Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects

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***Abstract*—Digital Twin (DT) is an emerging technology surrounded by many promises, and potentials to reshape the future of industries and society overall. A DT is a system-of-systems which goes far beyond the traditional computer-based simulations and analysis. It is a replication of all the elements, processes, dynamics, and firmware of a physical system into a digital counterpart. The two systems (physical and digital) exist side by side, sharing all the inputs and operations using real-time data communications and information transfer. With the incorporation of Internet of Things (IoT), Artificial Intelligence (AI), 3D models, next generation mobile communications (5G/6G), Augmented Reality (AR), Virtual Reality (VR), distributed computing, Transfer Learning (TL), and electronic sensors, the digital/virtual counterpart of the real-world system is able to provide seamless monitoring, analysis, evaluation and predictions. The DT offers a platform for the testing and analysing of complex systems, which would be impossible in traditional simulations and modular evaluations. However, the development of this technology faces many challenges including the complexities in effective communication and data accumulation, data unavailability to train Machine Learning (ML) models, lack of processing power to support high fidelity twins, the high need for interdisciplinary collaboration, and the absence of standardized development methodologies and validation measures. Being in the early stages of development, DTs lack sufficient documentation. In this context, this survey paper aims to cover the important aspects in realization of the technology. The key enabling technologies, challenges and prospects of DTs are highlighted. The paper provides a deep insight into the technology, lists design goals and objectives, highlights design challenges and limitations across industries, discusses research and commercial developments, provides its applications and use cases, offers case studies in industry, infrastructure and healthcare, lists main service providers and stakeholders, and covers developments to date, as well as viable research dimensions for future developments in DTs.**

***Index Terms*—Digital Twin, Digital Transformation, Smart Manufacturing, Industry 4.0, Structural Health Monitoring, 5G.**

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This work was supported in part by a UK India Education and Research Initiative (UKIERI) grant, ID 'DST UKIERI-2018-19-011', and in part by an Institutional Links grant, ID 429715093, under the Newton Programme Vietnam partnership. The grant is funded by the UK Department of Business, Energy and Industrial Strategy (BEIS) and delivered by the British Council.

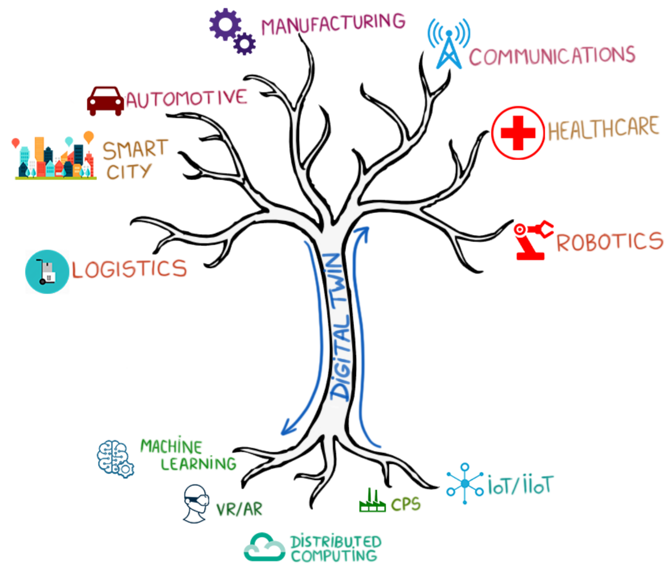

Fig. 1. The Digital Twin's central role in the Industry 4.0 era.

I. Introduction

THE Fourth Industrial Revolution is in full bloom, and the current global Covid-19 pandemic has even further accelerated the digital transformation by several years. The travel restrictions, lockdowns, and pending economic decline have forced industry executives to adapt their business prospects and shift their focus from saving costs to increasing investments in digital development [1]. Additionally, the global viral outbreak has imposed a dynamic uncertainty upon the economic world, and companies found themselves compelled to cope with and quickly adapt to ever-changing conditions and restrictions in order to survive or even rise above the circumstances [2]. However, even before the sanitary crisis, the efforts towards digitalization were considerable. Cisco published their annual Internet report in the first fiscal quarter of 2020, and they predicted a significant growth in worldwide Internet users (66% of the population in 2023, compared to 51% in 2018), networked devices (3.6 devices per person in 2023, as opposed to 2.4 in 2018), and reduced communication latency that encourages the development of real-time interactive applications [3]. This forecast expansion of Internet coverage, speed, and connections is giving way to an increased rate of information dissemination, availability, and accessibility, as well as growing opportunities of development and innovation.

