoors: terrestrial laser scanners (TLS) and hand-held scanners	+	–	+
Reflective surfaces	-(problems with reflective and transparent surfaces)	-(problems with reflective and transparent surfaces)	-(problems with reflective and transparent surfaces)	+	+
The autonomy of measurements	+	+	+	-(only at the system installation stage)	-(only at the system installation stage)
Advantages	commonly used, inexpensive, high-speed, 3D model	accuracy, commonly used, high-speed, 3D model	accuracy, commonly used, inexpensive, high speed	commonly used, inexpensive	accuracy, small sensor, inexpensive
Disadvantages	influenced by the environment	expensive, redundant data and noise in the point cloud	influenced by the environment, the impossibility of building a 3D model	influenced by the environment, the impossibility of building a 3D model	only angular measurements, the impossibility of building a 3D model

2.6. Data processing and integration into the DT

DT is a complex system that demands ongoing management, updates, and optimization. Therefore, when creating a DT, it is critical to establish a reliable virtual model that accurately reflects the physical and geometric properties, changes, and behavior. The accuracy of the virtual model impacts the effectiveness of DT. Segovia et al. (2022) identify three primary components that make up the virtual model of DT [23].

- Behavioral model, which represents the behavior of physical objects.
- Structural Model, which outlines structures and connections.
- Geometric model, which depicts the geometric shape, size, and position of the components of physical objects.

The foundation of a virtual model is a geometric representation that outlines the physical characteristics, shape, composition, and interconnections of an object. For example, in the case of a building, a geometric model can also encompass information on the location, specifications, and construction materials of structural components, as well as data regarding loads and other relevant factors.

Brilakis et al. (2019) introduce a geometric DT, which is a fundamental component of comprehensive DT [11]. The geometric DT, as defined by the author, is a model that incorporates both geometric and semantic information about physical objects. The author highlights two methods for constructing a geometric DT: "bottom-up" and "top-down". The "bottom-up" method involves constructing the DT from lower-level components, while the "top-down" method involves starting from high-level components and breaking them down into lower-level components. These methods provide a comprehensive approach to constructing a geometric DT, which is crucial for the advancement of DT.

When updating geometric DT data, it is essential to pay attention to the following considerations [23].

- The Complexity of the DT data update system: DT is a complex system, and any disruption to one component can affect the entire model. This highlights the importance of monitoring the components and ensuring that they are working correctly.
- The interaction between DT and the physical object: the relationship between DT and the physical object is crucial to consider, as it can directly or indirectly affect the data update process. If the interaction is not properly managed, it can lead to errors and conflicts in the system, which in turn result in unreliable outcomes and predictions.

Building geometry data can be updated in real time or periodically, as shown in Fig. 6. In periodic updating, data is collected and integrated into the database at a predetermined interval or schedule. In case of unexpected changes to the building's geometry due to reconstruction, restoration, or emergencies, irregular updates can be performed one or multiple times. The data collection, processing, and analysis method should be selected based on the desired update frequency.

Building geometry is updated in real time through the use of AI and ML (Machine Learning) in the IoT cloud. The process involves collecting geometry data from a system of sensors or other equipment and sending them to the IoT platform through a communication network for analysis [12]. The resulting virtual model accurately reflects the current state of the physical object and provides a basis for making informed decisions. However, it is important to consider the potential for an excess of data to be collected, as this could result in increased costs and require additional time and hardware to manage, store, share, and analyze the data.

Building geometry data can be updated periodically through various methods such as UAV/photogrammetry, laser scanning, total station, or a combination of these. The use of a total station provides high-precision measurements, making it a good option to partially update the model or transform it to increase the spatial accuracy of the data. However, it should be noted that using a total station alone does not allow the creation of a 3D model. Laser scanning is another option to update building geometry data, but one should be aware of potentially redundant or irrelevant data, such as equipment or mechanisms that do not reflect the actual geometry

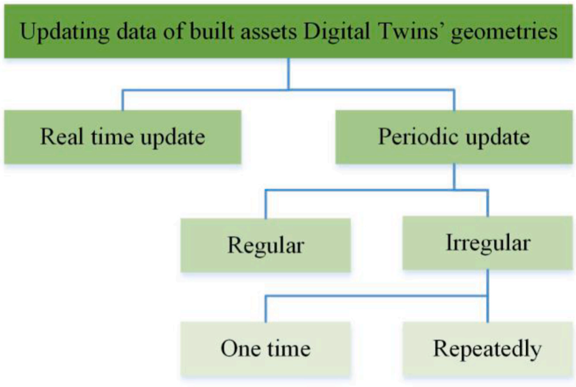

Fig. 6. Periodicity of updating data of built assets DT geometry.

of the building. Additionally, there may be difficulties in recognizing objects in the point cloud during processing, as the point cloud is unordered and lacks texture and color. This type of data can also be more challenging to process using convolutional neural networks (CNN) compared to images obtained through UAV/photogrammetry. To date, the identification of objects within a point cloud is done primarily through two techniques: point-based and voxel-based methods, or a combination of the two [24].

When it comes to integrating and processing geometric data into a DT, a good example to consider is the LocLab ToolChain concept [11]. This concept has been adapted to incorporate technology for collecting data on building geometry, as shown in Fig. 7. The method used to integrate and process building geometry data is specific to each situation and depends on factors such as the data collection method, the characteristics of the physical object and existing DT. It is determined individually based on the intended purpose and requirements.

An additional concern that requires particular attention is data interoperability, particularly when it comes to the geometry of the building. This is because various types of equipment may be used to collect data, each with its own distinct formats. As a result, data interoperability and standardization of data become a significant concern. Without adequate attention to this issue, there is a risk that incomplete or inaccurate data is used in critical decision-making processes. The interoperability of data in DT is ensured through the use of various tools and standards. The Information Delivery Manual (IDM) and the Model View Definition (MVD) play a crucial role in ensuring the flow of necessary information from the source model to other applications. This makes it possible to use DT as a foundation for Building Energy Performance Simulation (BEPS) and other similar applications. The use of non-proprietary standards like Industry Foundation Classes (IFC) and the International Framework for Dictionaries further helps in ensuring seamless data transfer and compatibility. Additionally, the Unified Construction Classification System (UniClass) and Construction Classification System (OmniClass) can be applied to unify the content of the model and make it consistent across different systems. These tools and standards work together to ensure that the data in DT is interoperable, accessible, and useable by different applications and stakeholders.

After conducting a background analysis, the study has identified existing knowledge gaps that need to be addressed through a subsequent SLR. Analysis has shown that the implementation of DT in the construction industry is still laggard behind other industries. Therefore, more research is needed to develop standardized and unified processes that can facilitate the widespread adoption of DT in construction. This will enable a more comprehensive implementation of DT in the industry.

The DT classification distinguishes Intelligent DT as a fully automated data flow system that offers significant advantages in processing real-time data related to the geometry of the building. Therefore, future efforts should prioritize the development of a system architecture that facilitates the collection and updating of data through sensors and other equipment. It is important to note that the geometry remains relatively stable throughout its life cycle, making this system suitable for regular monitoring of the current state of the building or critical structures.

Based on the analysis of the relationship between DT, BIM, and life cycle stages, it is crucial to update the existing BIM model to the level of DT. However, in cases where a BIM model does not exist, and partial or fragmented data are available, challenges arise in creating a 3D building model (e.g., CAD – to – BIM, FEM (Finite Element Method) - to – BIM) and converting it to the IFC format. These challenges are particularly difficult for buildings with free-form structures that cannot be easily described using simple mathematical figures (e.g., columns with capitals, decorative elements, etc.). Consequently, the geometric modelling methods currently

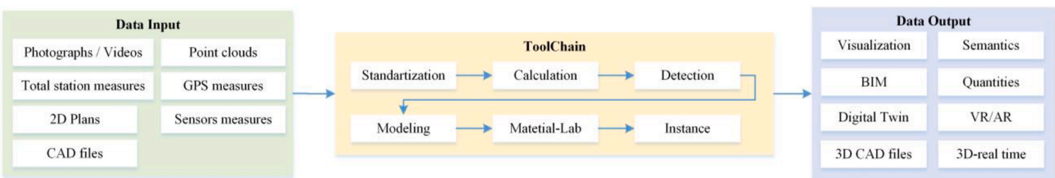

Fig. 7. LocLab's ToolChain concept for data on built assets DT' geometries [11].

prevalent in software, such as Constructive Solid Geometry (CSG) and Boundary Representation (B-Rep), require more detailed investigation to describe the irregular geometry more accurately.

The accuracy of the collected data poses significant challenges that depend on the type of equipment used during data collection. For example, when using UAV and GPS technology, the accuracy of building geometry data may be limited, which might not be sufficient to create a high-precision model. Additionally, collecting data in the indoor environment and automating the data collection process (such as with autonomous UAV flights along predetermined routes) can be challenging. Another factor that requires further investigation is the impact of reflective surfaces, such as white, mirror, or glass surfaces, on equipment performance. Such surfaces can hinder the recognition of objects during subsequent data processing stages.

