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Digital twin technologies for bridge lifecycle management—Literature insights and a pilot study on the Nibelungen Bridge

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ABSTRACT

Digital Methodologies, particularly digital twin technology, have the potential to enable data-driven design, construction, operation, maintenance, and demolition of bridges, fostering a fundamental digital transformation of their entire life cycle management. To comprehensively explore its potential, this work presents a two-part study comprising a state-of-the-art review of digital twin applications in bridge engineering and a pilot case study. In the first part, a systematic investigation of scientific publications on bridge digital twins is conducted. Initially, relevant data are systematically collected and analyzed. This is followed by an elaboration of general definitions, classifications, and modeling approaches related to bridge digital twins. Subsequently, key data technologies relevant to digital twin applications, including data acquisition, transmission, and integration, are examined in detail. In the second part, the digital twin of the Nibelungen Bridge in Germany, developed using cutting-edge, market-available technologies, is comprehensively presented. Finally, the study concludes with a discussion and an outlook on future developments.

1. Introduction

The digital twin (DT) is considered a revolutionary and core technology in Industry 4.0. Since its proposal in 2002 [1], it has been primarily applied in various fields, including aviation, healthcare [2], wind energy [3], and manufacturing [4–6], and recent year expanded to many other fields in such as electric vehicles [7,8], robotics [9], as well as construction [10], etc. It is a rapidly evolving technology that involves the use of digital models to replicate physical entities. In the widely adopted cross-industry definition, any change in the physical system is directly reflected in the digital model, and conversely, changes in the model affect the physical system. The integration of digital twins with emerging smart technologies has accelerated their adoption and development within the construction industry. DTs enable entire life cycle management of constructions, spanning design, construction, operation and maintenance (O&M), as well as retrofitting, upgrading, and demolition [11]. However, the construction industry, particularly the bridge industry, faces distinct methodological and practical challenges, as bridges are unique structures characterized by large dimensions and significantly longer service lives than most other assets [12,13].

In Germany, over 65 % of the bridge areas on the Federal highways are >30 years old, and only 70 % of all bridge areas are in good and satisfactory structural condition according to the Federal Highway Research Institute. The demand for bridge maintenance is expected to rise substantially in the near future, driven by the need to extend service life while conserving resources. Similar to other nations, the inspection of bridges in Germany is also periodic and regulated by standardized procedures, DIN 1076 [14] and RI-EBW-PRÜF [15] for road bridges, while Guideline 804 [16] applies specifically to railway infrastructure. These frameworks define a highly formalized inspection regime: a major inspection every six years and a simplified inspection in the intervening third year. Additional inspections or local component measurements are only performed when visible damage is detected during scheduled inspections or when recalculations reveal deficiencies in load-bearing capacity. Consequently, maintenance was often carried out only after partial or complete failure of components. Structural damage can occur unnoticed and worsen between inspection intervals, resulting in secondary damage, higher rehabilitation costs, and, in some cases, safety

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risks. Hence, current strategies for infrastructure management remain largely problem-oriented, labor-intensive, and reactive, with limited automation. Similar challenges have been observed worldwide, including in countries such as Japan [17]. Besides, as various authorities and organizations are involved in planning, constructing as well as operating and maintaining individual bridges, the related documents, protocols, information and data are of very heterogeneous format and are commonly saved separately in silos and are not available or accessible or even known by interested engineers or users [18,19].

To address these challenges, new concepts are required that ensure at least the same level of safety as current regulations while improving the central management of information and data as well as their continuity, efficiency, and reliability. In this context, digital twin technologies are increasingly explored and applied within bridge engineering not only for their potential to support predictive maintenance, enhance data continuity, and extend structural service life but also for their ability to provide a much more quantitative overview and understanding of the specific limitations inherent in conventional maintenance methods (such as periodic visual inspections), including aspects like cost, safety, and data discontinuity through the integration of innovative data technologies.

This study comprises two fundamental parts. Part I (Sections 2 to 4) involves a systematic review and critical analysis of existing Bridge Digital Twins (BDTs) in the literature. Part II (Section 5) focuses on the implementation of the BDT for the Nibelungen Bridge Worms (NBW). The objective is to establish a comprehensive understanding of the capabilities and constraints of BDTs in bridge engineering, using a specific pioneer case as a reference for future applications. Finally, Section 6 concludes the work with outlooks.

Part I: Systematic literature review and analysis

2. Data feature representation and dataset construction

The first step in this research was to identify relevant practical applications of BDT in research papers, which included selecting the target journals. According to Scimago Journal Rank, all journals classified under “Civil and Structural Engineering,” “Building and Construction”, and “Architecture” across Q1–Q4 were selected to ensure coverage of the most relevant and qualified publication outlets. The ISSN numbers of these journals were used to construct the search query. It was also necessary to choose keywords that correspond to research on BDTs. Therefore, the following terms were used to construct the search query: "bridge", "Digital Twin", "BrIM", "bridge information modeling", "as-is BIM", "existing BIM", "as-is building information modeling", "existing building information modeling", "cyber-physical", and "cyber physical". The authors also used the German and Chinese terms for "DT" and “bridge” to include German and Chinese papers in the search process and limited the search to publications between 2016 and 2025. A query that combined these two steps and criteria resulted in 145 papers in the Scopus database, see Fig. 1. Subsequently, after manually filtering out irrelevant keywords and corresponding papers, we selected 76 papers that discussed DT applications for bridges in the civil engineering sector.

To understand trends in this research area, the BDT applications were analyzed descriptively concerning their authorship and year of publication. Fig. 2(a) shows that 16 countries have published relevant articles to BDT applications. Research on BDTs is particularly active in Europe, China, and North America, with China leading in journal publications, closely followed by Germany. The USA, the UK, and South Korea show significant research activity. Besides, Egypt and India have also a few publications. It’s important to note that the absolute numbers may be biased, as the analysis focused on articles in English, German, and Chinese, while excluding other languages (e.g., Spanish, French, Portuguese etc.) due to the authors’ language limitations. Thus, these results should be interpreted with caution. Furthermore, the temporal development of the research field was considered. Fig. 2(b) shows a nonlinear increase in journals from 2018 to 2024 characterized by an increasingly steep curve. However, in 2024, there is a slight decrease in publications compared to 2023, indicating an interruption of the previous trend. By 2025, when the manuscript was written, additional papers on BDT had already been published. These papers were not included in this work. Altogether, the increase in the number of publications in the field of BDT concepts and their sustained high volume indicate the growing importance of this research area and points to a further increase in research activity in the future.

3. Definition and development of digital twins in bridge engineering

To date, there are various similar but still different definitions of DTs in the construction industry. According to [20], a DT includes a physical entity in the real world, a virtual entity replicating the physical entity in a virtual space, and a bidirectional information flow between them. The DT serves as a service platform that provides all the necessary information on the physical entity for the respective application. While the academic debate is ongoing, it is well documented that different communities interpret DTs in diverse ways—ranging from 3D models, FEM-based simulations, to real-time visualizers. At the same time, formal definitions have been published, such as those in related technical report CEN/TR 18077 [21] by CEN/TC 442/WG 9 and in the international standard ISO/IEC 30173 *Digital twin – Concepts and terminology* [22].

In this work, the BDT is defined as a real-time data-driven framework that connects the physical bridge construction with its digital representation and integrates human–machine interaction to enable data-

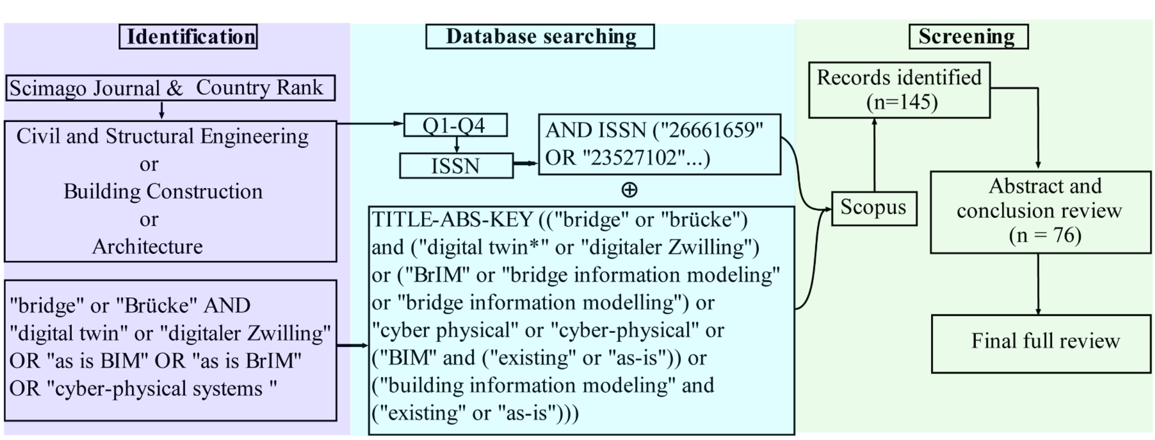

Fig. 1. Literature review process.

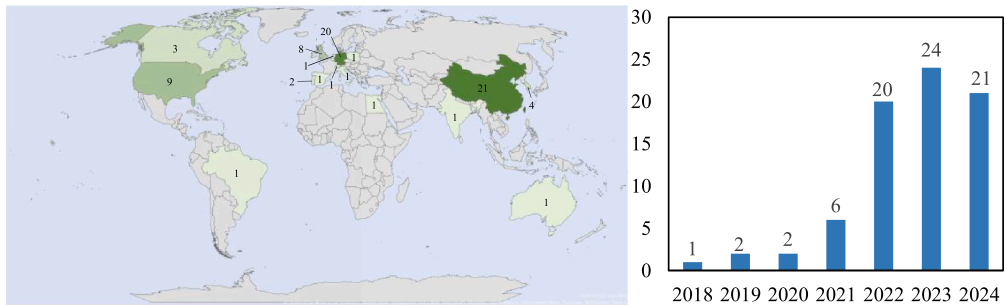

Fig. 2. Journal articles distributed: (a) left: according to the country of the first author university; (b) right: per year.

informed decision-making. This chapter refines this definition and classifies the 76 relevant research papers according to different focus points. For example, it considers which modeling approach was chosen for the BDT in each paper and in which phase of the real building's life cycle the BDT was applied.

3.1. Digital twins and their connections

The concepts for DTs presented in the literature aim to minimize human intervention through extensive automation of processes. For BDTs, full automation of the data flow is challenging to achieve, as a plausibility check of the results by a human is crucial before deciding on necessary interventions. Currently, data acquisition and transfer to the DT are only partially automated or completely manual, as in the case of visual inspections. Moreover, the required compensation and maintenance activities can only be carried out on-site by human personnel. Consequently, human interaction is an essential component of the BDT.

