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ARTICLE

Digital twins for engineering structures—An Industry 4.0 perspective

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Abstract
The term “digital twin” is becoming increasingly prevalent in both research and politics with regard to infrastructure structures. Industry is making significant advancements in the fields of automation and autonomy. While numerous definitions are in circulation, some of which are identical, many are similar in nature. This work examines the digital twin from its original industry perspective and considers its relevance to the constructional engineering sector. The objective of this study is to provide an overview of the current approaches in the Industry 4.0 and constructional engineering industry, examining the associated technical opportunities and challenges. The study compares the definitions, requirements and projects executed in this field. The technologies under examination are contrasted on the basis of their position within the data model. The preliminary findings suggest that some solutions for Industry 4.0 have already been developed for the construction engineering sector. However, it must be acknowledged that some solutions have yet to be fully validated.

KEYWORDS
automation, autonomy, BIM, bridge maintenance, decision-making, digital twin, Industry 4.0, IoT, life cycle management, point cloud, predictive maintenance, sensor, simulation, structural health monitoring

1 | INTRODUCTION

The global advancement of digitalization is occurring at an accelerating pace, with countries' governments playing a pivotal role in this process. The terms digitization, digitalization, and digital transformation are often used interchangeably. However, each is to be understood individually. The former refers to a conversion from analog to digital, while digitalization utilizes digitized information to enhance processes.[1] Digital transformation, on the other hand, entails the elevation of a company, organization, industry or similar entity to a higher level of digitalization in a strategic manner.[1,2] The Federal Republic of

Abbreviations: AAS, asset administration shell; AI, artificial intelligence; BIM, building information modeling; CAD, computer-aided design; CDE, common data environment; CFD, computational fluid dynamics; CNC, computer numerical control; CPS, cyber–physical system; DFOS, distributed fiber optic sensing; DT, digital twin; FE, finite element; FEA, finite element analysis; IoT, Internet of Things; ML, machine learning; MQTT, message queuing telemetry transport; NDE 4.0, nondestructive evaluation 4.0; NDT, nondestructive testing; PLM, product life cycle management; SHM, structural health monitoring; UAV, unmanned aerial vehicles.

Germany, for instance, has established a Digitalization Index, which is compiled on an annual basis. The 2023 report[3] indicates that digitalization has reached a plateau, with a slight increase observed between 2020 and 2022. It is evident that regions and cities with a strong industrial base, as well as large industrial companies, are spearheading this transition. The construction industry continues to lag behind other sectors in terms of digitalization, with the lowest scores across the country. The European Commission has also observed this trend. As a replacement for the Digital Economy and Society Index,[4] the Digital Decade Policy Programme 2030 was adopted in 2022. The Report on the State of the Digital Decade 2023[5] presents an analysis of the digital objectives of member states and evaluates their results to date. Germany scores averagely among European countries, with significant potential for expansion in the digitalization of infrastructure, public services, business and skills in general, for example. The key areas of focus are big data and artificial intelligence (AI).[5] In addition, there are opportunities for adaptation within the construction industry. One such opportunity is the interaction between citizens and the administration, as exemplified by the building application process as a public service.[6] Another use is the life cycle of infrastructure, which encompasses the planning, construction, operation and dismantling of transport infrastructure such as roads, bridges, and tunnels.

A variety of approaches have been employed in Germany to date with the objective of digitizing bridge structures. Haardt[7] presented a concept for a management system for the maintenance of bridges and engineering structures. The aim of this initiative is to create a nationwide platform for condition assessment, as well as for determining the strategy and financial requirements for maintaining the structures. This is based on the ASB-ING, which is a directive for the digital documentation of engineering structures on behalf of the German government.[8] The outcome is the SIB-BW management software in 1998.[9] The software allows for the documentation of structural information in accordance with ASB-ING.

The German government has issued a statement outlining the objectives for the digitalization of infrastructure buildings by 2020.[10] In a follow-up document, the integration of real-time data in *building information modeling* (BIM) and the use of AI for road infrastructure are addressed for the first time, without specification.[11] BIM for bridges has thus far been employed as a planning tool rather than a management system for the operation of structures. Consequently, commercially available BIM software products lack the requisite functionality for maintenance management. Nevertheless, the masterplan already anticipates the utilization of a so-called *digital twin* (DT) throughout the entire life cycle of a structure.[11] The sequence of phases over time is also referred to as a *digital thread*.[1] To this end, BIM test fields for DTs are to be established, particularly for the processing of operational data, such as sensor measurement data.[11]

This requires substantial development work to integrate a digital component into a data format based on static versions, which are unsuitable for dynamic sensor input.[12,13] In contrast, the systems currently being developed in the context of Industry 4.0 are based on dynamic, scalable frameworks. We are investigating the potential for applying existing methods to bridge structures. To this end, we present the requirements and definitions of DTs and showcase projects from industry and construction. Based on this, we derive a consolidated catalog of requirements for bridge structures and discuss their feasibility.

2 | REQUIREMENTS OF DTs

2.1 | DTs in Industry 4.0

The term "DT" is typically applied in industrial context, with Dr. Michael Grieves being the first to use it in 2003 and subsequently introducing it in 2014.[14] Despite its aerospace industry origins, a Google Scholar search reveals that the majority of publications on the subject are in the manufacturing industry. Initially, the utilization of DTs focused on physical and virtual products,[14] but it is now being used to replicate complex processes. Examples for this application can be found in algorithms for manufacturing processes and the machines required for them[15,16] or the resulting products as DTs. The definition of the DT also varies with the increased and distinct requirements depending on the industry. The term is typically defined as a physical or virtual machine or computer-aided model that can simulate, emulate, mirror, or "twin" the life cycle of a real unit (e.g., object, process, person) as a digital thread.[17–20] Another Industry 4.0 development is the *cyber–physical system* (CPS).[12,21] A CPS is not significantly different from a DT.[22,23] Therefore, our research will focus on DTs.

To categorize and compare the different implementations of DTs, different levels have already been defined. Kritzinger et al.[24] differentiate the DT at the level of integration of *digital models* and *digital shadows*. A digital model is a description of the physical object (e.g., simulation model or mathematical model) to which data is added manually. A change to the model has no effect on reality and vice versa. A digital shadow is analogous to a digital model, with the distinction that the data flow between the digital shadow and the physical object is automated and unidirectional. Consequently, a change to the physical object has an effect on the digital shadow, but not vice versa. Finally, with the DT, the data exchange is bidirectional, whereby changes to the real object cause changes in the model and vice versa.[24] The findings of the literature review[24] indicated that the majority of projects and concepts do not reach the level of integration associated with a DT. This conclusion was also reached by Lindner et al.[25] and the researchers identified a lack of definition as a potential reason for this discrepancy.

