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Review Article

Digital Twin Technology for Bridge Maintenance using 3D Laser Scanning: A Review

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There has been a significant surge in the interest in adopting cutting-edge new technologies in the civil engineering industry in recent times that monitor the Internet of Things (IoT) data and control automation systems. By combining the real and digital worlds, digital technologies, such as Digital Twin, provide a high-level depiction of bridges and their assets. The inspection, evaluation, and management of infrastructure have experienced profound changes in technological advancement over the last decade. Technologies like laser scanners have emerged as a viable replacement for labor-intensive, costly, and dangerous traditional methods that risk health and safety. The new maintenance techniques have increased their use in the construction section, particularly regarding bridges. This review paper aims to present a comprehensive and state-of-the-art review upon using laser scanners in bridge maintenance and engineering and looking deeper into the study field in focus and researchers' suggestions in this field. Moreover, the review was conducted to gather, evaluate, and analyze the papers collected in the years from 2017 to 2022. The interaction of research networks, dominant subfields, the co-occurrence of keywords, and countries were all examined. Four main categories were presented, namely machine learning, bridge management system (BMS), bridge information modeling (BrIM), and 3D modeling. The findings demonstrate that information standardization is the first significant obstacle to be addressed before the construction sector can benefit from the usage of Digital Twin. As a result, this article proposes a conceptual framework for building management using Digital Twins as a starting point for future research.

1. Introduction

Digital Twin, in a simple term, is a virtual representation of an operation, product, or service that enables real-time data flows between the physical and virtual assets. This fusion between the virtual and physical environments enables data processing and control tools to avoid downtime, create new opportunities, and even predict the future conditions. In other words, the Digital Twin serves as a connection between the physical and smart components connected to a cloud-based system to process data about real-time status [1].

1.1. The Definition of Digital Twin. Having a digital model for an asset is not enough to provide whole-life cycle asset management, especially in the maintenance and operation phase. Therefore, there is ongoing research on how to incorporate the Digital Twin concept that integrates artificial intelligence, machine learning, and big data analytics to create dynamic models that can learn and update the status of the physical counterpart from multiple heterogeneous data sources [2]. What can Digital Twin offer to the building sector? To answer this question, it is necessary to first look into what a Digital Twin is. As several industries are using this concept (e.g., space and air force, marine, offshore, and aerospace industry), there are multiple definitions of the term. However, the CIRP Encyclopedia of Production Engineering [3] released a definition of the phrase Digital Twin in 2019 that seems to cover most use cases, which is as follows: "a digital twin is a digital representation of an active unique product (real device, object, ma-chine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases." The definition uses the phrase "unique product," and the reason for this is to emphasize the need for a Digital Twin to represent only one asset because of the accumulation of information. The product's history is essential, as previous damage or repairs will significantly affect how the product will respond to loads in the future. Another aspect that is worth looking closer into in the definition is the following phrase: "[..] or even across multiple life cycle phases." It is to underline the possibility to letting the Digital Twin follow the product even after the end of its life cycle in the event of refurbishing or reusing some of the components in other projects, and the history of the components will be valuable.

1.2. The Origin of Digital Twin. The origins of the Digital Twin concept are, by many [4–7], credited to Michael Grieves, who, in 2002, held a presentation about product life cycle management. In the presentation, Grieves showed all of the essential parts of a Digital Twin model, these being the real space, the virtual space, and the gathering and processing of data in-between the physical asset and the digital replica. Grieves initially referred to it as a "conceptual ideal for product life cycle management." Later on, Grieves changed it to "Mirrored Spaces Model" and then called it "Information Mirroring Model." Grieves wrote an article in 2011 with John Vickers, who worked for NASA, and in this article, the term "Digital Twin" was used [3]. Thus, the main parts of Digital Twin can be seen in Figure 1.

Michael Grieves published recently a chapter about the commonly wrong understanding that the Digital Twin does not exist unless there's a physical object [7]. According to Grieves, the primary criterion for determining if a digital model is a Digital Twin is whether the model is designed to become a physical product with a physical counterpart. He gives a nice example here. A flying carpet digital model will never become a Digital Twin, because we have no ability to make it a physical object.

1.3. The Development of Digital Twin. Using models to represent the real world is not new within the engineering field. NASA built physical "twins" of the spacecrafts in the Apollo program in 1967–1972 [9]. However, it is only in the last quarter of the 20^{th} century that it became possible to create virtual replicas within computers' digital space. The improved algorithms and computational power that the modern computer technology has brought forward have made designing, analyzing, visualizing, and communicating engineering projects more efficient. Prior to this technological development, there was an immense challenge to ensure that all of the 2D drawings fit together when translated into 3D models. Significant time, and thereby cost, was wasted in building physical assets only to identify clashes and errors during construction and then having to go back to the drawing board and starting the design process all over again [10]. However, with the latest technology in place,

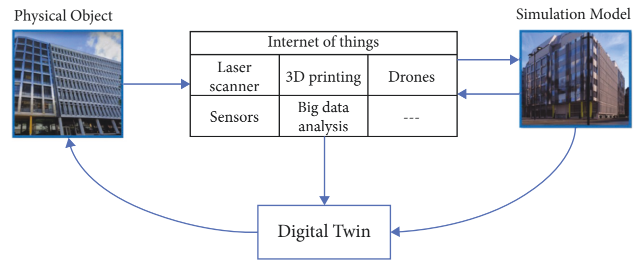


Figure 1: Digital Twin technology [8].

the conflicts are detected in the design phase, and construction does not occur before a significant number of issues in the design phase are solved.