Fig. 3 schematically illustrates the interaction between the physical construction, the digital representative, and human users. All connections, indicated by arrows, may coexist. Blue arrows represent direct, fully automated data flows that characterize high-maturity DTs, typically applicable to selected sources such as IoT sensor data. In contrast, orange arrows denote connections involving human interaction. For instance, inspection data must often be acquired manually or semi-automatically, and maintenance actions can be carried-out by humans based on insights from the digital representative. This bidirectional exchange is facilitated via human–machine interaction (HMI), enabling users to both input data into the digital representative and retrieve information about the condition of the physical construction. The digital representative thus functions as a single source of truth (SSoT), supporting informed maintenance decisions.

3.2. Classification and application of BDTs

(1) Basic classification for DTs

Kritzinger et al. [23] proposed a classification of DTs into three subcategories, according to the automation level of the data flow between the physical and digital entities: digital model, digital shadow, and DT. A digital model is a digital representation of a physical object that does not involve any automated data exchange between the physical and digital entities. If there is a one-way automated data flow between the physical and the digital entities, it is called a digital shadow. In comparison, a DT involves a two-way data flow and can act as a controlling instance of a physical entity. However, this classification does not consider other important characteristics of DTs, such as the life cycle phases of a civil engineering structure. To address this, a detailed classification cube was developed according to [24] to provide a three-dimensional view of a DT in construction industry, considering temporal and spatial relationships, see the Fig. 4.

Based on the level of hierarchy, individual components, such as bridge piers or beams, can be represented as component twins, while their combination forms an asset twin representing the entire structure. Connecting multiple asset twins creates a system twin. Moreover, network twins are formed when system twins from different domains are combined, such as linking bridge twins with the vehicles that operate on them. Besides, maturity levels are used to grade DTs according to the scope and complexity of their capabilities. The concept of maturity levels for a BIM-based DT has been defined by buildingSMART [25], which represents an extension of the BIM methodology. This approach

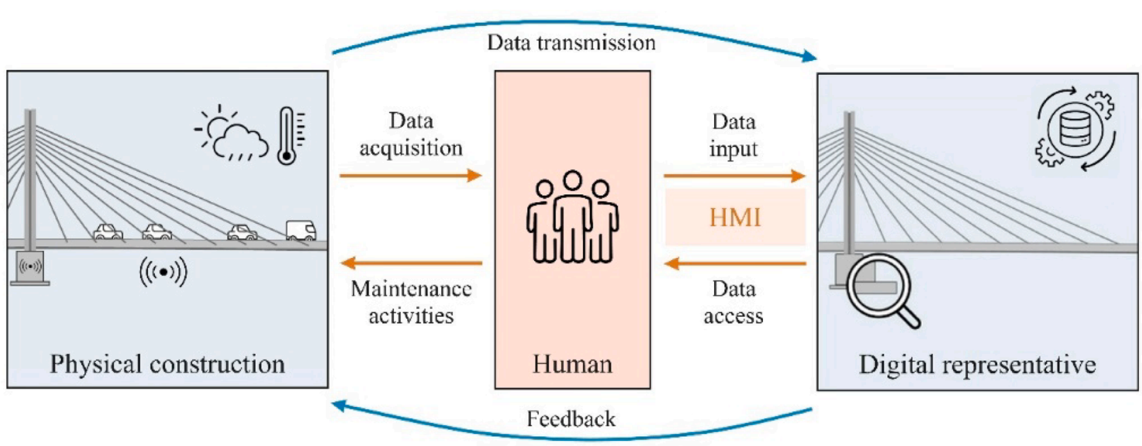

Fig. 3. The interaction between human, physical construction, and digital representative in the context BDT.

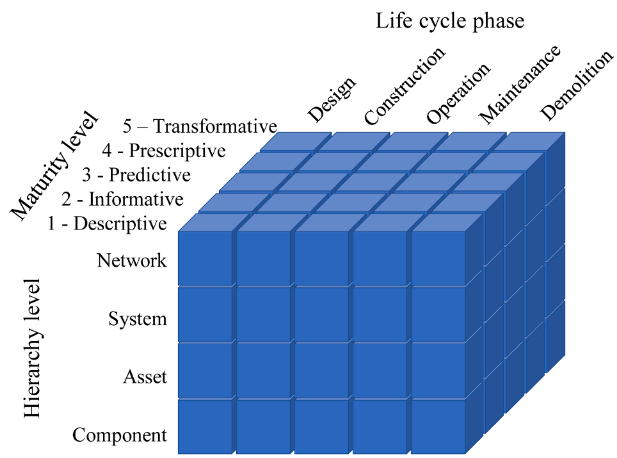

Fig. 4. Classification cube for digital twins in the construction industry, own illustration according to [24].

enables the formulation of specific requirements for a DT, with higher maturity levels encompassing features of lower levels. A descriptive DT corresponds to a BIM model containing current state data. Higher maturity levels primarily differ in their data processing capabilities. An informative DT is capable of aggregating and analyzing collected data. A predictive DT involves prediction of future conditions. A prescriptive DT generates recommendations, while a transformative DT operates autonomously. Also, a DT should be ideally used throughout the entire life cycle of structures, including design, construction, operation, maintenance, and demolition phases, according to [11] (see the life cycle phase dimension in Fig. 4). During the design phase, DTs represent the environment of the future asset and the existing infrastructure. During the construction phase, a DT is utilized for the monitoring and management of the construction site. In O&M phases, the focus of DTs is on maintaining the structural integrity of the structure. In the last phase, the data derived from a DT can be utilized for planning the demolition process and for the recycling of building materials.

(2) Literature analysis

Based on the 76 collected literature, the BDT concept is primarily applied to individual BDT assets, accounting for 71 % of cases (54) in the collected literature. Component BDTs are used occasionally, representing 16 % (12), while system and network BDTs are rarely utilized, with a combined share of just 13 % (10). This percentage distribution may be explained by the fact that the DT method is researched on individual components or structures of a system or network, rather than the entire system or network, to enable easier representation and validation of the method. In addition, network BDTs require the integration of fields such as environmental and transportation infrastructure sciences, which significantly expands the scope of a project.

A detailed listing of the collected BDTs regarding their hierarchy level, life phase, maturity level as well as services and functionalities can be found in Table 1. Most reviewed BDTs are concentrated at the asset level on the O&M phase and maturity level 2. These DTs offer functionalities such as condition and safety assessment, real-time structural monitoring, damage detection, and visualization. They are primarily used as supportive tools during bridge operation, assisting in the planning of maintenance and repair activities for an individual bridge structure based on collected operational data that is processed by the DT. However, decision-making and intervention planning remain human-driven.

Regarding the hierarchy level, fewer studies focus on BDTs at the system or component levels. These BDTs have similar functionalities at the asset level, but there are also important differences in scope and application. System-level BDTs are applied for life cycle management

Table 1
The three dimensions of the BDT model and its services and functionalities.

Hierarchy	Life phase	Maturity	Paper	Services and Functionalities
System	O & M	3	[26–28]	Structural monitoring, safety assessment, predictive maintenance, lifecycle management, data-driven analysis, decision support.
Asset	Construction, O & M	2	[13,29]	Condition monitoring and assessment.
	Operation	2	[30–36]	Real-time monitoring, system identification, identification of vehicle loads or wind-induced vibrations, prediction of structural response, fatigue assessment.
	O & M	1	[37–43]	Modal analysis, BIM/AR-based visualization, point cloud semantic segmentation, VR/AR-supported bridge inspection, decision making enhancement.
		2	[12, 44–64]	System identification, condition and safety assessment; real-time damage detection, location and quantification, 3D visualization of structural defects, digital inspection.
		3	[65–78]	Condition and safety assessment; traffic prediction, seismic hazard prediction, prediction of bridge structural behavior and condition, service life quantification risk-based predictive maintenance.
		4	[79]	Real-time monitoring, analysis and support of decision-making.
Component	Construction	2	[80]	Construction progress tracking, facility documentation, multi-temporal data integration, and semantic querying for construction monitoring.
	Operation	2	[81]	Seismic fragility assessment.
	O & M	2	[82–87]	Automated bridge component recognition, damage assessment, seismic fragility assessment, condition assessment, evaluation of sensor data and structural dynamic models, fatigue damage detection.
		4	[88,89]	Bridge performance indicators, prediction of bridge deterioration, maintenance and repair recommendations, inspection and monitoring planning.

across multiple assets, offering insights that go beyond individual bridge structures. System-level BDTs require at least maturity level 3, as the prediction of future developments is crucial for enabling strategic decision-making at the infrastructure network level. No current implementations have reached maturity level 4 at the system level, presumably due to the high complexity of maintenance strategies that include multiple bridges and structures. In contrast, component-level DTs are typically used for high-resolution monitoring and analysis of specific structural elements, such as steel members. These models enable detailed assessments of localized damage, fatigue behavior, and material degradation. Compared to asset-level BDTs, which provide an overview of the entire structure's condition and performance, component-level BDTs offer more granular insights. No BDT applications at the network level have been identified in this review process. Developing such BDTs involves the integration of models and data across multiple domains. This level requires interoperable platforms for interdisciplinary collaboration and the development of interfaces for the real-time data exchange.

During the construction phase, BDTs are used for construction progress tracking and as-built documentation. This phase provides a valuable foundation for subsequent O&M phase to support long-term asset management. In the operation phase, the focus of BDTs lies on real-time monitoring of bridge structural behavior under dynamic loads, e.g., under traffic, wind-induced vibrations or seismic influences, including system identification and fatigue assessment. In the maintenance phase, the focus shifts to damage detection and predictive maintenance, leveraging both real-time and historical data. The reviewed papers show no application of BDTs in the design or demolition phases of bridges.

The BDTs in maturity level 1 are limited to displaying current and historical data without any analytical processing. They serve as a digital representation for visualization or inspection support and are used exclusively at the asset level. In contrast, BDTs with maturity level 2 can perform automated data evaluation, enabling damage detection, condition assessment, and semantic segmentation. Most BDTs analyzed in Table 1 fall into this category. A smaller number of BDTs reach maturity level 3, where they can predict future structural conditions, traffic development, fatigue life, and damage progression over time. Only a few BDTs achieve maturity level 4, which also provide maintenance recommendations, risk-based planning, and strategic decision support. No BDT has yet reached maturity level 5, which would require a system to autonomously take actions (e.g., initiation of maintenance activities or traffic diversions without human intervention). In the context of bridges, this level remains unattained due to the safety requirements and the need for human control in decision-making concerning public infrastructure.

3.3. Modeling approaches for BDTs

A digital representative serves as the basis for the implementation of the entire BDT. Song et al. [90] identified five fundamental types of digital representatives commonly used for BDTs: (1) information models; (2) data-driven surrogate models; (3) analysis models; (4) 3D surface models, and (5) combined models. The chosen modeling approach essentially influences the functionalities and services of a DT. Table 2 below summarizes the advantages and limitations of the introduced modeling approaches for BDTs.