In a study of various open-source *Asset Administration Shells* (AAS), Jacoby et al.[26] identify a gradation in maturity and data migration. An AAS is a digital representation of an asset that was defined by the Industry 4.0 platform[27] and corresponds to a DT. The study distinguishes between three types of AAS: *Type 1*, *Type 2*, and *Type 3*. Type 1 describes a file-based *passive* exchange of AAS, Type 2 a *reactive* exchange that occurs via APIs (e.g., http/REST), and Type 3 a *proactive* AAS that enables communication between AAS and real objects or between AAS and AAS.[27] In the IEC 63278,[28] the AAS is defined as an interoperable manifestation of a DT of manufacturing. It enables close integration across the life cycles of the production system, product management and supply chain management.

These requirements are based on the maturity level with regard to data integration. Barricelli et al.[18] refer to this as a seamless data connection, which also describes dynamic measurement data from the DT. Communication takes place either between the physical and DT, between DTs or between the DT and the operator.[18] Rosen et al.[19] emphasize that only an autonomous system constitutes a DT. They differ from automatic systems in that they can perform tasks on the basis of explicitly represented knowledge about the machine, the task and the environment, without the need for fixed, carefully worked out sequences of actions that automatic systems require.[19] These are employed, for instance, to fill the machines or to maintain the operational chain through autonomous troubleshooting. The corresponding gradation is *informational*, *supporting*, and *autonomous* DT.[29] The former corresponds to a digital model that is fed by the user. It is used, for example, to develop new products. The supporting DT automatically analyses the data fed in, provides service life forecasts for production systems, for example, and supports people in the decision-making process. The autonomous DT is capable of making decisions independently and controlling the physical twin without human intervention.[29] In the context of data processing, gradations such as descriptive, predictive and prescriptive also exist.[18,30,31] These are illustrated as part of the Federal Highway Research Institute (BASt)

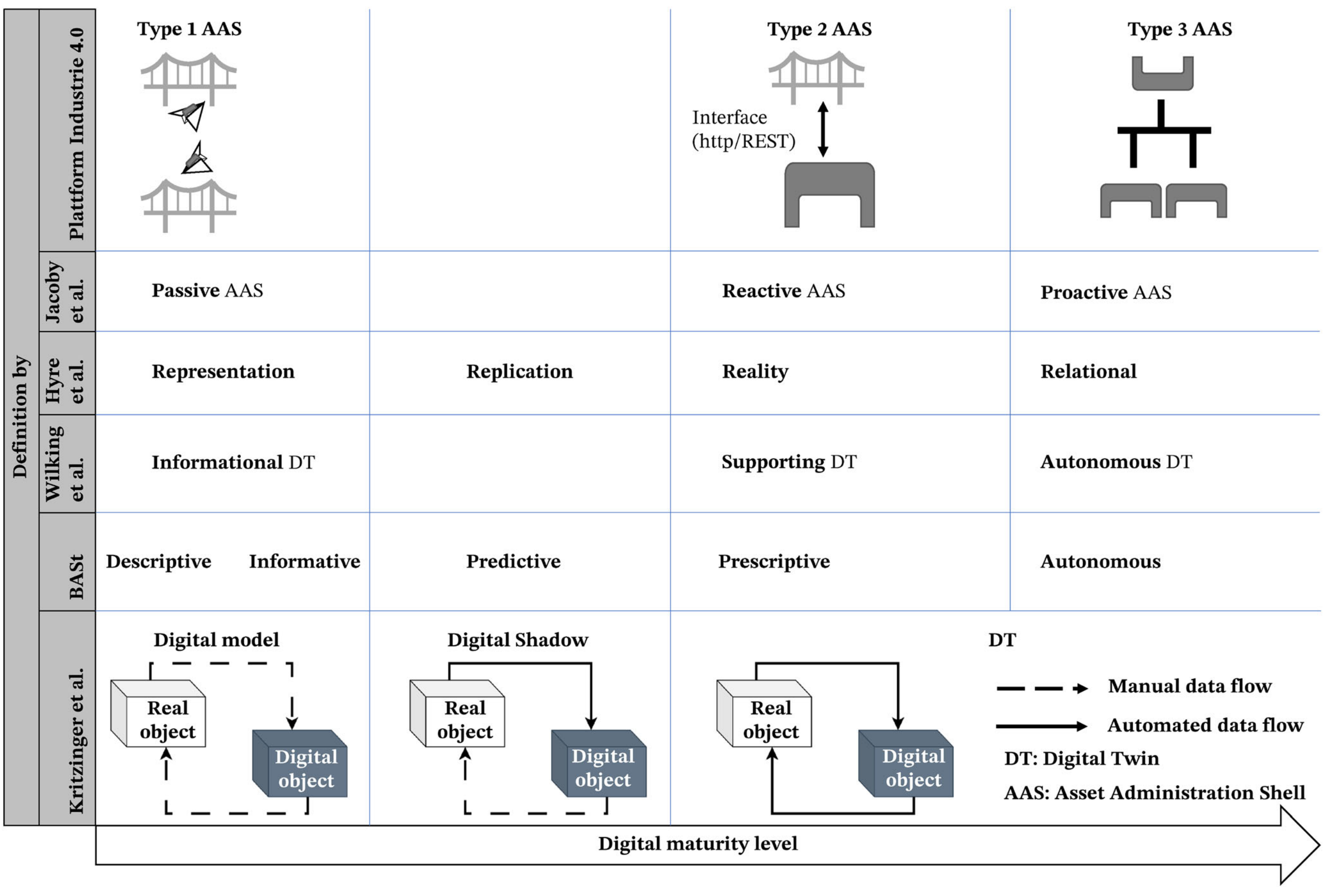

FIGURE 1 Definitions of digital twins by their maturity level: Platform Industry 4.0,[27] Jacoby et al.,[26] Hyre et al.,[32] Wilking et al.,[29] Federal Highway Research Institute (BASt),[33] Kritzinger et al.[24]

gradation in Figure 1 and explained in the following Section 2.2 for the sake of clarity.

An alternative approach is to divide the different levels of *representation* (automated data flow, visualization), *replication* (model updating), *reality* (prediction), and *relational* (autonomous) (4R) into four categories, with the capability and complexity increasing in order.[32] A comparison of the previous definition methods and terms is given in Figure 1 and roughly categorized according to their level of maturity.