3. Research methodology

A systematic literature review (SLR) involves several steps grouped into three stages: Planning, Implementation, and Analysis of Results. The methodology used is thoroughly explained in references [25–27]. Figs. 8 and 9 show the overall process of the SLR and its key stages.

3.1. Stage 1 – planning

3.1.1. Determination of the research question

In the planning stage of this research, the authors defined the research questions (RQ) and sub-questions (SQ) to be addressed through the literature review. As mentioned in the Introduction Section, the main RQ is: What is the state-of-the-art in the area of updating the geometry of DT in construction? This question is broken down into three SQs: (1) What is the relationship between the geometry of the DT, the BIM model, and the life cycle of the building? (2) What is the relationship between DT and equipment, methods of collecting and integrating geometry data of a physical object? (3) What are the gaps and challenges for further research on updating the geometry of DT?

3.1.2. Definition of databases or scientific repositories

For this study, we selected the Web of Science and Scopus databases as they are widely used for similar studies due to their comprehensive and relevant data, as demonstrated by several systematic reviews of the literature [25,28–32].

3.1.3. Formation of queries and search criteria

Two types of queries were formed to identify relevant publications for the study. The first query aimed to identify publications related to the concept of DT in construction and the building life cycle, while the second query aimed to identify publications on DT and measurement methods, equipment, and data processing.

The following inclusion criteria were applied: articles published in the past 10 years (2012-01-01 – 2022-01-01); document type – only articles; language – English.

Query 1:

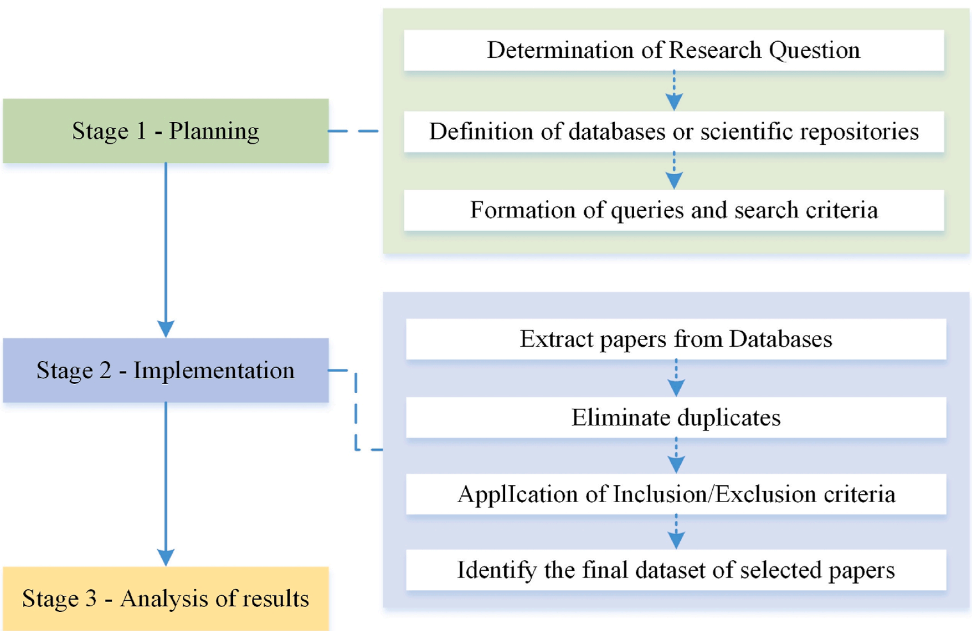

Fig. 8. Stages of a systematic review of the literature [25–27].

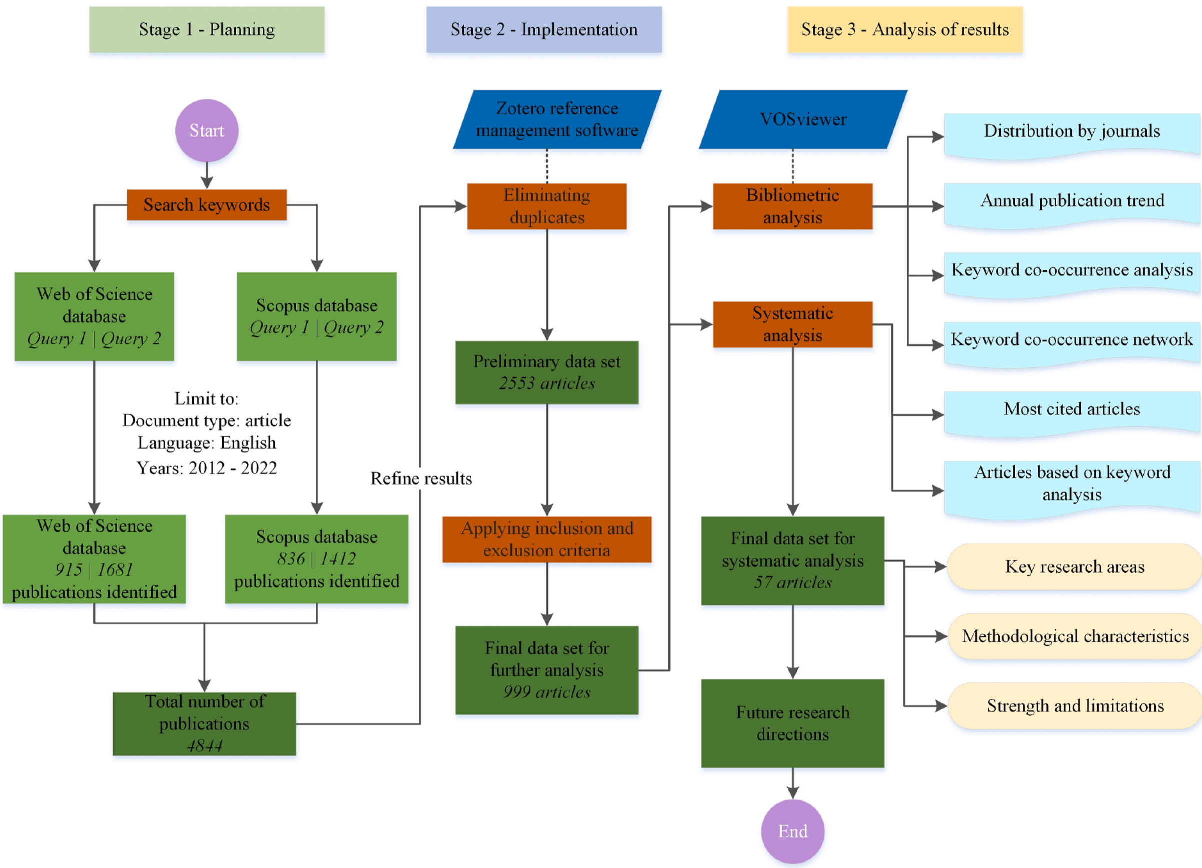

Fig. 9. The systematic literature review process workflow.

Web of Science: ((ALL = ((“digital twin*" and “geometry”) OR (“digital twin*" and “life cycle”) OR (“digital twin*" and “BIM”) OR (“digital twin*" and “construction”) OR (“digital twin*" and “update”) OR (“digital twin*" and “automation"))) AND DT = (Article)) AND LA = (English).

SCOPUS: TITLE-ABS-KEY ((“digital twin*" and “geometry”) OR (“digital twin*" and “life cycle”) OR (“digital twin*" and “BIM”) OR (“digital twin*" and “construction”) OR (“digital twin*" and “update”) OR (“digital twin*" and “automation")) AND (LIMIT-TO (DOCTYPE,"ar”)AND (LIMIT-TO (LANGUAGE,"English”).

Query 2:

Web of Science: ((ALL = ((“digital twin*" and “laser scan*") OR (“digital twin*" and “scanning”) OR (“digital twin*" and “photogrammetry”) OR (“digital twin*" and “UAV”) OR (“digital twin*" and “total station*") OR (“digital twin*" and “GPS”) OR (“digital twin*" and “sensor*") OR (“digital twin*" and “measure*") OR (“digital twin*" and “point cloud*") OR (“digital twin*" and “IoT”) OR (“digital twin*" and “Artificial Intelligence”))) AND DT = (Article)) AND LA = (English).

SCOPUS: TITLE-ABS-KEY ((“digital twin*" and “laser scan*") OR (“digital twin*" and “scanning”) OR (“digital twin*" and “photogrammetry”) OR (“digital twin*" and “UAV”) OR (“digital twin*" and “total station*") OR (“digital twin*" and “GPS”) OR (“digital twin*" and “sensor*") OR (“digital twin*" and “measure*") OR (“digital twin*" and “point cloud*") OR (“digital twin*" and “IoT”) OR (“digital twin*" and “Artificial Intelligence")) AND (LIMIT-TO (DOCTYPE,"ar”) AND (LIMIT-TO (LANGUAGE,"English”).