1.4. Bridge Inspection and Maintenance. Technological advancements in multiple domains have been exceedingly exceptional, such as the Internet of Things (IoT), artificial intelligence (AI), and cloud computing [11]. These technologies have enabled the digitalization of various assets, systems, and processes across different industrial sectors over the last few decades. Sensors and intelligent data acquisition assist in improving any asset's life cycle that may include steps from extraction, design, production, distribution, maintenance, all the way to recycling [12]. The digital twin (DT) idea, likewise, uses the technologies above and integrates a virtual object with a real thing throughout its life cycle [13]. These new technologies provide the necessary foundation for study in various fields, including defect prognostics and production efficiency, to name a few. The demand for inspection, evaluation, and management has expanded drastically over the last few years, especially for bridges. According to a report published in the American Society of Civil Engineering (ASCE), bridges need rehabilitation and service at some point throughout their lifespan, suggesting that roughly around 40% of American bridges are over 50 years old, with 13.6 percent of them being functionally deficient [14]. Similar trends can also be found globally, in places like Australia, the U.K., and most European nations, including Norway [13]. Aside from the few pre-existing characteristics like design and construction, several postexisting elements influence bridges' structural efficiency and general condition. Environmental influences, structural age (lifespan), and maintenance procedures are among them [15]. The established monitoring and inspection methods are primarily responsible for maintenance plans [16].

Traditional periodical inspection and condition assessment methods based on on-site physical inspection are time-consuming, expensive, and potentially dangerous. Furthermore, maintenance omissions or delays may result in significant future expenses [17]. It can be even more important when the structure is of particular use or value. Bridges are among the most vulnerable and critical components of the road network system, and they must be thoroughly inspected and maintained. These vital structures are frequently built in difficult-to-reach locations in a rough terrain [16]. As a result, putting in place an effective inspection procedure and a regular maintenance/rehabilitation strategy is vital. Hence, these excessive expenses can be significantly reduced by cost-effective and proactive inspection and monitoring methods and asset management [18]. The construction industry needs digitalization and new technology because of the lack of productivity, research and development, and poor technological advancement. The construction industry is mentioned as the least digitalized industry and especially slow to innovation in digital technologies. Digital technologies like the digital twin (DT) are already being used in manufacturing, and automotive industries are widely used [19].

1.5. Laser Scanning. Three-dimensional (3D) laser scanning is a new noncontact measuring tool for quickly gathering surface topography data points. The obtained data points are specified by x, y, and z coordinates associated with attributes, such as the laser beam's intensity. Aerial, mobile, and terrestrial laser scanning systems can be categorized depending on the location of the laser sensors during data acquisition. Using terrestrial laser scanners (TLS) is becoming prevalent and widespread. TLS offers considerable promise for inspection operations because of its rapid speed, submillimeter precision, and low cost compared to existing inspection methods. TLS is used in building and maintenance [20]. Because of TLS's widespread use, multiple review articles have been written on its state-of-the-art. Son et al. [21] examined developing ways to extract and analyze BIM models from obtained data points for FM and production monitoring (PM). Pătrăucean et al. [22] offered an overview of an automated as-built BIM model construction using laser scanner data. Lu and Lee [23] outlined image-based 3D model development using point cloud data. Wang and Kim [24] examined TLS in the construction sector and analyzed data collecting settings and laser scanning data quality. Kim et al. [25] examined works on a laser scanner-based geometry quality inspection of civil constructions. Spencer et al. [26] reviewed modern computer vision monitoring approaches for civil infrastructure condition assessment. Czerniawski and Leite [27] recently detailed 10 years of research in automatically digitizing structures. None of those mentioned above review publications detailed TLS's vast uses in bridge engineering, inspection, and maintenance. This research uses scientometric and state-of-the-art review methodologies to examine the applicability of TLS in bridge engineering.

1.6. Point Clouds. 3D point cloud data may be acquired from numerous data sources, such as laser scans, pictures, and videos [23, 28]. Reality capture methods that create 3D point cloud data have matured and become ready to use, enabling more precise and inexpensive point cloud data collection.

As point cloud data collecting systems advance, the requirement to capture 3D point cloud data for existing buildings and infrastructures grows. BIM improves project performance from design to construction and facilities management (FM). As-planned BIMs are prepared throughout project planning and design to show design intent. However, because of design modifications made during construction, the intended BIM typically does not match the actual project circumstances. As a result, an as-built BIM is required after the building phase. Additions and alterations may be made during FM, rendering the as-built BIM outdated. An as-is BIM for existing facilities is required to provide FM functions in this situation. Thus, the 3D point cloud data may be utilized to construct as-built/as-is BIM models. Point cloud data use includes building and infrastructure geometry quality checking and construction progress tracking.

Several review papers have been published to summarize the state-of-the-art 3D point cloud data for construction applications. The three review papers above focus on processing laser scan or image data to create as-built/as-is BIM models. The automated reconstruction of as-built BIM models from laser-scanned point cloud data was examined by Tang et al. [28]. Pătrăucean et al. [22] examined as-built BIM model reconstruction studies, focusing on modeling building element geometries from point cloud data. Lu and Lee [23] evaluated image-based BIM model rebuilding. Son et al. [21] analyzed the point cloud data for production monitoring and civil infrastructure architecture. Ma and Liu [29] reviewed 3D civil engineering rebuilding approaches and applications. However, none of the available review papers describe 3D point cloud data bridge applications across a project lifecycle.

This study reviews 3D point cloud data's uses. After reviewing several construction applications, how to obtain and handle point cloud data is discussed. Literature evaluation and in-depth conversations identify research gaps and offer future research topics.

The rest of the paper is arranged accordingly. Section 2 explains the methodology used for the scientometric analysis. Section 3 defines the state-of-the-art digital solutions for bridges, including BIM, IoT, BAS, Data-driven, and machine learning, and classifies the reviewed papers into application domains. Section 4 discusses the future trends of Digital Twin from various perspectives. Section 5 presents the conclusion.