DTs are operational throughout the entire product life cycle management (PLM) process, as data is generated in every phase.[34] Figure 2a provides an overview of this, showing PLM and examples of data transferred within it. They are roughly divided into the design phase, development/production phase, operational phase and dismissal phase, which can then be subdivided even further.[18,34] It is conceivable to have the DT start in each phase.[18] In the initial phase, which may be considered the "beginning of life," product developments and the production are initiated. In the subsequent phase, which may be designated the "middle of life," the maintenance or repair of a product is undertaken. Finally, in the "end of life" phase, the life of the product is summarized, and conclusions are drawn about successors following the demolition or recycling of the product.[29] However, DTs not only depict products, but also processes, performance, or production itself.[35,36]

The scope of DTs encompasses technical, engineering PLM, and business aspects.[37] In research, the technical aspect is often the primary focus. This involves communication, such as the choice of data transfer between the twins and representation, including the selection of database, data storage, and ontology for data understanding.[18,37] The latter describes a data model that is accessible, comprehensible, and accepted by all relevant parties. Another technical aspect under consideration is the utilization of novel measurement methodologies, such as sensors or nondestructive evaluation 4.0 (NDE 4.0). The latter delineates the inspection of production components and products in accordance with the tenets of Industry 4.0, which encompass DT.[38] A significant proportion of the research is devoted to the computational aspects of DTs, including the processing of big data, the utilization of *descriptive*, *predictive*, and *prescriptive* algorithms, as well as *feature selection* and *extraction*.[18,37] A further area of investigation is the relationship between the microservices and the simulation models.[37] In engineering PLM, the transferability of DTs to other industries and the cradle-to-grave approaches of the value chain are also covered by the research.[37] Finally, the DT addresses business aspects such as strategies, customers and the market, as well as value generation.[37]

Nevertheless, the researchers concur that there are numerous unanswered questions pertaining to ethics, sensitive data, security, trust and privacy (protection against hackers), costs (risk of oligopoly), government regulations (which predictive measures may be carried out), end user design (applicability not only for computer scientists, but also for engineers and technicians), and technical limitations (edge computing, data load).[18,21,37,39,40] In addition, preliminary efforts were undertaken to evaluate the fidelity of the model with respect to the investment.[41] Moreover, further standardization is required.[21,37,39]

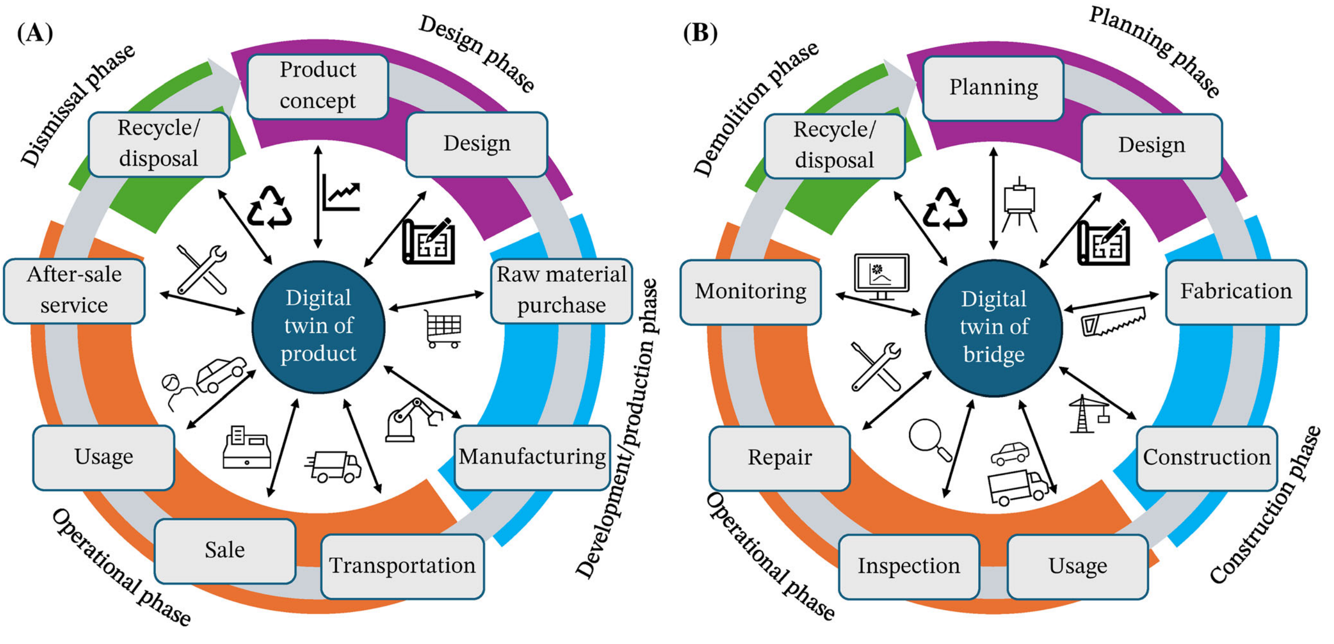

FIGURE 2 Life cycle of assets: (a) product life cycle; (b) bridge life cycle.

2.2 | DTs in constructional engineering

The concept of DTs is being employed with greater frequency in the context of constructional infrastructure. The initial physical requirements for a digital city were established in the pioneering work on this subject.[42] Over time, the term has been increasingly supplanted by the term "smart cities." Platforms for various sub-applications, such as those pertaining to the electricity grid (smart grids[43]) or smart buildings,[44] often have the objective of providing a sustainable solution for traditional cities. The terms "smart city" (concept) and "urban digital twin" (tool) have now been used collectively.[45–47] These approaches are also used for transport infrastructure.[48]

The term DT was initially employed in the context of bridges as a synonym for digital models, such as those based on BIM.[49,50] Subsequently, the definitions from Industry 4.0 have been adopted in the field of construction engineering.[51,52] The categorization of digital models, digital shadows and DTs is now widely accepted.[48,52,53] In a report by the Federal Highway Research Institute,[33] the concept is translated into five levels of maturity. Maturity increases from a purely *descriptive* model (virtual replica) to *informative* (condition can be derived by information), *predictive* (predictions are made due to relevant information), *prescriptive* (recommendations for action are made by DT), and *autonomous* (DT acts autonomously). These levels are oriented toward Industry 4.0[54] and BIM, where slightly different expressions are used.[55] Moreover, there are classifications in terms of spatial scope (individual components vs. complete streets) and level of detail according to the *Level of Information Need*[56] that is typical of BIM for collaboration. These include the *Level of Geometry*, *Level of Information*, and *Level of Documentation*,[33] which play a significant role in defining the requirements. The impulse for the development of an intelligent bridge management system, or subsequently, a DT for roads and bridges, can be attributed to two primary factors: the need to address the deterioration of existing infrastructure and the increasing volume of traffic,[52,57] and the necessity to implement structural health monitoring (SHM) and nondestructive testing (NDT) to ensure the continued functionality of the infrastructure and to facilitate emergency response.[58] The latter is frequently the consequence of the former.