(1) Information model-based BDTs

The function of an information model is to store and manage information throughout the entire lifecycle of the bridge. Information models, and in particular BIM models, are most frequently utilized for building BDTs. The application of BIM methodology to bridge structures is also known as Bridge Information Modeling (BrIM). In [13,29], the concept of an as-maintained BIM model is used synonymously with a BDT, encompassing information from planning, construction and operation. BIM provides a foundation for data structure, navigation and visualization. Linked Data, ICDD-containers (Information Container for linked Document Delivery) and ontology techniques are often used to connect the data from different sources with the bridge components. Besides, BIM's industry standardized format IFC facilitates data enrichment and interoperability with other model types [74,78] present an alternative approach to BIM-based DTs based on an Asset Administration Shell (AAS). The use of AAS as the base for DTs facilitates the direct processing of dynamic measurement data within the DT, rather than through a linked platform.

(2) Data-driven BDTs

In data-driven BDTs, the assessment of the bridge condition relies solely on data, without accounting for physical relationships. The data can be evaluated using either conventional analysis methods or machine learning approaches, refer to [97] and [74,76]. For the interpretation of the measurement signal, a comparison can be made between the current state and a previously defined reference state. Algorithms can not only be used to filter data and to report threshold exceedances but also to recognize patterns in the data. With a data-driven BDT, rapid analysis of the bridge condition based on available data, identification of hidden relationships, predictions, and early warning systems become possible.

Table 2
Advantages and limitations of various model types used in the bridge digital twin implementations.

Model type	Advantages	Limitations
Information model (BIM) [91,92]	– IFC-format standardizes the storage of building data; – Basis for navigating, visualizing, linking and locating data in frontend	– No continuous updates or automated data processing; – Creating BIM models for existing structures can be time and cost intensive.
Data-driven surrogate model [93,94]	– Allows continuous updating; – Enables advanced data science techniques – No knowledge of physical relationships required.	– No direct 3D visualization; – Lack of information on changes in unmonitored components; – Management of large datasets is technically challenging; – Reference measurements for the healthy state are necessary for damage detection
Analysis model [93,94]	– Provides a transparent, physically grounded basis; – Identifies critical points on the structure; – Scenario simulation is possible.	– Simplified assumptions and uncertainties in the modeling may distort the results; – Precise knowledge of the physics is required; – High computational effort for complex models is required.
3D surface model [95,96]	– UAS assists visual inspections in difficult-to-access areas; – Provides a high-resolution surface capture; – Automated capture of as-built geometry facilitates derivation of updated BIM or FE models.	– Recording quality is limited by camera technology and image data analysis methods; – Information on materials and structural condition inside of the structure remains undetected; – Processing and segmentation of point clouds can involve high computational and manual effort.
Combined approaches [90]	– Take advantages of multiple methods while mitigating their disadvantages.	– Lack of interfaces for connecting and synchronization of different models and data sources; – Lack of unified open-source platforms and software products for model integration.

(3) Analysis model-based BDT

Physics-based analysis models, such as Finite Element Modeling (FEM) or other numerical models, are used to assess the structural condition and derive results from mechanical calculations. In analysis model-based BDTs, which often integrate physics-based models with measurement data, model validation or updating is often performed using monitoring data. By combining the monitoring data with a physical model that describes the behavior of the entire structure, the limitations of locally limited measurements inherent in purely data-driven methods can be compensated [98]. Typically, data-supported models also support system identification, as in [52,59,75,85], and the assessment of structural degradation.

(4) 3D-surface model-based BDT

High-resolution 3D surface models obtained from laser scanning and photogrammetry, which represent the current surface condition of a structure, are also used as digital representations in BDTs. For instance, the potential of supporting bridge inspections with unmanned aerial systems (UAS) was investigated in [55,95,96,99]. The high-resolution cameras provide extensive data sets that facilitate the identification of visual anomalies (such as concrete spalling, cracks, vegetation, and discoloration) on the structure, which can be directly integrated in the corresponding BDTs. In these cases, AI methods have been developed to automatically recognize different damage classes in images using semantic segmentation. By linking discrete images captured at different times, a condition history can be created and evaluated by a BDT. Since creating as-built models of existing structures can be very time- and labor-intensive, 3D surface models can also facilitate updating geometry in BIM and FE models, as detailed in [62].

(5) Combined approaches

Combined approaches use several of the aforementioned model types. For example, BIM and 3D surface models are linked by matching camera images to the relevant component surfaces in [62]. This federated model provides insight into the current state of damage and facilitates updates to the FEM. Also, in [51], a multi-layered environment is created in which BIM, sensor data, and structural analysis are integrated. The sensors establish a connection between the bridge's actual behavior and the validated FEM, which can be utilized to simulate additional as-if scenarios. In addition, knowledge graphs are used for the representation of the complex relationships between the entities (i.e., data sources) and the environment. This flexible system can adapt to new requirements and incorporate new information and services as needed. However, finding suitable interfaces for linking and synchronizing several model types, which are often created using different software products, remains challenging.

3.4. Discussion

In general, a systematic classification of different DT use cases enables an overview, facilitates comparison, and ensures accurate description. The analysis of Table 1 shows that BDTs are already applied in a variety of specialized use cases. The current focus remains in asset-level applications during the O&M phase at maturity level 2, where BDTs can perform automated condition assessments and support maintenance decisions with reasonable implementation effort. Although many approaches in the literature address O&M, the consistent integration of the planning, construction, and dismantling phases into digital twin concepts is still often lacking. This limits the traceability and reusability of condition data over the service life of the bridge. Moreover, the literature focuses predominantly on individual structures. There is a lack of concepts and practical examples addressing digital twins for bridge networks or systemic infrastructures, a necessary step to support strategic maintenance decisions at the network level. While these solutions are practical, future developments should target higher levels across all three dimensions, hierarchy level, lifecycle phase, and maturity level Advancements in these areas would enable lifecycle optimization, cross-asset assessments, and infrastructure management at the network level. It should also be emphasized that the human role is crucial for interpreting results and making decisions concerning critical infrastructure, as described by the HMI. Besides, BIM-based BDTs are currently the most widely applied in practical and are often regarded as the optimal solution due to their standardized open format, their capability to link heterogeneous data, and their function as the SSoT.

4. Data technologies of digital twin applications

Data is the core of any DT and can be very complex and heterogeneous in terms of type, format, source, and content. Real-time processing, structuring large amounts of data, and an effective dynamic data management present significant challenge. The implementation of a DT requires technologies for data handling that can be divided into five layers according to [100]: digital modeling, data acquisition, data transmission, data integration and the service.

In this work, the digital modeling is understood as the set of approaches for digital presentation of the physical construction and connecting the other layers within the DT, see Section 3.3. The service layer, in turn, defines the functions for which the DT is designed and facilitates interaction between human users and the DT. These functions have already been addressed in the classification cube of BDTs (maturity level, hierarchy level, and life cycle phase); see Section 3.2 and Table 1. Since both aspects extend beyond the scope of data handling, they are not further considered here. Accordingly, a modified version of the data layers, excluding digital modeling and service, is presented in Fig. 5.

Based on the literature review. The data acquisition layer consists of technologies for data collection (e.g., sensors, inspections, computations) and collected data sets. The transmission layer transfers the required data to the integration layer. It consists of the network, communication, and protocol technologies for transferring the data. The data integration layer enables the storage, integration, and fusion of multiple data sources and model types, as well as data processing and analysis, visualization, and simulations. The following Sections 4.1 to 4.3 provide a detailed analysis of applied technologies for data acquisition, transmission, and integration, as identified through the literature review.

4.1. Data acquisition layer

Advances in modern sensing and modeling technologies have enabled the acquisition of a wide range of data acquisition methods, as summarized in Table 3.

As a basis, inventory documents including technical drawings and calculation reports are commonly used to establish the initial digital models of the DTs. Major data resources in the reviewed papers are inspection, monitoring, and modeling. Regular and extraordinary inspection reports are typically available for existing bridges. These reports provide information on the physical structure and can be aggregated and integrated into the DT as periodic condition data. Moreover, SHM is considered a key component of a DT with real-time

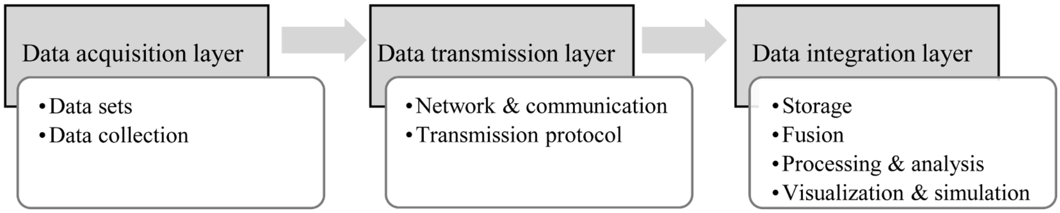

Fig. 5. Modified data layer characteristics considered in the literature review.

functionality, as it enables continuous, real-time data input. Conventional SHM sensors to monitor strain, displacement, inclination, as well as environmental sensors for temperature, humidity, and solar radiation are frequently used in many DTs for the assessment of structural behavior under static actions. Besides, accelerometers are most frequently used for the assessment of structural dynamic behavior.

In recent years, fiber optic sensors (FOS), particularly distributed fiber optic sensors (DFOS), have been intensively studied due to their ability to provide continuous measurements in both time and space. Efforts have also been made to integrate DFOS results into DTs. However, DFOS data have typically been monitored at intervals rather than continuously, due to limitations in data volume handling and hardware capabilities. Geographic Information System (GIS) data is also frequently used to provide extensive spatial information. Additionally, point clouds, images, and video data are increasingly captured using cameras, laser scanners, unmanned aerial vehicles (UAVs), radar, and other photogrammetric methods to deliver high-resolution imaging and point-based data for bridge condition and damage assessment. Furthermore, new robotic technologies have been developed to enable close-range inspection of bridge surfaces, particularly under challenging conditions where access is typically limited. In addition, numerical simulations, especially FEM, are commonly employed to generate synthetic data for hypothetical scenarios and predictive assessments.

4.2. Data transmission layer

The data transmission applications across reviewed BDTs are summarized in Table 4. Notably, this layer is not always clearly described in the analyzed papers; however, it is of great importance for understanding existing BDTs and should be thoroughly elaborated. Currently, both wired and wireless networks up to 4 G are commonly used. This depends heavily on the development in current practical technology within the industry. For BDTs used exclusively in laboratory tests and investigations, internet cables, manual data/information entry, as well as USBs are still commonly used. However, for industry level BDTs of real bridge constructions, systematic solutions are necessary. Wired communication technologies such as ethernet, fieldbus systems, fiber optics and wireless technologies including 4G/5 G networks and Wi-Fi, are often utilized in hybrid configurations for smooth, continuous and real-time transmission of large volumes of data produced by SHM and other data acquisition systems. Additionally, edge computing has been employed to reduce data transmission load by processing data close to the source before sending essential info to the cloud or DT backend. The HTTP protocol is commonly used for transmitting data in RESTful APIs,

Table 4
Data transmission in BDTs.