The goals of Industry 4.0 (I4.0) align perfectly with this fast-paced and continuously-evolving digital transformation. I4.0 aims to automate all the traditional, bare-metal industrial practices, and it hopes to do so by bringing as much of the of the equipment from the physical space into the virtual domain. And this is where Digital Twins come into play. DTs emerged as an experimental technology set to enable replication of elements, functions, operations and dynamics of physical systems into digital world, with better control at testing, analysis, prediction and hazard prevention for sensitive processes. However, the supporting technologies, until recently, were not advanced enough to develop DTs for complex systems or systems-of-systems. The recent developments in Machine Learning, Artificial Intelligence, data integration Virtual/Augmented Reality, sensing, security, cloud storage, Transfer Learning, data visualization and ultra-reliable low latency communications (uRLLC) have enabled the implementation of the DT and its extended applications across several industries. A technology thought to be capable of dealing with isolated operations and processes, the DT can now offer potential applications eventually replicating the processes, elements, dynamics, firmware, connections and operations of physical systems in digital world. Figure 1 illustrates the DT as a supplier of various services across industries in I4.0.

The formation of a mirror image of a physical system in the digital world offers unlimited possibilities. Interlinking the physical and digital systems through seamless data transfer allows the virtual system to exist simultaneously with the physical system. Real-time data communications between the physical and digital systems enable a synchronized and coherent operation of the real and virtual counterparts. Once in the digital domain, optimized learning, information transfer, analysis, visualization, optimization and planning can easily be incorporated to see the potential improvements with suggested changes. Thus, the DT can be used effectively to assess, observe and validate the physical system, suggest changes and visualize the potential improvements. Previously deemed as an impossibility, DTs have arisen as one of the key technologies with potential to reshape the future.

This survey paper aims to shine light on the recent advancements in the DT paradigm by reviewing the relevant literature published over the last few years, in order to establish a common understanding of this technology, explore its market potential and trends, enumerate its most prominent enabling technologies, offer an in-depth look at several applications, frameworks, and case-studies that have been thoroughly documented, and finally discuss and share the learned lessons and remaining challenges of this technological pacesetter.

A. Background and Motivation

The Digital Twin gained traction in 2002, after Michael Grieves held a presentation at the University of Michigan, which was entitled “Conceptual Ideal for Product Lifecycle Management”. The original slide containing the proposed concept was reproduced by Grieves and Vickers in [4] and it can be noted that the early architecture of what would later become the DT consisted of three main components:

- the *real space*,
- the *virtual space*,
- the *link* serving as a communication medium between the two spaces.

The implications of this idea were revolutionary for the manufacturing industry, and other economic domains would later pick up on this as well. The most important advantage of the original DT was the conjoined lifetimes of the real and virtual entities, starting from the creation of the pair, and ending in their disposal. This feature suggests that the virtual asset would, at all times, mirror the most recent representative characteristics of the physical system, allowing remote monitoring throughout the whole lifetime of the physical object. As such, while it was initially intended as a tool for monitoring the lifecycle of a manufactured product, academia and the industry soon realised that the DT concept can be fruitfully applied to other economic domains as well.

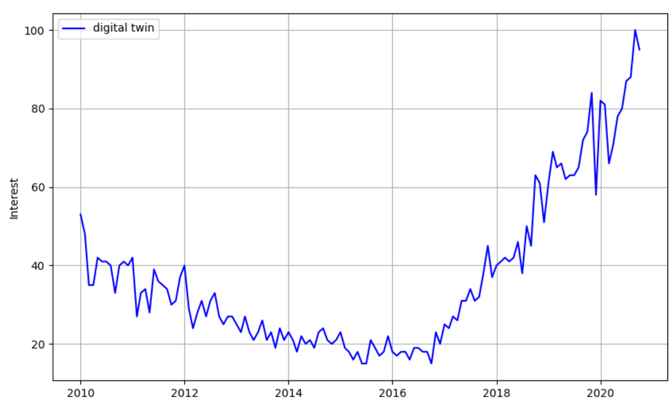

Fig. 2. Interest trend in Digital Twin as seen through Google searches.

