DTADD Systematic Review Preprint

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Abstract

Bridge infrastructure has great economic, social and cultural value. Nevertheless, many of the infrastructural assets are in poor condition as has been recently evidenced by the collapse of several bridges. The objective of this systematic review is to collect and synthesise state-of-the-art knowledge and information about how bridge information modelling, finite elements, and bridge health monitoring are combined and used in the creation of digital twins (DT) of bridges, and how these models could generate damage scenarios to be used by anomaly detection algorithms for damage detection on bridges, especially in those bridges with cultural heritage. A total of 76 relevant studies from 2017 up to 2022 are included in this review. The synthesis results show a general consensus towards the future adoption of DT for bridge design, management and operation among the scientific community and bridge practitioners. The main gaps identified are related to the lack of software interoperability, the required improvement of the performance of anomaly-detection algorithms and the approach definition to be adopted for the integration of DT at the macro scale. Other potential developments are related to the implementation of Industry 5.0 concepts and ideas within DT frameworks.

Keywords

Bridges, Digital Twins, Anomaly Detection Algorithms, Finite Element Method, Cultural Heritage Conservation, Bridge Information Modelling, Bridge Health Monitoring

1 Introduction

In 2018 the Morandi bridge collapsed in Genova, Italy, killing 43 people, forcing the displacement of 200 families living below the bridge, causing damages of EUR 422 million and yearly losses of EUR 784 million to the industry sector in the region (Xuequan, 2018). During the last 2 decades, the collapse of more than 120 bridges worldwide has caused economic losses and casualties (Wang et al., 2022). A total of 9 661 structures representing the 12.4% of all bridges and tunnels in Canada are reported to be in poor/very poor condition (Infrastructure, 2019), whereas 46 154 bridges, equivalent to the 7.5% of this kind of asset in the United States are considered structurally deficient (ASCE, 2021). In comparison, the percentages of deficient bridges in European countries such as France, Germany and the United Kingdom are even higher, 39, 30 and 37% respectively (Commission et al., 2019). Besides, many old bridges are considered to have a Cultural Heritage (CH) value and some of them are even inscribed on the UNESCO World Heritage List (World Heritage Centre, 2023) thanks to their outstanding universal cultural value. In addition to human and economic losses, the damage or collapse of a historical bridge also entails the painful loss of a cultural asset.

Because of the large number of existing bridges and the limited availability of human and economic resources (PIARC, 2023), it is not feasible to continuously inspect and assess the structural condition of every bridge using conventional methods. In the current practice, bridge inspections are performed on a code-prescriptive fixed-scheduled periodic basis varying between two to six years (EuroStruct, 2020). However, those periodic revisions have proven to be ineffective, as damage could appear after a periodic inspection and not be detected until the next one, leading to further deterioration of the bridge and increased cost of its eventual repair or replacement, if not to its collapse. In addition to the particular condition of a bridge, other factors can be considered in scheduling and performing bridge inspections. Most approaches consider the current and future usage of the bridge, its role in the transportation network, as well as other environmental, political and social factors. It is of paramount importance to integrate CH values with bridge management methodologies, in agreement with international principles of conservation (Petzet, 2004), otherwise irreplaceable parts of our built environment may be lost forever.

A theoretical way to tackle the issue of insufficient resources at a network level, while adequately considering the CH value of a bridge, is to adopt a novel Digital Twin (DT) paradigm. A DT contains a virtual replica of a real-world bridge and a connectivity module that allows both the physical and virtual assets to be synchronized along the life cycle stages of the bridge. The 3D geometry of the bridge can be created through a Bridge Information Modelling (BrIM) approach, whereas a mechanical twin can be constructed in Finite Element (FE) software. Sensors installed during a Bridge Health Monitoring (BHM) process can provide data about the environmental conditions, loads and response of the structure to those loads, either at local-element or global bridge scale. A series of damage and decay scenarios can be simulated on the virtual asset, which will reproduce the structural response of its physical counterpart through a series of FE models. This digital approach allows testing the bridge and generating the required data under several “normal” and “damaged” scenarios necessary for training Artificial Intelligence (AI) data-driven models such as anomaly detection algorithms (ADAs) capable to detect damage in quasi-real time. The bridge management stakeholder uses the generated information to make an informed decision, thus optimising the resources it has at its disposal. Therefore, a DT methodology leads to improved bridge performance and CH conservation, an increase in the bridge service life and an eventual reduction of the maintenance and operation costs of the bridge network.

The aim of this systematic review is to collect and synthesise state-of-the-art knowledge and information about how BrIM, FE and BHM are combined and used in the creation of DTs of bridges and how these models could generate damage scenarios to be used by AI ADAs for damage detection on bridges (especially in those bridges with CH value). To this end, the proposed systematic review answers the following questions; (a) what are the most efficient ways to build bridge DTs based on BrIM, FEs and BHM?, and (b) what are the best ADAs that could be used on the damage detection of conventional and CH bridges?

The value of this paper lies in the need of having a comprehensive perspective of the current state of the art as the keystone for further research and development. The rest of this paper is organized as follows: Section 2 presents the methodology applied for the search strategy, bibliometric analysis and synthesis of the found information, Section 3 contains the bibliometric results and Section 4, the narrative synthesis. Finally, in Section 5 some conclusions are drawn, highlighting the gaps and further research suggestions derived from the systematic review work.

2 Methodology

The PRISMA 2020 methodology (Page et al., 2021a), although mainly developed and used in the medical and clinical sciences, can also be applied in engineering, as it provides methodology guidance to identify, select, appraise and synthesize the available literature. Thus, this systematic review has followed the checklist provided by PRISMA and a protocol was developed in accordance to the guidelines of the PRISMA-P Explanation and Elaboration (Page et al., 2021b). In accordance with the guidelines, our systematic review protocol was registered in the Open Science Framework (OSF) Registries with registration number sh9b2 (Jimenez Rios et al., 2023b). The protocol of this systematic review can be consulted in Jimenez Rios et al. (2023c)

2.1 Search strategy

Quality of systematic reviews heavily relies on the search strategy implemented for the information retrieval process. Nevertheless, search strategies are commonly not adequately reported. This systematic review has adopted a search strategy methodology based on the PRISMA-S checklist (Rethlefsen et al., 2021).

The search strategy implemented in this systematic review was performed in Scopus because of its wide coverage of the literature, its high-quality content and its advanced data extraction capabilities (Elsevier, 2023). Initially, seven main keywords of interest were selected, namely, “bridge”, “digital twin”, “bridge information modelling”, “finite element methods”, “bridge health monitoring”, “anomaly detection algorithms” and “cultural heritage”). These keywords (and similar terms such as “bridge” and “bridges”) were combined to obtain six search queries in which every search combined a keyword with the “bridge” keyword. Thus, the queries obtained were:

- bridge* AND “digital twin*”
- bridge* AND (BrIM OR “bridge information model*”)
- bridge* AND (FEM OR FEA OR “finite element method*” OR ”finite element analy*”)
- bridge* AND (“bridge health monitoring” OR ”structural health monitoring”)
- bridge* AND (ADA OR “anomaly detection algorithm*”)
- bridge* AND (“cultural heritage” OR “monument* bridge*” OR “old bridge*” OR “ancient bridge*” OR “historic* bridge*”)

where * represents the wild character, AND and OR are Boolean operators, “·” are used to group individual words into multi-word keywords and (·) are used to group several similar terms. The six searches were limited to journal articles, conference papers, reviews and book chapters written in English that were published after 2017 on the subject of Engineering. The searches were performed within the fields of title, abstract and keywords. Table 1 presents the full queries used in the search, which was performed on 10/12/2022, and the respective number of records found for each one of them.

Table 1. Full queries used for the search and the respective number of records found.

Query	# of records found
TITLE-ABS-KEY (bridge* AND ”digital twin*”) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (SUBJAREA , ”ENGI”)) AND (LIMIT-TO (LANGUAGE , ”English”)) AND (LIMIT-TO (DOCTYPE , ”ar”) OR LIMIT-TO (DOCTYPE , ”cp”) OR LIMIT-TO (DOCTYPE , ”re”) OR LIMIT-TO (DOCTYPE , ”ch”))	178
TITLE-ABS-KEY (bridge* AND (brim OR ”bridge information model*”)) AND (LIMIT-TO (SUBJAREA , ”ENGI”)) AND (LIMIT-TO (DOCTYPE , ”ar”) OR LIMIT-TO (DOCTYPE , ”cp”) OR LIMIT-TO (DOCTYPE , ”re”) OR LIMIT-TO (DOCTYPE , ”ch”)) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (LANGUAGE , ”English”))	56
TITLE-ABS-KEY (bridge* AND (fem OR fea OR ”finite element method*” OR ”finite element analy*”)) AND (LIMIT-TO (SUBJAREA , ”ENGI”)) AND (LIMIT-TO (DOCTYPE , ”ar”) OR LIMIT-TO (DOCTYPE , ”cp”) OR LIMIT-TO (DOCTYPE , ”re”) OR LIMIT-TO (DOCTYPE , ”ch”)) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (LANGUAGE , ”English”))	5137
TITLE-ABS-KEY (bridge* AND (”bridge health monitoring” OR ”structural health monitoring”)) AND (LIMIT-TO (SUBJAREA , ”ENGI”)) AND (LIMIT-TO (DOCTYPE , ”ar”) OR LIMIT-TO (DOCTYPE , ”cp”) OR LIMIT-TO (DOCTYPE , ”re”) OR LIMIT-TO (DOCTYPE , ”ch”)) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR	2941

LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (LANGUAGE , ”English”))	
TITLE-ABS-KEY (bridge* AND (ada OR ”anomaly detection algorithm*”)) AND (LIMIT-TO (SUBJAREA , ”ENGI”)) AND (LIMIT-TO (DOCTYPE , ”ar”) OR LIMIT-TO (DOCTYPE , ”cp”) OR LIMIT-TO (DOCTYPE , ”re”) OR LIMIT-TO (DOCTYPE , ”ch”)) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (LANGUAGE , ”English”))	10
TITLE-ABS-KEY (bridge* AND (”cultural heritage” OR ”monument* bridge*” OR ”old bridge*” OR ”ancient bridge*” OR ”historic* bridge*”)) AND (LIMIT-TO (SUBJAREA , ”ENGI”)) AND (LIMIT-TO (DOCTYPE , ”ar”) OR LIMIT-TO (DOCTYPE , ”cp”) OR LIMIT-TO (DOCTYPE , ”re”) OR LIMIT-TO (DOCTYPE , ”ch”)) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (LANGUAGE , ”English”))	351

A total of 8 673 records were found. Bibliometric information about all those records was downloaded from Scopus both in .ris and .csv format and it is available in the open-source database Jimenez Rios et al. (2023a). Deduplication, filtering, screening and eligibility assessment of all those records was carried out in accordance with PRISMA flow chart Page et al. (2021a) (see Figure 1).

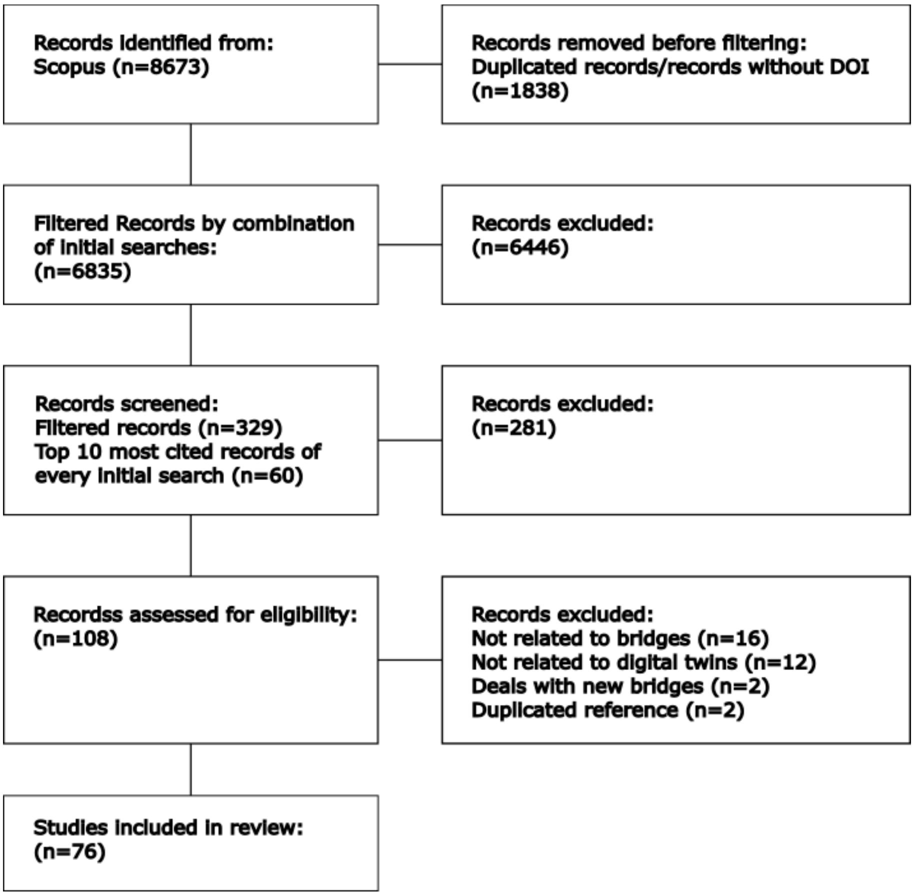


Figure 1. PRISMA flow diagram.