3.2. Stage 2 - implementation

Stage 2 involved extracting relevant publications from databases, removing duplicates, applying additional inclusion and exclusion criteria, and forming the final set of publications for detailed analysis.

3.2.1. Extraction of papers from databases

Queries and criteria were executed on the Web of Science and Scopus databases on December 5, 2022. The results were as follows.

- Query 1: 915 articles were obtained from Web of Science and 836 articles from Scopus.
- Query 2: 1681 articles were obtained from Web of Science and 1412 articles from Scopus.

A total of 4844 articles were identified and exported to Zotero reference management software.

3.2.2. Eliminate duplicates

The articles were analyzed using Zotero reference management software, resulting in the elimination of duplicates and a sample size of 2553 articles.

3.2.3. Application of inclusion/exclusion criteria

The influence of scientific research on the international community is crucial, and its performance can be assessed both qualitatively and quantitatively. Peer review is key for qualitative analysis, while bibliometric indicators are significant for quantitative assessment. However, bibliometric indicators must be accurate, up-to-date, sophisticated, and used with expert knowledge and care [9]. In this study, we used the science mapping method to analyze the literature on updating the geometry of DT in different fields. Science mapping allowed us to visualize critical patterns and trends in bibliographic data and large bodies of literature. Our bibliometric analysis focused on the distribution of articles by journal, year of publication, and keyword co-occurrence networks related to DT in general and DT geometry updates specifically.

To narrow down the number of publications, additional criteria were applied: articles had to be published in journals with an impact factor of 1.8 or greater (to date 2022), and the journal had to contain at least 5 articles included in the sample. This resulted in the identification of 44 journals and a sample of 999 articles published in them. The distribution of the articles analyzed by the journal is shown in Fig. 10, and the sample was analyzed by year of publication, as shown in Fig. 11. It is worth noting that the criteria were applied to only those publications no older than 10 years. Analysis of the period 2012–2016 revealed that no publications met the criteria; however, there was a rapid growth in the number of relevant publications from 2017 to 2022, indicating an increase in interest in technology within the construction industry.

The next step involved analyzing the keywords present in the selected articles using the VOSviewer tool. This tool facilitated a keyword co-occurrence analysis, yielding 8541 keywords. Keywords that occurred more than 20 times were selected and, after removing duplicates, 51 keywords were identified. These keywords were then organized into a Keyword Co-occurrence Network com-

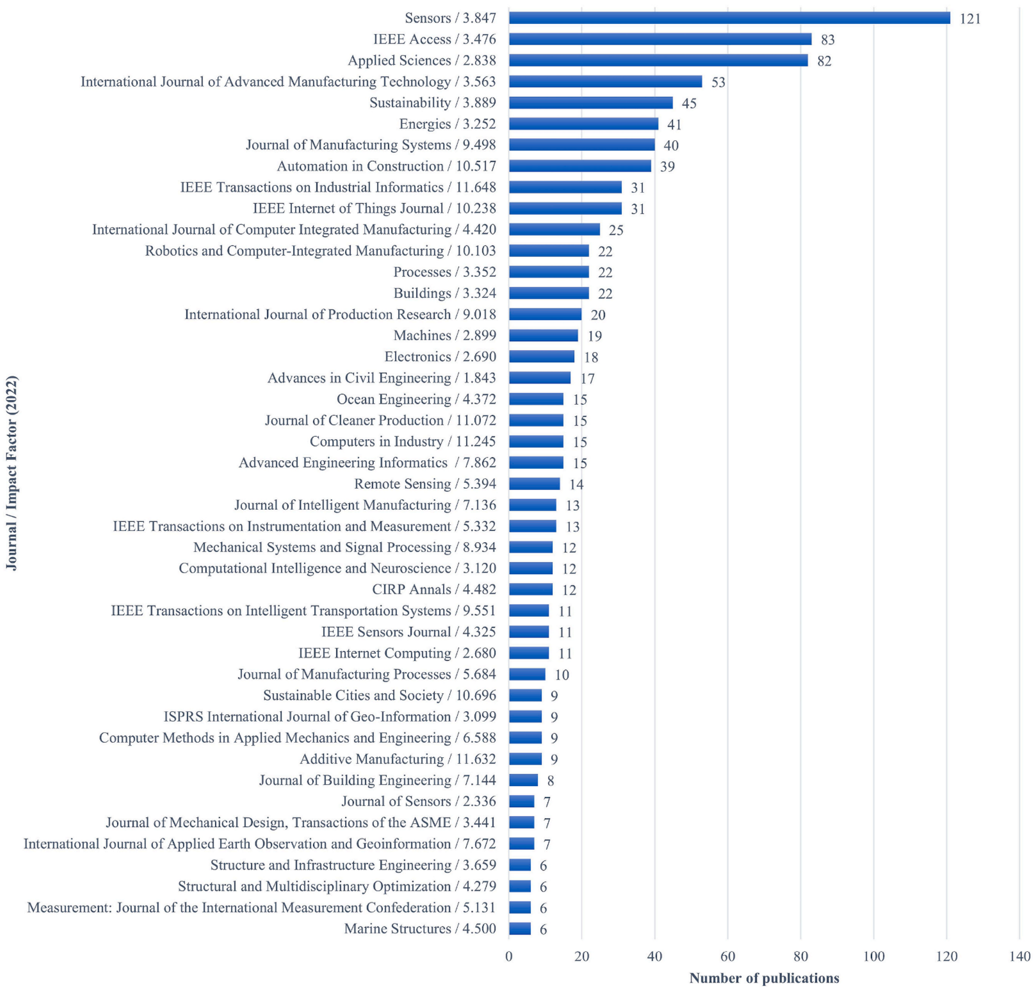

Fig. 10. Distribution of the number of articles in the sample by journals.

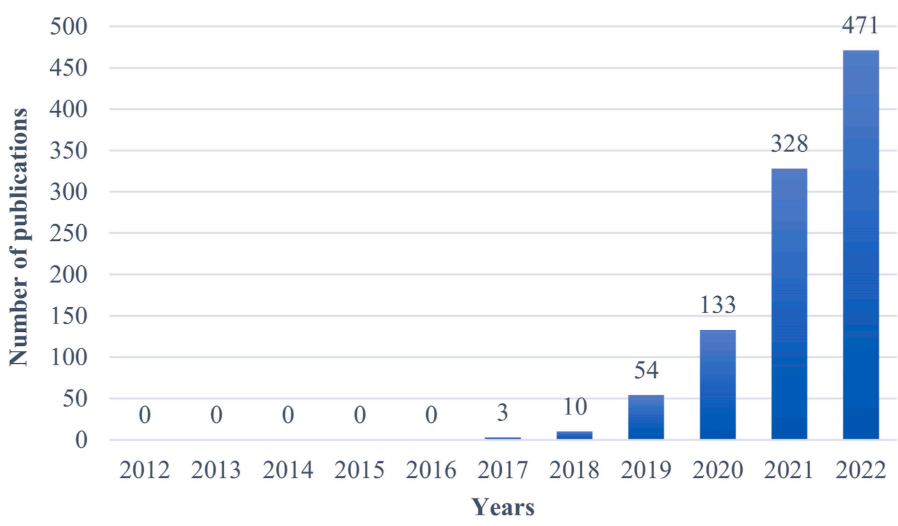

Fig. 11. Distribution of articles in the sample according to the year of publication.

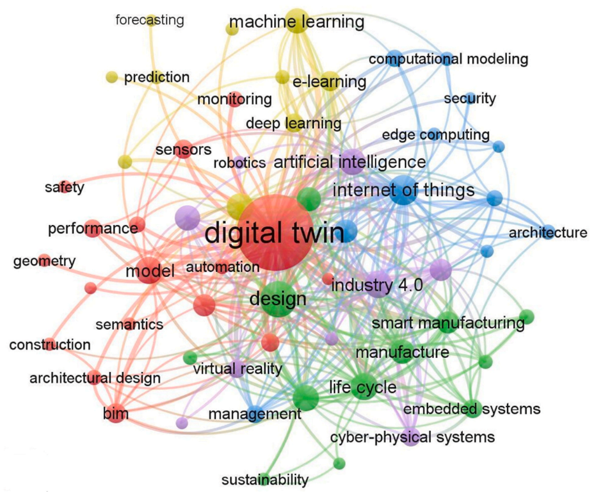

Fig. 12. Keyword co-occurrence network.

prised of 4 clusters as shown in Fig. 12 and Table 2. After analyzing the frequency of connections, it was found that there is a link between DT and ML. This connection suggests the potential use of trained neural networks for pattern recognition in point clouds obtained from laser scanning or photogrammetry. Additionally, the IoT can be used to develop a system of sensors that monitor changes in the geometry of buildings in real time. Furthermore, DT can be applied in the context of Industry 4.0, which shows its evolution and implementation in various industries, including the manufacturing cluster. The existing practice of updating geometry can be adopted for the construction industry. Finally, the model cluster represents the link between DT and modelling processes, particularly in the creation of a 3D model and its geometry. Furthermore, the analysis determined the keywords most closely associated with the geometry concept in the context of DT as shown in Fig. 13. In this instance, the geometry is highly interconnected with simulation processes, decision-making, design, and the building's life cycle. This highlights the critical role of geometry throughout the lifespan of a building.