A review of the life cycle of a bridge (see Figure 2b) reveals a multitude of requirements for DTs for bridge structures. The planning and design phases, as well as the fabrication and construction phases, are combined, while the operation and demolition stages remain distinct. A variety of data is generated from the DT in one phase, yet it can be utilized across all subsequent phases.[12,59]

The data is collected in data acquisition from a wide variety of sources over the entire life cycle, which is approximately 80–100 years long (see Figure 2b). Static and dynamic data exist for this purpose. Table 1 provides an overview of this. The data transfer and thus also the import into the DT is carried out manually or automatically, depending on the source. The DT therefore requires a multifunctional interface that stores the acquired data according to the *FAIR* (findable, accessible, interoperable, reusable) principles.[51] The semantics of the bridge are defined in an ontology, which originates in part from BIM[13,60] or ASB-ING,[61,62] for example.

In the age of big data, the objective for the operator of a structure is to obtain only pertinent information on the condition of the structure from a vast array of data.[33] To achieve this, the collected data is processed in a multitude of models. For data from SHM that is dynamic in nature, there are various approaches to operating simulation models that are *data-driven*, *physics-based*, or a *hybrid twin* (a combination of the former), in a *reduced order* or as a *baseline model*.[63–65] With regard to static data, there is research for image processing with semantic bridge damage segmentation[66] or for updating a 3D model using recorded point clouds.[50] From these sources,

TABLE 1 Examples of data generated by life cycle stage.

Stage	Static data	Dynamic data
Planning	Geological data, costs, sketches	–
Design	Time plan, plans, BIM model, static calculations, simulation models	–
Fabrication	Pictures, material specifications	Quality control, safety management[12]
Construction	Pictures, protocols, invoices, point clouds	Surveillance systems, monitoring data, webcam, logistics and scheduling, quality control, safety management[12]
Operation	Protocols, nondestructive testing (NDT) data, point clouds, as built models, static calculation	Monitoring data, webcam
Demolition	Static calculation, recycling plans, pictures, NDT data, point clouds	Surveillance systems, monitoring data, webcam

the DT can be automatically enriched with deterioration information.

The standardized acquisition, transfer and processing of data in the DT still requires further research.[33,48,50,65,67,68] To gain the benefit and trust of structure operators, the networkability, machine readability and real-time capability of the data for human-technology interaction must be demonstrated in application-related test fields.[33,61] Moreover, open-source solutions are also necessary.[33]

2.3 | Merging the requirements

A comparison of the two preceding sections reveals both similarities and differences for the use of DTs in Industry 4.0 and constructional engineering. There is a multitude of definitions for DTs in both Industry 4.0 and constructional engineering, which is a consequence of the extensive range of potential applications.[32] From a technical perspective, the rapid progress of hardware development is beneficial for all fields. For instance, the expansion of battery capacity, the growth of high-speed mobile internet, and the increase in computing power benefit both construction technology and Industry 4.0.

Market-ready software based on the Internet of Things (IoT) is already in use in industry.[48] Wireless sensor networks or sensors that are connected to a company intranet can be connected there via a network.[23] Standards exist for the structure of the frameworks.[28] The requirements of the construction industry for the output of the software are similar to those of industry: mapping the condition of a physical twin, detecting a change, predicting further changes, and deriving actions from this. Research is currently being conducted on these products for the construction industry, but they have not yet reached the market in a scalable manner. The algorithms necessary for this have to be tailored to the infrastructure of each individual structure, a process that is inherently time-consuming. In industry, one algorithm can be used to cover several machines, sometimes tens of thousands of products.

The security, reliability and traceability of the data in the DT are of equal importance for Industry 4.0 and constructional engineering. While the data for companies must be protected from industrial espionage, reliability and liability issues and hackers, public operators have a particular interest in preventing political spies from accessing the data. In addition, many stakeholders are involved in the life of an infrastructure project, and responsibility for quality and reliability must be ensured.

A significant distinction exists between the service life of production facilities and products in industry, which typically span only a few years or decades, and that of infrastructure structures, which can endure for a century. The data generated during this period from the structure, the subsoil, and traffic are of significant value and are to be collected to an as yet undefined extent over the entire lifespan of the infrastructure. However, the life cycles of infrastructure and industry have similarities (see Figure 2).

One can observe that there are numerous parallels between the construction industry and the concepts of Industry 4.0. Table 2 provides a comprehensive summary and further elaboration on this topic.

3 | PROJECTS OF DTS

3.1 | General project elements

A holistic DT is complex, with many individual components and therefore many interfaces. The data system can be roughly divided into the core elements of the physical twin and the DT (or shadow/model). In between is the connection or transfer of data. This is referred to as a three-dimensional model. In comparison, data and services complement each other to form a five-dimensional model, with the different dimensions being interconnected.[34,71] The connection can be manual, automatic or autonomous. Automatic/autonomous control mechanisms take place on the physical twin, with additional data acquisition and optional handling of the data (cleaning, filtering, etc.) at the physical twin (data edge processing). The physical twin and its condition can be influenced from the outside by engineers, technicians, laborers, and so forth. The DT accesses the stored data, where the databases are located (in the cloud, at the edge or in between). All stages of analysis and simulation are combined in another level, at the end of which is validation as data analysis. To make the data understandable to the user, the data is visualized and key information is filtered. Dashboards provide access for the operator, external users or maintenance, for example. Consequently, the system is capable of making decisions autonomously or independently (self-decision), or alternatively, the operator may choose to retain control over the decision-making process and allow the system to provide support in this regard (human decision).[72] A compact diagram is shown in Figure 3.

3.2 | Projects in Industry 4.0

In the conducted literature research, project concepts were analyzed using methods for creating a DT. The

TABLE 2 Comparison of the requirements of digital twins for Industry 4.0 and engineering structures.

Criterion	Industry 4.0	Engineering structures
Lifespan	Production: 1–20 years, product: 3–30 years (e.g., cars: 10.3 years mean[69])	Planned: 80–100 years,[70] actual: 40–≥150 years[a]
Life phases	Design phase—development phase—operational phase—dismissal phase	Planning phase—construction phase—operational phase—demolition phase
Twinned assets	Production, product, processes	Construction and operation of roads, railways, tunnels, bridges and the action and impacts (temperature, traffic, humidity, etc.) on it
Main beneficiaries	Producer, customer	Operator (including engineers, technicians), citizen
Starting point	Design phase, operational phase[18]	Design phase, operational phase
Deterioration rate	Quick, within minutes/hours/days	Medium—slow, within months/years
Reactivity	Quick, seconds/minutes	Depending on task: quick (SHM, emergency monitoring), seconds. medium (damage detection, load model), days/months
Researching and developing organizations	Industrial Digital Twin Association (IDTA), Digital Twin Consortium (DTC),[26] universities, research groups, companies	Mainly universities/research groups, engineering companies
Benefits	Producer: increase of productivity and margin, predictive maintenance; customer: improvement of support and service	Operator: support of decision-making, automation, predictive maintenance, cost and time saving; citizen: safer and more fluid infrastructure
Challenges met	Data acquisition, data transfer standards, scalable software, predictive maintenance of single machines	Development and choice of sensors, automatic model generation
Open challenges	Data security, government regulations, end user design, technical limitations, standardization, storage and processing of big data	Standardization (data acquisition, transfer, analysis), data security, government regulations, end user design, technical limitations, storage and processing of big data, test fields, open-source solutions

[a]Depending on the type of road, construction method, building materials, and so forth.