All duplicated records (based on the DOI number) and those records without a DOI number were removed. In total, 1 838 records were discarded after this first filtering. As a second filter, a search combination was performed. The initial six searches were combined with each other using the AND operator (resulting in 15 new searches) in order to obtain relevant records dealing with at least three of the initially selected keywords (as the “bridge” keyword was used in all original six searches). Thus, 6 446 records were excluded and only 389 records remained, including the top-ten most cited papers from each one of the original searches (60 papers in total). The most cited papers were deemed to be of paramount importance to the state-of-the-art of the field due to their major impact on all related publications.

The title and abstract of the remaining 389 records were manually screened. Based on the authors' criteria and previous knowledge of the field. Those records that did not fully fit within the scope of the review were excluded. Thus, 108 works remained and were subjected to full paper examination to assess their eligibility. From this list of 108 works, 2 were removed as they were duplicates, 2 more were excluded as they only dealt with the construction of new bridges, 12 more were not considered as they did not deal with DTs, and lastly, 16 papers were rejected as they were not related to bridges. A total of 76 studies were finally included in this systematic review.

2.2 Bibliometric methodology

A bibliometric analysis represents a quantitative methodology by which meaningful insights can be obtained from large quantities of data (Broadus, 1987). The main outcomes of a bibliometric analysis are the identification of emerging research trends in a field, collaboration and publication patterns, and exploration of literature structure. The approaches of a bibliometric analysis could be categorized into two main groups: performance analysis and science mapping (Solorzano and Plevris, 2022).

In this systematic review the performance analysis was carried out by querying, filtering and sorting the bibliographic database obtained from the search strategy, whereas the science mapping was performed using the VOSviewer version 1.6.18 software (https://www.vosviewer.com/). Performance analysis is presented in terms of publications per year, most cited authors, most cited records, documents per country, keyword occurrence and most used source for publication. On the other hand, the science mapping focuses on analysing the co-authorship relationships in terms of authors and countries, as well as the co-occurrence relationships between keywords (both author and index keywords). Keywords mapping allows visualizing the interconnections of core concepts and topics within a certain research area. For further insights into how the maps are created interested readers can consult van Eck and Waltman (2014) and the software manual van Eck and Waltman (2022).

2.3 Synthesis methodology

The information of the studies included in this systematic review has been qualitatively summarized in a narrative synthesis as the findings are characterized by heterogeneity. Data has been analyzed and classified within 6 major themes, namely, DTs; BrIM and FE modelling; BHM and AI; ADAs; Unmanned Aerial Vehicles (UAVs), satellite monitoring and other emerging technologies; and historical and CH bridges. Based on this classification, the findings of the systematic review are presented, the strengths and limitations of the studies are highlighted, their influence on practice and research is discussed, and future research recommendations are suggested.

3 Bibliometric Results

3.1 Performance analysis

Regarding the number of publications per year, Figure 2 shows that over 1 000 papers containing the keywords of interest of this systematic review were constantly published yearly between 2017 and 2020. The trend though shows an increase in the number of publications from the last two years, with 25 and 50% increments on the number of yearly publications for years 2021 and 2022 respectively.

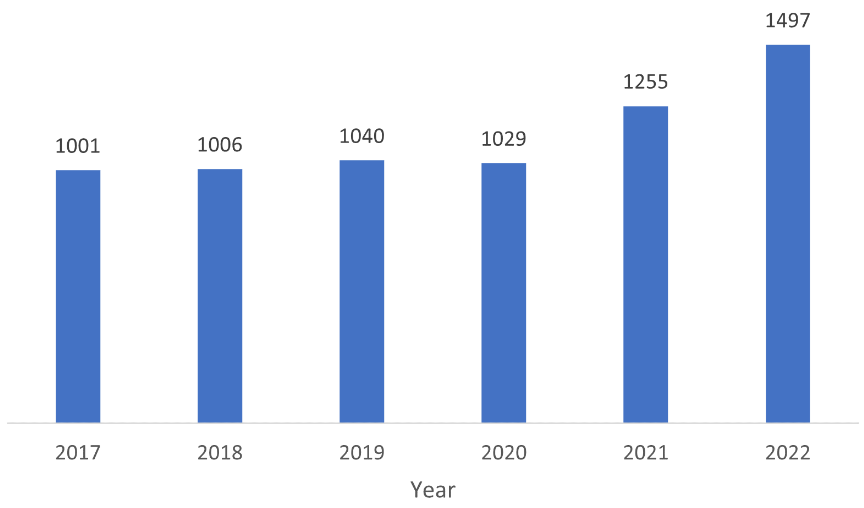


Figure 2. Publications per year.

Table 2 presents the top 20 most cited works. The paper with the most citations is "Shaping the DT for design and production engineering" (Schleich et al., 2017) with a total of 644 citations. Nevertheless, after the filtering process shown in Figure 1, this paper was not included in this systematic review as it is not directly related to bridges. The paper included in this systematic review with more citations is "Structural Health Monitoring Using Wireless Sensor Networks: A Comprehensive Survey" (Noel et al., 2017) with a total number of 273 citations.

Table 2. Most cited records.

Title	Reference	# Citations
Shaping the digital twin for design and production engineering	Schleich et al. (2017)	644
Structural Health Monitoring Using Wireless Sensor Networks: A Comprehensive Survey	Noel et al. (2017)	273
A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line	Zhang et al. (2017)	266
Computer vision and deep learning–based data anomaly detection method for structural health monitoring	Bao et al. (2019b)	228
Building Information Modeling (BIM) for transportation infrastructure – Literature review, applications, challenges, and recommendations	Costin et al. (2018)	216
Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system	Lin et al. (2019)	193
Experimental validation of cost-effective vision-based structural health monitoring	Feng and Feng (2017)	190
The State of the Art of Data Science and Engineering in Structural Health Monitoring	Bao et al. (2019a)	173
A review of the piezoelectric electromechanical impedance based structural health monitoring technique for engineering structures	Na and Baek (2018)	170
Review of Bridge Structural Health Monitoring Aided by Big Data and Artificial Intelligence: From Condition Assessment to Damage Detection	Sun et al. (2020)	170
Autonomous UAVs for Structural Health Monitoring Using Deep Learning and an Ultrasonic Beacon System with Geo-Tagging	Kang and Cha (2018)	156
Convolutional neural network-based data anomaly detection method using multiple information for structural health monitoring	Tang et al. (2019)	154
Environmental effects on natural frequencies of the San Pietro bell tower in Perugia, Italy, and their removal for structural performance assessment	Ubertini et al. (2017)	135

Digital twin in smart manufacturing	Li et al. (2022)	128
A review on deep learning-based structural health monitoring of civil infrastructures	Ye et al. (2019)	128
Structural Displacement Measurement Using an Unmanned Aerial System	Yoon et al. (2018)	126
A state of the art review of modal-based damage detection in bridges: Development, challenges, and solutions	Moughty and Casas (2017)	125
Structural health monitoring of bridges: a model-free ANN-based approach to damage detection	Neves et al. (2017)	124
Investigation of dynamic properties of long-span cable-stayed bridges based on one-year monitoring data under normal operating condition	Mao et al. (2018)	118
Recent progress and future trends on damage identification methods for bridge structures	An et al. (2019)	114

Another interesting metric related to citations is one of most cited authors. This parameter considers the accumulated number of citations for all papers of an author. Thus, Wang, H., Li, H. and Bao, Y. are the most cited authors with 1308, 1276 and 1222 citations respectively (see Figure 3).

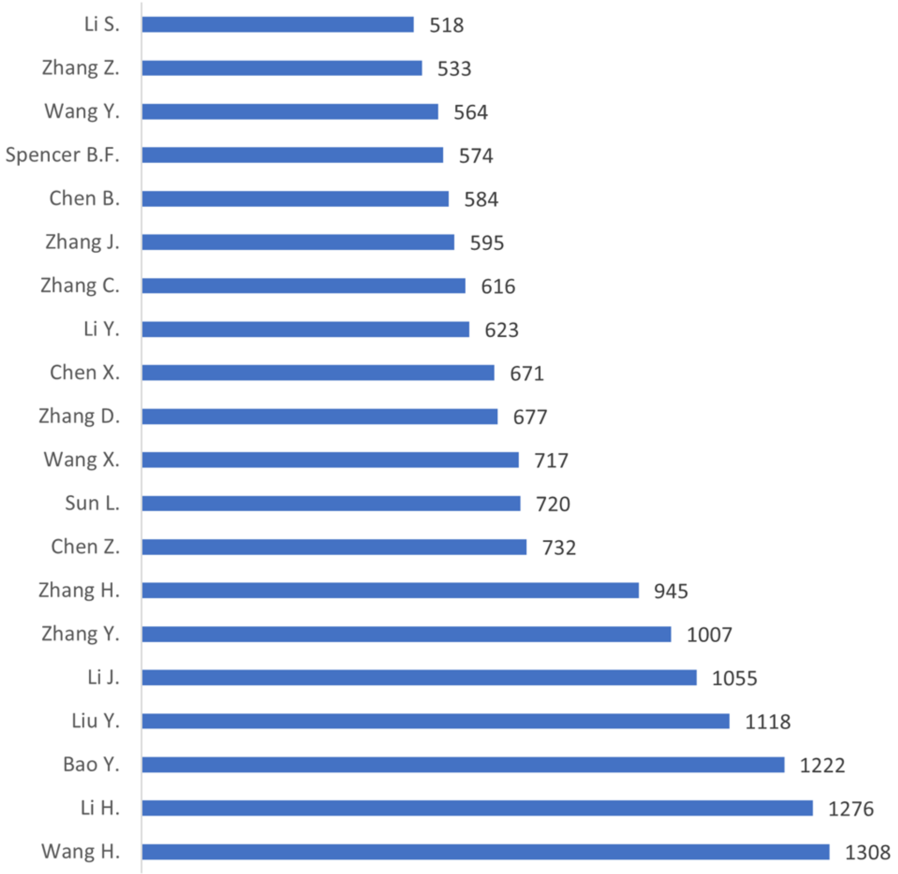


Figure 3. Most cited authors.

Without disregarding the important role of the European Union in supporting research and science, research is normally fostered at a national level by the National Research Council of each country. This is important to understand where most of the work is done in a specific field (as this may be accompanied of Geo-political implications). Thus, in Figure 4 the countries with at least 100 publications in the field over the past 6 years are shown. China is the country with the most publications (2599) followed by the United States and the United Kingdom with 1282 and 420 publications, respectively. The last country on the list is Turkey, with a number of 105 publications. Note that the number of publications per country is based on the country of the authors' affiliations, not on their nationality.