2. Scientometric Review

The scientometric review is a quantitative assessment of current research on the formation of science that evaluates the effect of journals, organizations, and nations in a specific research field. This reviewing strategy can give better knowledge, providing a thorough summary of presently published publications and citation effect [30, 31]. Visualizing laser scanning in bridges can help readers understand research trends and patterns. A quantitative approach is proposed for evaluating laser scanning papers in bridge engineering and asset management in this work. This methodology applies bibliometric tools to published literature to trace the structure and evolution of specific concerns and aims [31]. Network modeling and visualization analyze the current research area's intellectual environment and identify important topics that researchers may strive to answer. The identification of influential scholars that shape the topic of study is based on keyword and abstract analysis.

Co-occurring keywords analysis and coauthor analysis by country of origin [21, 32] also reveal research tendencies. For bibliometric mapping, VOSviewer [33] was used.

2.1. Methodology to Find Literature. Although there has been a tremendous amount of research published in conference proceedings and scientific journals over the past decade, the research about the Digital Twin technology is still limited, especially for bridge maintenance. Therefore, the literature search has primarily focused on high-ranked journals and reputable conferences in civil engineering, construction management, and structural health monitoring. Scopus, a database of more than 75 million records of articles and books, was the primary source of information for the literature search. In addition, a search of Google Scholar and Web of Science was also carried out as an additional literature check. An overview of the literature search process is shown in Figure 2. As shown in Figure 3, the quantity of papers produced between 2017 and 2022 is presented annually. During this period, the quantity of articles linked to Digital Twin for bridges has increased. The trend is even more evident in 2019 with the growing quantity of research publications. Thus, the exponential increase of Digital Twin research in bridges demonstrates the dramatic influence on the construction industry. After manually avoiding duplicated research between databases, we ended up with 108 documents from Scopus, 47 documents from Google scholar, and 31 papers from Web of Science. Keywords, such as "3D point cloud," "Laser scanner," "Digital Twin," "Building information modeling," and "Laser scanning," were utilized in the early stages of the literature search. In the beginning, 186 documents were recognized. Some of the publications were from fields unrelated to the research topic, such as astronomy, physics, medicine, and mathematics. As a result, we used two different sets of criteria at this point. Papers were initially excluded from consideration based on their topic matter before limiting to the 2017–2022 (no papers about the topic before 2017 and the study included the papers until 16.06.2022) publication date. As a result of the first standard, 53 documents were removed, and as a result of the second, 24 documents were removed. A total of 78 documents were discarded, leaving 108 documents.

As seen in Table 1, this process is carried out by finding the most respected publications and conferences. The most published articles connected to the application of Digital Twin for bridge maintenance and assessment are found in Automation in Construction and Sensors, as indicated in Table 1.

2.2. Co-Occurrence of Keywords Analysis. Keywords are necessary for presenting a published work's core concepts and topic areas and demonstrating a brief overview of the study horizons [34]. The co-occurrence of keywords was examined using VOSviewer to develop and study the map of the current knowledge domain in Digital Twin for bridge engineering and evaluation. The literature search results were processed and displayed using the keywords network, as shown in Figure 4. The keywords network is displayed in a distance-based diagram by the VOSviewer. Table 2 shows the number of occurrences, average year published, number of linkages, and overall link strength for this network, which has 44 nodes and 653 links. Each term in this network is referred to as a node, and the connections between them are referred to as links. The distance between two nodes determines the strength and weakness of a link. A greater distance between two keywords/nodes suggests a weaker association, whereas a smaller distance indicates a more vital link [35]. The total link strength is the sum of the connection strengths associated with a single node. Furthermore, the size of the given nodes represents the number of papers in which the term was formed, and a variety of colors indicate different study years [36].

Table 2 shows the frequency of each keyword as the number of occurrences. "Digital Twin" and "Life cycle" are the two primary terms that often appear in this table, indicating substantial research in this field. Based on the data presented, the frequency of keywords, such as "bridge inspection," "damage detection," "laser scanner," and "point clouds" indicates that research into bridge inspection and assessment, as well as their connections to digital twins and

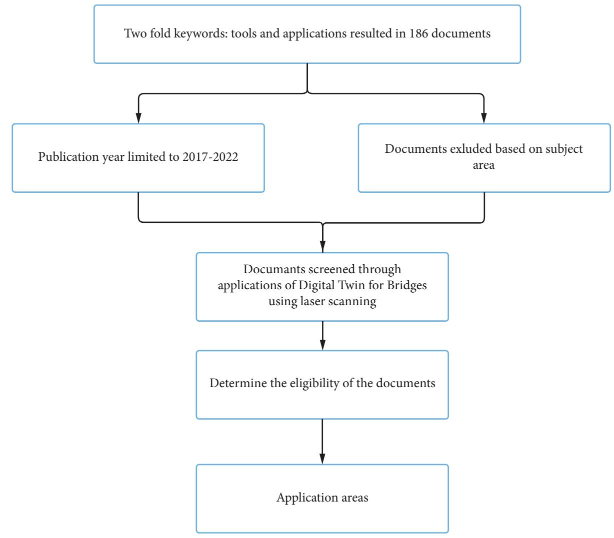


Figure 2: Scienmetric review procedure flowchart.