Paper	Data transmission
[37]	Manual entering of defect information by inspectors
[63]	Internet cables
[59]	Coaxial cables to acquisition modules mounted on an USB chassis
[74, 76–78]	Automatic transmission from IoT routers to the AAS; mobile phone network (4 G), fiber optic network; SFTP and MQTT protocols
[32]	System relies on cyber-physical networks (CPS), wired/wireless sensor networks, and SCADA systems for real-time data exchange
[28]	Data is transmitted via real-time sensor networks, IoT-enabled devices, and ITS-based communication systems
[51]	MQTT, HTTP, CoAP, LoRA, WebSocket
[13,29]	USB-transfer; wireless IoT sensor networks
[106]	5 G, cloud communication and computing
[83]	Wired connections for the climbing robot and wireless transmission for UAV-based data collection
[44–46]	IoT OGC Sensor things Server; MQTT and HTTP
[64]	4 G network
[90]	Automatic two-way data flow; 3 G, 4 G, 5 G, optical fiber transceiver system, WIFI
[104]	Wireless (Narada sensing nodes)
[71]	Via GSM to an LBX server and via Ethernet to the LBX client
[34]	via ADO.NET environment through USB and Cable Link
[103]	Data is transmitted via real-time monitoring networks and cloud, utilizing HTTP for data storage and processing
[60]	Hybrid wired and WSN (wireless sensor network); MQTT
[72,41, 105]	Wireless sensors
[48,49,47]	Real-time transmission through optical cable and wireless connection, cloud server and computing

Table 3
Data acquisition in BDTs.

Paper	Data acquisition
[101,51,53,37,84,85]	Inspections
[26,44–46,33,68,69,71,102,56,34,103] [57,65,74,76–78,35,59,41,32,72,50,104,60,12,105, 106,13,29,51,107,64,63,84–86,89]	Conventional SHM sensorics including strain, displacement, inclination sensors as well as temperature, humidity and solar radiation sensors, accelerometers, Weigh-in-motion systems, and imaging systems such as traffic cameras, long-term/short-term SHM in bridges, real time monitoring
[80,75,87,42,30,12,106,55,95,96,28,82,53,107,62,40, 89]	GIS data and laser such as LiDAR scanning, photogrammetry, ground-penetrating radar (GPR), and other close-range sensing techniques to collect geometric and texture data
[28]	ITS data, geospatial data from GIS, and visual inspection reports
[13,29,70,64,48,49,47,90]	Distributed fiber optical fiber sensors, FBG sensors
[54]	High-resolution RGB images using a DSLR camera, with ground control points (GCPs) for precise georeferencing
[38,103,106,64,63]	Videogrammetry: photos and videos from cameras, DIC
[58,83,90,89]	Inspections (general, principal, and special inspections) with high-quality photos and videos including UAV recording and Laser scanning, Ground-penetrating radar (GRP), close-range photogrammetry (CRP) high-resolution imaging from unmanned aerial vehicles (UAVs) and an adhesive climbing robot equipped with cameras for close-range inspections, visual inspections
[108,61,63,105,84,85]	FEM simulations, model updating

following a request-response model. The MQTT protocol is typically employed for real-time sensor data streaming and remote monitoring. It has also been shown to be useful for various digital twin functionalities.

4.3. Data integration layer

With regard to the data integration layer, a variety of technologies and methods are used. For instance, edge processing, as demonstrated in [105], optimizes real-time data analysis at the source. Cloud databases, such as Common Data Environment (CDE), serve as centralized repositories for heterogeneous datasets. Machine learning (ML) algorithms, such as deep learning (DL) and artificial neural networks (ANN), facilitate the detection and segmentation of damage in point clouds, the uncovering of patterns, and the prediction of sensor conditions, as well as insights into the condition of the bridge. Computer vision algorithms (e.g., YOLOv3 detector) are used for traffic monitoring. Model updating can be supported by Bayesian optimization algorithms. In conjunction with web-based platforms and VR/AR techniques powered by gaming engines such as described in [38,109,110], the DT provides an intuitive and information-rich spatial context. This allows information to be visually located within the bridge structure and evaluated as a whole. To get a better overview over this wide field of various technologies, data integration layer can be divided into three key components: (1) data storage; (2) data processing & analysis and (3) data visualization & simulations. The following sections provide an individual analysis of these perspectives.

(1) Data storage

Data storage technologies enable the management of complex, large-scale datasets from heterogeneous sources using hierarchical data structures, efficient data query, and cloud-based storage solutions. Appropriate data storage is essential to ensure scalability and high performance of BDTs. There are three major types of databases that were used for data storage in BDTs in the reviewed papers: time-series databases for dynamic sensor data, relational databases such as SQL databases, and non-relational NoSQL databases. BIM models and CDEs are often used as the object-oriented foundation of BDTs for centralized data storage throughout the bridge's lifecycle. Knowledge graphs, ontologies and a linked data approach enable a connection of data from other domains (e.g., SHM data, environmental data, maintenance activities, inspection data, traffic data, results of diagnostics and mechanical analysis results, etc.) with the bridge components modeled within a BIM-environment. Table 5 provides an overview of the collected storage possibilities in literature.

Table 5
Data storage in BDTs.

Paper	Storage
[27]	Database servers hosted in the cloud
[80]	Local unified RDF-based data management system
[105]	Local RAM and flash storage in sensor nodes
[56]	Local, project specific PC solution Nominal geometry as a 3D CAD model created in Rhino 3D
[63]	Metadata, annotation, OPC UA server (probably local)
[60]	Local Database, InfluxDB time-series database
[52,75]	File-based: Autodesk Revit files for BIM data, pdf files linked to the sensor entities
[34]	BIM, open-source structured query language (SQL) database - Local
[101]	BIM-Input-Database, Revit and Navisworks (only BrIM, not really a DT)
[39]	Integration of discrete inspection data in BrIM model
[90]	BrIM, ontologies
[88]	SQLite database server (commonly local), BrIM (Bridge Information Management) input databases
[74,76–78]	Local storage for a failure case; object-based database (S3 storage, cloud)
[70]	Cloud and local based storage, BIM
[106,66,79]	Cloud server, cloud/edge computing and supporting remote database
[64]	Cloud-based cyber-physical system (C2PC architecture); rational database PostgreSQL
[37]	Cloud-based DynamoDB (NoSQL database) for event stream data, BIM (Autodesk Revit, Autodesk BIM360)
[58,35]	Cloud-based inspection database, BrIM database
[38]	Cloud-based Platform, object-based 3D-model
[104]	Cloud-based data management and computing platform Scalable database system, NoSQL database management system (Apache Cassandra)
[48,49,47, 111]	Cloud server
[51]	CDE and knowledge graphs for connection of multiple sources; open-source IoT-platform Mainflux; time-series database; SQL databases
[13,29, 44–46]	CDE EPLASS; ontologies; ICDD-container approach, CDE; Linked Data approach
[68,69]	CDE Squirrel (object-oriented model)
[71]	CDE, local database of historic post-processed data (.csv files)
[108]	CDE/Cloud-based network collaboration
[12]	Cloud-based data base system; ontologies; Linked Data
[62]	Extensible Markup Language for the spreadsheet data; asset, inspection and repair database; **CDE**; object-oriented parametric BIM-modeling
[95,96]	Data base of damage; Linked Data and ICDD container approach
[72]	Big/Smart Data technologies; linked data approach; ICDD-container-based approach; ontologies

(2) Data processing & analysis

Data processing & analysis components running in the back end of BDTs involve manipulation, analysis, and integration of data and models e.g., through ML-driven methodologies such as neural networks. The automated algorithms enable dynamic updates of asset condition and maintenance information, allowing diagnostic, predictions, simulations (especially FEM), and data anomaly detection. The collected data from sensors and non-contact sensing techniques were often used for updating data, BIM and FEM models. Many researchers have developed their own algorithms while utilizing open-source programming languages such as Python. Organizing these algorithms into flexible microservices enhances the adaptability and scalability of BDTs, facilitating integration with diverse data sources and applications. As a key component of a BDT, this aspect often constitutes the core and most substantial part of each study. Table 6 provides an abstract summary of the methodologies applied in the reviewed literature.

Notably, both data storage and data processing for BDTs can be performed on-site, using local storage and edge computing, or in a cloud-based environment. Bridge locations may have challenges such as restricted communication, which can lead to a temporary data loss. On-site storage and processing offer the advantage of shorter data transmission paths, making the system more resilient in the event of a failure. The key benefits of cloud-based database systems and cloud computing are their scalability and real-time updates, which make them ideal for handling big data and operative decision-making.

(3) Data visualization & simulations.

Data visualization techniques enable the clear and consumable presentation of both raw and processed data. Table 7 summarizes the various approaches. Some of the reviewed papers employed web-based platforms, allowing different user groups to monitor the as-is condition of the asset or implement their own software solutions. Others utilized the model views available directly through the corresponding modeling software, such as BIM, FEM, or surface models. Visualization tools often include dashboards that display both graphical and non-graphical data, such as heatmaps, contour plots, diagrams, histograms, overview tables, photos, plans, and other visual elements. An interactive front end, created by a graphical user interface (GUI), supports the navigation through models and data. Game engine technologies enhance real-time rendering and user-machine interactions. Furthermore, emerging

Table 6
Data processing and analysis in BDTs.