This stage involves a thorough analysis of the central keywords related to the selected topic, with a focus on understanding the connections between them and the role of the physical object's geometry in the given context. The outcome of this stage is a clear understanding of the most used keywords and the significance of the physical object's geometry in the selected context.

3.2.4. Identifying the final data set of selected papers

At the end of the analysis, 57 articles were selected for further examination based on keyword analysis, frequency, relationships, and reviews of abstracts of the articles. However, after a closer look, 8 articles were deemed not related to the topic and 7 articles were added from the reference analysis, leaving a total of 56 articles used in the analysis.

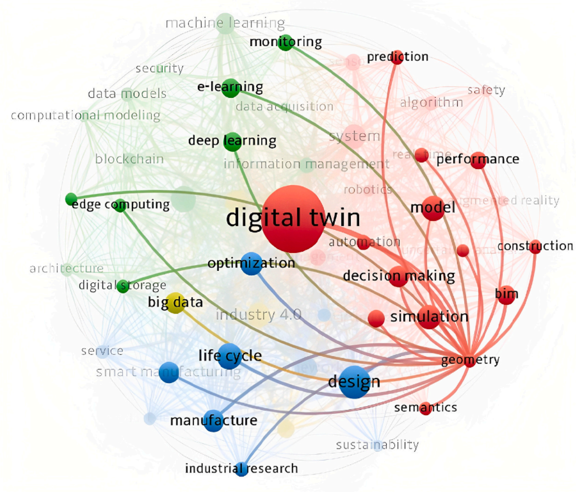

Fig. 13. Network visualization of keyword co-occurrence of Geometry and DT.

3.3. *Stage 3 – analysis of the results*

Based on the results of the analysis, the articles were classified into 6 themes, as presented in Table 3. These themes should guide future research, addressing the existing knowledge gaps outlined in Section 2.

3.3.1. *DT and UAV/photogrammetry*

The combination of DT and UAV/photogrammetry technology has found applications in various fields such as visual inspection and observation of bridges and transport infrastructure [48,76,79,81], monitoring construction dynamics [87,88], simulation of UAV flights [38,47,76,86] and inspection of buildings damaged by an earthquake [77,81]. The technology is also used in the general inspection of buildings [49], monitoring of dangerous industrial facilities (nuclear plants, hazardous production, etc.) [85], in smart city development [52,60,73], and in the context of a comparison of digital photogrammetry and laser scanning technologies [72,79].

However, the analysis of articles in this field reveals several challenges in the use of this combination. One of the major challenges is the lack of semantic information in the 3D models created using UAV/photogrammetry data. This makes it difficult to perform further analysis or automatic conversion to FEM or IFC models. Yoon et al. (2022) presented a methodology for conducting seismic fragility analysis on deteriorated bridges, which uses an updated DT based on UAV inspections. The methodology comprises two phases: (1) an updated DT phase using UAV inspections and (2) a seismic fragility analysis phase [81]. This highlights the possibilities of transforming point clouds into a numerical model. However, the methodology was tested only on a single bridge, which significantly limits the identification of potential challenges.

Another challenge is the accuracy of the 3D models obtained using UAV/photogrammetry. It can be difficult to meet the set requirements for accuracy, as well as scaling and merging image-based point clouds with BIM or DT. Mohammadi et al. (2021) proposed a methodology to assess the quality of digital point clouds generated using different techniques, including imagery acquisition and detailed 3D reconstruction models, for bridge inspection. The study suggested several general and specific data evaluation approaches to compare and evaluate point clouds in terms of point distribution, data completeness, surface deviation, and geometric accuracy. The findings revealed missing data and greater scaling errors, which resulted in lower geometric accuracy for the UAV-generated point cloud [79]. Additionally, recognizing objects in image-based point clouds, especially those with complex geometry, can be difficult.

The use of UAV indoors and ensuring their autonomous flight in outdoor environments can present significant challenges. Shen et al. (2022) introduced BCDDPG (Behavior-Coupling Deep Deterministic Policy Gradient), a Deep Reinforcement Learning (DRL) method enabled by DT, for the multi-UAV system. The central server builds the DT to train the DRL model. Following the training phase, the DRL model can be immediately deployed to the actual UAV using the link between the physical unit and the digital model. This should facilitate the autonomous flight of the UAVs team in external environments [38]. Song et al. (2022) propose an integrated framework for achieving fully autonomous flights for LiDAR (Light Detection and Ranging)-carrying UAVs in AEC applications, while also considering safe and energy-efficient UAV trajectories. The framework consists of various components, including BIM-supported map construction, waypoint-based scan planning, shortest collision-free path planning, kinodynamic trajectory generation, and flight control [47]. Bono et al. (2022) propose a strategy that combines cutting-edge technologies from IT and robotics to create a bridge management system. This approach involves using a DT representation of the bridge to plan the trajectory of a UAVs fleet and conducting numerical inspection simulations. However, several aspects require further investigation in this area, including accurately estimating the pose of UAV in areas where a Global Navigation Satellite System (GNSS) is not available by solving the Perspective-n-Point (PnP) problem; transmitting the collected data to the Ground Control Station through communication channels; and avoiding unknown objects, such as vegetation or other obstacles, that may be present along the planned paths [76]. Sun et al. (2022) proposed a framework for monitoring complex industrial facilities based on UAV inspections and IoT. They identify the development of onto-

Table 2
Selected keywords with network parameters.

Keyword	Occurrence	Total link strength
digital twin	638	1820
design	156	563
Internet of things	112	471
life cycle	96	415
industry 4.0	95	387
system	95	328
model	91	312
framework	89	367
artificial intelligence	87	362
simulation	83	278
machine learning	78	257
optimization	77	289
manufacture	73	327
big data	64	307
smart manufacturing	63	292
decision making	62	262
bim	55	195
e-learning	55	234
deep learning	51	181
cyber-physical systems	50	206
sensors	48	144
management	45	230
virtual reality	44	173
information management	43	197
performance	42	142
data models	38	159
blockchain	37	181
monitoring	37	114
algorithm	36	117
service	32	173
architecture	31	140
automation	30	118
computational modelling	29	130
maintenance	29	117
product design	29	130
industrial research	28	117
prediction	27	87
real-time	27	109
robotics	26	97
semantics	26	78
construction	25	93
geometry	25	60
sustainability	25	86
digital storage	24	130
edge computing	24	104
safety	23	86
augmented reality	22	73
data acquisition	22	82
cloud computing	21	107
security	21	81
uncertainty analysis	20	62

Table 3
Literature analysis themes.

Themes	Articles
DT and UAV/photogrammetry	38, 47, 48, 49, 60, 72, 73, 76, 77, 79, 81, 85, 86, 87, 88
DT and Laser scanning	39, 43, 46, 47, 54, 57, 60, 62, 66, 72, 78, 79, 80, 84, 87, 91, 92, 93
DT and Manufacturing	41, 42, 44, 45, 51, 53, 55, 56, 58, 59, 61, 63, 64, 68, 71, 83
DT and Data visualization	65, 66, 67, 70, 72, 74, 75, 78, 80, 82, 87
DT and Modular construction	40, 60, 89
DT and Structural monitoring	69, 75, 76, 77, 81, 85, 87, 88, 90

logical models that describe intelligent monitoring systems using UAV and IoT technologies in various situations and environmental conditions, as well as the development of separate and joint DT models for decision-making centers and for the implementation of optimal procedures for the recovery of critical objects [85]. However, the primary areas of research have focused on enabling UAV to operate autonomously in outdoor environments, leaving their potential applications indoors uncertain.

There is also a challenge in the automatic recognition of objects, damages, and the state of materials based on the inspection data obtained. The training of neural networks to perform these tasks can also be difficult. Levine et al. (2022) developed a DT framework that connects components observed in UAV images or 3D point clouds with their corresponding elements in a BIM to assess post-earthquake building damage and streamline the process of pattern recognition. This approach allows component damage to be evaluated based on its design, anticipated seismic behavior, and importance to the building's safety and stability. However, the study also highlighted several issues that need to be addressed. Notably, the BIM does not always accurately reflect the building's true geometry, as some components might be simplified. Furthermore, the quality of the initial BIM alignment affects component labelling, especially in areas where significant damage is anticipated. These limitations emphasize the importance of accurately measuring and documenting building components during the initial walk-through to improve the precision of the BIM geometry [77]. In conclusion, while the combination of DT and UAV/photogrammetry technology has found applications in various fields, the challenges faced in the use of this combination need to be addressed to fully realize its potential.