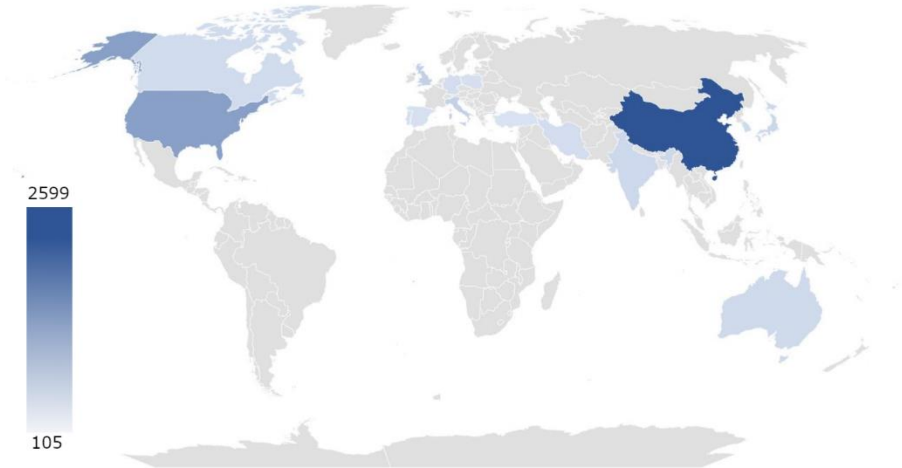


Figure 4. Documents per country.

In terms of keywords occurrence, it is not surprising to find out that "bridges", "FEM" and "SHM" are among the most recurrent keywords (based on the graphical information presented in Figure 5) as they were explicitly included in the search queries. On the other hand, the absence of terms such as "digital twins" and "bridge information modeling" may be explained by their relatively new adoption in the field, whereas the absence of keywords related to "cultural heritage" or "conservation" is directly tracked to the generalized lack of attention towards this topics by the research engineering community.

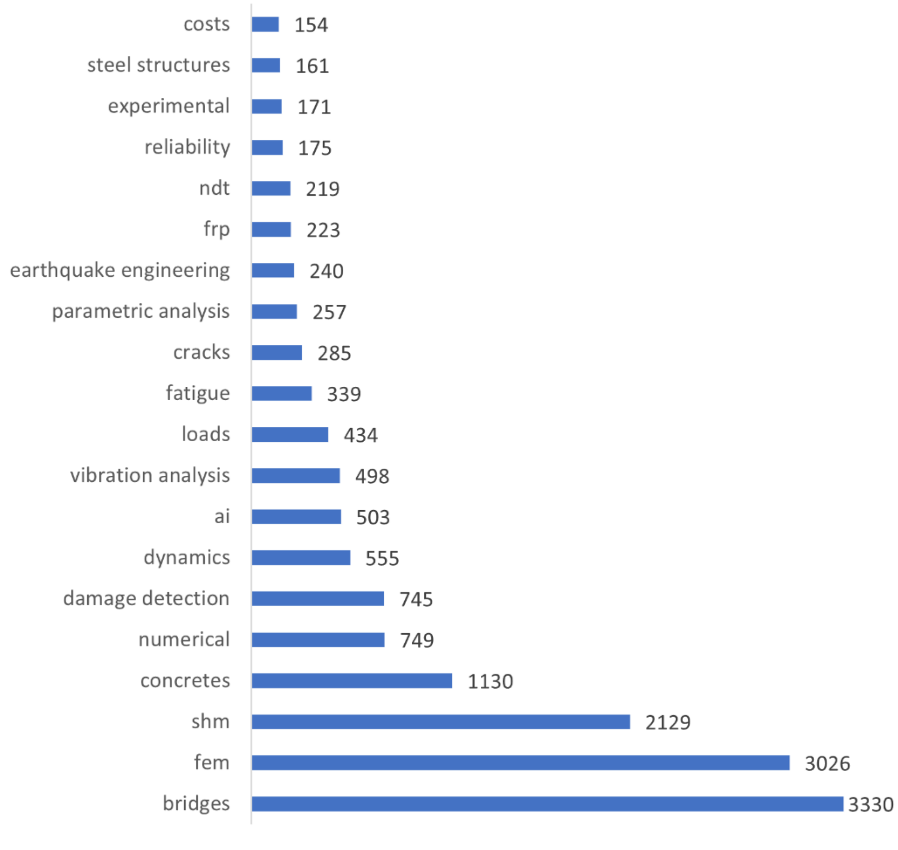


Figure 5. Keyword occurrence.

Most of the research found in this systematic review has been published in three main scientific journals, namely, Engineering Structures, Journal of Bridge Engineering and Lecture Notes in Civil Engineering, 445, 254 and 182 works in each one respectively (see Figure 6). The total number of works concentrated in only these three main sources of publication represents 12.9% of the total number of records after deduplication found from the initial searches of this systematic review

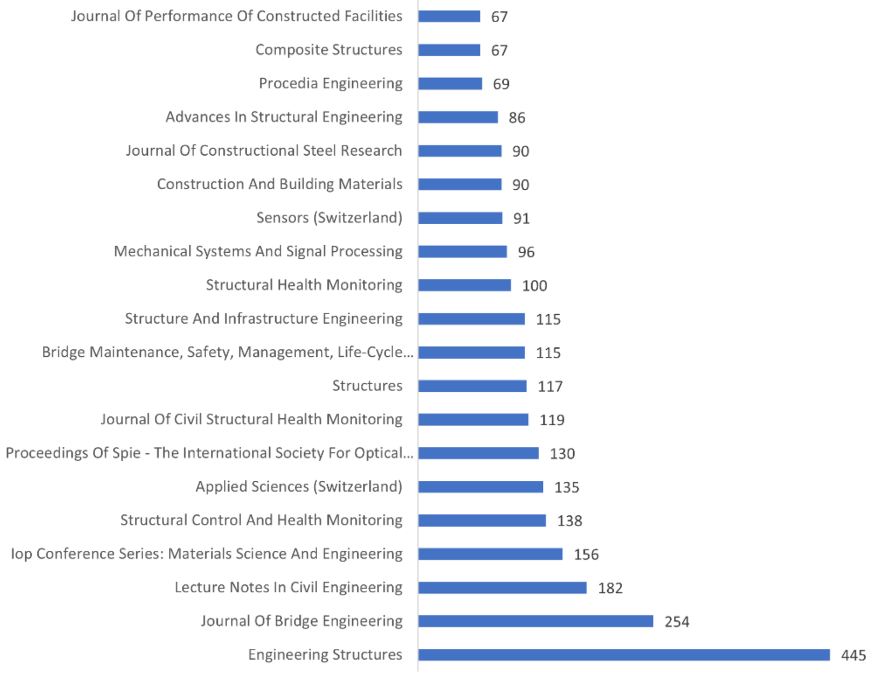
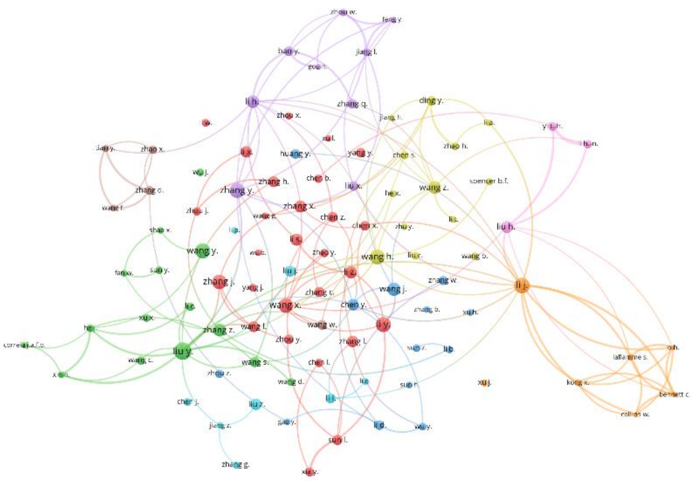


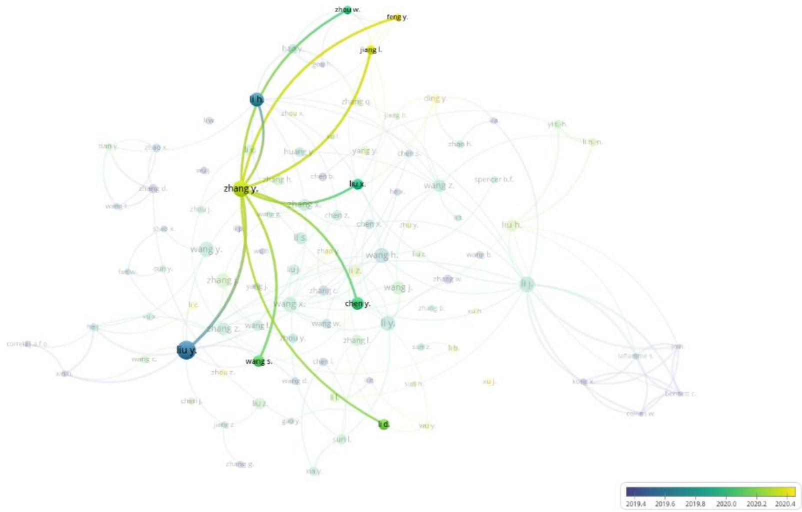
Figure 6. Most used sources for publication.

3.2 Science mapping

Co-author relationships are qualitatively analysed using a network visualization map. Each circle in Figure 7 represents one of the top 100 authors with more publications, as found after performing the search strategy previously discussed. The size of each individual circle depicts its strength or weight within the network (larger circles belong to authors with a larger number of publications). Moreover, the lines that are observed in this figure represent co-authorship links, in other words, who works with who. Analogously to the size of the items, the thickness of the links depicts their strength, i.e., the strength of the co-authorship links of a given researcher with other researchers.



(a)

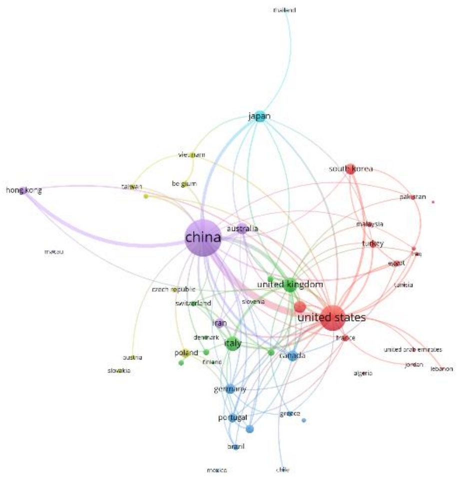


(b)

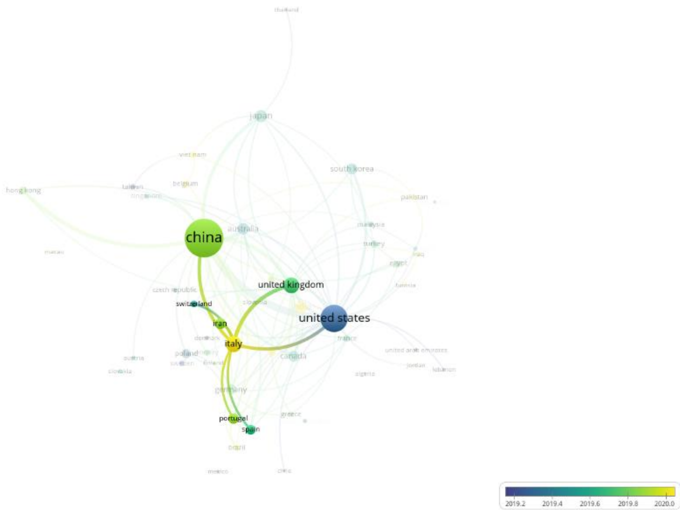
Figure 7. Co-authorship relationships in terms of authors: (a) Authors clusters and (b) Most recent average publication author, Zhang Y.

The items in Figure 7 (a) are colour-coded into nine different clusters based on network connectivity. Furthermore, Figure 7 (b) shows an overlay visualization of the co-author relationships colour-coded in terms of average publication year based on the scores assigned to each individual item of the network. It can be observed in Figure 7 (a) that Liu Y. (green, 121 publications), Li J. (orange, 100 publications), Li Y. (red, 90 publications), Zhang Y. (pink, 90 publications) and Wang H. (yellow, 88 publications) are the centroids of the five more prominent clusters identified in the network. From these five networks, it can be seen in Figure 7 (b) that the research group spear-headed by Zhang Y. is the one with the more recent average year of publication (2020.3).