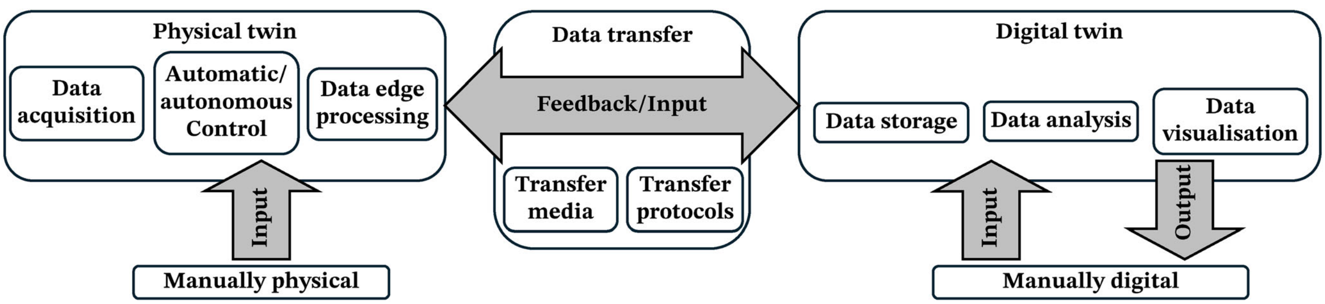

FIGURE 3 Data path of a digital twin system.

examples can be divided into data-based DTs and physics-based DTs. The former are data-driven, so not all technical information is needed. With the latter, the twin gets better the more you know about the system. A combination of the two forms the hybrid twin. Simulation models such as computer-aided design (CAD), finite element analysis (FEA), and computational fluid dynamics (CFD) can evolve into a physics-based DT by updating the model. Adamenko et al.[73] compare different software for this purpose.

3.2.1 | Physics-based DT

One application in product development is the automated synchronization of prototypes with simulation models. This can eliminate the need for time-consuming and costly prototype testing.[74,75] Venturini et al.[74] use this for the development of steel wheels; strain gauges are used as a data source in the test setup. The resulting DT will also be used for the product in the future. This is a typical example from the automotive sector; the data from product development will later support autonomous driving with changes, suggestions, and alarms.[75] However, aerospace products are also being developed using, for example, fiber Bragg grating sensors and digital image correlation to compare experiments and finite element (FE) models.[76] The objective is to train mathematical models to create a meta-model that communicates with the physical object to obtain a surrogate model with damage-related variables and to produce better products in the future using the data from the operation.[76] The data from a product twin can be used not only for product development, but also for the manufacturing process. This methodology is employed in the production of white products with thermoforming by equipping the production machine with temperature sensors, a thermal imaging camera and vacuum pressure sensors.[77] The machine communicates with the DT during data acquisition and experimentation, during simulation and modeling with FEA, and provides feedback leading to an increase in productivity.[77] Most of the literature deals with process twins. These are often linked to the monitoring of ideal production conditions or to the predictive maintenance of machines. In metal bending, this is done by updating via the OPC UA industrial protocol from an FE model with sensor data of applied load and displacement.[78] In the future, it will also be possible to verify residual stresses.[78] Furthermore, the cooling behavior of pressed parts can be predicted in this way. A virtual sensor is developed training machine learning (ML) models on coupled FE simulation data, with data coming from temperature sensors and thermal imaging cameras on the press.[79] A comparable method is also used to determine the ideal use of coolants when processing difficult materials.[80] The simulations are carried out in FE and CFD models, and the sensors measure, for example, the applied machine force or temperature, as well as the residual stresses.[80] For measuring the latter in laser net shaping, measurements are taken on plates with distributed fiber optic sensing (DFOS) and compared with FE in a thermal and mechanical analysis.[81] The whole process is analyzed as a digital shadow.

3.2.2 | Data-based DT

In pure data-based approaches, the quality of the sensors is important, such as the requirements for measurement function, operating conditions, hardware, and organization.[82] A high level of understanding of the system is required to select the right sensors and algorithms.[82] Fett et al.[82] investigate the use of different sensors, the literature on this is scarce. One example is the development and operation of batteries, where fiber optic sensors are used to better understand the inner workings of the battery and to improve the models.[83] Other sensor technology is used by Mendi.[84] For a production robot and a computer numerical control (CNC) machine, he describes a complete chain of data acquisition with temperature, dust and tachometer frequency sensors, their transmission with message queuing telemetry transport (MQTT), visualization and analysis using AI. An increase in productivity and a reduction in costs are also described.[84] Friederich et al.[85] describe a framework for these DTs.

3.2.3 | Hybrid DT

In addition, data-based approaches can be combined with physics-based, so-called hybrid approaches. These are used, for example, to predict the contour error of a tool path in CNC systems during the manufacturing process and to map it as a DT.[86] They are also used to learn the uncertainties in a production chain with its processes and machines with the help of ML and thus improve the modeling.[15] The objective of these so-called physics-enhanced ML approaches is to enhance the accuracy of the model, improve the quality of predictions, and accelerate the processing time.[87] With regard to complex systems, those characterized by multi-scale, multi-physics and nonlinear time-varying dynamics, the hybrid approach remains a topic of ongoing research.[87]

The project literature shown and some reviews are assigned to the respective elements in Section 3.1 together with the technologies used. A summary can be found in Table 3. The technologies often include several sub-elements. The evaluation of the approaches and the categorization of which method is the most suitable for which application are beyond the scope of this report. It is also noteworthy that companies operating within the Industry 4.0 framework utilize comparable technological solutions, which are tailored to align with their internal operational procedures and product offerings.

3.3 | Constructional engineering

Liu et al.[65] categorize civil infrastructure projects according to the method of data setup and processing. They distinguish between FE-based methods (generally: *physics-driven* or *system driven*), *data-driven* approaches and approaches to *reconstruct 3D models* with image data from unmanned aerial vehicles (UAVs) or 3D point clouds from laser scans. The output of the latter is similar (meshed surfaces), only the way of processing the measured data differs. Furthermore, only the first two

TABLE 3 Technology used in digital twin projects of Industry 4.0.