3.3.2. DT and laser scanning

The use of laser scanning technology in construction is a widely researched topic, with various articles exploring its applications. The main areas of focus are the following: scanning of architectural heritage objects (the focus is on using laser scanning to create a point cloud of an object, which is then transformed into an IFC model or VR construction) [50,57,78,84]; seismic analysis (the focus is on using laser scanning to create a point cloud of a building, bridge, or other structure, which is then used to create a numerical model for seismic analysis, which is particularly useful for existing or earthquake-damaged buildings) [43,62,91,92]; inspection of buildings, structures, and tunnels (the focus is on using laser scanning for inspection purposes, for example to detect damage) [39,54,93]; other directions (this area includes creating an as-built model based on a point cloud [46,87], comparing laser scanning and photogrammetry technology [47,72,79], enriching a DT based on the recognition of elements in a point cloud [66], developing BIM models based on laser scanning data and existing 2D documentation [80], and smart city development [60]).

Upon analyzing the set of articles, we have identified several primary challenges in the application of laser scanning technology. One of the significant challenges is object recognition, which refers to the categorization, segmentation, and identification of objects in a laser-scanned point cloud. Baek et al. (2022) have presented a 3D global localization technique that can be employed in underground mines using mobile LiDAR mapping and point-cloud registration to identify object locations. The first step was the generation of a prior global point cloud map for the entire mine, which was then converted into a global Universal Transverse Mercator (UTM) coordinate system. The proposed method offers a solution to 3D position recognition. However, the construction of a live data collection and processing system was found to be challenging due to the complexity of the algorithms, a large amount of point cloud data, and the use of individual 3D mobile LiDAR and processors [39]. Furthermore, this method is more focused on determining the position of the object in the point cloud, with less emphasis on general pattern recognition within the point cloud.

Another aspect that needs to be carefully considered is the lack of semantic information. The point cloud obtained from laser scanning does not inherently contain semantic information, which can make interpretation challenging. Pan et al. (2022) have proposed a pipeline for enriching the geometric DT of building with small objects and text information through the recognition of small objects in point clouds. Deep learning techniques are used for image recognition to detect semantic information, which is then mapped to a 3D point cloud to obtain point clusters of different classes [66]. The entire processing pipeline is almost completely automated, with the only manual step being the registration of the point cloud. Based on an analysis of this method, it is assumed that combining 3D deep learning in the point cloud and 2D deep learning in images within one framework can improve segmentation performance and enriching the 3D model with semantic data. Tan et al. (2022) introduced an approach for architectural archaeology research that combines a semantic-rich BIM model with point cloud data. The researchers not only employed a scan-to-BIM approach, but also extended it by incorporating architectural archaeological dating studies. The primary advantage of this method over traditional approaches is its effectiveness in handling uncertain clues in archaeological research and establishing connections with the corresponding components [57]. However, it should be noted that this method is not fully automated and requires significant human involvement.

Another challenge identified is the difficulty in developing parametric models, especially for existing buildings. Structural components may be invisible or atypical, making it difficult to create a parametric model from a point cloud according to the IFC format. Moyano et al. (2022) have presented a systematic approach to creating parametric objects from the point cloud. The study used automatic meshing from TLS (Terrestrial Laser Scanner) data and analyzed the modelling workflow in both a Revit family and an adaptive mesh process in ArchiCAD [84]. However, the main challenge encountered during the automation of the Mesh-to-BIM process was the need to simplify the mesh for algorithm processing. This research also highlights the importance of an informative 3D model to support decision-making for future interventions and maintenance activities. Building components should be enriched with semantics about the evolution of the construction, previous interventions, decay mapping over time, and diagnostic tests. Additionally, the study pursued the interoperability of BIM, which has been achieved through the sharing of BIM in the open IFC standard.

Lu et al. (2019) have proposed an object-fitting method that uses four types of point clusters to generate a geometric DT of existing reinforced bridges in IFC format. The resulting bridge DT has a LOD of 250–300 and uses a stacked slice representation. The spatial precision of the generated DT is evaluated using distance-based metrics [62]. However, automating the digital twinning process for existing bridges and buildings from point clouds remains a challenge. While current methods can detect objects in point clouds as labelled point clusters, accurately fitting 3D shapes to these clusters still requires significant human involvement. This is mainly due to the irregular geometries of the existing structures. Existing methods often rely on fitting simple geometric primitives to point clusters, which oversimplifies the real geometry of the structure. Moreover, none of the existing methods has explicitly addressed the challenge of evaluating the resulting IFC data models in terms of spatial accuracy using quantitative measurements. This highlights another challenge, which is the lack of a single approach to creating a parametric model based on a point cloud, making it challenging to standardize the process.

Rausch et al. (2021) proposed an approach to create geometric agency in BIM using their parametric capabilities, the accuracy of 3D point clouds, and the versatility of metaheuristics. The outcome is a dynamic BIM, referred to as a "dyna-BIM," that can adjust its geometry to match a 3D point cloud. The authors demonstrated the effectiveness of this approach through a case study of cast-in-place concrete foundations, where the average error between the BIM and the as-built conditions was reduced from 50.4 to 5.69 mm [46]. However, the authors also noted that an initial BIM, referred to as a "proto-BIM," could be automatically updated to reflect as-built conditions by altering the shape and pose of BIM elements. In many cases, this approach would be preferable to scan-to-BIM.

One of the challenges that need to be addressed when working with laser scanning data is the absence of texture. The data obtained from laser scanning can often lack the necessary details, and the quality of the data may be impacted by other factors such as variations in point densities, surface roughness, reflectivity, scene clutter, and occlusions. Wu et al. (2021) proposed a method called "Registration Based on Architectural Reflection Detection" (RegARD) to create high-quality and cost-effective DT of buildings. This approach uses 3D point clouds captured by ubiquitous mobile devices and available 2D drawings of existing buildings as low-cost data sources. Preliminary experiments have shown that RegARD can efficiently and accurately register point clouds captured by smartphones with CAD drawings. Using the results of RegARD, DT can be automatically generated with realistic textures mapped from point clouds, as well as parametric geometry and rich semantics filtered from drawings [80]. Although this method addresses the issue of the high cost associated with TLS, the authors did not discuss the accuracy of the data obtained and the potential applications of the resulting 3D model.

In conclusion, laser scanning technology is a rapidly evolving field that has a wide range of applications in construction. Despite its many benefits, there are still several challenges that must be overcome to fully realize its potential. To address these challenges, more research is required in the areas of applying ML, computer vision, and data processing.

3.3.3. DT and manufacturing

The analysis of the articles in this block highlights the main directions of research in the field of physical object modelling and simulation using DT. The key areas of focus include improving the geometric accuracy of the modelling of physical objects [41,53,61], controlling the geometry of physical objects in real time during the production process, and considering the impact of environmental factors and related processes [42,44,45,55,64,68]. Additionally, other areas of research focus on prototyping physical objects using DT, simulating the production process with DT [52,63,71], and providing a general overview of DT in the aerospace industry and manufacturing [56,58,59,83].

Despite the progress made in these areas, the analysis of the articles also reveals several challenges that need to be addressed. One of the main challenges is that most techniques for improving geometric accuracy are only applicable to individual parts or components of mechanisms. This limitation makes it difficult to use these techniques for more complex objects, such as buildings or construction processes. Ghorbani et al. (2022) developed a methodology for generating a damage-free DT of a damaged blade, which can be used to create the geometry for additive restoration. The approach uses a region-growing segmentation method to remove the data points corresponding to the damaged regions of the blade. The geometric error between the scanned data and the CAD model is evaluated using the Euclidean distance and angular difference between the normal vectors of each measured data point and its closest point on the CAD model. A non-rigid CAD-to-scan registration algorithm is proposed to match the CAD model to the scanned point cloud of the undamaged regions of the blade while preserving the local rigidity of the data points [51]. Although the proposed approach is accurate and effective, the non-rigid registration method is computationally expensive. Therefore, future research could focus on simplifying scan and CAD point clouds or using voxel-based models to improve the efficiency of the algorithm.

Wang et al. (2021) proposed a method for analyzing assembly precision using a Part Digital Twin Model (PDTM) to predict the quality of assembled parts. This approach involves integrating various forms of data from different stages of the product life cycle and mapping the assembly information from assembly semantics to geometric features [44]. An optimization method based on current assembly precision analysis can be used to further enhance this approach, enabling real-time feedback control in digital twin-driven assembly.

Another challenge is that the methods used for controlling the geometry of physical objects in real time during the production process need to be more standardized and stable to be scalable and applied in the construction industry. Liu et al. (2021) proposed a DT mimic model that simulates physical machining processes from three perspectives: geometry, behavior, and context. The DT model is self-adaptive and can synchronize workpiece changes during machining, enabling it to reflect product processing and support decision-making. The feasibility of the method was verified by applying it to the air rudder in missile study products [59]. However, there are still some limitations that need to be addressed. First, the modelling speed could be improved by utilizing cloud-based approaches. Second, the lag issue of physical model simulation remains unsolved, making it difficult to perform complex simulations in the machining process. Therefore, more research is required to enhance speed and accuracy.