Another interesting co-authorship relationship, now in terms of countries, is showcased in Figure 8. In this instance, three main clusters can be observed from Figure 8 (a) whose strongest items are; China (pink, 2599 publications), United States (red, 1282 publications) and United Kingdom-Italy (green, 420 and 415 publications respectively). Being Italy among them, the country with the most recent average publication year (2020.09, see Figure 8 (b)).



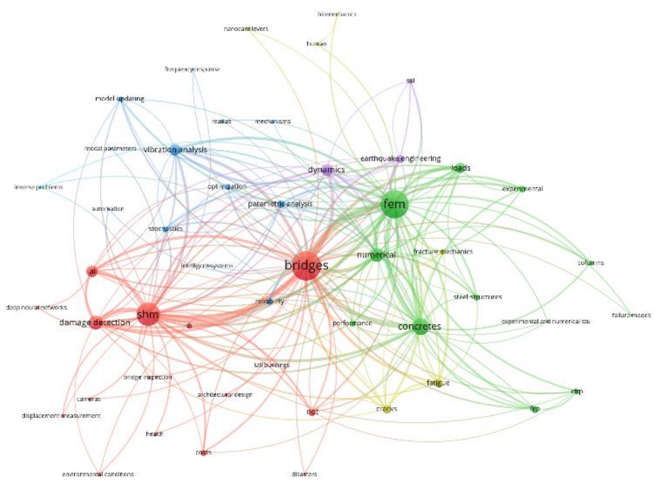
(a)



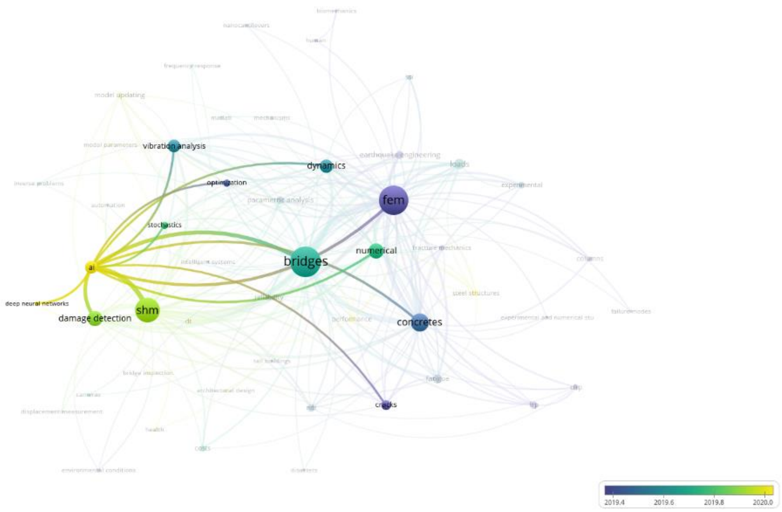
(b)

Figure 8. Co-authorship relationships in terms of countries: (a) Countries clusters and (b) country with the most recent average publication, Italy.

The co-occurrence relationships between keywords have similarly been analyzed through network and overlay visualization maps as displayed in Figure 9. The “bridges” keyword plays a predominant role in this network, which is not surprising because it is the main topic of interest in this systematic review. It is closely related to “SHM” and “Damage detection” as they belong to the same cluster (red) and have thick link lines (see Figure 9 (a)). Regardless of its relatively small strength, “AI” has one of the more recent average publication years (2020.36), which shows its relatively new adoption in the field of bridge engineering (see Figure 9 (b)).



(a)



(b)

Figure 9. Co-occurrence relationships between keywords: (a) Keywords clusters and (b) AI links.

4 Narrative Synthesis

4.1 Digital twins

The life-cycle stages of a bridge include (i) Planning and design, (ii) Construction, (iii) Inspection and maintenance, (iv) Rehabilitation or replacement and (v) Demolition or decommissioning. Accounting for the entire life-cycle of a bridge within the DT paradigm requires the parallel evolution of both the digital and physical assets from the planning and design phase (inspection and maintenance for existing bridges) until the final demolition or decommissioning of the structure. For such purposes, deterioration models that can predict the progressive decay of structural performance of the physical asset are of paramount importance (Cervenka et al., 2020; Jiang et al., 2021). Thus, Giorgadze et al. (2022) suggested an ontological modelling approach that includes not only components related to the structural elements of the bridge itself but also resources, processes and risks related to the management and operation activities along the life of a bridge.

In terms of maturity, Shim et al. (2019) group DTs into three progressive categories based on their Level of Detail (LOD); partial DT (LOD 200-300, used during conceptual and detailed design/analysis), clone DT (LOD 400, which provides construction information) and augmented DT (LOD 500, capable of assisting during operation and management stages). Analogously, Kang et al. (2021) classify DT maturity into three progressive levels of complexity: functional, connected and intelligent. Yet another classification based on the DT features and scopes has been identified by Saback de Freitas Bello et al. (2022). On this threefold classification, a digital model replicates a physical asset but lacks data connectivity between the two, a digital shadow possesses automated one-way data connectivity between the physical and digital counterparts, and finally, in a digital twin the real-time data connectivity is granted in both directions and the digital asset evolves along with the physical one through its service life.

The multi-scale nature of DTs is explored in the work presented by Lu et al. (2020), where they developed a hierarchical architecture to build a DT at both city and building levels. According to these authors' vision, the DT of a bridge could as well be integrated within the DT of a city, and this city DT would eventually form part of a DT at a national level. Although this vision makes sense for urban bridges, the integration of most bridges as part of transportation networks in rural or natural areas would perhaps be more appropriate if a DT is created at the transportation network level (including DTs of roads, tunnels, etc.) which could additionally be benefited from traffic data sharing tools as explored by Dan et al. (2022). This suggests that the direction for the creation of macro-DTs that integrate DT of individual infrastructure assets is still not clearly defined and it needs to be determined whether a geographical, systemic, or another kind of ontological integration approach would be more favourable for grouping of bridge DTs into the macro-DT of an entire transportation network, country or continent.

A key component for the successful implementation of the DT paradigm in bridge monitoring is the integration of Cloud Computing (CC) within the adopted framework. Jeong et al. (2019) build on top of the OpenBrIM schema proposed by Jeong et al. (2017) and develop an Infrastructure as a Service (IaaS)/Platform as a Service (PaaS) CC environment in the Microsoft Azure cloud platform where an open-source distributed NoSQL database (Apache Cassandra) was employed to ensure scalability, flexibility, fault-tolerance and high-performing data management. IaaS was offered in the form of virtual machines (VMs) that can be scaled either vertically (increasing the computational capabilities of the VM) or horizontally (by adding extra VMs). Furthermore, Software as a Service (SaaS) is provided through an online platform from where the user can query the information of interest and download the model that can be regenerated in structural engineering software such as CSIBridge.

To further improve the performance of a DT, Dang et al. (2022) propose the implementation of an intermediate level defined as Fog Computing (FC, computing done in the data generation device itself), which is capable of filtering the great amount of data generated by BHM systems before transferring only the relevant data to the CC layer. They also recognize the need for having several sub-models as part of the digital replica of a DT, each suitable for particular tasks, namely, analytical models based on mechanics and probability theory capable of providing exact and fast results in terms of structural response, reliability and safety for relatively simple idealized structures, physics-based numerical models (i.e., FE) which can replicate the structural response of complex systems for undamaged/damaged scenarios, be used for prognosis purposes and to generate synthetically augmented data. This data, along with the one collected from the BHM of the physical asset, can be exploited by a third type of data-driven models, capable of performing real-time damage detection.

Along with FC intermediate data filtering, the implementation of enhanced data acquisition techniques such as compressive sampling, suitable for sparse data signals (Bao et al., 2019a), can drastically reduce the amount of data that would be stored and analysed in the DT. In terms of visual acquisition data, the amount of information required for processing could be reduced if appropriate compression techniques and image quality percentages are adequately determined as done for example by Ri et al. (2020). By using a BrIM model in combination with Genetic Algorithms (GA) and Discrete Event Simulation (DES), Nili et al. (2021) propose a simulation-based framework to optimize bridge intervention (maintenance, rehabilitation and replacement) considering crew limitations. The framework is developed using Microsoft Visual Studio environment, Microsoft Access for the data management and data query, Autodesk Navisworks Manage as the BrIM application software, GA engine for the planning and sequencing modules, and a DES engine of Simphony core service, with a customized .Net programming language code. Nevertheless, this framework lacks consideration for CH conservation philosophy and methodologies when applied to bridges with CH value.

4.2 BrIM and FE modelling

The concept of BrIM is the adaptation of Building Information Modeling (BIM) methodologies applied to bridges (McKenna et al., 2017), whereas that historical BIM (HBIM) has been developed having CH buildings in mind (Pepe et al., 2020). Based on the life-cycle stage of the bridge in which the BrIM model is built, it could be classified as either as-designed, if the model is produced since the planning and design stage, or as-built, if it is created after the construction phase, or as-is, if the model has been effectively interconnected with the physical asset and is capable of updating its status along the further life-cycle stages of the structure (Hosamo and Hosamo, 2022).

Therefore, by following a multi-level and multi-modal approach as suggested by Xiao et al. (2017), an augmented as-is historical bridge information modeling (AI-HBrIM), would be the adequate tool to implement BIM methodology for existing historical bridges within the context of the DT paradigm. It is estimated that the adoption of this approach could result into up to 30% reduction on traffic-related costs and a 10% reduction on the overall management and operation activities along the entire life of a bridge (Saju et al., 2022).

A suitable methodology to keep AI-HBrIM digital models interconnected to the physical asset is through FE model updating. FE model updating is informed by the actual measured data coming from the physical asset (Yu et al., 2022). Ramancha et al. (2020) implement an advanced Bayesian inference approach using Sequential Monte Carlo (SMC) simulations to update the material and damping model parameters of a full-scale reinforced-concrete column under dynamic loading based on the heterogeneous data collected by accelerometers, strain gauges, GPS displacements and potentiometers. Similarly, by applying a Bayesian inference approach, Ghahari et al. (2022) successfully update an FE model including soil-structure interaction effects. This was possible thanks to the motion identification at foundation level based on the acceleration measurement data obtained from the BHM.

While nowadays there are several data formats (specific protocols for data storing and retrieving) and schema (organization and structure such as XML, STEP, etc.) proposed for achieving AI-HBrIM interoperability, the OpenBrIM Platform (ope, 2023) seems to be the most up-to-date option, whereas Industry Foundation Classes (IFC) (ifc, 2023) development team is currently preparing a new standard (IFC5) including data definitions required for both buildings and bridges over their life cycle. Both OpenBrim and IFC are XML schema-based. On this regards, Jeong et al. (2017) have expanded the OpenBrIM standard by enriching it with libraries for structural elements (e.g., mesh, constraints and coordinate systems), load and analysis conditions (e.g., vehicle loads, modal, static and multi-step) and sensors (e.g., accelerometers, strain gauges and thermistors). The input data is organized and stored in a NoSQL database and Python is used to create the interface between the database and the analysis software (CSI Bridge) by parsing the XML objects. On the other hand, Park et al. (2018) propose to use the functional meaning of bridge components (i.e., column, beam, etc.) to improve the usability of IFC applied to bridges by exploiting IFC basic modular structure and its framework for the sharing of information between various areas of the construction industry.

Another practicality that has received attention by researchers is the initial geometry modeling process of the AI-HBrIM model. Lu and Brilakis (2019) propose an automatic geometry modeling method to advance on the creation of HBrIM models characterized by a slicing-based object fitting approach. They recreated the geometry of an existing concrete bridge using 3D solid elements in IFC format based on a pre-processed labelled point cluster, work previously presented by the same authors in Lu et al. (2019). Although their work was limited to a LOD level of 250 and to only four general bridge elements, namely, slab, pier cap, pier and girder, they achieved an impressive time reduction in comparison with manual geometric modelling techniques currently in practice.

Also in this subject, McKenna et al. (2017) present a case study where 3D laser scanning was undertaken to capture as-is geometry and condition data using a Leica P20 pulse-based Terrestrial Laser Scanner (TLS). Scans are coloured using imagery obtained from a Nikon

D200 camera mounted on a Nodal Ninja bracket to create high-resolution 360◦ panoramic images and then processed using Leica Cyclone proprietary software to create a 3D solid Autocad model of the structure. Two approaches are followed to transform the CAD model into a HBrIM one. Leica CloudWorx for Revit is used first and then Autodesk ReCap software. Most of the modeling work is done manually, though.