Criterion	Used technology
Data acquisition	Sensors general,[16,17,19,20,24,28,29,32,34,35,37,39,40,75,78,82,85,88] specific sensors (analog, digital, fiber optic, MEMS),[15,72,74,76,77,79–81,83,84,86,89–92] cameras,[16,32,77,79,80,88] customer,[37,85] actuators,[39,89] NDE 4.0[38]
Data edge processing	Data reduction,[72,82] data reliability (cleaning, verification, metadata)[15,38,72,85,89]
Data transfer	Protocols: OPC UA,[28,37,78,79,92] MQTT,[15,37,72,84,89,92] HTTP[28,92]
Data storage	Local databases,[29,32,40,74,80,84,85] cloud services[19,37,39,40,77,92]
Data analysis	Physics-driven,[16,17,24,37,74,76–81,88] data-driven,[16,32,34,35,37,38,43,72,73,85,88–92] hybrid,[15,16,86,88] generative[a93]
Data visualization	Virtual reality (VR),[37,38,40,84] augmented reality (AR),[38,40,84] extended reality (XR),[32] 3D,[72,88,93] 2D,[43,72,89] generally[24,39]
Human decision	Predictive maintenance,[15,16,20,29,39,73,88,89] human decision-making[15,20,29,32,37,39,40,84,85,88,89,92]
Self-decision	Describes automatic decision,[19] performs automatic decision,[72,84,91,92] describes autonomous decision,[19,29,32,39,72,75,84,88] performs autonomous decision[72,91,92]

[a]See Figure 3.

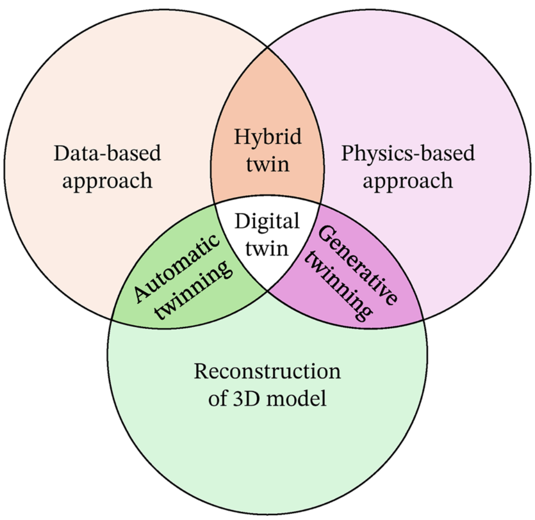

FIGURE 4 Venn diagram for digital twin analysis approaches.

methods process data from monitoring (continuous data acquisition).[64] Figure 4 presents these methods in a Venn diagram, with the overlap between the data-driven approach and the physics-driven approach labeled *hybrid twin*.[63] To designate the remaining intersections, we propose the following terms. *Automatic twinning* describes a model that was generated or updated from point clouds or similar using data-driven approaches; *generative twinning* was generated or updated using a physics-based approach. All of the civil infrastructure projects presented can be categorized in terms of their methods. However, a distinction must be made as to whether a platform is an analysis method that is being tested in a laboratory or an actual physical object that is being examined. Furthermore, a distinction can also be made according to the degree of maturity (see Figure 1).

The projects presented frequently originate from the BIM concept, yet the virtual representation of the physical twin is typically merely a 3D model. Updating is achieved through a manually intelligent data processing of point clouds for ML, bridge management systems, bridge information modeling, and 3D modeling.[94] The sources for point clouds may be terrestrial laser scans and photogrammetry from UAV, with the former offering greater accuracy and the latter being more cost-effective and time-efficient.[95] Semantic segmentation can be employed to process these data into BIM models or ASB-ING schemes.[50,96] Furthermore, FE models with damaged areas can be generated automatically.[97] In addition to the 3D geometric information, time, cost, carbon footprint, materials, and all maintenance work data can be included manually in the BIM models.[98]

As these updates are not continuous, the models cannot be updated quasi-live. This is currently only possible with sensor-based DTs, whose data acquisition and data analysis is similar to that of SHM. Many cable-supported bridges already have such an SHM system consisting of acceleration and cable tension force sensors; with the help of UAV scanning methods, BIM models can be generated, simulation models can be derived and these can then be updated in the sense of a digital shadow.[49] Nevertheless, the utilization of measurement data differs from that of a digital shadow. For instance, measurement data from accelerometers on a bridge is contrasted with FE models, with the objective of identifying damage. However, the maturity of a digital model is contingent upon the absence of automated data transfer (Figure 1, digital model).[99] AAS is one possible architecture for automation. An automated generation of AAS from BIM models was developed for a fabrication plant for prefabricated concrete elements. This is operated as a Type 1 AAS, as there is no direct communication between the two systems.[100] The Industry 4.0 AAS was also implemented for bridges with the configurator for AAS, BBox, utilizing ASB-ING. This was operated as a digital model to determine traffic load models and service life forecasts.[61] The platform has all the advantages of Industry 4.0, namely the complete implementation with containers for the use of all microservices and interfaces to numerous simulation and visualization programmes. Furthermore, the BBox was subjected to an experiment in which a Type 3 AAS was employed in conjunction with a data-based digital representation. The experiment involved transferring measurement data from the bridge in question using MQTT,[48] with the intention of generating a substantial quantity of data with which to train ML algorithms. A range of sensors were utilized, including accelerometers, strain, inclination, deflection, temperature, pressure, weather sensors, DFOS, to obtain the maximum possible amount of data.[57,70]

The integration of BIM into digital shadows is feasible through a linked data approach. The DALUX software enables the visualization of measurement data, including moisture, corrosion, strain, laser scans and images, within a BIM model.[52] The measurement data is stored in databases, while the analysis is conducted through microservices, with the visualization occurring within the BIM model.[52,101] The states of the bridge, the statics, the load and the sensors can then be displayed there.[13] A common data environment (CDE) can also be used as an interface for the data. As shown in the IDA-KI research project, only low rates of change are accepted there, dynamic data is stored in databases and the CDE only shows processed data.[102] A research bridge was established for this purpose, with which research is being conducted into automated data preparation, the evaluation of DFOS data and the provision of information in the maintanied model.[102,103] In the Ashvin research project, the Mainflux IoT platform was employed for the measurement data. In the context of a hybrid twin, a model update of an FE model was conducted with automated pre-processed data from accelerometers utilizing MQTT.[104] Key performance indicators and performance indicators for bridges were determined for productivity, resource efficiency, health and safety, and costs.[105] Another hybrid approach is the monitoring of fatigue cracks in welding by residual stress. For this purpose, models of traffic load and pavement temperatures were created, which were recorded with acceleration and displacement sensors.[106] Krüger et al.[51] present another system. In the PreMainSHM research project, a web-based software tool is used for the georeferenced 2D visualization of structures, sensors and sensor data. The 3D visualization is carried out with a game engine. They argue in favor of enriching the measurement data with meta data and semantic data.