Paper	Data process
Conventional data-based methods	
[103]	Framework integrates multi-source sensor data with Bayesian inference, Fast Fourier Transform (FFT), Fast Bayesian FFT Method, Kalman filtering, and PCA-based anomaly detection for comprehensive structural assessment
[88]	Stochastic fuzzy logic decision support system, bridge gamma stochastic deterioration modeling; multi-criteria decision-making approach (MCMD); QFD and TOPSIS processes
[62]	Open-source programming language for photo-based damage detection; surface division; mapping of BIM and surface models
[42]	Continuous model update as new data is collected.
[105]	Edge computing; OMA analysis, Fast Fourier Transform
[87]	Monte Carlo dropout and Variational Inference to quantify uncertainty and improve the quality of predictions
[37]	Supportive inspection system with unity game design engine's custom APIs
[12]	Automated algorithms for Data abnormally detection, FEM, aggregation of information
[55]	photogrammetry-based SfM-MVS workflow. Structure-from-motion with multi-view stereo Algorithms; 3D reconstruction via Agisoft Metashape; cloud-to-cloud (C2C) distance for detecting deterioration
[34]	BIM and MATLAB interface, damage identification algorithm
FEM simulation without updating functionality	
[35]	Measurement data to FEM (includes calculation of dynamic properties in ANSYS and fatigue computation in MATLAB) and from FAS to BIM (Revit and DYNAMO)
[56]	Import into ABAQUS for FE modeling
[108]	Calculation Module (calculation of dynamic properties with FEM, and calculation of fatigue damage for different scenarios in MATLAB)
[61]	FEM, Model matching and mirroring, optimization algorithm
[41]	3D FEM (Software: CSIBridge)
[64]	Backend engine (parallel working containers on the cloud platform), conventional FEM and probabilistic statFEM simulations, open-source programming languages
FEM simulation with updating functionality	
[31]	Bayesian model updating algorithm, Hamilonian Monte Carlo simulation, wavelet based operational modal analysis
[28]	BDT integrates BIM for geometry, SHM for real-time condition updates, ITS for traffic/load data, and GIS for spatial analysis into a single model for enhanced decision-making
[51]	MatchFEM (Grasshopper plug-in) for BIM and FEM model updating with sensor data; Multiple Operational Modal Analysis Platform (MOMAP); Python software for signal analysis; microservices
[52]	Fast Fourier Transform, extraction of MATLAB and modal responses from vibration data with Second-order Blind Identification (SOBI) method, FEM Autodesk program RSA for structural analysis
[74,76–78]	Edge processing; ML algorithms (PCA-method, JupyterHub)
[75]	Point cloud registration software Leica Cyclone REGISTER 360; Autodesk Inventor for defining the sections, AutoCAD, SAP2000 for FE-analysis (OMA)
[82]	Framework integrates unsupervised segmentation techniques, self-prompting AI models, and visible point rendering to classify bridge components from raw point cloud data
[40]	Automatic development of high-level numerical models using point clouds, meshes, NURBSs, BIM, orthoimages and a sum of discrete points; discrete element method (DEM) and FEM; ML for automatic block definition
[38]	ML for semi-automatic segmentation of point-clouds; vectorization and semantization
[32]	Data is integrated through cyber-physical modeling, operational control algorithms, and cybersecurity defense mechanisms to ensure resilient structural operation
[33]	Measurement integration in the data-driven model for updating the model-driven DT
[71]	Integration of SHM data in BIM and FEM model for model updating
[57]	Integration of data into nonlinear updated FE model in MATLAB, MSC.Marc and Python, seismic collapse prognosis
[65]	Sensor-data based FEM model updating,
[95,96]	ML for automated damage detection of and semantic segmentation; FEM model updating
[58]	Damage detection, classification by damage mapping algorithm and measurement; model update algorithm
[59]	Automatic algorithms for the dynamic identification (AutoOMA) and model updating of FEM;
[60]	Simulation of response of the structure with 3D FEM (Midas Gen Software); python based linking software for sensor data integration in FEM, validation and updating of model parameters
[63]	FEM, Bayesian model updating, optimization algorithm
[111]	continuous FE model updating
[81]	mask R-CNN algorithm for damage detection, FE model update, seismic fragility analysis
[73]	FE model update, nonlinear fatigue damage analysis in MATLAB
[48,49,47]	On-site computing, cloud computing, 3D FEM updating, strain characteristic function (damage indicator)
[53]	The framework combines finite element models, real-time monitoring data, and degradation models into a flexible DT for predictive maintenance and lifecycle assessment, FEM-model-updating
[102]	data updating FE model for probabilistic fatigue life prediction, Bayesian inference, Monte Carlo simulation
[89]	Numerical experiment design (high-fidelity FEM, ABAQUS) and surrogate model (probabilistic fatigue deterioration model, event tree model, Bayesian inference), MATLAB
Machine Learning and other AI approaches	
[27]	Computer vision algorithms YOLOv3 and YOLOv3-tiny for truck detection, real-time image processing on the sensor node, baseline linear models, deep-learning-based forecasting framework
[13,29]	Data-based approach for damage detection using ML
[106]	Machine vision fusion, monitoring of bridge traffic loads, ML (Yolov3), different mechanical analysis models, using measured traffic loads as links
[83]	Framework integrates deep learning-based crack segmentation (ACS-Former), 3D reconstruction methods, and quantitative assessment models for real-time bridge monitoring
[66]	Deep learning algorithms for predictions, computer vision and automatic anomaly detection and classification, motion amplification algorithm, numerical analysis with FEM
[107]	Framework integrates JSON-based bridge defect information modeling, triple-based roadmap graphs, GIS spatial data, and real-time sensor data into a structured decision-support system
[79]	AI-based edge computing algorithms for time synchronization, preliminary analysis and decision-making
[44–46,68, 69]	ML/AI Simulation for prognostics
[84,85]	Matching of damages with calculation results; ML; dynamic compatibility check of trains with existing bridges
[86]	Probabilistic deterioration models, and reinforcement learning-based maintenance optimization into a single DT for predictive maintenance
[70]	ML framework: Linear regression, Ridge & Lasso regression, (FEM simulations for validation) for structural analysis such as bending moment and deflection
[104]	ML for truck detection (YOLOv3-tiny and YOLOv3); cloud computing (Microsoft Azure);
[72]	ML, deep learning
[54]	Framework integrates damage-segmented images, NeRF-based 3D reconstructions, and deep learning-based feature extraction to create a high-fidelity 3D DT for structural health monitoring
[50]	Transfer learning, FEM, CNN, Bayesian optimization algorithm
[30]	convolutional neural network (CNN) is adapted with a proposed pixel scale factor (PSF) method to Tracking the motion and dimension of vehicles, finite element (FE) simulations are integrated into the approach to predict the vehicle-inducted structural response

technologies such as augmented reality (AR), virtual reality (VR), and mixed reality (MR) enable a more intuitive and spatial exploration of data and information. BDT platforms integrate multiple data sources and model types into a unified view with aggregated information, making it easier for users to understand and interpret data. In addition, a BDT can highlight potential critical points by flagging unusual values, marking areas of concern within the structure, or sending alerts when predefined thresholds are exceeded.

Table 7
Data visualization in BDTs.

Paper	Description
[27,106,83–85,104,34]	Only results diagram, no specific 3D visualisation of the physical entity
[31,86,71,102,89,56,65,60,61, 41,105,30,50,63,48,49,47,81, 73,36]	Visualisation of the physical entity using FEM models, commonly have updating functions
[82,54,55,95,96,42]	Point-clouds model with information and results plotting such as cracks
[52,13,29,68,69,101,12,34,57, 88,38,39]	3D geometric BIM-Model with dashboard
[35,108]	BIM central with FEM
[74,76–78,51,67,59,62]	Dashboard, decentralised, parallel
[79]	3D geometric BIM-Model with dashboard Additionally with GIS
[44–46,37,58]	Additionally with GIS VR/AR/MR functions

4.4. Discussion

Tables 5–7 condense detailed information, allowing readers to quickly identify relevant studies for further research. The listed technologies for data acquisition, transmission, and integration in BDTs enable straightforward comparisons across different studies, highlight frequently applied methods as well as less explored approaches, and can support the selection of appropriate technologies for specific use cases. Even there have been various solutions in dealing with data's especially with the emerging of IoT technologies and various advanced AI methods, main challenges remain in the interoperability of heterogeneous systems. The integration of different subsystems (BIM, SHM, FEM, IoT) requires a high level of technical interoperability, which is made more difficult by a lack of standards, proprietary data formats and different modeling depths. Above all, tailored data solutions are still essential for the BDTs. Besides despite comprehensive system coupling, the digital twin remains at a limited level of maturity, as bidirectional model-data interactions, automation of forecasts and real-time adaptation of models have only been partially implemented.

Part II: Pioneer BDT in Germany

5. Pioneer case study: BIM-based BDT of the NBW

This chapter showcases a pioneer BIM based BDT of the NBW including its physical construction and digital representative as well as the detailed data processing to demonstrate the current industrial level of BDT applications in Germany.

5.1. Physical construction of the NBW

The Nibelungen Bridge in Worms (NBW) is the first prestressed concrete bridge over the Rhine and one of the first bridges built using the cantilever construction in 1953 [4]. Its river bridge has a span configuration of approximately 23.22 m - 101.63 m - 114.22 m - 104.25 m. Due to historical reasons, it has suffered from two serious presentative deficits: (1) the absence of a stirrup in the cross-section resulting from immature design principles in the 1950s, therefore, it suffers from insufficient shear load capacity according to current EN 1992–2 [112]; and (2) corrosion of the reinforcements due to insufficient concrete cover as well as corrosion on the prestressing tendons, which was limited by the construction and prestressing technologies at the time. In the last 70 years, this bridge has been undergone several renovations. In 1968, the expansion joints were exchanged. In 1974, a waterproof sealing was installed on the deck for the first time, followed by a further improvement in 1981. From 2010 to 2013, an extensive renovation project [6] was carried out for strengthening and further extending its service life. However, due to a lack of technical and economic solutions, it was decided not to improve the shear load-bearing capacity, and a remaining useful life of 15 to 20 years was set [7]. The maintenance strategy at the time envisaged dismantling the bridge in 2025 and replacing it with a new structure in 2028. Due to the high architectural and cultural significance of the bridge, this conservation strategy was recently revised, with the result that the bridge can be used beyond 2025 by means of suitable measures to extend its service life. In cooperation with the Federal Ministry of Transport (BMV), this bridge was selected as a pilot project as well as a validation project in the German Research Foundation-funded Priority Program "Hundred plus - extending the service life of complex structures through intelligent digitalization". In this scope, the digital twin method is being developed on a pilot area (see Fig. 6, the first two spans, red marked) of this bridge.

5.2. Digital representative of the NBW

The BDT of the Nibelungen Bridge is developed using BIM as the central information linking hub and visualization. The BIM model of the bridge is based on the "as-is" condition. In particular, the geometry of the pilot area was recorded using high-resolution terrestrial laser scanning. Prior to scanning, a control network was established for the entire structure with a standard deviation of <5 mm, ensuring a high accuracy in current and future measurements. All scans were performed while stationary and georeferenced using at least four control points from the control network. This allowed a redundant and thus precise linkage of all scans. The point cloud obtained from the laser scanning has a point spacing of 2 cm, as shown in Fig. 7(a). Subsequently, the point cloud was manually converted into a 3D BIM-model with a Level of Detail (LOD) 300, see Fig. 7(b).

This model includes the two bridge piers, the abutment at side of Worms and the bridge boxes as well as the piers from the inside. The modeling accuracy is 5 cm for the superstructure and 10 cm for the piers. All modelled objects with deviations of >3 cm from the point cloud are attributed via property fields. This BIM model serves as the 3D-geometric model for the visualisation of the bridge as well as the host and model for the linkage of coordination, semantic, inspection and monitoring data for the DT of the bridge.