Söderberg et al. (2018) suggested the implementation of a DT system to improve the quality of welded components. This approach merges a process model framework that manages all relevant information regarding the geometry assurance of welded structures with simulation capabilities that can optimize geometrical quality in real time. Using this system, it is possible to create a platform that supports personalized mass production, leading to increased quality without imposing tighter tolerances or incurring higher machining costs. The concept uses rapid welding simulation together with activities that ensure geometric assurance, such as selective assembly, virtual matching, and variation simulation, to improve geometric quality [45].

Grégorio et al. (2021) proposed a hybrid virtual representation to facilitate DT implementation, which ensures compliance with geometrical functional requirements during assembly processes. This model incorporates a geometrical skeleton and a geometrical representation of the components as configurable surfaces. The hybrid representation accurately reflects the product during the assembly process by updating the geometry and skeleton features. The B-Rep formalism is used to represent component geometry, enabling the full utilization of current CAD environments. Local changes in the initial geometry of the designed component are implemented through direct modelling. The component topology is preserved during the update from as-designed to as-built or interface state [41]. An important direction for the future development of the method is to optimize the acquisition process to streamline the collection and processing of 3D data. A key consideration is whether the proposed method can handle sparse or missing data, such as non-digitized surfaces. Furthermore, the authors of the study acknowledge that greater complexity may arise when dealing with larger products, where the choice of interface components may vary depending on the specific product and its geometrical deviations. This could limit the applicability of the method in the construction sector.

3.3.4. DT and data visualization

The articles in this block of research concentrate on several key areas, including pattern recognition and neural network training [66,67,75,87], as well as enhancing the visualization of data models [65,72]. In addition, the creation of DT based on a variety of initial data sources is also explored, such as CAD files, historical data, paper drawings, and scanning using manual portable equipment [70,74,78,80,82].

Despite advances in DT technology, the authors of the articles in this block highlight several challenges that need to be addressed. These include defining the structural elements and relationships within raw data, improving shape representation methods and IFC geometric representation, ensuring data accuracy and completeness, and addressing data interoperability issues. Zhang et al. (2022) introduced a geometric construction model for video stereo space that addresses the limitations of existing methods in terms of video space construction and geographic data organization. The proposed approach combines the video characteristics and application requirements with a GeoSOT grid coding framework and a camera imaging model. The method establishes a correlation between the video and the real world using a stereo grid that contains geographic information, enabling the grid representation of the video stereo space with strong data organization and integration capabilities. Moreover, this model facilitates the integration and fusion of video space with external geographic and other information, which is essential for the effective digital analysis of massive video data [70]. However, the proposed concept was applied in the context of digital smart city data, which has a broader scope. Therefore, the potential use of this approach for individual buildings remains undefined.

Braun et al. (2020) introduce a machine learning-based object detection method to monitor construction progress by comparing element categories with expected data from a digital model. Results indicate that this approach can increase the detection of built elements by up to 50% compared to a purely geometric as-planned vs. as-built comparison based on Structure-from-Motion (SfM) techniques, depending on the type of construction and occlusions. By using image-based color detection and a higher threshold for elements with possible formwork, the method can correctly identify elements in construction at the time of image capture [87]. Research has demonstrated the effectiveness of using object detection methods in accurately detecting elements that may have been misclassified by other approaches. By training the network with automatically labelled images using scan versus BIM techniques, the method creates significant synergies. Moreover, using image-based object detection increases the reliability of the status detection process due to the higher density of pixel-based information compared to pure point-cloud-based approaches. However, it is important to note that the use of image data is only possible through photogrammetry and the estimation of the underlying camera poses. Laser scanners do not provide this data, which makes them unsuitable for this approach. Another limitation is that the ML approach is currently limited to training data, which can make the network biased and unsuitable for some cases.

Taraben et al. (2021) propose a method for discretizing 3D geometries into voxel-based representations, which can be assigned to elements in BIM. They also demonstrate how to compare multitemporal damage scans to determine discrete geometric differences. This enables automated determination of the position of affected building elements and the absolute change in individual damage. The clustering method is used to allow the grouping of unrelated damage mappings into areas of interest, facilitating targeted inspections. The voxel decomposition can be further optimized using octree structures. In addition, rule checks for damage parameters can be implemented to automate the process. The metadata provided can also enrich the damage information, particularly when assigning scanned damage to elements in the BIM model [75].

Lu et al. (2020) have developed a semi-automatic approach to creating a digital twinning system based on images and CAD drawings. The framework comprises three modules. The first module, Building Framework Construction and Geometry Information Extraction, identifies the locations of each structural component by recognizing special symbols in a floor plan and extracting data from CAD drawings using Optical Character Recognition (OCR) technology. The second module, Building Information Complementary, supplements additional building components using a neuro-fuzzy system (NFS) and image processing procedures. Finally, the Information Integration and IFC Creation module integrates information and creates as-is IFC BIM [82]. However, the Building Information Complementary module only focuses on recognizing regular building drawings at the current stage, and the generated IFC BIM is limited to the individual storey level. The entire building, including different storeys, needs to be further converted to the resulting IFC BIM. Additionally, to achieve an information-rich DT, more building information needs to be included, such as MEP (mechanical, electrical, and plumbing) information and movable components through continuously collected images.

Additionally, there is a lack of a single software solution for information processing and a single algorithm for processing, reconstruction, segmentation, and modelling of a point cloud or an image-based point cloud. Memory capacity, processing time, and hardware requirements associated with large amounts of raw data also pose challenges.

Huo et al. (2021) proposed a concept that improves the utilization of large-scale oblique photogrammetry model visualization from three perspectives. Firstly, the unified quadtree method improves the indexing efficiency of a large dataset. Secondly, an MPE-based loading scheduling method was proposed for the data scheduling stage to solve the unified scheduling problem of the oblique photogrammetry model under different production standards. Third, a parent-child relationship-based culling and asynchronous loading strategy based on binary encoding for quadtree was proposed for data loading and memory management. These methods were implemented in a large-scale oblique photogrammetry model visualization platform based on Unreal Engine, demonstrating their efficiency in real-time visualization and overall memory usage [65]. As areas of future research, the authors note that oblique photogrammetry models can be further simplified to reduce rendering pressure and improve visualization performance. In addition, combining visual content with video streaming is another promising direction for further research. Cruz Franco et al. (2022) proposed a workflow that enables the use of virtual twins created from the building of architectural heritage. This is achieved by working with DT obtained by photogrammetry, using technologies such as databases, metaverses, virtual reality (VR), augmented reality (AR), or gamification [78]. However, research has primarily focused on the application of VR and AR technologies to heritage, with less attention given to the technical aspects involved in creating such systems, its accuracy, and its potential for uses beyond providing visual information.

3.3.5. DT and modular construction

The articles reviewed focus on two main directions: evaluating the geometry of prefabricated units both as-design and as-built [40,89]; exploring the potential of modular construction and the concept of DT for the development of smart cities [60].

In this set of articles, we have identified various challenges related to comparing as-built point-cloud data with the as-designed model that includes semantic information. Additionally, we have discussed the process of creating an accurate as-built model from point-cloud data and enhancing it with semantic information in previous paragraphs. Tran et al. (2021) have developed a framework for assessing the geometric quality of prefabricated facades built in place during the construction process. The framework uses a 3D as-designed model and a 3D as-built semantic model to enable a DT approach, which allows for automatic quantitative comparison between the 3D as-built digital replica, generated from the 3D as-built LIDAR point cloud, and the 3D as-designed model. The framework includes automated correspondence identification and element-based comparison based on three criteria, which ensure a comprehensive measurement of the geometric quality of as-built façades in terms of accuracy, completeness, and correctness. Experiments carried out on a synthetic façade system and a prefabricated façade of an actual construction project have demonstrated the ability to detect inconsistencies and perform a quantitative evaluation and localization of geometric errors in as-built prefabricated façades in an efficient and timely manner [40]. However, it should be noted that the method mentioned above has not yet been used to assess the quality of other irregular construction components or free-form structures. Furthermore, more research is required to apply this method using input data obtained through image capture techniques. Integrating IoT and AI technologies to enable real-time assessment is one of the next challenges that need to be addressed.

Wei et al. (2022) proposed a model for DT of off-site construction, which is quantified through an assessment tool named Off-site Construction Digital Twin Maturity Level. This model was developed by conducting a literature review on DT in modular construction and recursive interviews with industry professionals on the construction process. The framework covers all aspects of wood panel construction, and the progress is measured using the assessment framework scoring system [89]. However, the research is limited by the participation of only a few off-site construction companies, and it focuses only on a particular type of off-site construction, which is off-site panelized wood construction, while neglecting other types like precast/prefabricated construction, etc.

In conclusion, the articles explore the importance of understanding the geometry of prefabricated units and the role of modular construction and DT in the development of smart cities. The authors aim to address the challenges associated with comparing as-designed and as-built models and enhancing the accuracy of as-built models with semantic information.