The project literature reviewed and some reviews are presented in Table 4. The structure is similar to Table 3, with the technologies used assigned to the respective elements in Section 3.1.

TABLE 4 Technology used in digital twin projects of constructional engineering.

Criterion	Used technology
Data acquisition	Sensors general,[33,49,58,67,100,107,108] specific sensors (analog, digital, fiber optic, MEMS),[13,51–53,56,57,61,63–65,68,70,101–104,106,109] cameras,[65,68,70,95,104] point clouds[49–51,62,65,70,94,95,97,100,104]
Data edge processing	Data reduction,[68] data reliability (cleaning, verification, metadata)[48,51,62,65,94,95,101–104,107]
Data transfer	Protocols: OPC UA,[68,100] MQTT,[48,68,104] HTTP,[68,100,101,104] LoRaWAN,[51] SFTP[48]
Data storage	Local databases,[48,49,53,61,67,68,98,101,102,108] cloud services[13,51,57,65,67,68,109]
Data analysis	Physics-based,[49,64,65,68,94,101,104,106,107,110] data-based,[13,48,52,53,58,61,64,65,67,68,99,103,109,110] reconstruction of 3D model,[49,62,94,95,97,98] hybrid,[63,64,106] automatic,[62,96] generative[97]
Data visualization	Virtual reality (VR),[52,53,65,94,100] augmented reality (AR),[49,52,67,100] BIM,[13,49,51,52,56,58,60,64,65,67,94,98,101,108,109] 3D,[13,48,51,58,61,68,101,104,105,109] 2D[48,51,101,105,109]
Human decision	Predictive maintenance,[13,33,48,53,61,65,67,100,101,103,105–108] human decision-making[33,49,51,53,56,58,64,65,67,94,100,104,105,107–110]
Self-decision	Describes automatic decision,[53,99] performs automatic decision,[100] describes autonomous decision[33,53,67]

4 | DISCUSSION: AN INDUSTRIAL DT FOR CONSTRUCTIONAL ENGINEERING

From the preceding sections, it becomes evident that there are both similarities and differences between DTs in Industry 4.0 and constructional engineering. It is also obvious that the maturity of industry projects is more advanced. This is due to a number of factors, which are elucidated below using the example of the "bridge."

- *Capacity*: The pace of development in the commercial sector is faster than that of publicly financed developments. The systems are customized to the respective companies by the manufacturers' own specialist staff or development teams.[111] Small structure operators lack the financial resources to cover the costs, while large structure operators have too many structures to identify and further develop an existing system in a scalable manner. On the other hand, cooperation between governments and the private sector appears to produce higher quality results for the public sector, although it takes more time.[112] Joint research between

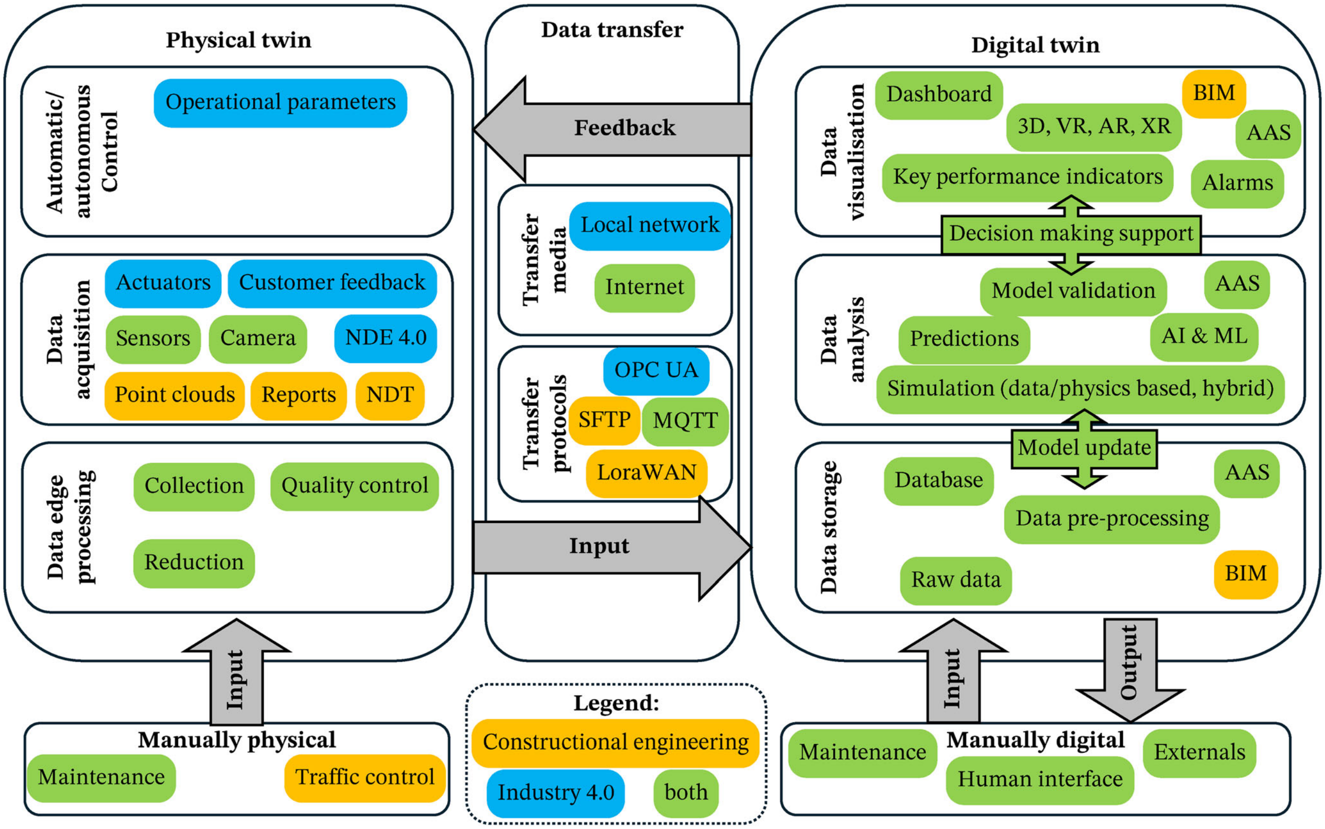

FIGURE 5 Data path of a digital twin system, comparison of technology used in Industry 4.0 and constructional engineering.

companies and academic institutions is therefore recommended.[112]