As an alternative to conventional geometry data capture of existing bridges necessary to build a DT, Rashidi and Karan (2018) propose a low cost, automatic, videogrammetry methodology. It consists on videotaping the bridge from several views and directions to reduce occlusions, transforming the 2D images captured into a 3D points cloud through the use of a patch-based multi-view stereo algorithm (PMVS), applying computer vision algorithms to identify the bridge components and exporting those elements to an XML format compatible with major BrIM software (RM Bridge, LEAP Bridge Enterprise, AutoCAD Civil 3D, Revit Structure, and Tekla Structures).

Although limited to presenting the applications, challenges and recommendations of BIM on transportation infrastructure (without integration within the DT methodology), Costin et al. (2018) present a comprehensive review about BIM. They highlight the lack of interoperability within the different tools and methodologies currently in practice (Del Rio et al., 2020; Polania et al., 2022; Bouzas et al., 2022) as one of the main needs to be addressed to facilitate the implementation of BIM on the field of transportation infrastructure. Other significant challenges are the assurance of data quality, methodology cost reduction, inherent limitations, and institutional barriers as well as resistance to change by the industry agents.

4.3 BHM and AI

BHM aims to improve asset performance by measuring and learning from in-service structural behaviour (Ye et al., 2022). Moreover, in earthquake-prone countries, BHM supports emergency management actions (Limongelli et al., 2019) and it can even be used to provide real-time traffic information (Burrello et al., 2020). BHM systems are usually designed based on the structural response observed on an a-priori FE model (Ye et al., 2020). Although model-based BHM approaches (Gonen and Soyoz, 2021; Gonen et al., 2023) have shown to be accurate and useful for the prediction of future structural response of bridges under idealized load scenarios, due to the high computational resources and the relatively long simulation periods required, their use results unfeasible for real-time damage detection applications. With the rapid surge and adoption of AI, a new BHM and damage detection paradigm has recently gain importance: the model-free, also known as data-driven, paradigm. Data-driven methodologies can provide quasi-real-time results when damage occurs, on the other hand, they require of large data to be trained and it is difficult to assign a physical meaning to the detected damage. Moreover, databases containing information from real damaged bridges are scarce, as highlighted by Kim et al. (2021).

Neves et al. (2017) present a data-driven damage detection approach based on Machine Learning (ML). They test their methodology and overcome the lack of large data by creating a synthetic database with the help of an FE model. The data set consists on accelerations from 300 simulations of healthy and two damage scenarios of a bridge, of which 150 are used for training of an unsupervised Artificial Neural Network (ANN) and the remaining 150 for validation and verification purposes. Even though their approach is effective, the authors list a series of necessary improvements before it could actually be put into practice, such as considering the effect of environmental and operational conditions, including multiple damage scenarios, extending it for damage location and dealing with factors such as minimum reliability levels (the CH value of the bridge must as well be considered) for the determination of the threshold value. In that regard, Kostic and G ̈ul (2017) try to include environmental and operational effects into their proposed ANN damage detection methodology by implementing a time series analysis, which allows the successful detection of damage under low levels of temperature induced noise (< 3%).

By leveraging the mutual advantages of model-based and data-driven approaches, Zhang and Sun (2021) develop a physics-guided ML monitoring strategy. Their methodology consists in training an ANN using a baseline undamaged condition from observations of a bridge and enriched with damage scenarios data synthetically generated through a FE model. To detect damage, it uses the Normalized frequency Change Ratios (NFCR) and the change of the first several mode shapes of the bridge, combined in a novel cross-entropy loss function. According to the authors, this mixed approach is not only capable of detecting damage, but also of locating and quantifying it.

While some authors have focused on the development of damage-detection data-driven methodologies, others have tried to improve the BHM, which is traditionally based on bridge instrumentation and results economically unfeasible for short and medium-span bridges. Sreevallabhan et al. (2017) present a comprehensive literature review of Structural Health Monitoring (SHM) using Wireless Sensor Networks (WSNs), which are a low-cost alternative of the wired sensor networks commonly used nowadays. Wang et al. (2022) explore the installation and operation of novel piezoelectric transducers, which use a Coda Wave Interferometry (CWI) technique, to asses the condition of existing concrete bridges based on waves generated by the passing vehicles.

On the other hand, OBrien et al. (2017) propose an indirect bridge monitoring approach based on the instrumentation of the vehicles driving through the bridge. This so called drive-by monitoring, provides acceleration data that can be decomposed into three main components; vehicle frequency, bridge natural frequency and pseudo frequency associated with vehicle speed. These three components are obtained through the means of Empirical Mode Decomposition (EMD). Drive-by monitoring approaches have proved effective not only on damage detection, but also on damage location. A research gap identified by them that need to be address to improve the effectiveness of drive-by monitoring is the effect that road roughness has on indirect monitoring. More recently, Locke et al. (2020) present a drive-by monitoring approach capable of not only considering road roughness, which is modeled based on power spectral density functions (for Standardization, 2016), but also variable environmental and operational conditions.

Another alternative proposed for BHM cost reduction consists on the use of non-contact vision-based displacement sensors to measure bridge displacements, which is a parameter directly related to the stiffness of the structure. These approaches exploit a series of available template matching/registration techniques such as Up-sampled Cross Correlation (UCC), pattern matching, edge detection, Orientation Code Matching (OCM), Digital Image Correlation (DIC), Hough transforms and RANSAC (Feng and Feng, 2017). More recently, Shao et al. (2020, 2021) propose a holographic visual sensor coupled with computer-vision-based algorithms in a non-contact displacement and vibration measurement system, capable of capturing bridge full-field displacement and vibrations. Nevertheless, vision-based displacement sensors efficiency highly relies on image quality, which is commonly affected by illumination variation, partial target occlusion, partial shading, and background disturbance, factors usually present on normal bridge operational conditions. On this regard, Shao et al. (2020) suggest the use of denoising and contractive auto encoders to reduce low image-quality errors and improve visual-based monitoring effectiveness.

4.4 ADAs

The problem of damage detection in bridge monitoring may seem like a simple classification problem, i.e., identifying whether there is or there is not any damage in the bridge. However, the individual and highly complex nature of bridges may result in different dynamic responses and thus add to the complexity of this task. Conventional classification approaches are rarely successful due to the important imbalance between normal and anomalous cases, resulting in too many false negatives. An excessive number of false negatives may hinder the detection of actual damages or substantial decay, ultimately affecting the performance of a bridge and, in critical cases, leading to its collapse. Conversely, a large number of false positives would lead to unnecessary spending of resources. By contrast, an acceptable number of false positives may be even desirable for damage detection on CH bridges, which could be obtained with the application of a fine-tuned ADA. Table 3 presents a compilation of the diverse ADAs methodologies found on this systematic review.

Table 3. Various ADAs found on the works included in this systematic review.

Reference	Description	Type
Lu et al. (2020)	Cumulative Sum Charts (CUSUM) to automatically detect vibration deviations on a pump.	Vibration-based
Shim et al. (2019)	Edge detection algorithms combined with fuzzy logic to automatically analyse images captured via UVAs.	Visual-based
Perry et al. (2020)	Black Hat Transform and Canny Edge Detector damage detection algorithm in conjunction with a module to automatically track the change of a defect over time based on an Affine Transform. Damage mapping technique to relate the defects on 2D images to the 3D point-cloud by applying camera, intrinsic and extrinsic matrix multiplications.	Visual-based
Neves et al. (2017)	ANN to predict the expected accelerations of a bridge based on accelerations at previous instant in time.	Vibration-based
Obrien et al. (2017)	Implementation of Intrinsic Mode Functions (IMFs) and pseudo frequency component obtained from indirect drive-by monitoring of a bridge.	Vibration-based
Kang and Cha (2018)	Deep Convolutional Neural Network (CNN) to analyze the images captured by an UAV and effectively detect concrete cracks.	Visual-based
Bao et al. (2019b) and Tang et al. (2019)	Two-steps computer vision and deep learning-based data-driven damage detection method: Transformed registries of time series signals into gray-scale image vectors which were subsequently labeled and used to train a deep neural network (DNN) capable of classifying data pattern anomalies.	Mixed-visual-vibration-based
Garcia Macias and Ubertini (2020)	Automated ADA based upon the pruned exact linear time (PELT) method.	Vibration-based
Al Ghalib (2022)	Pipe-lined methodology combining Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).	Vibration-based
Meixedo et al. (2022b)	PCA combined with autoregressive exogenous input (ARX) and clustering algorithms.	Vibration-based
Meixedo et al. (2022a)	Continuous Wavelet Transform (CWT) combined with ARX and clustering algorithms.	Vibration-based
Febrianto et al. (2022)	Statistical FE modeling and confidence intervals.	Strain-based
Weinstein et al. (2018)	Bootstrapping scheme for the training of an ANN.	Strain-based
Soman et al. (2018)	Multi-metric data fusion combined with a flexibility index approach.	Mixed-strain-vibration-based*
Dohler et al. (2018)	Subspace-based residual function and a $\chi 2$-test for a hypothesis testing.	Vibration-based
*The use of heterogeneous data fusion particularly in combination with denoising techniques has resulted in better data quality obtained from BHM, as reported by Ravizza et al. (2020), from which the different proposed damage detection techniques could benefit.		

A comprehensive review of supervised learning, unsupervised learning, novelty detection and deep neural network methodologies used for generalized damage detection is provided by Sun et al. (2020). Furthermore, Ye et al. (2019) list a series of deep learning techniques specifically used for crack detection, damage detection, loosened bolt detection and damage state classification of bridges. Finally, a comprehensive list of damage detection methods classified either as model-based (FE model updating) or data-driven (ML and statistical methods) can be found in Vagnoli et al. (2018).

4.5 UAVs, satellite monitoring and other emerging technologies

One recurrent topic found on this systematic review is the use of UAVs both to capture bridge geometry and generate HBrIM models, and to automatically detect damage and decay mechanisms based on visual computing techniques (Mongelli et al., 2017; Roselli et al., 2018). Over the past few years, the use of UAVs has increased thanks to the reduction of their costs, improvement of stability and maneuverability, as well as the development of more efficient visual computing techniques. They provide more advantages than manual inspections in terms of time, accuracy, safety, and costs (Albeaino et al., 2019). Furthermore, the GPS signal lost suffered by UAVs below bridge decks during inspections, has been overcome by the implementation of an array of navigation sensors such as optical, infrared and ultrasonic sensors as proved by Kang and Cha (2018). The ongoing development of automatizing UAV flights would further boost the use of UAVs for bridge monitoring as it would result into operational time reductions and path re-usability.

For example, Perry et al. (2020) report UAVs as a key element of an automatic streamlined bridge inspection system capable of identifying and locating bridge surface defects, and generating as-built BrIM models for the storage and visualization of damage information. Their methodology includes photogrammetry software (Meshroom) for the creation of 3D point cluds and photorealistic models, Gaussian Mixture Model and Agglomerative Clustering using Python Scikit-learn for element identification along with the use of Revit and Dynamo for the creation of the AI-HBrIM model containing 3D geometry and damage cubes. However, their approach lacks dealing with the integration of FE and structural analysis tools.

Yoon et al. (2022) assess bridge condition based on images capture with a UAV from which damage is automatically detected through a mask region-based convolutional neural network (R-CNN) algorithm. The methodology proposed by these authors also included a FE model updating module based on a linear stiffness reduction corresponding to the level of bridge condition assessment, as per the damage grades defined in South Korean accepted codes.

The main limitation of visual-based damage detection techniques is that they cannot identify sub-surface damages such as reinforcement corrosion and concrete delamination. These techniques need to be complemented with the application of remote sensing technologies such as ground-penetrating radar (GPR), infrared thermography (IR) (Xu and Turkan, 2020), or with the use of piezoelectric electromechanical sensors that can detect internal damage in a relatively inexpensive way (Na and Baek, 2018). Furthermore, in a comparative study between UAV photogrammetry scanning capabilities against a conventional TLS, Mohammadi et al. (2021) concludes that TLS provides more accurate results and is more suitable for the complex implementation of creating an AI-HBrIM model within the DT paradigm.