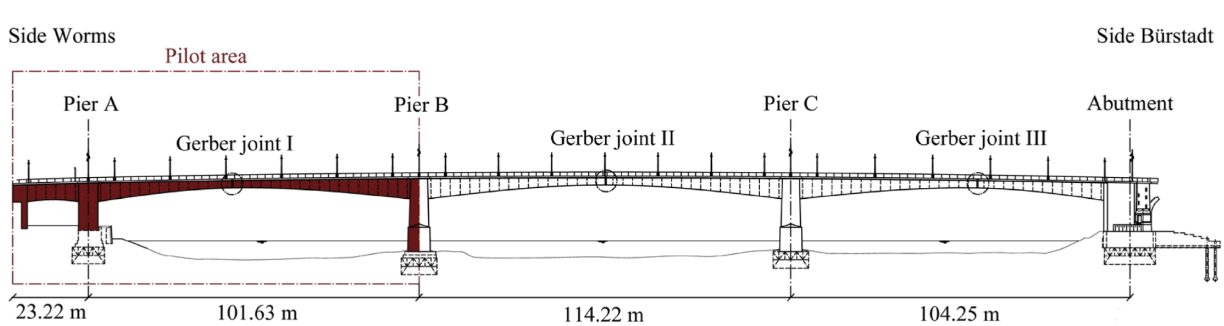

Fig. 6. Side view of the Nibelungen Bridge Worms (river bridge).

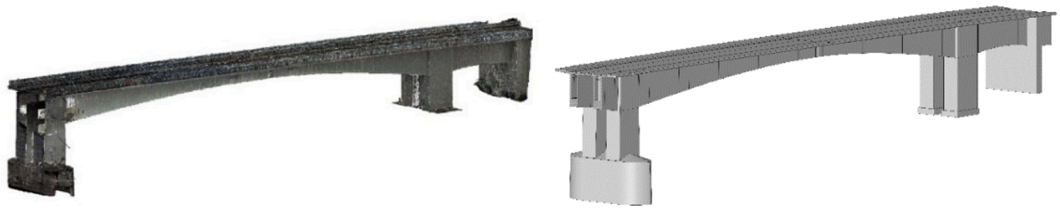

Fig. 7. 3D model of the NBW: (a) left: point cloud from laser scanning and (b) right: BIM of the pilot area.

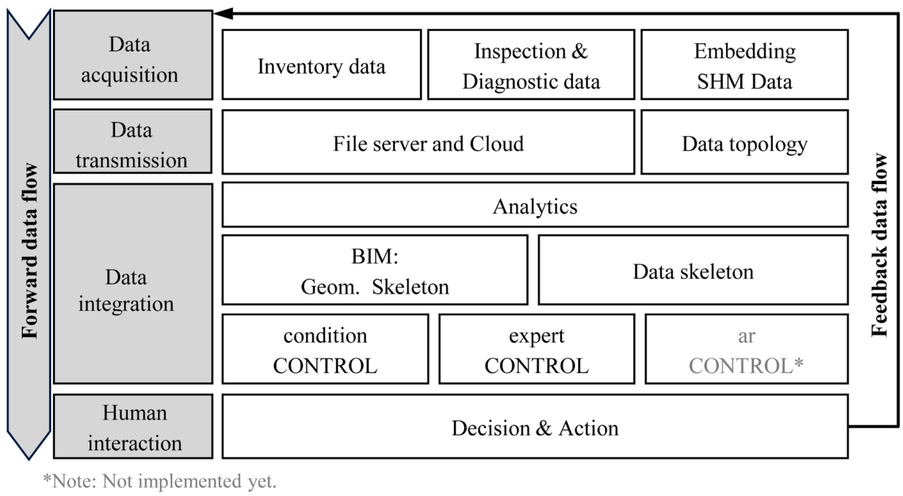

Fig. 8. Data processing of the BDT of the NBW.

5.3. Data processing in the BDT of the NBW

The data processing framework of the BDT of the NBW is illustrated in Fig. 8. The following sections will detail the configuration of different layers.

5.3.1. Data acquisition

There are three major data resources for the DT of the NBW: inventory data including inspection results, calculation reports, diagnostic data, and sensor data from the SHM-system. The inventory data and diagnostic data were manually obtained, analysed, and prepared for further procedures by experienced engineers and researchers.

The monitored 'weak points' or critical points in the bridge structure were identified following differentiated sensitivity analysis: (a) model-based numerical analysis, e.g., recalculation, (b) condition-based analysis considering inspection results, (c) design-based analysis, comparing present design to similar designs documented in literature and (d) experience-based analysis considering the know-how of the asset manager. As a result, 24 sensors were installed, including 1 solar radiation sensor, 1 precipitation sensor, 3 air temperature sensors, 8 component temperature sensors, 4 inductive displacement sensors, 2 inclination sensors, and 2 accelerometers. All sensors measure continuously at specified frequencies. As the SHM-system is not the focus of this work, it will not be specifically elaborated; more details can be found in the authors' other work [113].

5.3.2. Data transmission

The inventory and structural inspections, as well as diagnostic data, are stationary data and uploaded to a cloud-based file server for further data process procedure. In contrast, SHM data are non-stationary and

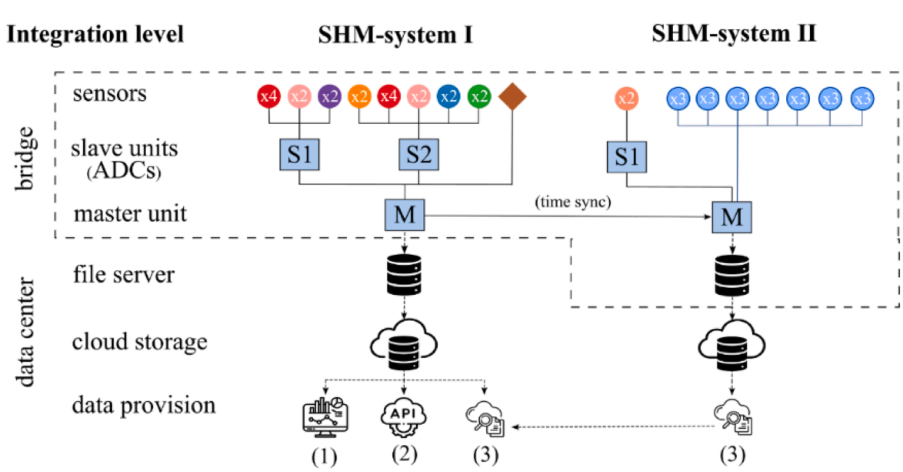

Fig. 9. Topology of the SHM system I and II at the Nibelungen Bridge Worms.

continuously generated, requiring systematic processing. The NBW is an iconic bridge in Germany and has served as a pilot project in recent years, attracting significant interest from various stakeholders. Currently, three different stakeholders are involved: two participated in the planning phase of the SHM system, while the third joined at a later stage. Consequently, two distinct SHM systems have been designed and installed on the bridge by different professionals at different times. This aligns perfectly with the current trends in collaborative SHM. However, it also raises challenges in handling data from different SHM-systems. Fig. 9 shows the overview data topology of the SHM-systems.

First, the analog sensor signals are combined and digitized in separate Analog-to-Digital Converter (ADC). The digitized signals are transmitted from the slave to the master unit via bus lines. Each master unit, equipped with a data acquisition system and mobile router, controls measurements and temporarily stores data before transmitting it to a secure server with regular backups. Data are then replicated to cloud storage for processing, ensuring redundancy, traceability, and on-demand retrieval. Exceptionally, the acceleration sensors in SHM system II are digital and feature a CAN bus interface. They are connected via a single bus cable (two wires for data transmission, two for power) along the bridge box girder to the system's high-speed CAN port. Data are locally stored on an external hard drive and transferred to a shared network via an industrial computer and LTE router for remote analysis. To synchronize the DAQ systems of SHM systems I and II, a synchronization cable is installed. The main challenge in this context relates to the real-time transmission and processing of big data, as well as the synchronization of data streams from different SHM systems. These systems naturally inherit differences in aspects such as system clock (time), measurement frequency, data format and descriptions, and associated metadata, etc. The robustness and adaptability (retrofitting, repair, and extension) of SHM systems, as well as the associated DTs, require not only technical considerations but also the establishment of clear guidelines for the relevant stakeholders, including owners, bridge maintenance personnel, and safety staff. This is essential in order to maximize the use and reuse of data and models.

Next, all the original measurement data and derived variables in SHM system I are made available through different solutions, including: (1) graphical visualization of data via the expertCONTROL platform: A web-based platform is available for visualization of data, including key measurement data, parameters and derived data, using diagrams (see Fig. 12); (2) provision via a REST API; and (3). provision via a cloud storage. In comparison, only the third solution is currently possible in SHM system II. Current data records are stored on a file-based cloud storage at regular intervals. End users can retrieve these data records manually using client software. Each system has its own authentication system, which can be used to provide user-specific or user group-specific access. Data is transferred exclusively via encrypted transmission standards.

5.3.3. Data integration

The primary goal of the DT of the NBW is to extend its service life while simultaneously offering research opportunities for interested stakeholders. Therefore, it is essential to conduct goal-oriented analyses of the bridge while also providing fundamental data to assess and understand its current condition. In general, data analytics plays a decisive role in exploring the value of acquired data. After the data have been aggregated, analyzed and evaluated, the resultant information is then located and integrated into a 3D-geometric model, in our case, the developed BIM-Model through a data skeleton using Information Container for Document Delivery (ICDD) [114]. Afterwards, this information is made available to different target groups via three different portals, which are the conditionCONTROL, expertCONTROL, and arCONTROL solutions. More specifically, the conditionCONTROL is designed to provide a central overview as a *single source of truth* platform and interpreted results and indicators of the various damages and conditions of the bridge asset and its components for goal-specific authorities and users.

The expertCONTROL is intended for engineers and scientists and other interested users to access time-dependent raw monitoring data and dirgrams for further insights and evaluation. The arCONTROL, which is still under development, is primarily intended for inspectors and field engineers to enable accurate and direct allocation and observation of structural components as well as damages and sensors. The combination of these technologies is necessary, as it provides a more efficient and goal-oriented approaches for different useres. Moreover, comprehensive solutions are currently lacking in the market that provide fully integrated functionality due to the bottlenecks in processing and visualizing the growing volume of data, especially in real time.

As a final result, notifications and alarms regarding the bridge's condition are generated not only for the end user/stakeholder but also fed back to the initial data acquisition layer. This enables their use as input data for subsequent analyses, enhancing the continuity and accuracy of assessments. For a better understanding, detailed use cases are elaborated in the following parts.

(1) Use case: Inventory, inspection, and diagnostic results

Stationary data, including inventory, inspection, and diagnostic data, are analyzed, aggregated, structured, and then incorporated into the BIM model.

i. Inventory data, including detailed structural data of the bridge regarding its superstructure, substructure, and foundation, as well as detailed component information such as tendons, bearings, caps, etc.
ii. Currently, in Germany, inspections are conducted according to DIN 1076, which mandates manual major inspections of bridges every six years, along with regular smaller inspections every three years between major inspections. The inspection results shall be documented in a report and in the meantime, digitized and uploaded to a bridge management Software called SIB-Bauwerke by the BASt-Bundesanstalt für Straßen- und Verkehrswesen (Federal Highway Research Institute). For the NBW, the inspection data since 2008 has been taken into account.
iii. Different diagnostics have been carried out to examine the behaviour of the bridge. For instance, material testing of the concrete, pressing quality of the pre-stress tendons on drilled specimens, corrosion condition assessment of the reinforcement and prestressed steel bars using Potential field measurement etc., have been thoroughly analysed and aggregated.