As a result of this realisation, research output has surged and interest and representation of the digital twin has grown. Figure 2 shows the global trend of interest into the term “digital twin” as expressed via the normalized number of Google searches across the last 11 years, and it can be noted that the last few years have drawn increased attention to the concept that Michael Grieves introduced back in 2002. The “interest” shown on the Y-axis takes values between 0 and 100, where a value of 100 denotes the highest popularity the search term has seen during one month of the given time window, and a value of 50 represents half of that maximum popularity.

While the Google Search trend is a representation of the DT’s increasing general popularity across the years, it is important to assess and understand how this growing attention has been reflected in the research output throughout the same time period. In this regard, we analysed the number of publications within the Scopus document database that included the phrase “digital twin”, for each year in the last decade. Figure 3 shows the results of this analysis and, indeed, it can be noted that increasing attention has been allocated to the research and development of this revolutionary paradigm as well. The bar plot shown in Figure 3 is the result of leveraging the Scopus Search API to search for articles that contain the specific phrase “digital twin” in their abstracts. While not all of the found articles might have been devoted entirely to the DT concept, it is still noteworthy that more and more academics have taken some level of interest in the technology over the years. It is also important to mention that the search was accomplished via the "pybliometrics" package of Python, developed by Rose and Kitchin [5].

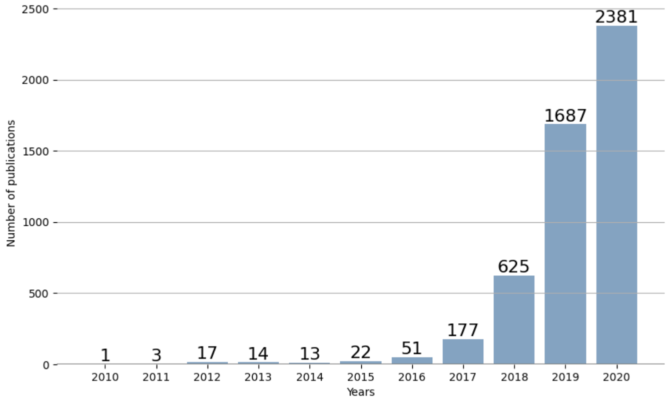

Fig. 3. Number of articles in the Scopus database whose abstracts contain the phrase "digital twin" across the years.

B. Related Surveys

There is currently a considerable number of publications across literature that are dedicated to advance the concept of a DT. In fact, there are so many articles that academics have also put out a number of survey papers that were designed to review the state-of-the-art in DT development, illuminate fellow innovators on possible research gaps, questions and directions, as well as guide the industry towards possible DT use cases that might generate significant business value in their specific domain. This work aims to complement the other existing survey efforts and facilitate a complete understanding of the DT, with its definitions, enabling technologies, applications, and detailed use-cases and case-studies.

As such, Table I displays a comparison between a collection of other survey articles covering comprehensive DT-related literature, and the survey paper at hand. Table I puts in contrast the contributions of this paper with other surveys', in order to highlight the novelty brought by the work at hand. The findings of this study are analysed below in more detail.

Barricelli et al. [6] propose a study on the DT's definitions, characteristics, applications, and design implications. The paper provides full coverage of the DT's evolution, from Michael Grieves' concept to the state-of-the-art at the time of its publishing. The authors set out to answer three research questions, regarding the various definitions that the DT has accumulated across the years, the paradigm's main characteristics (feature selection and extraction, that facilitate the DT-characteristic Big Data analysis, pattern recognition and ML, predictive and prescriptive analytics, etc.), as well as the main domains where the DT had been applied at the time of writing. In particular, the authors detail several DT implementations across three different application domains: manufacturing, healthcare, and aviation. The paper ends with the design implications and challenges that developers should take into account when considering such a system. In contrast, this work's goal is to expand Barricelli et al.'s contributions by additionally discussing the market potential of the DT, going into further details on the technologies that enable a DT's characteristics, and also providing a closer look at possible use-cases in different industry domains.