Another monitoring technology that has grown in importance over the past few years thanks to its capability for real-time remote monitoring of displacements in bridges is the Interferometry Synthetic Aperture Radar (InSAR). This technology has benefited from the increase number of available satellites and their specialized tools capable of performing millimeter accuracy measurement. Alani et al. (2020) use InSAR in combination with GPR to assess the integrity of a historical masonry bridge and the effects that local floods has on its displacement seasonal trends. More recently, by taking advantage of the improvements on data processing techniques and the availability of larger SAR databases, Gagliardi et al. (2022) manage to detect the seasonal deformation components of a historical masonry bridge based on an enhanced Multi-Temporal InSAR (MT-InSAR) methodology. One more bridge satellite monitoring case, coupled with hydraulic monitoring of river conditions, is reported by Bianchi et al. (2022).

Regardless of the impressive advancements on UAVs, satellites and AI applications experienced over the past few years, it is evident that the human component cannot be entirely removed from any DT framework. On this regard, Karaaslan et al. (2022) develop a human-centered approach using Mixed Reality (MR) to improve the quality and effectiveness of conventional bridge inspections. This is achieved through the use of Hololens (https://www.microsoft.com/en-us/hololens), which provide the bridge inspector with visual information in real-time about the bridge condition and defects.

4.6 Historical and CH Bridges

Historical bridges with CH value require an extra layer of care and special considerations from the part of bridge managers and operators as they not only play a key role in transportation networks, but also hold important social, cultural, and artistic value (Pachón et al., 2018). Any intervention performed in this type of bridge, must abide to the principles of evidence-based, minimum and incremental intervention, removable and distinguishable measures, and material compatibility established in the Venice Charter (ICOMOS, 1964) and strive to preserve the bridge authenticity (ICOMOS, 1994). Furthermore, guidelines and recommendations found in the ISCARSAH documents (ICOMOS-ISCARSAH, 2003b,a) and in annex I of the ISO 13822 standard (ISO, 2010) must be followed to ensure the correct conservation of such valuable assets.

Interventions on CH bridges must be performed by a multidisciplinary team as shown by the work done by Conde et al. (2017) and Bautista-De Castro et al. (2018). Conde et al. (2017) carry out a comprehensive field survey fully based on non-destructive testing techniques, followed by accurate and detailed 3D FE simulations calibrated using the results obtained from a dynamic identification campaign based on an operational modal analysis approach. Bautista-De Castro et al. (2018) perform TLS, ambient vibration test and minor destructive tests. These works result in the detailed assessment of the corresponding bridges structural condition and in the determination of their acceptable safety level. The full adoption of a DT approach is desirable during interventions of CH bridges. A DT would have the ability to monitor in real-time the structure and detect any possible damage induced by the intervention procedure itself as validated by Andersen et al. (2019) in the case of the Henry Hudson I89 Bridge in New York, thus complying with the observational approach suggested by conservation guidance.

Perhaps one of the most advanced tools for damage detection of bridges (in which the CH value is also considered), is the one presented by García-Macías and Ubertini (2020). Their MOVA/MOSS software is capable of automatically perform Operational Modal Analysis (OMA) and system identification through four different techniques: Enhanced Frequency Domain Decomposition (EFDD) and Polyreference Least Squares Complex Frequency Domain method (p-LSCF), both frequency-domain-based, Covariance driven Stochastic Subspace Identification (COV-SSI) and data-driven Stochastic Subspace Identification (DATA-SSI), this last two being time-domain-based. Subsequently, it executes frequency tracking and detects changes in the dynamic properties of the structure by applying statistical process control tools, namely, Hotelling, Multivariate Cumulative Sum (MCUSUM) and Multivariate Exponentially Weighted Moving Average (MEWMA). Finally, automatic damage detection is done through the implementation of the Pruned Exact Linear Time (PELT) Method. Their tool unfortunately, is not part of any DT framework and compatibility issues may arise during integration with other modules of available frameworks.

Along with the conservation of CH value, a sustainable DT framework must as well account for robustness and resilience. Structural robustness is the capability of a structure to sustain certain amount of damage without suffering full collapse, whereas the resilience of a structure refers to its ability to mitigate hazards, absorb the effects of discrete shocks, adapt and recover from damaging events while minimizing disruptions (Hajdin et al., 2018). Assessing both the robustness and resilience of a bridge, implies dealing with a series of uncertainties related to material resistances and external loads. An adequate assessment methodology could be, as suggested by Futai et al. (2022), the implementation of reliability-based and risk-based performance indicators. It has been proved that modeling uncertainties can greatly be reduced by the adoption of a DT framework (Rojas-Mercedes et al., 2022)

5 Conclusion

Although not all research works' scope found on this systematic review encompass the DT paradigm, and regardless of all the challenges and limitations still in place for its full deployment and implementation in real practice, there seems to be only one school of thought and a general consensus towards the future adoption of DT for bridge design, management and operation among the scientific community and bridge practitioners.

A suitable DT framework capable of accounting for the CH of existing bridges would be primarily based on the creation of an AI-HBrIM model with fully inter operable data, geometry, FE and data-driven modules. The AI-HBrIM would be kept interlinked to its physical asset counterpart through the implementation of a and multi-metric BHM system that constantly generates data about the structural, environmental and operational conditions of the bridge. That data would be effectively generated by optimized sampling methodologies and would pass through an intermediate FC layer before its final processing at a CC service.

Current research gaps on the practical development and implementation of DTs are mainly related to (i) the lack of interoperability among the different proprietary and open-source software used along the DT model generation pipeline; (ii) performance improvement of currently available ADAs; and (iii) the direction for the creation of macro-DTs that integrate DT of individual infrastructure assets, needs to be determined and the benefits/drawbacks of whether it is done at geographical, systemic, or other kind of ontological integration approach, assessed.

The DT paradigm was born within the Industry 4.0 era. Future potential developments in the field are related to the implementation of Industry 5.0 concepts and ideas within DT frameworks such as sustainability, human-centrism and resilience (Commission et al., 2022)

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

All authors contributed to conception and design of the study. AJ wrote the protocol and search strategy, carried out the search, organized the data and created the database, performed the bibliometric analysis, did the synthesis of the literature and wrote the first draft of the manuscript. VP and MR supervised the work. All authors contributed to manuscript revision, read, and approved the submitted version. All authors have as well contributed to the obtaining of the necessary funding to carry out this work.

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Data Availability Statement

The datasets generated for this study can be found in the Zenodo repository Jimenez Rios et al. (2023a).

References

[Dataset] (2023). Ifc bridge design to construction information exchange.

[Dataset] (2023). Openbrim platform where bridge engineering happens.

Al-Ghalib, A. A. (2022). EnglishStructural damage detection of old ada steel truss bridge using vibration data. Structural Control and Health Monitoring 29. doi:10.1002/stc.3098

Alani, A. M., Tosti, F., Ciampoli, L. B., Gagliardi, V., and Benedetto, A. (2020). EnglishAn integrated investigative approach in health monitoring of masonry arch bridges using gpr and insar technologies. NDT and E International 115. doi:10.1016/j.ndteint.2020.102288

Albeaino, G., Gheisari, M., and Franz, B. W. (2019). EnglishA systematic review of unmanned aerial vehicle application areas and technologies in the aec domain. Journal of Information Technology in Construction 24, 381–405. doi:10.36680/j.itcon.2019.020

An, Y., Chatzi, E., Sim, S.-H., Laflamme, S., Blachowski, B., and Ou, J. (2019). EnglishRecent progress and future trends on damage identification methods for bridge structures. Structural Control and Health Monitoring 26. doi:10.1002/stc.2416

Andersen, J. E., Rex, S., (Gala), A., et al., Hardesty, Hanover, et al. (2019). EnglishStructural health monitoring of henry hudson i89 (COWI, Lyngby, Denmark: International Association for Bridge and Structural Engineering (IABSE)), 2121–2131

ASCE (2021). 2021 report card for america's infrastructure (American Society of Civil Engineers) Bao, Y., Chen, Z., Wei, S., Xu, Y., Tang, Z., and Li, H. (2019a). EnglishThe state of the art of data science and engineering in structural health monitoring. Engineering 5, 234–242. doi:10.1016/j.eng.2018.11.027

Bao, Y., Tang, Z., Li, H., and Zhang, Y. (2019b). EnglishComputer vision and deep learning-based data anomaly detection method for structural health monitoring. Structural Health Monitoring 18, 401–421. doi:10.1177/1475921718757405

Bautista-De Castro, , S ´anchez-Aparicio, L. J., Ramos, L. F., Sena-Cruz, J., and Gonz ´alez-Aguilera, D. (2018). EnglishIntegrating geomatic approaches, operational modal analysis, advanced numerical and updating methods to evaluate the current safety conditions of the historical b ˆoco bridge. Construction and Building Materials 158, 961–984. doi:10.1016/j.conbuildmat.2017.10.084

[Dataset] Bianchi, S., Biondini, F., D'Angelo, M., Ballio, F., Anghileri, M., Rosati, G., et al. (2022). EnglishSatellite-based structural and hydraulic monitoring of a 50-year-old bridge over the oglio river in italy. doi:10.1007/978-3-030-91877-4 44

Bouzas, , Cabaleiro, M., Conde, B., Cruz, Y., and Riveiro, B. (2022). EnglishStructural health control of historical steel structures using hbim. Automation in Construction 140. doi:10.1016/j.autcon.2022.104308

Broadus, R. N. (1987). Toward a definition of "bibliometrics". Scientometrics 12, 373–379. doi:10.1007/BF02016680

Burrello, A., Brunelli, D., Malavisi, M., Benini, L., IEEE, Instrumentation, I. E. E. E., et al. (2020).

EnglishEnhancing structural health monitoring with vehicle identification and tracking (DEI, University of Bologna IIS, ETH, Zurich, Switzerland: Institute of Electrical and Electronics Engineers Inc.), 9128641. doi:10.1109/I2MTC43012.2020.9128641

Cervenka, J., Jendele, L., Zalsky, J., Pukl, R., Novak, D., Zhao, B., et al. (2020). EnglishDigital twin approach for durability and reliability assessment of bridges (Dep. of Civil Engineering, Technical University of Brno, Brno, Czech Republic: International Federation for Structural Concrete), 1840–1848

Commission, E., Centre, J. R., Gkoumas, K., Balen, M., Grosso, M., Pek ́ar, F., et al. (2019). Research and innovation in bridge maintenance, inspection and monitoring : a European perspective based on the Transport Research and Innovation Monitoring and Information System (TRIMIS) (Publications Office). doi:doi/10.2760/16174

Commission, E., for Research, D.-G., Innovation, Renda, A., Schwaag Serger, S., Tataj, D., et al. (2022). Industry 5.0, a transformative vision for Europe : governing systemic transformations towards a sustainable industry (Publications Office of the European Union). doi:doi/10.2777/17322

Conde, B., Ramos, L. F., Oliveira, D. V., Riveiro, B., and Solla, M. (2017). EnglishStructural assessment of masonry arch bridges by combination of non-destructive testing techniques and three-dimensional numerical modelling: Application to vilanova bridge. Engineering Structures 148, 621–638. doi:10.1016/j.engstruct.2017.07.011

Costin, A., Adibfar, A., Hu, H., and Chen, S. S. (2018). EnglishBuilding information modeling (bim) for transportation infrastructure - literature review, applications, challenges, and recommendations. Automation in Construction 94, 257–281. doi:10.1016/j.autcon.2018.07.001

Dan, D., Ying, Y., and Ge, L. (2022). EnglishDigital twin system of bridges group based on machine vision fusion monitoring of bridge traffic load. IEEE Transactions on Intelligent Transportation Systems 23, 22190–22205. doi:10.1109/TITS.2021.3130025

Dang, H., Tatipamula, M., and Nguyen, H. X. (2022). EnglishCloud-based digital twinning for structural health monitoring using deep learning. IEEE Transactions on Industrial Informatics 18, 3820–3830. doi:10.1109/TII.2021.3115119

Del Rio, I., Cabaleiro, M., Conde, B., Riveiro, B., Caama ̃no, J. C., El Naggar, H., et al. (2020). EnglishHbim application to historical steel structures: The case study of lapela bridge (Department of Materials Engineering Applied Mechanics and Construction, School of Industrial Engineering, University of Vigo, Vigo, CP 36208, Spain: Avestia Publishing), 160–1–160–7. doi:10.11159/icsect20.160

[Dataset] D ̈ohler, M., Hille, F., and Mevel, L. (2018). EnglishVibration-based monitoring of civil structures with subspace-based damage detection. doi:10.1007/978-3-319-68646-2 14

[Dataset] Elsevier (2023). Scopus EuroStruct (2020). Risk-based Monitoring and Assessment of Bridges (YouTube).