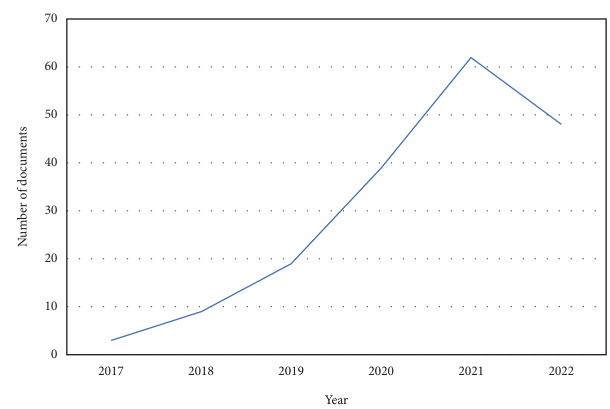


Figure 3: Scienmetric review procedure flowchart.

Table 1: Top journals and conferences with relevant published papers (2017–2022).

Source	Documents	Citations	Total link strength
Automation in construction	33	528	2357
Sensors	14	44	1028
Applied sciences	11	54	943
IEEE access	10	295	886
Computers in industry	8	64	789
Sustainability	16	141	767
Journal of building engineering	4	30	538
20th congress of IABSE	3	4	13
Proceedings of the 37th international symposium on automation and robotics	4	9	3
IOP conference series: earth and environmental science	5	5	0

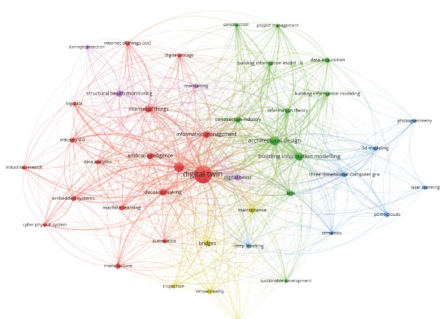


Figure 4: Network of co-occurring keywords.

bridge lifecycle, is limited. Thus, there is a clear and urgent need for more research in this area.

2.3. Coauthorship Analysis. The coauthorship network was obtained based on the bibliometric technique, showing the research work of the significant authors and the cooperation between them in the presented field. The number of publications produced by a researcher determines the node size, and the thickness of the link indicates the level of the author's cooperation. Figure 5 includes 1000 nodes and 3082 links, as shown in Table 3. Based on the given information, the list of the most productive authors who have the most published papers is presented in Table 4.

2.4. Network of Countries. VOSviewer software was used to generate a network depicting the distribution of research articles to illustrate nations' contributions on the subject. This network consisted of 27 nodes and 334 connections. As indicated in Figure 6, the following nations contributed the most articles to this field of research: China (111 papers), the United States (70 papers), the United Kingdom (65 papers), Germany (49 papers), and Italy (31 papers).

3. State-of-the-Art Review

The research methodology was extended to a comprehensive review of Digital Twin and TLS applications in bridge engineering and asset management based on four major categories: (1) machine learning, (2) bridge information modelling (BrIM), (3) bridge management system (BMS), and (5) 3D modeling.

3.1. Machine Learning. The BIM, laser scanning, and IoT digital infrastructure generate a large amount of data to support decision-making and monitoring processes in the bridges project [37]. Automating these processes with data-driven solutions becomes a need to improve construction management and reduce operational costs [38–42]. Hence, machine learning (ML) and data-driven algorithms are valuable tools for processing such data and computing valuable information about the bridges. Indeed, ML techniques may provide a data-driven bridge model to monitor the current operations, forecast possible situations in the future, and detect cracks. Algorithms such as artificial neural networks (ANN), convolutional neural networks (CNN), and dynamic graph convolutional neural network (DGCNN) are some tools that can assist in processing data for bridge assessment [43]. However, it is yet to be determined whether damage requires repair using automated inspection. The damaged region must be located in 3D space to identify whether the primary component is implicated. Hard coding has been proposed for bridge component categorization [44, 45]. However, in these systems, point cloud data segmentation is not automated. Only simple bridge types with vertical and horizontal components and no sophisticated forms could be used.

The region expanding approach [46, 47] has been proposed for segmenting components to categorize point cloud data from bridges automatically. This method extracts a curved surface and plane by extending seed points into an area until an edge is reached in the point cloud data, where the change in the vector surpasses a specific threshold and where the seeds are manually or automatically entered. Schnabel et al. [48] suggested a random sample consensus (RANSAC)-based technique for forming a model at the site where the sum of the distances is reduced by comparing samples randomly taken from point cloud data with a 3D geometry model (e.g., a sphere or cylinder). Xu et al. [49] adapted this approach into an octree with a high processing speed for point cloud data obtained from a construction site. For a grid-like steel construction, Laefer and Truong-Hong [50] suggested a method for filling occluded sections using a repetitive pattern. However, these model-based solutions cannot be used on bridges without a grid-like structure or basic geometry (e.g., spherical or cylindrical).

Previous research on automatically identifying bridge components was unable to process the segmentation of

Table 2: Keywords linked to network data.

Keyword	Occurrence	Links	Total link strength
Machine learning			
Artificial intelligence	34	37	135
Automation	18	28	63
Big data	15	27	80
Cyber physical system	15	23	66
Data analytics	16	30	82
Decision making	42	39	174
Digital storage	18	32	79
Digital twin	279	43	574
Embedded system	24	27	99
Industrial research	16	20	53
Industry 4.0	25	28	93
Information management	43	42	206
Internet of things	41	37	193
Internet of Things (IoT)	20	31	85
Life cycle	88	42	303
Machine learning	25	30	85
Manufacture	29	27	80
Bridge information modeling			
Architectural design	75	42	365
BIM	32	35	127
Building information modeling	22	29	98
Bridge information modeling	59	40	239
Construction	15	26	86
Construction industry	33	35	145
Data acquisition	23	28	88
Information theory	29	37	168
Project management	15	26	78
Sustainable development	15	23	44
Bridge management system (BMS)			
Bridge	16	20	42
Bridges	35	31	127
Inspection	16	26	68
Maintenance	32	33	137
Virtual reality	20	29	59
Damage detection	16	18	51
Digital twin	39	38	104
Monitoring	25	27	75
Structural health monitoring	38	29	105
3D modeling			
3D modeling	22	23	79
Laser scanning	16	14	27
Photogrammetry	16	18	42
Point clouds	23	22	64
Semantics	18	29	69
Three dimensional computer graphics	24	28	86