Minerva et al. [7] proposed a comprehensive survey on the architectural models of a DT, and they also discussed the technical features of this concept (or, in other words, the technical "must-haves") that consolidate the DT definition. The paper surveys different DT characteristics that were highlighted in literature pertaining to various technological and industrial domains, like manufacturing, AR/VR, multiagent systems, virtualisation, and especially IoT. Additionally, the authors applied proactive thinking and evidentiated some other important characteristics of the DT that are often overlooked in other research works, like data ownership, contextualisation, augmentation, servitisation, etc. The paper covers the value of the DT concept, including its market potential, before diving into various detailed use-cases, like the digital city and the digital patient. The survey ends with a consolidated DT architectural model and illuminates the upcoming challenges. While the article proposed by Minerva et al. contours the definitions, enabling technologies and applications of a DT, it does not go into details about which technologies can be integrated into the DT in order to build those applications. The survey at hand will attempt to fill that gap.

Löcklin et al. [8] published a survey paper that tackles the DT's use for verification and validation (V&V) purposes. The authors mention that there are multiple DT definitions in the literature, before settling on one definition that makes a distinction between the Digital Twin, which is mainly referred to as a tool for monitoring, verification and validation, and the Intelligent Digital Twin, that can provide meaningful feedback to its corresponding asset based on the acquired data. Furthermore, the survey is conducted around three research questions that tackle how the DT can enable verification and validation, the industrial domains where the DT is used for V&V, and a classification of modalities in which the DT is leveraged in the reviewed papers. As the title of the survey suggests, it is dedicated to studying the application of verification and validation within multiple industrial domains.

Biesinger et al. [9] conducted a survey on the necessity of a DT in the automotive industry's integration planning processes. Unlike the previously presented articles, which focused on reviewing scholarly works, this study has been conducted by interviewing 22 production planners from various automotive manufacturing companies. The scope of the paper, which is a case-study by itself, covers the demand of an easily accessible and configurable DT for the specific use-case of integration planning. As such, it is a great indicator of the market potential that the DT has in this industrial sector, but it does not delve into the possible solutions or enabling technologies that could help implement a DT that is compliant with the definitions that the authors provide in their work.

He et al. [10] proposed a survey focused mostly on the monitoring and surveillance capabilities of the DT, and their

TABLE I
COMPARISON BETWEEN THIS SURVEY PAPER'S CONTRIBUTIONS AND OTHER RELATED WORKS IN THE LITERATURE.

Literature \ Contributions	Definitions	Market Potential	Enabling Technologies	Applications	Case Studies	Challenges
[6]	✓✓	×	✓	✓✓	×	✓✓
[7]	✓✓	✓	✓	✓	✓✓	✓✓
[8]	✓	×	×	✓	×	×
[9]	✓	✓✓	×	×	✓	✓✓
[10]	×	×	✓	✓	✓✓	✓✓
[11]	✓	×	✓	✓✓	✓✓	✓✓
[12]	✓	✓	✓✓	✓✓	×	✓✓
[13]	✓	✓✓	✓	✓✓	×	✓✓
[14]	✓	×	✓✓	✓✓	×	✓✓
[15]	✓✓	✓	✓✓	✓✓	×	✓✓
This survey	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓

✓✓- in-depth coverage of the subject;
✓- partial coverage of the subject;
× - subject not addressed.

provided definition ("a dynamic digital replica of physical assets, processes, and systems, which comprehensively monitors their whole lifecycle") reflects this aspect of the study. Although the authors do not emphasise the full extent of the DT definition, they do present the technologies that enable the DT to become an avant-garde methodology for the specific application of surveillance. The survey concludes with an industrial use-case of the DT, dubbed Pavatar, and presents the technical advantages and challenges of implementing this project for an ultra-high voltage converter station.

Pires et al. [11] present a compact review of the DT's definitions, enabling technologies, and applications, ending the paper with the exemplification of a case-study of the DT and the challenges the concept will face before the industry integrates it into its businesses. The authors also provide a look at on-going research efforts towards building a DT for a UR3 collaborative robot. The manuscript at hand aims to complement this work with a wider array of references and case studies.