Febrianto, E., Butler, L., Girolami, M., and Cirak, F. (2022). EnglishDigital twinning of self-sensing structures using the statistical finite element method. Data-Centric Engineering 3. doi:10.1017/dce.2022.28

Feng, D. and Feng, M. Q. (2017). EnglishExperimental validation of cost-effective vision-based structural health monitoring. Mechanical Systems and Signal Processing 88, 199–211. doi:10.1016/j.ymssp.2016.11.021

[Dataset] for Standardization, I. O. (2016). Iso 8608:2016 mechanical vibration: Road surface profiles: Reporting of measured data

Futai, M. M., Bittencourt, T. N., Carvalho, H., and Ribeiro, D. M. (2022). EnglishChallenges in the application of digital transformation to inspection and maintenance of bridges. Structure and Infrastructure Engineering 18, 1581–1600. doi:10.1080/15732479.2022.2063908

[Dataset] Gagliardi, V., Ciampoli, L. B., D'Amico, F., Alani, A. M., Tosti, F., Benedetto, A., et al. (2022). EnglishRemote sensing measurements for the structural monitoring of historical masonry bridges. doi:10.1007/978-3-030-91877-4 72

Garc´ıa-Mac´ıas, E. and Ubertini, F. (2020). EnglishMova/moss: Two integrated software solutions for comprehensive structural health monitoring of structures. Mechanical Systems and Signal Processing 143. doi:10.1016/j.ymssp.2020.106830

Ghahari, F., Malekghaini, N., Ebrahimian, H., and Taciroglu, E. (2022). EnglishBridge digital twinning using an output-only bayesian model updating method and recorded seismic measurements. Sensors 22. doi:10.3390/s22031278

Giorgadze, I. M., Vahdatikhaki, F., Voordijk, J. H., Autodesk, de la Construccion (CAMACOL), C. C., Construsoft, et al. (2022). EnglishConceptual modeling of lifecycle digital twin architecture for bridges: A data structure approach (Department of Construction Management Engineering, University of Twente, Netherlands: International Association for Automation and Robotics in Construction (IAARC)), vol. 2022-July, 199–206

Gonen, S., Demirlioglu, K., and Erduran, E. (2023). Modal identification of a railway bridge under train crossings: A comparative study. In Dynamics of Civil Structures, Volume 2, eds. H. Y. Noh, M. Whelan, and P. S. Harvey (Cham: Springer International Publishing), 33–40

Gonen, S. and Soyoz, S. (2021). Dynamic identification of masonry arch bridges using multiple methodologies. In Special Topics in Structural Dynamics & Experimental Techniques, Volume 5, ed. D. S. Epp (Cham: Springer International Publishing), 37–47

Hajdin, R., Powers, N., Frangopol, D. M., Al-Mahaidi, R., Caprani, C., et al., et al. (2018). EnglishManaging existing bridges - on the brink of an exciting future (Faculty of Civil Engineering, University of Belgrade: CRC Press/Balkema), 63–87

Hosamo, H. H. and Hosamo, M. H. (2022). EnglishDigital twin technology for bridge maintenance using 3d laser scanning: A review. Advances in Civil Engineering 2022. doi:10.1155/2022/2194949

ICOMOS (1964). International Charter for the Conservation and Restoration of Monuments and Sites (London; ICOMOS)

ICOMOS (1994). The nara document on authenticity. Ratified at Nara Conference on Authenticity in Relation to the World Heritage Convention, held at Nara, Japan, from 1-6 November, 1–6

ICOMOS-ISCARSAH (2003a). Principles for the analysis, conservation and structural restoration of architectural heritage. Ratified by the ICOMOS 14th General Assembly, in Victoria Falls, Zimbabwe, October

ICOMOS-ISCARSAH (2003b). Recommendations for the analysis, conservation and structural restoration of architectural heritage

[Dataset] Infrastructure, C. (2019). Canadian infrastructure report card

ISO (2010). Iso 13822:2010 bases for design of structures - assessment of existing structures

Jeong, S., Hou, R., Lynch, J. P., Sohn, H., and Law, K. H. (2017). EnglishAn information modeling framework for bridge monitoring. Advances in Engineering Software 114, 11–31. doi:10.1016/j.advengsoft.2017.05.009

Jeong, S., Hou, R., Lynch, J. P., Sohn, H., and Law, K. H. (2019). EnglishA scalable cloud-based cyberinfrastructure platform for bridge monitoring. Structure and Infrastructure Engineering 15, 82–102. doi:10.1080/15732479.2018.1500617

Jiang, F., Ding, Y., Song, Y., Geng, F., and Wang, Z. (2021). English Digital twin-driven framework for fatigue life prediction of steel bridges using a probabilistic multiscale model: Application to segmental orthotropic steel deck specimen. Engineering Structures 241. doi:10.1016/j.engstruct.2021.112461

[Dataset] Jimenez Rios, A., Plevris, V., and Nogal, M. (2023a). Bibliographic Data from the Digital Twin Anomaly Detection Decision-Making for Bridge Management Systematic Review. doi:10.5281/zenodo.7548017. This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Sklodowska- Curie grant agreement No 101066739.

[Dataset] Jimenez Rios, A., Plevris, V., and Nogal, M. (2023b). Digital twin anomaly detection decision-making for bridge management (dtadd). doi:10.17605/OSF.IO/SH9B2

[Dataset] Jimenez Rios, A., Plevris, V., and Nogal, M. (2023c). Dtadd systematic review protocol (amended). doi:10.5281/zenodo.7546576. This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Sklodowska- Curie grant agreement No 101066739.

Kang, D. and Cha, Y.-J. (2018). EnglishAutonomous uavs for structural health monitoring using deep learning and an ultrasonic beacon system with geo-tagging. Computer-Aided Civil and Infrastructure Engineering 33, 885–902. doi:10.1111/mice.12375

Kang, J.-S., Chung, K., and Hong, E. J. (2021). EnglishMultimedia knowledge-based bridge health monitoring using digital twin. Multimedia Tools and Applications 80, 34609–34624. doi:10.1007/s11042-021-10649-x

Karaaslan, E., Zakaria, M., and Catbas, F. N. (2022). EnglishMixed reality-assisted smart bridge inspection for future smart cities (Department of Civil, Environmental, and Construction Engineering, University of Central Florida, Orlando, FL, United States: Elsevier). 261–280. doi:10.1016/B978-0-12-817784-6.00002-3

Kim, C.-W., Zhang, F.-L., Chang, K.-C., McGetrick, P. J., and Goi, Y. (2021). EnglishAmbient and vehicle-induced vibration data of a steel truss bridge subject to artificial damage. Journal of Bridge Engineering 26. doi:10.1061/(ASCE)BE.1943-5592.0001730

Kostic, B. and G ¨ul, M. (2017). EnglishVibration-based damage detection of bridges under varying temperature effects using time-series analysis and artificial neural networks. Journal of Bridge Engineering 22. doi:10.1061/(ASCE)BE.1943-5592.0001085

Li, L., Lei, B., and Mao, C. (2022). EnglishDigital twin in smart manufacturing. Journal of Industrial Information Integration 26. doi:10.1016/j.jii.2021.100289

[Dataset] Limongelli, M. P., Dolce, M., Spina, D., Gu ´eguen, P., Langlais, M., Wolinieck, D., et al. (2019). EnglishS 2 hm in some european countries. doi:10.1007/978-3-030-13976-6 13

Liu, Q., Zhang, H., Leng, J., and Chen, X. (2019). EnglishDigital twin-driven rapid individualized designing of automated flow-shop manufacturing system. International Journal of Production Research 57, 3903–3919. doi:10.1080/00207543.2018.1471243

Locke, W., Sybrandt, J., Redmond, L., Safro, I., and Atamturktur, S. (2020). EnglishUsing drive-by health monitoring to detect bridge damage considering environmental and operational effects. Journal of Sound and Vibration 468. doi:10.1016/j.jsv.2019.115088

Lu, Q., Parlikad, A. K., Woodall, P., Don Ranasinghe, G., Xie, X., Liang, Z., et al. (2020). English Developing a digital twin at building and city levels: Case study of west cambridge campus. Journal of Management in Engineering 36. doi:10.1061/(ASCE)ME.1943-5479.0000763

Lu, R. and Brilakis, I. (2019). EnglishDigital twinning of existing reinforced concrete bridges from labelled point clusters. Automation in Construction 105. doi:10.1016/j.autcon.2019.102837

Lu, R., Brilakis, I., and Middleton, C. R. (2019). Detection of structural components in point clouds of existing rc bridges. Computer-Aided Civil and Infrastructure Engineering 34, 191–212. doi:https://doi.org/10.1111/mice.12407

Mao, J.-X., Wang, H., Feng, D.-M., Tao, T.-Y., and Zheng, W.-Z. (2018). EnglishInvestigation of dynamic properties of long-span cable-stayed bridges based on one-year monitoring data under normal operating condition. Structural Control and Health Monitoring 25. doi:10.1002/stc.2146

McKenna, T., Minehane, M., O'Keeffe, B., O'Sullivan, G., and Ruane, K. (2017). EnglishBridge information modelling (brim) for a listed viaduct. Proceedings of the Institution of Civil Engineers: Bridge Engineering 170, 192–203. doi:10.1680/jbren.16.00007

[Dataset] Meixedo, A., Ribeiro, D., Santos, J., Calc¸ada, R., and Todd, M. D. (2022a). EnglishReal-time unsupervised detection of early damage in railway bridges using traffic-induced responses. doi:10.1007/978-3-030-81716-9 6

Meixedo, A., Santos, J., Ribeiro, D., Calc¸ada, R., and Todd, M. D. (2022b). EnglishOnline unsupervised detection of structural changes using train-induced dynamic responses. Mechanical Systems and Signal Processing 165. doi:10.1016/j.ymssp.2021.108268

Mohammadi, M., Rashidi, M., Mousavi, V., Karami, A., Yu, Y., and Samali, B. (2021). EnglishCase study on accuracy comparison of digital twins developed for a heritage bridge via uav photogrammetry and terrestrial laser scanning (Department of Information Engineering and Computer Science, University of Trento, Italy: International Society for Structural Health Monitoring of Intelligent Infrastructure, ISHMII), vol. 2021-June, 1713–1720

[Dataset] Mongelli, M., De Canio, G., Roselli, I., Malena, M., Nacuzi, A., De Felice, G., et al. (2017). English3d photogrammetric reconstruction by drone scanning for fe analysis and crack pattern mapping of the ”bridge of the towers”, spoleto. doi:10.4028/www.scientific.net/KEM.747.423

Moughty, J. J. and Casas, J. R. (2017). EnglishA state of the art review of modal-based damage detection in bridges: Development, challenges, and solutions. Applied Sciences (Switzerland) 7. doi:10.3390/app7050510

Na, W. S. and Baek, J. (2018). EnglishA review of the piezoelectric electromechanical impedance based structural health monitoring technique for engineering structures. Sensors (Switzerland) 18. doi:10.3390/s18051307

Neves, A. C., Gonz ´alez, I., Leander, J., and Karoumi, R. (2017). EnglishStructural health monitoring of bridges: a model-free ann-based approach to damage detection. Journal of Civil Structural Health Monitoring 7, 689–702. doi:10.1007/s13349-017-0252-5

Nili, M. H., Taghaddos, H., and Zahraie, B. (2021). EnglishIntegrating discrete event simulation and genetic algorithm optimization for bridge maintenance planning. Automation in Construction 122. doi:10.1016/j.autcon.2020.103513