input data. They can interpret certain forms, however, they cannot segment or categorize parts or categories. As the component class to which a segmented object belongs cannot be recognized, it cannot be utilized to automate maintenance. Kim et al. [51] provided a methodology for segmenting and categorizing bridge components based on the semantic segmentation of point cloud data using PointNet [52], a deep learning-based system that concurrently segments and classifies data. PointNet can learn unstructured cloud data, however, it does not learn information about the local link between points, and the data are learned separately [53]. The sorts of components in a bridge might differ depending on their connection to other components and the shape information of each component. To determine a bridge's safety class, an algorithm capable of precisely identifying and segmenting each component and differentiating major from auxiliary components is required.

3.2. Bridge Information Modeling (BrIM). One of the causes of the high expenses of bridge maintenance is the time-consuming inspection and assessment processes. Efforts have been undertaken to identify bridge surface degradation automatically. From photos collected by unmanned aerial

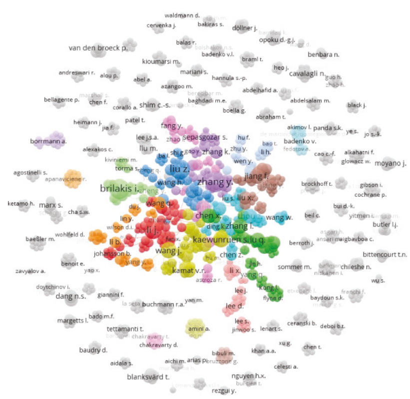


Figure 5: Network of coauthorship.

Table 3: The coauthorship network's general characteristics.

Network	Nodes	Links	Total link strength
Coauthorship	1000	3082	3220

Table 4: List of the top 6 most productive authors (2017–2022).

Author	Documents	Citations
Zhang Y.	9	219
Brilakis I.	9	111
Liu Z.	9	53
Li J.	7	40
Kaewunruen S.	6	61
Wang J.	6	10

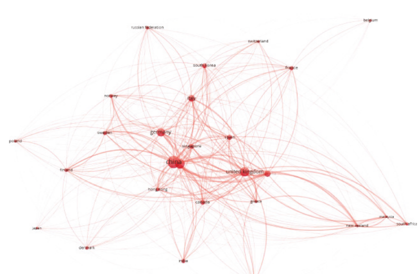


Figure 6: Network of countries.

vehicles (UAV), Kim et al. [54] used region with convolutional neural networks (R-CNN) to find fractures on the structural surface. Wang et al. [55] created a stitching technique to solve the problem of calculating long fractures that could not be shot in a single image. Their work, however, was limited to identifying localized damage. To complete a full condition evaluation, global geometric context is still required to incorporate local inspection data. Bridge management systems (BMS), such as AASHTOW are [56] being utilized to store and manage structured bridge condition data. However, instead of analyzing the structural state of a single bridge component, BMS is primarily designed for system-wide decision-making [57].

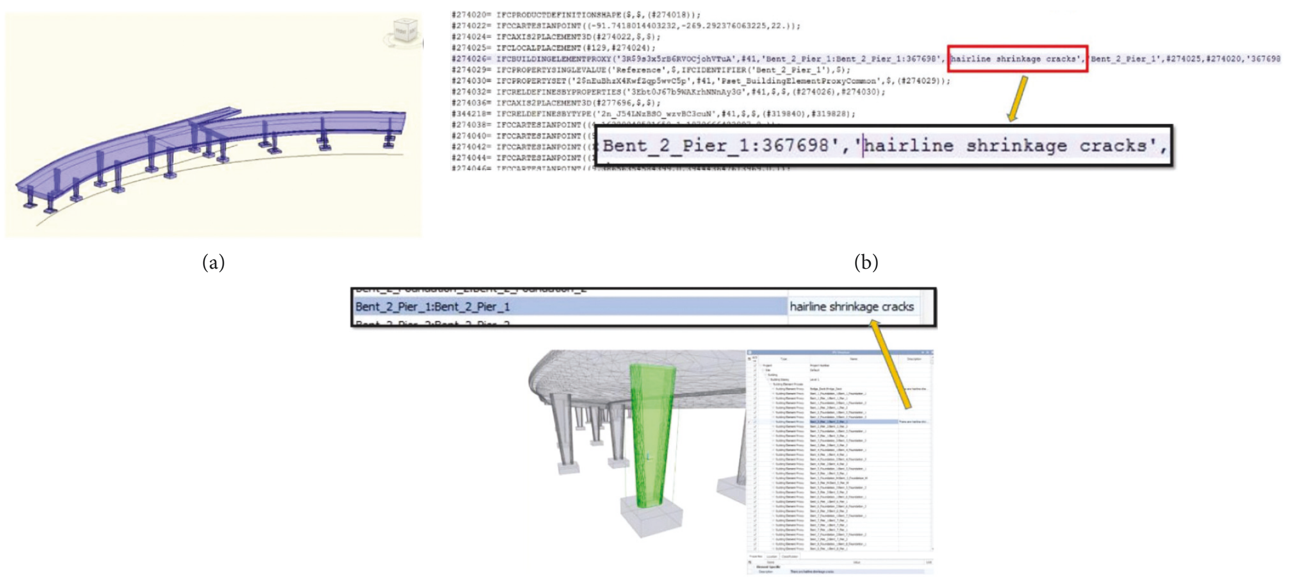
The bridge information model (BrIM) (Figure 7) is an alternate solution that can manage this information on both the structure and component levels. The United States National Building Information Model Standard Project Committee defines the Building Information Model (BIM) as "a digital representation of physical and functional aspects of a facility" [59]. The BrIM is not just a 3D physical model. It can also store component-level information for life cycle management [60]. Tanaka et al. [16] created a BrIM based on industry foundation classes (IFC) to manage inspection data. DiBernardo [61] examined the present data management process for existing bridge assets and developed a framework for organizing and analyzing inspection data that integrated BrIM and existing commercial bridge software products. In addition to storing inspection data, BrIM may help stakeholders collaborate and cooperate throughout the bridge life cycle, including structural health monitoring, rehabilitation, behavior modeling, and prediction [60].