Rasheed et al. [12] created a comprehensive DT survey that analyses the paradigm from the perspectives of its value (expressed via services and software platforms), applications, enabling technologies, and challenges. The paper brings together works from various domains where the DT has been tried and tested, as well as potential socio-economic impacts that such a technology can have (i.e., loss of jobs, training new workforce in DT specifics).

In [13], Tao et al. introduce a thorough analysis of 50 papers and 8 patents related to the DT. The authors cover the concept of DT via a study of four perspectives: interaction and collaboration between its constituents, data fusion, services, and DT modeling and simulation. Then, the authors describe the DT's applicability in three main areas in its most prominent industry, the manufacturing sector: DTs for product design, for production, and for prognostics and health management. As such, the paper draws its lessons from articles that are mostly focused on the state of the art of DTs in the manufacturing industry.

In [14], Huang et al. put together a detailed survey on the AI-driven DTs in the context of smart manufacturing and advanced robotics. The authors take into consideration the advantages of using a DT as a driver for sustainability goals in the manufacturing and robotics, by facilitating production planning and control, quality control, dynamics control, predictive maintenance, and many other services. Additionally, the authors focus on describing how AI techniques specifically enable DTs across these two domains.

Finally, Fuller et al. in [15] propose an extensive survey on DT, with a focus on its integration with IoT and data analytics technologies. The paper also points out that there is a need for a stable DT definition that consolidates all of the aspects that make up a true DT. Afterwards, the survey goes on to discuss

TABLE II
LIST OF ACRONYMS

Acronym	Description	Acronym	Description
AGV	Automated Guided Vehicle	LOF	Local Outlier Factor
AI	Artificial Intelligence	LSTM	Long Short Term Memory
ANN	Artificial Neural Network	ME-GP	Mixture of Experts and Gaussian Processes
AR	Augmented Reality	MES	Manufacturing Execution Systems
ARIMA	Autoregressive Integrated Moving Average	ML	Machine Learning
AUC	Area Under Curve	MQTT	MQ Telemetry Transport
BIM	Building Information Modelling	MR	Mixed Reality
BOCD	Bayesian Online Change-point Detection	O&M	Operations and Maintenance
CNC	Computerized Numerical Control	OPC	Open Platform Communications
CNN	Convolutional Neural Networks	OPC-UA	OPC - Unified Architecture
CoAP	Constrained Application Protocol	OSA-CBM	Open System Architecture for Condition-Based Maintenance
CP-Lab	Festo Cyber-Physical Factory	PCA	Principal Component Analysis
CPPS	Cyber-Physical Production Systems	PCB	Printed Circuit Board
CPS	Cyber-Physical Systems	PdM	Predictive Maintenance
DA	Diagnostic Analytics	PER	Prioritized Experience Replay
DBSCAN	Density-based Spatial Clustering of Applications with Noise	PLC	Programmable Logic Controller
DCNN	Deep Convolutional Neural Networks	PPO	Proximal Policy Optimisation
DDQN	Double Q Network	RL	Reinforcement Learning
DL	Deep Learning	RNN	Recurrent Neural Network
DNN	Deep Neural Network	ROI	Return On Investment
DoS	Denial of Service	RUL	Remaining Useful Life
DQN	Deep Q Network	SDOF	Single Degree of Freedom
DRL	Deep Reinforcement Learning	SHM	Structural Health Monitoring
DT	Digital Twin	SOA	Service Oriented Architecture
GA	Genetic Algorithms	SSAE	Stacked Sparse Autoencoder
HMI	Human-Machine Interactions	STDT	Socio-Technical Digital Twins
I/IoT	(Industrial) Internet of Things	TL	Transfer Learning
I4.0	Industry 4.0	uRLLC	Ultra-Reliable Low Latency Communications
IHSC	Industrial Hemp Supply Chain	V2X	Vehicle-To-Everything Communications
KNN	K-Nearest Neighbour	V&V	Verification and Validation
KPI	Key Performance Indicator	VR	Virtual Reality

the DT, its enabling technologies, and applications in three main use cases: smart city, healthcare, and manufacturing. The manuscript at hand aims to complement the aforementioned articles in providing a complete view of the DT.