Noel, A. B., Abdaoui, A., Elfouly, T., Ahmed, M. H., Badawy, A., and Shehata, M. S. (2017). EnglishStructural health monitoring using wireless sensor networks: A comprehensive survey. IEEE Communications Surveys and Tutorials 19, 1403–1423. doi:10.1109/COMST.2017.2691551

OBrien, E. J., Malekjafarian, A., and Gonz ´alez, A. (2017). EnglishApplication of empirical mode decomposition to drive-by bridge damage detection. European Journal of Mechanics, A/Solids 61, 151–163. doi:10.1016/j.euromechsol.2016.09.009

Pach ´on, P., Castro, R., Garc´ıa-Mac´ıas, E., Compan, V., and Puertas, E. (2018). EnglishE. torroja's bridge: Tailored experimental setup for shm of a historical bridge with a reduced number of sensors. Engineering Structures 162, 11–21. doi:10.1016/j.engstruct.2018.02.035

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021a). The prisma 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372. doi:10.1136/bmj.n71

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021b). Prisma 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. BMJ 372. doi:10.1136/bmj.n160

Park, S. I., Park, J., Kim, B.-G., and Lee, S.-H. (2018). EnglishImproving applicability for information model of an ifc-based steel bridge in the design phase using functional meanings of bridge components. Applied Sciences (Switzerland) 8. doi:10.3390/app8122531

Pepe, M., Costantino, D., and Garofalo, A. R. (2020). EnglishAn efficient pipeline to obtain 3d model for hbim and structural analysis purposes from 3d point clouds. Applied Sciences (Switzerland) 10. doi:10.3390/app10041235

Perry, B. J., Guo, Y., Atadero, R., and van de Lindt, J. W. (2020). EnglishStreamlined bridge inspection system utilizing unmanned aerial vehicles (uavs) and machine learning. Measurement: Journal of the International Measurement Confederation 164. doi:10.1016/j.measurement.2020.108048

Petzet, M. (2004). International Charters for Conservation and restoration = Chartes Internationales sur la conservation et la restauration = Cartas internacionales sobre la conservacion y la restauración (ICOMOS)

[Dataset] PIARC (2023). Piarc asset management manual

[Dataset] Polania, D. R., Tondolo, F., Osello, A., Fonsati, A., De Gaetani, C., Trincianti, C., et al. (2022). EnglishDigitalization processes and bridge information modeling for existing bridges. doi:10.1007/978-3-030-91877-4 108

Ramancha, M. K., Astroza, R., Conte, J. P., Restrepo, J. I., Todd, M. D., and Mao, Z. (2020). English Bayesian nonlinear finite element model updating of a full-scale bridge-column using sequential monte carlo (Facultad de Ingenier´ıa y Ciencias Aplicadas, Universidad de los Andes, Santiago, Chile: Springer), 389–397. doi:10.1007/978-3-030-47638-0 43

Rashidi, A. and Karan, E. (2018). EnglishVideo to brim: Automated 3d as-built documentation of bridges. Journal of Performance of Constructed Facilities 32. doi:10.1061/(ASCE)CF.1943-5509.0001163

Ravizza, G., Ferrari, R., Rizzi, E., Dertimanis, V., Chatzi, E. N., Papadrakakis, M., et al. (2020). English An integrated monitoring strategy for current condition assessment of historic bridges (ETH Z ¨urich, Institute of Structural Engineering, Department of Civil, Environmental and Geomatic Engineering, Stefano-Franscini-Platz 5, Z ¨urich, CH-8093, Switzerland: European Association for Structural Dynamics), vol. 1, 1373–1387

Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., et al. (2021). Prisma-s: an extension to the prisma statement for reporting literature searches in systematic reviews. Systematic Reviews 10, 39. doi:10.1186/s13643-020-01542-z

Ri, S., Tsuda, H., Chang, K., Hsu, S., Lo, F., and Lee, T. (2020). English Dynamic deformation measurement by the sampling moir ´e method from video recording and its application to bridge engineering. Experimental Techniques 44, 313–327. doi:10.1007/s40799-019-00358-4

Rojas-Mercedes, N., Erazo, K., and Di Sarno, L. (2022). English Seismic fragility curves for a concrete bridge using structural health monitoring and digital twins. Earthquake and Structures 22, 503–515. doi:10.12989/eas.2022.22.5.503

Roselli, I., Malena, M., Mongelli, M., Cavalagli, N., Gioffr `e, M., De Canio, G., et al. (2018). English Health assessment and ambient vibration testing of the “ponte delle torri” of spoleto during the 2016-2017 central italy seismic sequence. Journal of Civil Structural Health Monitoring 8, 199–216. doi:10.1007/s13349-018-0268-5

[Dataset] Saback de Freitas Bello, V., Popescu, C., Blanksv ¨ard, T., T ¨aljsten, B., Pellegrino, C., Faleschini, F., et al. (2022). EnglishFramework for bridge management systems (bms) using digital twins. doi:10.1007/978-3-030-91877-4 78

Saju, S., of Engineering, M. B. C., and (MBCETAA), T. A. (2022). EnglishSmart bridges based on bridge information modelling (Bridges Design Unit, Chief Design Office, Kerala Public Works Department, Trivandrum, India: Institute of Electrical and Electronics Engineers Inc.), 279–284. doi:10.1109/SPICES52834.2022.9774179

Schleich, B., Anwer, N., Mathieu, L., and Wartzack, S. (2017). EnglishShaping the digital twin for design and production engineering. CIRP Annals - Manufacturing Technology 66, 141–144. doi:10.1016/j.cirp.2017.04.040

[Dataset] Shao, S., Deng, G., Zhou, Z., Rizzo, P., and Milazzo, A. (2021). EnglishStructural geometric morphology monitoring for bridges using holographic visual sensor. doi:10.1007/978-3-030-64908-1 1

Shao, S., Zhou, Z., Deng, G., Du, P., Jian, C., and Yu, Z. (2020). EnglishExperiment of structural geometric morphology monitoring for bridges using holographic visual sensor. Sensors (Switzerland) 20. doi:10.3390/s20041187

Shim, C.-S., Dang, N.-S., Lon, S., and Jeon, C.-H. (2019). EnglishDevelopment of a bridge maintenance system for prestressed concrete bridges using 3d digital twin model. Structure and Infrastructure Engineering 15, 1319–1332. doi:10.1080/15732479.2019.1620789

Solorzano, G. and Plevris, V. (2022). Computational intelligence methods in simulation and modeling of structures: A state-of-the-art review using bibliometric maps. Frontiers in Built Environment 8. doi:10.3389/fbuil.2022.1049616

Soman, R., Kyriakides, M., Onoufriou, T., and Ostachowicz, W. (2018). EnglishNumerical evaluation of multi-metric data fusion based structural health monitoring of long span bridge structures. Structure and Infrastructure Engineering 14, 673–684. doi:10.1080/15732479.2017.1350984

Sreevallabhan, K., Chand, B. N., Ramasamy, S., Vijayaraghavan, R., Senthilnathan, K., Saral, A. M., et al. (2017). EnglishStructural health monitoring using wireless sensor networks (School of Electrical Engineering, VIT University, Vellore-, Tamil Nadu, 632014, India: Institute of Physics Publishing), vol. 263. doi:10.1088/1757-899X/263/5/052015

Sun, L., Shang, Z., Xia, Y., Bhowmick, S., and Nagarajaiah, S. (2020). EnglishReview of bridge structural health monitoring aided by big data and artificial intelligence: From condition assessment to damage detection. Journal of Structural Engineering (United States) 146. doi:10.1061/(ASCE)ST.1943-541X.0002535

Tang, Z., Chen, Z., Bao, Y., and Li, H. (2019). EnglishConvolutional neural network-based data anomaly detection method using multiple information for structural health monitoring. Structural Control and Health Monitoring 26. doi:10.1002/stc.2296

Ubertini, F., Comanducci, G., Cavalagli, N., Laura Pisello, A., Luigi Materazzi, A., and Cotana, F. (2017). English Environmental effects on natural frequencies of the san pietro bell tower in perugia, italy, and their removal for structural performance assessment. Mechanical Systems and Signal Processing 82, 307–322. doi:10.1016/j.ymssp.2016.05.025

Vagnoli, M., Remenyte-Prescott, R., and Andrews, J. (2018). English Railway bridge structural health monitoring and fault detection: State-of-the-art methods and future challenges. Structural Health Monitoring 17, 971–1007. doi:10.1177/1475921717721137

van Eck, N. J. and Waltman, L. (2014). Visualizing Bibliometric Networks (Cham: Springer International Publishing). 285–320. doi:10.1007/978-3-319-10377-8 13

van Eck, N. J. and Waltman, L. (2022). Vosviewer manual. Manual for VOSviewer version 1.6.18 1

Wang, X., Niederleithinger, E., and Hindersmann, I. (2022). EnglishThe installation of embedded ultrasonic transducers inside a bridge to monitor temperature and load influence using coda wave interferometry technique. Structural Health Monitoring 21, 913–927. doi:10.1177/14759217211014430

Weinstein, J. C., Sanayei, M., and Brenner, B. R. (2018). EnglishBridge damage identification using artificial neural networks. Journal of Bridge Engineering 23. doi:10.1061/(ASCE)BE.1943-5592.0001302

[Dataset] World Heritage Centre, U. (2023). World heritage list

Xiao, R., Lian, Y., Sun, B., Zhao, X., Liu, Z., Tang, P., et al. (2017). EnglishMethod of bridge structural analysis based on bridge information modeling (School of Sustainable Engineering and the Built Environment, Arizona State Univ., P.O. Box 873005, Tempe, AZ 85287-3005, United States: American Society of Civil Engineers (ASCE)), 92–100. doi:10.1061/9780784480823.012

Xu, Y. and Turkan, Y. (2020). English Brim and uas for bridge inspections and management. Engineering, Construction and Architectural Management 27, 785–807. doi:10.1108/ECAM-12-2018-0556

[Dataset] Xuequan, M. (2018). Morandi bridge absence costs italy ”784 mln euros a year in lost gdp”: Report

Ye, C., Kuok, S.-C., Butler, L. J., and Middleton, C. R. (2022). EnglishImplementing bridge model updating for operation and maintenance purposes: examination based on uk practitioners' views. Structure and Infrastructure Engineering 18, 1638–1657. doi:10.1080/15732479.2021.1914115

Ye, S., Lai, X., Bartoli, I., and Aktan, A. E. (2020). EnglishTechnology for condition and performance evaluation of highway bridges. Journal of Civil Structural Health Monitoring 10, 573–594. doi:10.1007/s13349-020-00403-6

Ye, X. W., Jin, T., and Yun, C. B. (2019). EnglishA review on deep learning-based structural health monitoring of civil infrastructures. Smart Structures and Systems 24, 567–585. doi:10.12989/sss.2019.24.5.567

Yoon, H., Shin, J., and Spencer, J., B.F. (2018). EnglishStructural displacement measurement using an unmanned aerial system. Computer-Aided Civil and Infrastructure Engineering 33, 183–192. doi:10.1111/mice.12338

Yoon, S., Lee, S., Kye, S., Kim, I.-H., Jung, H.-J., and Spencer, J., B.F. (2022). English Seismic fragility analysis of deteriorated bridge structures employing a uav inspection-based updated digital twin. Structural and Multidisciplinary Optimization 65. doi:10.1007/s00158-022-03445-0

Yu, S., Li, D., and Ou, J. (2022). EnglishDigital twin-based structure health hybrid monitoring and fatigue evaluation of orthotropic steel deck in cable-stayed bridge. Structural Control and Health Monitoring 29. doi:10.1002/stc.2976

Zhang, H., Liu, Q., Chen, X., Zhang, D., and Leng, J. (2017). EnglishA digital twin-based approach for designing and multi-objective optimization of hollow glass production line. IEEE Access 5, 26901–26911. doi:10.1109/ACCESS.2017.2766453

Zhang, Z. and Sun, C. (2021). EnglishStructural damage identification via physics-guided machine learning: a methodology integrating pattern recognition with finite element model updating. Structural Health Monitoring 20, 1675–1688. doi:10.1177/1475921720927488

Annex A

Table 4. History of changes.

Version	Publication date	Change
1.0	24/02/2023	Initial version.

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