BIM use for newly constructed transportation infrastructures soared in Europe between 2012 and 2017, driven by the benefits. By 2017, however, just 52% of engineers and contractors had used BIM on at least half of their projects [62]. Only a few newly constructed bridges have BrIM as-designed, whereas most existing bridges still use traditional information management methods like datasheets. As a result, automatic production of as-built BrIM is critical for digitalizing the life cycle management of existing bridges.

There are four processes involved in developing an as-built BIM for an existing structure: 3D reconstruction, semantic modeling, geometrical modeling, and building information modeling [27]. Reality capture devices are used in 3D reconstruction to create digital representations of existing buildings, such as point clouds. Three modeling stages follow, intending to generate BIM from the digital representation. In semantic modeling, for example, the subsets of the 3D reconstruction are given labels in a BIM taxonomy. The parametric representation of each class instance's shape, position, and spatial connection will then be constructed in geometrical modeling. Finally, the semantic and geometrical characteristics in the building information modeling are combined and recorded to files in the BIM format (e.g., IFC), resulting in building information models.

Actual reality capture methods are widely used to generate point cloud representations for 3D reconstruction. To track the displacements of a supported steel beam, Park et al. [63] used terrestrial laser scanning (TLS) to create a point cloud model. Photogrammetry based on 2D photos was used by Brandon et al. [64] to construct the point clouds of bridges so that surface condition and geometry information could be seen. Roca et al. [65] used a lidar mounted on a UAV to acquire the point cloud data of structures to develop building envelope models and do energy analysis.

Despite substantial advances in data gathering systems, only a few as-built BrIM for existing bridges have been produced. The critical barrier is time-consuming, labor-intensive, and expensive modeling operations from point cloud to BrIM [45]. The third phase, geometrical modeling, and the fourth step, information modeling, were automated in several published studies. Geometric modeling is commonly achieved by fitting parametric geometry representations, such as planes and cylinders, to point clusters [61]. Nonparametric representations, such as polygonal meshes,



(a) (b) (c)

Figure 7: (a) 3D BrIM model in revit. (b) Sample IFC text file with crack information, and (c) integrated BrIM model opened in BIM Vision [58].

were also used for complicated forms that could not be characterized by parametric representations [66]. Lu and Brilakis [57] also devised a slicing-based method for directly constructing IFC entities from the labeled point clusters of bridge components and producing BrIM. Their technology has successfully automated geometrical and information modeling in RC bridges. Indeed, the automation of geometrical and information modeling approaches has advanced significantly in recent years, and a slew of commercial software products (e.g., ImageModeler, Leica CloudWorx, PolyWorks Modeler, and others) have developed to help [23]. The second phase, semantic modeling, however, remains challenging to automate. Although there has been progress in recognizing a few particular items in structures (e.g., pipelines [67], structural steels [68]), no one approach can complete the semantic modeling by identifying all needed objects. In the case of bridges, the geometries of point clouds from different bridge types are generally diverse, and outliers are frequently present. This challenge has been exacerbated by the lack of training data caused by the high reality capture cost, making the end-to-end deep learning model challenging to implement. As a result, no research has been able to perform accurate and reliable bridge component detection [51, 69].

3.3. Bridge Management System (BMS). Bridge management systems (BMS) are often used by road authorities to manage the facilities of bridge structures. Inspection, structural health monitoring (SHM), and rehabilitation are the primary functions of these systems [70]. By adopting more advanced computerized management systems, managing agents can better handle the quantity of information needed for successful infrastructure management [71].

To guarantee the safety of bridges throughout their design life and beyond, regular assessments and actions are necessary. To check the health of a bridge throughout its lifespan, systematic quality evaluation processes known as routine inspections are performed [72].

Table 5: Technologies for inspection, automatic damage identification, and references.

Tool	References
Laser scanning	[70, 75, 76]
Photogrammetry	[77, 78]
Ground penetrating radar (GPR)	[79–81]
Unmanned aircraft vehicle (UAV)	[82, 83]
Light detection and ranging (LiDAR)	[84]
Wireless sensor network (WSN)	[85]

Currently, most bridge inspections are carried out by hand, with inspectors performing extensive visual examinations and field measurements [73]. On the other hand, manual inspections take a long time and rely heavily on the inspector's familiarity with the studied system's structural behavior [72]. The notion of automating, systematic, and quantitative 3D point cloud evaluation in place of human visual perception is now being researched [74]. The most recent study integrates picture collecting techniques with damage identification and feature extraction approaches into an automated bridge inspection system [74]. Table 5 lists current technologies used to automate bridge inspection and damage identification.