C. Survey Contributions

To complement the previous works, this work provides a comprehensive survey on the DT concept, the enabling technologies involved, the applications and use cases for deploying DTs across various industries. The main contributions of this survey paper are summarized as follows:

- Overview of the DT definitions from the literature;
- Comprehensive discussions on the market potential of DT;
- The enabling technologies for DT are surveyed, such as: ML, cloud, fog and edge computing, IoT/IIoT, Cyber-Physical Systems, VR/AR, and modeling technologies;
- Existing solutions of DT frameworks are reviewed across three use cases examples, namely: smart factory, infrastructure, and future directions for 6th Generation Mobile Networks (6G). Then, we take a closer look at two DT services, irrespective of use case: anomaly detection and predictive maintenance;
- Three real use cases of DTs as applied to tea industry in India, Festo Cyber-Physical Factory in the United Kingdom, and structural health monitoring for Vietnam bridges are discussed in details;
- Lessons learned, remaining open challenges and future directions of DTs are identified.

D. Survey Structure

This survey paper is organized as follows: Section II provides a review and comparison of the existing DT definitions across the recent literature covered in this paper, as well as our own comprehensive DT interpretation, Section III evaluates the DT's potential for market adoption and current trends in DT development, Section IV delves into some of the most prominent DT enabling technologies and reviews how other researchers used them to build working DTs, Section V explores various DT frameworks and applications proposed in the literature, Section VI takes a closer look at three DT case studies, Section VII draws the lessons we learned throughout this survey, establishes the current challenges that