3.3.6. DT and structural monitoring

The articles in this block focus on three main directions of research and investigation: visual inspection of bridges [69,75,76,81], inspection of buildings and structures in seismically active regions [77,90], and monitoring of the dynamics of construction and hazardous industrial facilities such as nuclear plants and hazardous production sites [85,87,88]. The authors of these articles aim to address various issues and challenges in these areas.

One of the major problems discussed in these articles is the transformation of point clouds into models for seismic analysis, also known as “Scan to FEM.” This process involves converting data from a point cloud into a model that can be used for analysis and simulation of seismic activity. Minafò et al. (2022) present a case study of a multi-story historical structure that combines reinforced concrete and masonry. The study demonstrates the possibility of obtaining an accurate and detailed representation of the building, along with a reliable structural model. The seismic vulnerability is carried out using a multidisciplinary approach that includes four stages: (1) historical analysis and evaluation of the building's significance; (2) geometric survey and photographic documentation; (3) structural identification and material analysis; (4) implementation of BIM and structural modelling [90]. However, the results obtained are preliminary, as there was no detailed material characterization phase. Therefore, in the future, an appropriate diagnostic phase must be planned and conducted to confirm the results and design possible intervention strategies.

Another challenge discussed is the transformation of point clouds into parametric models, called “Scan to IFC”. The authors of these articles also highlight the importance of creating models that mimic the behavior of physical objects, through the combination of geometric models and behavior models. This approach, which has already been partially described in previous analysis sections, offers a more thorough and precise depiction of how a structure might react to changes in the external environment. Mahami et al. (2019) have developed an automated method for monitoring construction progress that has the potential to significantly improve the accuracy and efficiency of the monitoring process. The proposed approach utilizes Structured-from-Motion (SfM) and Multi-View-Stereo (MVS) algorithms, as well as photogrammetric principles, to detect coded targets and generate a precise and comprehensive 3D point cloud for indoor and outdoor progress monitoring throughout the project's duration. The coded targets assist in automatically determining the scale and increasing the accuracy of the point cloud generated using SfM and MVS techniques. After generating the point cloud, an as-built point cloud is created, and a CAD model is then generated and compared with the as-planned model [88]. However, the authors of the study do not provide information on the duration of the process of creating and comparing the as-built and as-planned models. Additionally, while the method shows promise for automation, it currently requires significant human involvement.

Finally, the authors also address the issue of sensor interaction with DT and the architecture of monitoring networks. To effectively monitor the safety and stability of structures, it is important to consider how sensors interact with digital models and the overall design of the monitoring system. Shao et al. (2020) conducted a study to validate a holographic visual sensor and computer vision-based algorithms for noncontact displacement and vibration measurement in a full-field capacity. The researchers used an experimental device of automatic camera patrol to collect original dynamic and static video monitoring data from a model bridge under various conditions of damage and activity. The study introduces a holographic geometric morphology tracking algorithm based on the temporal and spatial characteristics of the collected data [69]. The experimental results demonstrate the accuracy and sensitivity of the proposed method in extracting an accurate full-field holographic displacement signal, which reflects the real changes in structural properties under various conditions of damage and action. This method can serve as a foundation for future research on DT for large-scale structures, structural condition assessment, and intelligent damage identification.

4. Discussion and future research directions

The SLR conducted above led to the conclusion of the current state and the role of updating the geometry of DT in construction, which was the primary research objective. After analyzing the SLR results, we have identified the primary techniques and obstacles involved in updating the geometry of the DT at different stages. These are described in Table 4 and Table 5, respectively. Table 4 highlights the main techniques identified in each block of publications. Although some of these methods overlap over multiple blocks, others are unique. On the other hand, Table 5 illustrates the main challenges that require more extensive attention and consideration in the future.

Based on the previous review, we have identified the answers to the sub-questions that were determined during the development of the SLR methodology as follows:

Sub-question 1 (SQ1): It was found that updating the geometry of DT in construction is performed primarily during the operational stage, mostly for bridges or buildings in seismic zones, for regular surveys or post-damage inspections. The main objectives are to assess the current technical state of the structures (such as the presence of cracks, metal corrosion, material condition, etc.) or to create a numerical model based on collected data for seismic analysis. The main challenges faced in this regard include a lack of a previous BIM model, difficulties in recognizing objects and structural elements in image-based and laser scanning point clouds, and the typical geometric complexities of architectural heritage objects, including the presence of ornaments and decorations, which make their representation in IFC object families difficult.

The same problems of transforming point-cloud data obtained through laser scanning or photogrammetry into a parametric model are also encountered during the construction phase, when updating the as-designed model. Although the use of DT in manufacturing can achieve high accuracy in modelling and updating the geometry of physical object geometry, its implementation in construction

Table 4
Most of the approaches used are based on the SLR and their applicability to update DT geometry stages.

Themes of publications	Most used approaches		
	DT geometry updating stages		
	Data collection	Data processing	Modelling
DT and UAV/ photogrammetry	photogrammetry (monocular, stereo), videogrammetry	Close-range digital photogrammetry, registration, alignment, noise filtering, Iterative closest point algorithm (ICP), Least squares method (LSM), Scale-invariant feature transform (SIFT), Speeded up robust features (SURF), Random sample consensus algorithm (RANSAC)	data-driven, model-driven approaches, local and global descriptors, semantic segmentation and registration, voxel-based representations
DT and Laser scanning	TLS, mobile devices		
DT and Manufacturing DT and Data visualization DT and Modular construction DT and Structural monitoring	image-based techniques, range-based techniques, tagging, manual contact techniques, preexisting information	cloud-based approaches, the non-rigid registration method Convolutional neural network (CNN)-based object detection methods, Optical Character Recognition (OCR) technology	

Table 5
Main challenges based on the SLR and their applicability for updating DT geometry stages.

Themes of publications	Challenges		
	DT geometry updating stages		
	Data collection	Data processing	Modelling
DT and UAV/ photogrammetry	UAV flight autonomy, use in an indoor environment, effective flight trajectory, obstacle avoidance, use of SLAM techniques, Perspective-n-Point problem, transmission of collected data.	object recognition, manual or semiautomatic point cloud registration, data completeness, noise level, accurate fitting of 3D shapes, simplification of the mesh for algorithm processing, variations in point densities, surface roughness, reflectivity, scene clutter, occlusions	accuracy, lack of semantic information, simplification of the geometry of real structures, lack of texture
DT and Laser scanning	the SLAM technique for mobile autonomy devices		
DT and Manufacturing	the simple geometrical shape of physical objects, real-time feedback	high computational expensiveness	modelling speed, accuracy
DT and Data visualization	–	–	memory capacity, processing time, hardware requirements
DT and Modular construction	–	–	
DT and Structural monitoring	–	automatic conversion into the FEM model	

may be hindered by the unique nature of construction processes. This includes factors such as the uniqueness of each construction project even if built according to the same design drawings, also similar buildings by design can have different Heating, ventilation, and air conditioning (HVAC) control systems, etc., the temporary and changing nature of the construction team, the unstructured and nonlinear relationships between processes, limited resources, high complexity and uncertainty of construction, and the influence of external factors [72].

Sub-Question 2 (SQ2): According to the analyzed articles, laser scanning and UAV/photogrammetry are the most mentioned technologies for updating the geometry of DT. Both have their advantages and disadvantages, but both result in the creation of a 3D model from the collected data. The main challenges that arise include identifying structural elements in the point cloud, classifying according to the IFC format, accurately recognizing the image geometry with well-trained neural networks, and correctly merging and comparing the existing BIM model (if available) with the newly created 3D model.

When using a network of sensors, GPS receivers, or other real-time data collection equipment, the challenge lies in creating an efficient system architecture that can handle and analyze a large amount of data.

Another area in need of improvement is the availability of interoperable data and a unified software solution or automated process methodology.

Sub-Question 3 (SQ3): Based on the challenges identified in SQ1 and SQ2, it has been determined that current methods of updating the geometry of DT are not universally applicable or scalable for all types of buildings or structures. As a result, further research should focus on a specific case study, with a well-defined building type and life cycle stage, which can be generalized to similar structures in the future. Despite the type of equipment or method used to collect raw building geometry data and update the DT, the main area that requires improvement is the detection, segmentation and classification of objects in raw data and methods to integrate them into the DT.