In the literature, few studies use Digital Twin for bridges. During the Henry Hudson Bridge renovation in New York, Andersen & Rex (2019) [86] built an SHM system backed by a digital twin that could forecast reactions to probable catastrophic scenarios. Shim et al. [87] suggested a bridge maintenance system based on the notion of digital twins by developing the following three models:

(i) A three-dimensional geometry model
(ii) A model that depicts the bridge's current state.
(iii) An intermediate model between the first two.

The geometric digital twins of existing bridges have been constructed by Lu and Brilakis [57]. The authors argue that a platform-agnostic data format, IFC, should be used to express all the geometric and property information. It was the last of the three Digital Twin frameworks that Ye and colleagues [88] presented, which was evaluated in the case study of railway sleepers equipped with fiber optic sensor (FOS) systems.

Building information modeling (BIM) may be used to create digital models that can then be utilized to predict structural degradation using finite element methods (FEM) and foresee the consequences of such decay on the integrity of structures [79, 80, 89]. In a smart BMS, the precise modeling of the current state and forecasting of future behavior are crucial components [73]. Autodesk Revit, the most widely used commercial BIM software, has been recognized as one of the most sophisticated digital twinning systems by several writers in this study [73]. In addition, an industry foundation class (IFC) platform is provided, allowing data to be exchanged across nonnative file formats [90]. A neutral file format for transmitting digital building models, such as IFC, can help alleviate interoperability difficulties [74].

To design a BMS, several stages must be considered. The significance of conducting routine bridge inspections was first recognized. The critical concerns with present techniques and technology were improving inspection and damage detection. The second component, digital models, focused on BIM, FE modeling, and data integration tools across platforms. Finally, the third segment addressed digital twins, revealing a lack of clarity on the definition of the Digital Twin for the construction sector and the fact that, while expanding, the approach to bridge management is still in its infancy. As a result, the intended BMS should include the following while using Digital Twins:

(i) Inspection: an automated procedure that combines precise and dependable technology to enable the development of digital models and automatic damage identification with little to no reliance on the human eye or site visit.
(ii) BIM model: a semantically rich and comprehensive model built primarily automatically from geometry data and contains the original geometry, current status updated with inspection data, and the visualization of monitoring points.
(iii) Digital Twin: derived from the BIM model, the digital twin should be able to automatically update with site monitoring data and connect to additional layers, such as an FE model, for future behavior prediction.

The Digital Twin system should also include a study of optimal intervention techniques for the facility management element of the structure during its entire life cycle, predict

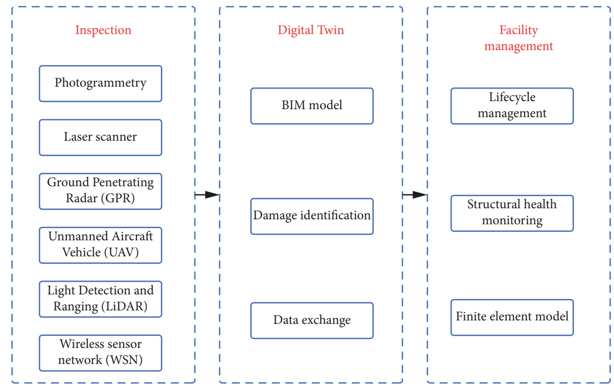


Figure 8: Bridge facilities management framework based on digital twins.

Figure 9: 3D point cloud of the crooked river bridge [91].

improvements because of future interventions, and handle intervention, inspection, and ancillary expenses, including traffic delays, accidents, and environmental damage. Allow for the storage of fundamental construction data, inspection data, and intervention history. The system should also be user-friendly, with features like attentive warnings when specific metrics approach warning or critical levels. The possible technologies discovered in the literature for each of these macro characteristics were summarized in the framework shown in Figure 8. Nondestructive testing (NDT) may be used to discover the inner geometry and material qualities using this framework, and diverse techniques can be coupled to create novel bridge facility management.

3.4. 3D Modeling. The most challenging task is to transform raw data into information that can be used for data collection and 3D model reconstruction. With properties like intensity and color, raw topographic point cloud data cannot be used to analyze object surfaces. The engineers desire an accurate 3D portrayal of this task's end outcome. Engineers may be able to make better management or assessment decisions using the 3D model generated for civil infrastructures, such as bridges. Data collection and 3D model development are the most frequent techniques for employing a point cloud in bridge engineering (Figure 9). Data collection techniques on-site should be optimized to maximize the number of scan stations and coverage areas.

Bridge engineering applications require large amounts of high-quality data point clouds, which are challenging to collect. A mistake in scanning or identifying an insufficient scanning location might result in missing data points in this step. Data collection is more difficult because infrastructures like bridges are more varied and complex in terms of kind, orientation, form, size, and the surrounding scene [73, 92].

Scanning processes are developed by engineers for the purposes of data collection and site surveying, and scanning parameters have been established [93, 94]. Optimizing hierarchical scanning was employed by Jia and Lichti to tackle TLS viewpoint planning issues. Hinks et al. [95] used a flight planning strategy to provide complete object coverage with little data redundancy.

Data capture rate (pixels per second), scanning time, and the amount of redundant data and noise are all affected by the data quality level. Scanning geometry, surface smoothness, reflectivity, and laser scanner properties can all affect the quality of the data points collected [96]. The resolution setting defines the lowest visual item dimension, commonly in centimeters for concrete and millimeters for steel [92]. TLS has difficulty identifying enough data points to represent edges in steel structural components since they are frequently narrow segments with edges [97]. Satisfactory resolutions must be considered for damage identification proposals to investigate moderate (at least) cracks, spalling, and scaling [98]. These researchers studied beam fractures using this method, as did Cabaleiro and colleagues [99]. TLS could detect fractures up to 3 millimeters wide using a one-millimeter resolution.