As a result, all this information can be visualized and located in the so-called conditionCONTROL web-based platform, Fig. 10 showcases the crack in the substructure.

(2) Use case: SHM data

Sensor data of the SHM-System are recorded and transmitted continuously since the operation of the SHM-systems. Compared to stationary data, SHM data are continuously updated and visualized. This poses significantly higher demands on the IT infrastructure, as well as the real-time linking and visualization capabilities of the DT, requiring substantial economic and computational efforts. In the meantime, the raw data might be of little/none interest to stakeholders or end users like bridge managers and inspectors. Taking both aspects into account, another platform called expertCONTROL has been developed. Similar to other stationary data, as shown in Fig. 11. On this page, interested users can access the expertCONTROL solution by clicking the provided link under the image.

In the expertCONTROL solution, the raw data from all sensors is linked and visualized according to the time sequence, with detailed location, installation, and metadata of the sensors also provided. Besides the raw data itself, some basic statistic values, including the average,

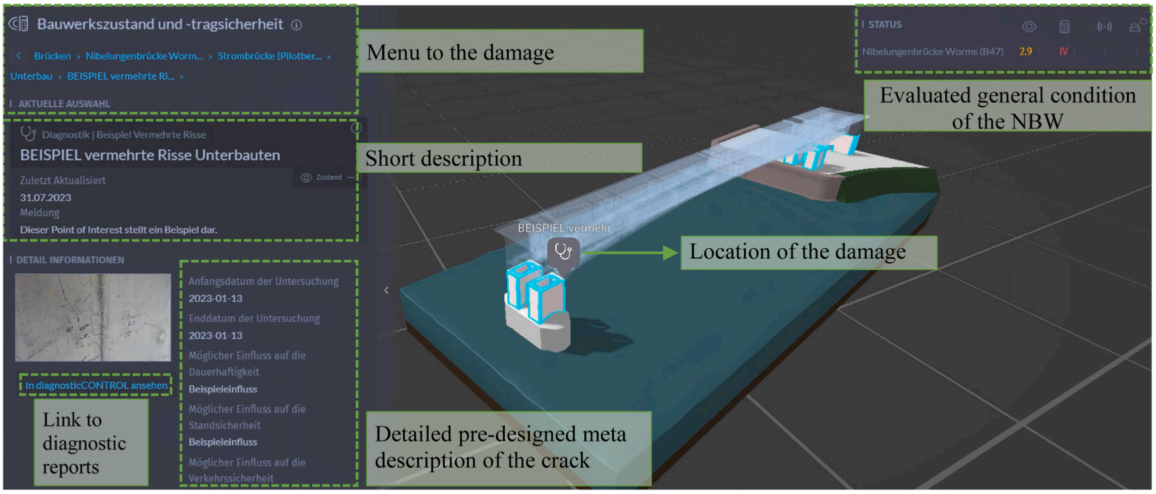

Fig. 10. conditioncontrol: crack in the substructure (with translation from German to English).

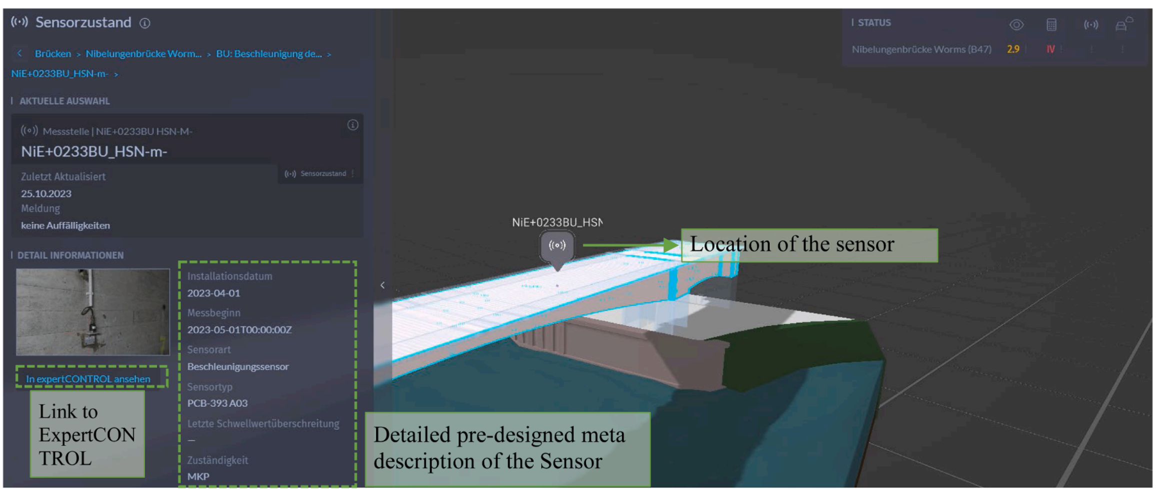

Fig. 11. Conditioncontrol: SHM sensor condition (with translation from German to English).

maximum, and minimum value of the measurements within the last 10 min, are continuously calculated and provided. Currently, the data are updated on the platform every three hours, with the potential for real-time updates with upgraded IT infrastructure. Fig. 12 showcases the inductive sensors used to measure the longitudinal displacement of the girder at the Gerber joint in the middle span of the pilot area.

(3) Use case: condition indicator – Corrosion

This condition indicator (CI) addresses the corrosion weaknesses of the bridge mentioned in Section 5.1. Due to the lack of proper non-destructive SHM technology to continuously monitor the corrosion state of the reinforcement and prestressing tendons in concrete, an indirect solution is employed in this work. Specifically, the absolute corrosion condition of the embedded reinforcements is not in focus in this context. Instead, the aim is to detect at an early stage whether the probability of corrosion is increasing. According to previous structural inspections, a high chloride load was detected in almost all components of the structure [12]. Once the depassivation of the steel has begun, the remaining influencing factors are oxygen and moisture, which drive the corrosion process. Since it can be assumed that oxygen is present, it remains to determine the influence of moisture. The defective drainage and sealing of the NBW carriageway led to moisture damage prior to the repair. After extensive repair work carried out between 2010 and 2013, it is assumed that the drainage, waterproofing, and external surface protection system are fully functional. Moisture can therefore only occur inside the box girder in the form of humidity or condensation. This condition indicator analyses the influence of condensation moisture on the corrosion process.

While condensation cannot be directly measured with sensors, it can be estimated by monitoring three components. Continuous measurements of relative humidity (RH) and ambient temperature (T) are taken at a single point within the structure, from which the dew point temperature T_d is calculated according to the well-known Magnus formula [115] based on these two variables:

$$\gamma(T,\ RH) = \ln\left(\frac{RH}{100}\right) + \frac{bT}{c + T};\ T_d = \frac{c\gamma(T,\ RH)}{b - \gamma(T,\ RH)}$$

Where b and c are empirical constants used to define the relationship between temperature, relative humidity, and the dew point temperature [116].

Additionally, the surface temperature of the component T_c is measured at the same location. Condensation occurs when the component temperature falls below the dew point temperature, satisfying the CI T_c - $T_d < 0$, indicating a risk of corrosion development. In the end, only the calculated CI results are directly incorpated into the conditionCONTROL solution, see Fig. 13.

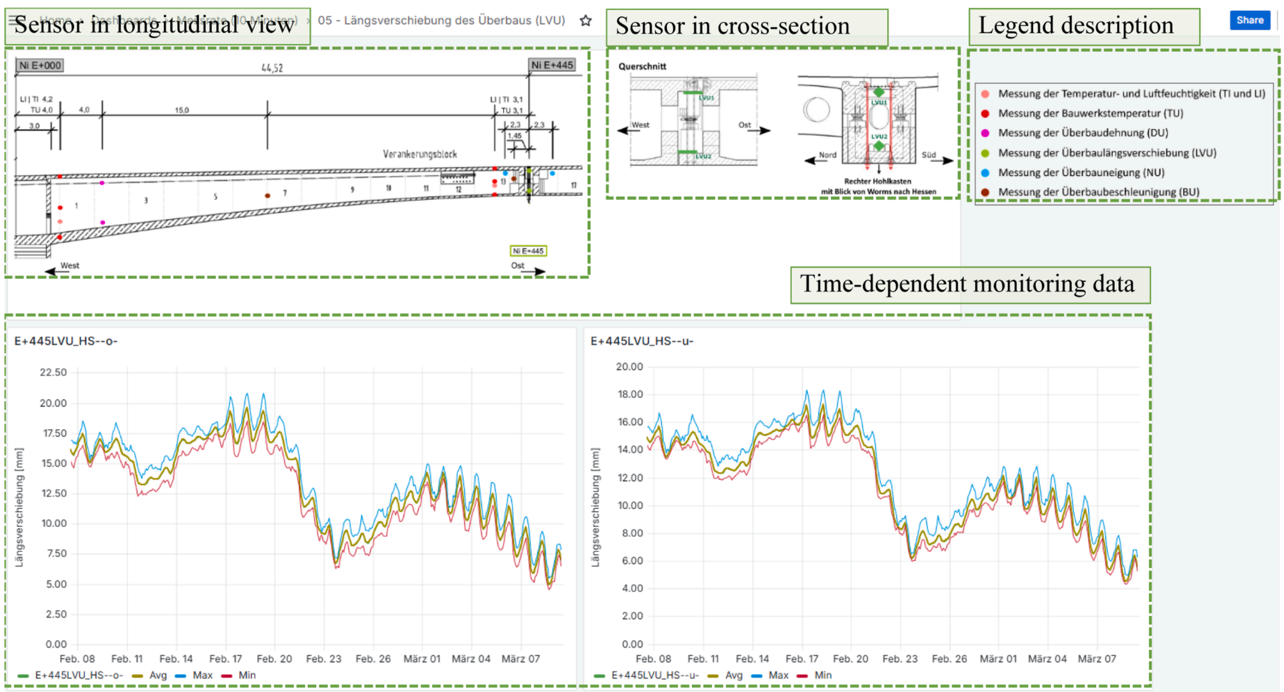

Fig. 12. Expertcontrol: longitudinal displacement in the gerber joint (with translation from German to English).