Our research findings align with previous studies and contribute to the ongoing exploration of future research directions, with a particular emphasis on the process of updating the geometry of DT. Volk et al. (2014) conducted a comprehensive review of more than 180 academic and applied publications related to BIM for existing buildings, examining technical, informational, organizational, and legal issues. They identified three key challenges and areas for future research: (1) automating data capture and BIM creation, (2) updating and maintaining information in BIM, and (3) handling and modelling uncertain data, objects, and relationships in existing buildings within BIM [10]. Although their study focused on the implementation of BIM in building operation, our study supports the notion that the technical aspects of updating the virtual model remain unresolved. Current approaches struggle to capture structural, concealed, or semantic building information under changing environmental conditions and transform these data into unambiguous semantic objects and relationships, regardless of whether we consider a BIM model or DT. Opoku et al. (2021) conducted a review on the application of DT in the construction industry and recommended that future research should focus on identifying critical success factors and barriers to successful implementation [9]. This would help practitioners better understand the concept of DT. Our study supports this recommendation by highlighting the importance of addressing technical challenges related to the management of DT geometry. Overcoming these challenges can improve understanding of the benefits of DT in construction and promote its adoption throughout the industry. Liu et al. (2021) analyzed 240 publications to provide a comprehensive review of the concepts, technologies and industrial applications of DT [3]. Although its research focused primarily on the application of DT in manufacturing, the key challenges related to the modelling and simulation procedures align with those identified in our research. Additionally, their study highlights the importance of building parametric models that describe the behavior rules and data of physical objects and implementing a life-cycle approach when utilizing DT.

4.1. Implications for practice and future research

Updating the geometry of a DT is a critical component of its effective use, but it has not received sufficient attention in recent publications. The process of updating the DT geometry is multifaceted and complex, with no standardized method or single solution to simplify or automate it.

This article provides a comprehensive review of past studies on managing DT geometry, not only in construction but also in other industries, and the current methods and approaches used. Understanding the state-of-the-art research and the primary challenges enables us to identify areas requiring additional research in the future. By implementing the SLR results, which include examples of main methods and complexities, according to our identified stages of the process of updating the DT geometry, we can account for some of the problems at the planning stage.

The process of updating the DT geometry is significantly influenced by the stage of the life cycle in which it is performed, the type of building, and the data collection equipment used. Therefore, it is crucial to test specific existing methods and practices on a case study, as defined in research sub-question 3, to determine their applicability. This aspect is one of the areas of future research.

4.2. Limitations of the study

Despite the valuable contributions of this study, it is important to note its limitations. The search was restricted to only two databases, Scopus and Web of Science, which means that other relevant publications on updating the geometry of DT may have been overlooked. Furthermore, employing a different SLR methodology could yield different results and result in a different final set of publications. Therefore, the research findings may not represent the entire available literature.

Despite the careful selection of relevant articles, some keywords may not have been included in the literature search or met the eligibility criteria. As such, these limitations provide opportunities for further research and should be considered when interpreting the study findings.

5. Conclusions

This paper presents a comprehensive review of the literature and a bibliographic analysis of research studies on the updating of DT geometry in the construction industry. Despite the increasing attention paid to this issue in recent publications, there is still a lack of comprehensive coverage of updating the DT's geometry for built assets. Most existing studies focus only on specific aspects or processes related to virtual modelling or data processing. Therefore, the purpose of this study is to offer a more comprehensive and generalized perspective on the interaction between building geometry and its representation in DT for the construction industry. The uniqueness of the study lies in its specific focus on the geometry of DT within the construction industry, distinguishing it from other industries where DT is also applied. This paper aims to establish a foundation for a unified maintenance method for virtual model geometry that can be widely utilized in construction. The novelty of this research is to identify crucial problem areas based on the current state of the industry, intending to develop a practical and scalable method for updating the DT geometry in the future. Furthermore, this article contributes to the overall body of knowledge in the field, since our research findings confirm previous studies' achievements.

The use of DT for the management of built assets is gaining popularity in the construction industry. However, more research is needed to better understand the relationship between the physical building geometry and its corresponding DT due to various factors. The complexity of building geometry poses a challenge in accurately representing and integrating it into a DT. Furthermore, since the geometry of the building remains stable after the construction stage, updates to the geometry information may not be frequent, making the investment in technology less attractive. The cost and technical demands of updating geometry information can also be significant, and errors in building geometry data can affect the performance and functionality of the DT. Therefore, it is crucial to establish clear criteria for updating the building geometry data. This will ensure that the DT accurately represents the building and that any updates are performed in a timely and efficient manner.

To address these issues, an SLR of 56 articles was conducted from the Web of Science and Scopus databases, which helped identify the main research gaps and directions for future research. The state-of-the-art in updating the geometry of DT was established, including the relationship between the geometry of DT, BIM models, and the life cycle stages of the building. Furthermore, the study explored the relationship between DT, equipment, and methods of collecting and integrating building geometry data. Based on the analysis of articles distributed across 6 sets according to their coverage, we identified the main methods that can be used at each stage of the DT geometry update workflow, as well as the main challenges that may arise at these stages.

Building facilities vary in terms of usage, age, and ownership. DT is commonly used for large and complex structures, and it can be derived from BIM if the data are available. However, for existing buildings that lack a BIM model but have some preliminary data, such as CAD drawings or numerical models, DT can still be implemented through laser scanning or conversion procedures. Currently, laser scanning and UAV/photogrammetry are the most widely used technologies for updating the geometry of DT. However, these methods are not universally applicable or scalable for all types of buildings or structures. Therefore, further research should focus on a specific case study approach to develop generalized solutions for similar structures in the future.

We have identified two primary approaches to determine when to update the building geometry data. The first approach focuses on the building's life cycle. During the construction stage, the building's geometry changes dynamically, and the priority is to create an "as-built" model that accurately reflects any deviations from the original design. In the operational stage, changes in geometry may occur due to renovations, damage, or deformation processes. The second approach is based on the type of building. Several categories of buildings require updates to their geometry data: buildings with a high risk of deformation, buildings with a high occupant density, and buildings that experience significant short-term loads.

The process of updating DT geometry involves three main steps: Data Collection, Data Processing, and Modelling. Building geometry data can be updated periodically or in real time, depending on the conditions. Regular updates involve collecting and integrating data according to a predetermined schedule, while irregular updates may be necessary due to unexpected changes in the building's geometry, such as emergencies. Various methods, such as UAV/photogrammetry, laser scanning, total station, etc., or a combination of these, can be used to periodically update geometry data. For high-precision measurements, a total station is a good option, although it does not allow for the creation of a 3D model. Laser scanning is another option, but it requires careful consideration of potentially irrelevant data that do not reflect the actual geometry. Processing point cloud data can also be challenging due to a lack of texture, color, and other issues related to reflective surfaces. On the other hand, real-time updates can be achieved using AI and ML in the IoT cloud. This involves collecting data from sensors or GPS equipment, but it's essential to consider the amount of data to be collected, which can increase costs and require additional time and hardware to manage, store, and analyze collected data.

The data processing stage aims to identify the geometry of the structural elements within the collected data. This involves registering the data into the DT coordinate system, which is typically done semi-automatically. Additionally, this stage involves filtering out noise and removing unnecessary data. The next step in data processing involves recognizing the structural elements of the building. There are various methods for object recognition, including data- and model-driven approaches, as well as local and global descriptors, semantic segmentation, and registration. In practice, a combination of these methods may be used, depending on the specific conditions. It is worth noting that object recognition in the collected data only yields geometric shapes without semantic information. As a result, the objective of this stage is to create parametric objects that can accurately represent the structural elements. Currently, in BIM software, object geometry is typically represented using CSG or B-rep methods of modelling. However, CSG has a significant disadvantage in the context of building geometry modelling, as it is limited by the primitives that can be used and are thus difficult to apply when modelling free-form geometric shapes. In contrast, the B-rep method is more flexible and easier to use to describe complex geometry but requires greater computational capacity. Therefore, most BIM applications utilize a combination of both methods or their key principles. The last step of this stage involves enriching geometric shapes with semantic information, which can be achieved through semantic segmentation or registration. In addition, relationship modelling should be used to establish connections between structural elements that define their position or displacement. These steps culminate in obtaining a parametric object-orientated model, usually in the IFC format.

After reviewing our previous analysis, we have identified several challenges that need to be addressed. These include the lack of a prior BIM model or various types of preliminary data, the need to identify structural elements in the point cloud and classify them according to the IFC format, the requirement for well-trained neural networks to recognize the geometry of the objects when using image-based techniques, merging and comparing the existing BIM model (if available) with the newly created 3D model, creating an efficient system architecture capable of handling and analyzing large amounts of data when using real-time data collection equipment, and ensuring data interoperability among different types of equipment used for data collection, and the software used for data processing with their native formats.

Current research indicates that the methods used to update the geometry of DT may not be universally applicable or scalable for all building types or structures. Therefore, future studies must focus on a specific case study of a well-defined building type and life cycle stage that can be generalized to other objects with similar characteristics. This study emphasizes the need to improve the detection, segmentation, and classification of objects in raw data, as well as the methods to integrate them into DT. Furthermore, future research could focus on developing interoperable data and a unified software solution to facilitate efficient updating of the DT. In conclusion, updating the geometry of DT in the construction industry still faces many challenges, and more research is needed to overcome these challenges. This review provides insight into the current state of research and identifies areas where future research could contribute to the development of more efficient and effective methods for updating the geometry of DT in construction.

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.

Data availability

No data was used for the research described in the article.

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