Ambient conditions, such as humidity, temperature, and light have a role in the initial step. The surface roughness of the exposed object is also a factor. The surface's smoothness, roughness, and color can affect laser beam traversal and return. The TLS location and incidence angle are two components of geometry scanning [24]. According to Laefer et al. [98], orthogonal distance and incidence angle might change fracture width detection results. This study demonstrates a 1.37 mm absolute error at a 5.0–7.0 m orthogonal distance. Some basic adjustments may be applied to the scanning mechanism. Selecting appropriate surveying equipment, such as a high-tech laser scanner and tripod with stabilizer, and having a defined scanning plan may decrease duplicate data acquisition for an effective monitoring operation like a bridge inspection.

For bridge information modeling (BrIM), assessment, and maintenance, this process builds a 3D model of the bridge structures from raw data points. From the beginning of the design process until the end, the virtual 3D model of the bridge may be used. Because of construction and use, a bridge's condition may vary over time, resulting in a state different from what was initially documented in the design documents. Large-scale structural changes can only be shown by an accurate, as-built 3D model derived from a thorough survey [100].

Preprocessing, segmentation, and CAD model construction are part of the 3D modeling process. Data cleansing and registration are two of the first steps in preprocessing. The noise in raw TLS data points affects the construction of 3D models. In the data clean-up stage, angle, median, and chordal filters can help reduce noise. Datapoint clouds must be aligned using target points and methods in the light of the multiple scan locations [101]. For this stage, TLS instruments and software have lately introduced innovative preprocessing methods that reduce the amount of office labor [102]. Segmentation turns the input into geometric shapes that represent the surface of the observed item [29]. The difficulty of establishing an adequate automatic segmentation method has risen because of the increasing number of data points. CSG and B-rep are the tools of choice when dealing with this issue. B-rep creates a 3D object from various surfaces, whereas CSG develops 3D solid models from volumetric primitives using Boolean operations [103]. The bounded fundamental primitives of solid models in CSG are stated as the following: cone/cylinder/sphere/cuboid. Edges, vertices, and surfaces are used in the B-rep technique to determine solid model boundaries. Using the CSG technique, all bridge components are broken down into basic subsets/primitives. B-rep and CSG have been combined in recent studies [103].

Feature-based segmentation ("feature-based segmentation") or segments based on data points meeting mathematical models were among the segmentation algorithms researchers aimed to develop ("model-based segmentation"). When using feature-based segmentation methods, such as region growth [47] and ray tracing [104], the curvature of a surface is determined by comparing data points gathered at various locations [105], such as the angle of normal and unit vectors [106].

The final step in producing an integrated geometric model from segmented data points is constructing a 3D CAD model. Standard practices call for fitting and sweeping. The first method uses segmented points to create basic primitives, while the second method extrudes a segmented object along a path to see 3D CAD [47, 100].

Sweeping has become the topic of more studies. Laefer and Truong-Hong [50] proposed an automated method for swiping the determined profile along its longitudinal axis to identify a steel structural component's cross-section. Laefer [107] discovered multiple cross-section cuts along a steel component's primary path in his research.

Yan et al. [108] used a three-phase voxel-based mesh generation technique to create a three-dimensional structural model. This method begins with voxel-based cross-sectional cut extraction and extrudes the identified cuts along their principal axes to use the correct component map.

4. Research Limitations and Future Studies

This work adds to the body of knowledge, however, it also has several limitations that need to be considered. Despite a thorough search for relevant content, it is possible that not all search phrases were identified. Scopus, Web of Science, and Google Scholar databases were only used in this research. As a result, additional articles on Digital Twins for bridges have not been presented. The results may not fully represent the literature on Digital Twin applications in bridges because of these limitations. It is possible that the study used subjective judgments to determine the actual articles and to identify their application in distinct lifecycle stages of literature. New advancements in natural language processing are also required to automatically prevent duplication from diverse databases, collecting material from all languages and encapsulating it to present an overview of research from a global viewpoint. Research findings should be interpreted in the light of the limitations outlined above, which should be considered.

5. Conclusion

Digital Twin technology will usher in a new era of digital information in the building sector. According to the literature analysis, initiatives to adopt the Digital Twin idea for bridges are underway. These initiatives, however, appear to be in the early stages. Much study is required to effectively include a full-scale high-fidelity Digital Twin model into the bridge-building. Parallel initiatives to enhance BIM to include the operation and management phase by applying Digital Twin technology appear to be underway. Even though there are issues with integrating BIM, laser scanning, sensor data, and processing the amassed data, BIM has the advantage of being adopted for many assets. The Digital Twin provides the advantage of a solid basis for data processing and BIM integration. However, when it comes to bridges, the Digital Twin technology is further behind in research and application.

In 2020, there was a considerable increase in digital twin research for bridges. Digital Twins are predicted to gain popularity despite being linked to several concerns, such as data exchange constraints, project inefficiencies, and the lack of a collaborative approach throughout the life cycle.

The most influential journals in Digital Twin for bridge maintenance are Automation in Construction, Sensors, Applied Sciences, and IEEE Access. “Machine learning,” “bridge information modeling (BrIM),” “bridge management system (BMS),” and “3D modeling,” according to scientometric study results, are four dominant research disciplines.

The analysis and mapping revealed that improving prediction and knowledge integration across the project lifecycle is critical in the near future.

To address the issues raised in this study, future research should take a holistic approach. The findings of this study will assist both construction industry stakeholders and academics by raising the knowledge of current research aims, research gaps, and long- and short-term future research trends in the field of Digital Twin research.

While the study used a small number of sources, the information obtained from them was constrained by bibliometric constraints. Furthermore, scientometric mapping and analysis uses solely academic research. Practical and commercial advances are, therefore, omitted. The future study may include data from practitioners and corporations to get better findings.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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