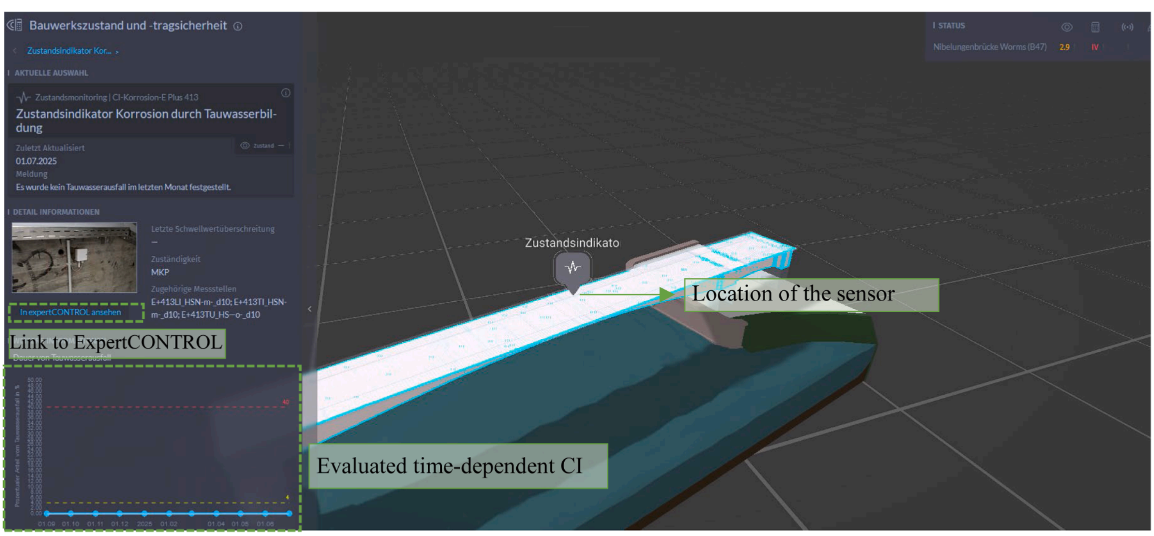

Fig. 13. ConditionCONTROL: CI – Corrosion (from 01.04.2024 to 01.01.2025, (with translation from German to English).

(4) Further use cases by other stakeholders

Due to the collaborative nature of this pilot project, various use cases are being developed by different stakeholders. For instance, Ramasetti et al. [117] developed a generic AI model based on CNN architecture to predict the movement of vehicles on the bridge, using monitoring data from accelerometers and traffic cameras, achieving a precision of 98 %. Arcones et al. [118] developed an updating scheme for the thermal simulation-based stochastic DT of the bridge. Additionally, Sprenger et al. [119] created a monitoring concept using parametric finite element modeling, incorporating nonlinear model updating with AI methods for damage detection. In the future, even more methods and models will be developed for this bridge.

5.3.4. *Human interaction*

One of the innovative aspects of this project is its openness to the public and should allow human involvement. The DT will be made as a 'open laboratory' where stakeholders but also non-specialists can access and review the DT to gain insights into the bridge's condition and performance through the integration process, fostering transparency and collaborative opportunities. Different users can obtain raw data and the condition status of the bridge through the various solutions, including the conditionCONTROL and expertCONTROL platforms as well as the REST API and file-based cloud storage for improved data interoperability. Furthermore, alarms and notifications will be sent to target groups via the conditionCONTROL platform. Afterwards, the corresponding responsible persons will take actions such as deciding on direct traffic control, carrying out diagnostic investigations, following maintenance protocols, or installing SHM sensors. The generated results will then be included as part of the acquired data and incorporated into the next loop using the currently available platforms and databases.

5.4. Discussion

The presented pilot BDT framework of the NBW, incorporating human interaction, relies on a BIM-based digital representation connected to the physical construction through an integrated data process (see Fig. 8). It first offers a comprehensive framework of the BDT which corresponds to the currently market available technologies in German bridge industry. Further discussions focus on its features and performance, as well as the associated limitations and challenges.

(1) Novel features and performance

First, a damage-specific SHM-data-based CI indicator for the NBW is developed. It provides a simplified approach to continuously monitor the risk of corrosion in steel reinforcement within concrete. As a result, it also delivers direct information to support decision-making for maintenance actions addressing corrosion risks. However, only six days between 2022 and 2025 of data slightly exceeds the threshold value has been monitored since the installation of the SHM systems. Consequently, the corrosion status has not yet been validated, but it will be verified in the near future once continuous corrosion risk is detected.

Second, it provides a multi-solution data visualization and access concept, enabling goal-oriented analysis and use of diverse data and results, thereby fostering data interoperability. This approach integrates multiple data sources direct or indirect into a single source of truth conditionCONTROL platform, enhances decision-making through clear visualization of accurate, quantified patterns, trends, and CIs, supports role-specific user access, improves communication among stakeholders, and increases efficiency by reducing redundant data processing. Consequently, this accelerates the decision-making process between relevant parties in a highly coordinated manner, which would otherwise require significantly more time for communication and data exchange across various decision-makers compared to conventional management methods.

Third, it showcases the potential of combining two SHM systems from two different stakeholders and their data topology (see Fig. 9) for future collaborative SHM and enhanced data interoperability in the scope of BDT. For lifetime management of a structure, various SHM use cases will emerge, involving a variety of technologies, stakeholders, and operators. In Germany in particular, the installation of any SHM-system must be put out to public tender for public infrastructure asset, making it inevitable that completely different SHM installers will be commissioned on the market. Combining ongoing and existing monitoring tasks poses significant challenges; however, it is highly desirable due to the costs of sensors and the value of the information they provide. For instance, understanding the entire structure's load history continuously and, of course, in relation to all environmental and operational conditions is crucial. This, however, presents a significant interdisciplinary challenge, particularly when considering the collaborative structure and the stakeholders involved. It is not detailed as it is beyond the focus of this work, further information can be found in the authors' other work [120].

(2) Limitations and challenges

The current maturity level of the BDT is between 2 and 3, with the potential to reach level 4 in the future based on the data process framework. The challenges preventing it from reaching level 4 primarily stem from the lack of suitable prognostic or predictive models for specific damage conditions, as well as the absence of comprehensive models covering the overall condition of the entire structure. In addition, current human feedback can only be integrated manually. To address this challenge, interdisciplinary competencies and approaches spanning structural engineering, computer science, and data science are necessary. Besides, the scope of the developed BDT currently focuses on the structural condition of the NBW, additional aspects, such as costs, maintenance strategies, and safety concepts, need to be incorporated for the life-cycle management of the NBW.

In general, the developed framework and data technologies can also be applied or adapted to other bridges, particularly prestressed and reinforced concrete bridges. However, the current implementation focuses on the NBW-specific issues, such as damage inspection and corrosion risk, etc. This focus reflects the general characteristic of concrete bridge structures, which are commonly considered unique due to their complexity. It remains necessary to analyses each bridge individually before planning any specific SHM systems or CIs. This also suggest immaturity of its adaption to a network-level DT, which requires much higher generalization and interoperability of BDTs.

6. Conclusions and outlooks

The systematic literature study shows that DTs in bridge construction are currently mainly focused on individual structures in the operation and maintenance phase, whereby higher levels of maturity and applications at system or network level have hardly been realized to date. The proposed classification helps to capture and describe the wide range of DT applications in bridge engineering. It provides a structured basis to identify current trends as well as potential research gaps in the field. It can be indicated that heterogeneous data form the core of every DT. The processing of this data is the key challenge. This study provides an overview of various technological solutions used for data acquisition, transmission, and integration. It enables the identification of commonly used approaches, their suitability for different lifecycle phases, and options for the design of future DT systems.

It can be also noted that most BDTs are currently used during the O&M phase, primarily because, during this phase, BDTs have the potential to maximize their technological, organizational, and economic feasibility and viability. During O&M, abundant inventory data is available, and continuous monitoring generates real-time data and information that enable accurate modelling and prediction of structural behaviour. BDTs can be integrated to support efficient inspections, repairs, maintenance, and decision-making. The resulting predictive maintenance reduces unexpected repair costs and extends bridge lifespan, while the safety improvements prevent costly failures, potentially providing immediate return on investment and actions. In contrast, during design, construction or dismantling, the benefits are limited: there is less real-world data (design), temporary or rapidly changing conditions (construction), or short-term operations (dismantling), making a full BDT less feasible or cost-effective.

Also, compared to other physical entities, bridges have a significantly longer lifespan than current DT implementations not only in construction industry, such as wind energy, but also in other sectors like machines. Therefore, continued operation and long-term analysis of DT implementations are essential to assess their suitability and effectiveness over time. At present, many DTs are developed during the O&M phase of a bridge, when structural damage has already occurred, thereby limiting their preventive potential. Future efforts should focus on establishing DTs in the early lifecycle phases of design and construction to unlock their full potential across the entire lifecycle. The absence of DTs in the design and demolition phases highlights a critical gap: without standardized data continuity across lifecycle phases, the transformative potential of digital twins in infrastructure management remains underutilized.

Moreover, BDTs are not only technological constructions, but also socio-technical systems. The coordination between multiple SHM systems at the NBW illustrates that stakeholder alignment and interoperability are as critical to success as the underlying sensing or modeling technologies. The shift from raw data aggregation to domain-specific condition indicators (e.g., corrosion risk based on dew point) marks a paradigm shift: future digital twins must not only collect data but contextualize it to create actionable insights tailored to bridge-specific failure modes.

Besides, the key challenge of current BDTs is in data interoperability, as the heterogeneity, complexity, and volume of data continue to grow, particularly within SHM systems operating under heterogeneous frameworks. To address this challenge, semantic web technologies, including knowledge graphs, ontologies [121], and semantic data models [122] are increasingly being incorporated into DTs to enhance knowledge representation, facilitate automated reasoning and support informed decision-making [123]. Such DTs are often called Cognitive Twins (CTs) [124]. They show strong potential to deliver innovative and efficient solutions on data aggregation, spatial alignment [125], and interoperability across different life-cycle phases of structures including manufacturing [126], construction [127], O&M [128,129]. Their potential is necessary to be further expended and explored.

Beyond the scope of an asset-level BDT, it is essential to extend the development and application of BDTs to a network level to optimize overall performance and enable more efficient, data-driven and coordinated decision-making across the traffic networks. However, various challenges remain in scaling the aforementioned asset-level BDTs to network-level DTs.

Firstly, it poses significant technical and scientific challenges. For instance, the integration of heterogeneous and inventory data systems necessitates the implementation of standardized architectures and the utilization of robust interoperability data solutions. Ensuring scalability, real-time performance, and cybersecurity across interconnected assets further increases complexity. Moreover, the development and validation of large, reliable, and efficient large-scale geometric and data processing models across various domains necessitate the innovation of advanced modelling strategies that strike a balance between accuracy and computational efficiency. To this end, well-trained personnel with interdisciplinary expertise across domains such as civil engineering, data science, computer science, etc. are urgently needed.

In addition, considerable challenges are also related to organizational, financial, and human factors. The coordination of multiple stakeholders, each with disparate objectives, necessitates the establishment of effective governance mechanisms and transparent decision-making processes. In conclusion, the successful adoption of a network-level DT relies on interdisciplinary expertise, and regulatory compliance, ensuring that the network-level DT is both technically robust and institutionally viable.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT solely to check the grammar and polish sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Chongjie Kang: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Maria Walker:** Writing – original draft, Visualization. **Jan-Hauke Bartels:** Writing – original draft, Visualization. **Gero Marzahn:** Writing – review & editing, Resources. **Steffen Marx:** Supervision, Resources, Funding acquisition.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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