- *Use*: Figure 5 illustrates the integration of the technologies presented in Tables 3 and 4, which are in addition to those depicted in Figure 3. Different colors are used to indicate which technologies are already being used in Industry 4.0, construction engineering, or both. These are assigned to the corresponding components of the DT system shown in Figure 3. This provides a clear indication of the specific areas in which each industry sector has already gained experience and is engaged in research activities. The technologies on the DT side are already well developed. There are numerous research initiatives focused on identifying an appropriate platform.[61,100,104] Further research is required to identify suitable sensors and their optimal positioning, given the more individual appearance of the structures compared to Industry 4.0. This is evident in Figure 5, which depicts data acquisition and transfer across a multitude of technologies. Meanwhile, machines and products have already been equipped with the requisite sensors and control elements.[18,35,39]
- *Location and hardware*: The implementation of DTs is more straightforward in factories, where the prevailing infrastructure (electricity, intranet, internet, limited size, indoors) is conducive to their use. This is in contrast to bridges, which are often exposed to the environment and the weather over several kilometers in remote locations without a power supply and at most with mobile internet. The sensors remain on bridges for a longer period of time, which requires them to be robust and stable over time. The necessary robust sensors already exist,[68] and investigations have already been carried out into the feasibility of installing sensors in bridges to utilize the concrete as a protective measure for the sensors.[70] Furthermore, studies have been conducted on the long-term behavior of the subject matter.[113] As countries become increasingly digitized, the bandwidth of mobile internet is expanding, potentially offering a solution to the challenges of data transmission. To address the issue of power supply on bridges, research is exploring the development of self-sufficient sensor systems that utilize local energy sources such as solar power.[113] In a pilot project, the power supply line that traverses the bridge was employed as a power junction during new construction for monitoring purposes.[57]
- *The necessity for a twin*: The extensive automation and autonomization of industrial plants can be easily tested and implemented. A consumer of a manufactured

product can also use its DT. In the event of a failure of the DT or the product during test operation, there is generally no significant risk. In the case of bridges, only the operating phase, which is by far the longest phase of the bridge's life, is usually implemented as a DT. This supports the operation of the structure, which is critical infrastructure. A failure may result in significant economic loss and, in the most extreme cases, even personal injury. Furthermore, the bridges physical twin cannot currently be controlled automatically or autonomously, which means that all DT attempts are operated as digital shadows at most. One can consider potential applications, such as autonomous traffic control by the DT (dynamic overtaking bans in critical environmental conditions for truck), if this can mitigate the deterioration of the structure. However, the regulations (economic, political, ethical) must first be established for this to be feasible. In most cases, existing simulations are used to make recommendations for decision-making or predictive maintenance. To conclude, the current focus of research efforts for DT in the context of bridges is the provision of support for structural management.[22,48,52,53,67,87,94]

- *Big data handling*: The data accumulated throughout a product's lifespan is processed for storage over the lifetime.[18] To illustrate, in the case of a vehicle such as a car, the data stored is the performance data, rather than the acceleration, temperature, fuel consumption or power data. In addition, recommendations such as "service required," "add fuel," or "check tire pressure" are also generated in response. A multitude of tests are conducted on a car to develop this feedback for the user, resulting in the generation of a substantial amount of data. In the case of bridges, the development of recommendations for action is still pending; the lack of available measurement data represents a significant obstacle to this process. It is therefore evident that pilot projects are required to generate these data sets.[33] For research purposes, it can be assumed that all the available data is being used. Once the necessary algorithms have been developed, processing can be carried out on the physical twin via edge processing, and only the processed data will be stored in the DT. Graduations for this, for example, the deletion of traffic load-free states of bridges, are proposed, but for some methods, such as principal component analysis, the comparison to the ambient states is important.[114]
- *Standardization*: The industry has already established standards (e.g., IEC 63278[28]) for the operation of platforms for DTs. Initial concepts for standards for DTs for bridges have already been discussed for SHM in the IM-SAFE think tank, but no standards are yet required due to the flexibility for bridge structures. The initial impulse for this should derive from Industry 4.0.[108] Other research teams have proposed the establishment of standards for the interfaces and data formats, with the objective of improving the connectivity between the platforms, which is also supported by large construction operators.[68] It is notable that there is a considerable number of smaller mid-span bridges made of prestressed concrete that have been constructed using similar methods. To facilitate the networking of these structures with each other (e.g., as part of an Internet of Bridges[48]), it is essential to have a uniform standard for data exchange.

DFOS is an example of an incomplete sensor measurement chain, from data acquisition to the visualization of results and decision-making support. Pilot projects are underway in research into robust installation in concrete bridges, but no best practice has yet been established (Figure 5, data acquisition). The system is used, for example, to detect cracks and determine their width, for which algorithms already exist (Figure 5, data analysis, data visualization).[103,109] The decision has not yet been made as to whether this solution should be used for temporary or continuous SHM. For the latter, edge processing and the subsequent data transfer need to be developed (Figure 5, data edge processing). With the former, only the maturity level of a digital model is possible due to manual data transfer (Figure 1). This is the case with many big data applications, where a lot of application-related development work is still needed to make these technologies usable for DTs.

5 | CONCLUSION AND OUTLOOK

The concept of a DT is increasingly being referenced in the context of the digitalization of the construction industry. There is a general consensus on the definition of DT within the context of Industry 4.0, and they are already being actively utilized. The objective is to achieve the greatest possible automation and autonomization of product development, production and product maintenance. It is also the objective of constructional engineering, in particular that of bridge construction and operation, to encourage the development of DT toward scalable application maturity. Following a definition and the requirements for DT in the areas of Industry 4.0 and constructional engineering, these are merged. Publications on existing DT projects in both industries are then analyzed with regard to the requirements, definitions and elements as well as the data flow technologies used in them. The differences and similarities are highlighted in the discussion. A synopsis is presented of the technologies that have already reached a state of the art in Industry 4.0, and of the major challenges, such as location factors or data acquisition interfaces, that still need to be overcome in constructional engineering.

The transition to DT technology in an Industry 4.0 context for bridge structures is still a considerable distance away due to the lack of autonomous control possibilities for the bridge. Currently, the focus is on developing a supporting DT with data for predictive maintenance and decision-making in operation as a digital shadow. In the future, research will continue in the direction of digital technology for constructional engineering with test fields and pilot projects.

AUTHOR CONTRIBUTIONS

Conceptualization: J.W. and T.B. Methodology: J.W. Validation: J.W. and T.B. Formal analysis: J.W. Investigation: J.W. Resources: T.B. Data curation: J.W. Writing—original draft preparation: J.W. Writing—review and editing: T.B. and J.W. Visualization: J.W. Supervision: T.B. Project administration: T.B. and J.W. Funding acquisition: T.B.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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