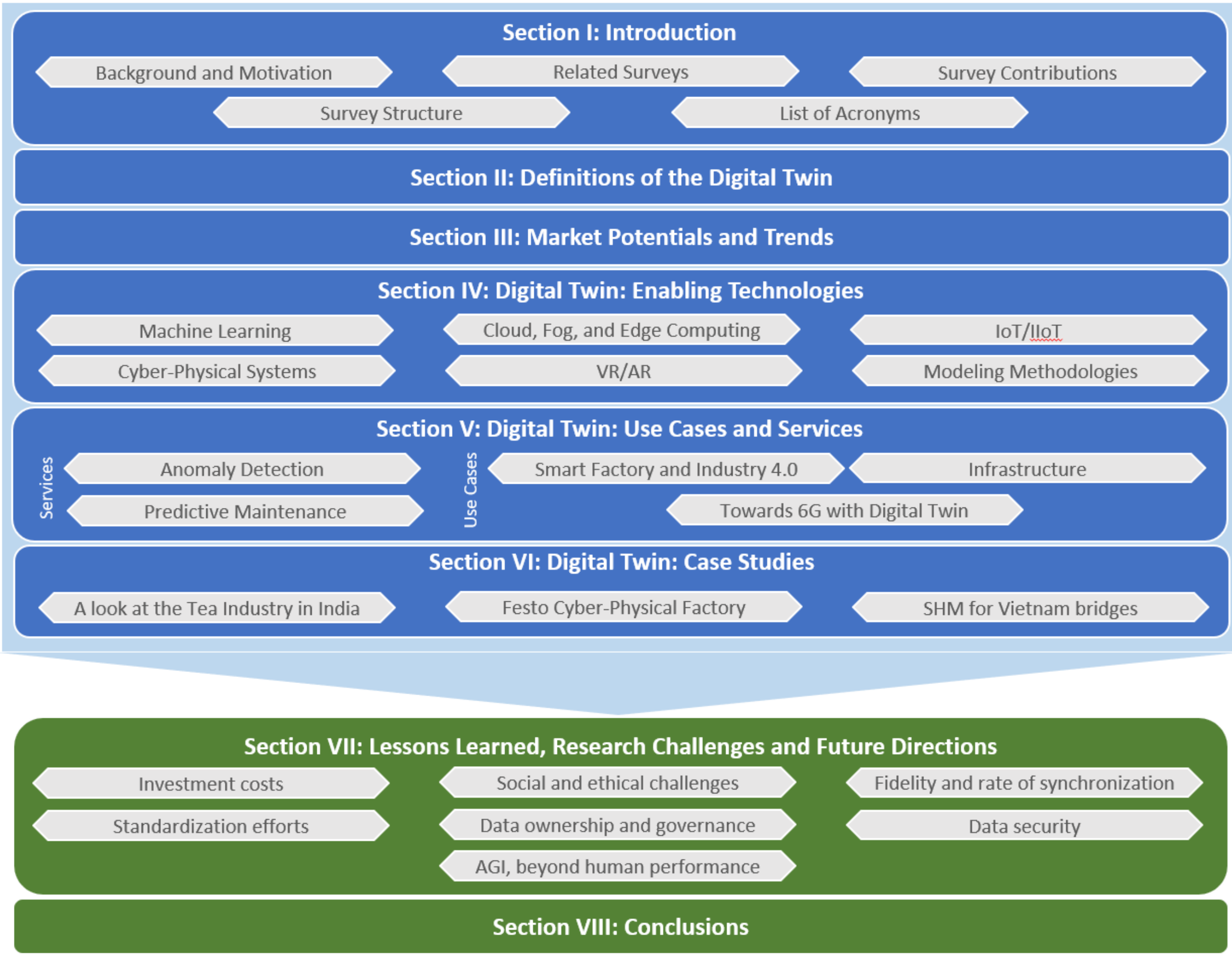

Fig. 4. An overview of the survey paper's contents.

the DT faces, and contours possible future directions, and finally Section VIII summarizes the conclusions of this paper.

An overview of the organization and structure of this paper is illustrated in Figure 4. Table II provides a list of abbreviations used in this article.

II. Definitions of the Digital Twin

The Digital Twin is not a new paradigm. The premises that initiated its advancements have been introduced more than 50 years ago, amongst NASA's many efforts of bringing man in space. Indeed, the idea of virtually simulating real-life scenarios that would normally require extensive resources could not have had a more appropriate origin than NASA's early space programme, where high-fidelity (relative to the technology standards at the time) simulators were used to train astronauts for their upcoming remote journeys in the outer space. But, surely, there is more to DTs than just simulation, so the true precursor of this paradigm actually came to light during NASA's Apollo 13 [16] mission, when an unexpected explosion caused a manned spacecraft to deviate from its intended trajectory, endangering the astronauts on-board. In response, the ground-based Mission Control was then tasked to urgently simulate, in almost real-time, the erratic behaviour of the spacecraft, and make optimal decisions to ensure its safe return on Earth, in ever-critical conditions. The engineers used the available spacecraft simulators, animated them with real data coming from the space-bound physical ship and its pilots, analysed possible scenarios, then communicated optimal instructions to the stranded pilots to maneuver their ship back home safely. The mission was a success.

Michael Grieves, in 2002, proposed a similar idea as a means to drive forward the Product Lifecycle Management paradigm (PLM), although, back then, he had not dubbed it as "digital twin", but as "Mirrored Spaces Model". This precursor of the DT consisted of the same three main pillars that lie at the base of this technology today: real space, virtual space, and the communication thread between them.

In the case of the Apollo incident, the real space was represented by the physical spacecraft stranded in space, the virtual space consisted of the ground-based simulators, and the link between the two was characterised by the continuous communication between the Mission Control, the spacecraft, the engineers, and the pilots. It was indeed the DT that saved the day back in 1970.

The actual definition of the DT has always been at least ambiguous, and the ever-growing number of publications in the last few years has only added to the diversity of DT meanings. It is generally observed, however, that the DT implementation attempts so far seem to have been accomplished with the support of a number of common enabling technologies, such as: ML [17], TL [18], distributed computing (i.e. cloud, fog, and edge computing) [19], the (Industrial) Internet of Things (I/IoT) [20], CPS [21], and VR/AR [22].

Consequently, to get a good grasp on the general understanding of the DT we analysed the recent literature on the DT definitions provided. The results indicate that the existing DT definitions seem to center around five approaches as summarised in Table III.

Each of the five definitions capture the essence of the DT, but there is not complete overlapping between them:

- The first definition is a very popular one, and arguably the oldest one, however it is very generic and it does not offer insight into the constituent parts of the DT.
- The second definition is more comprehensive, as it demystifies the DT and provides a bit of understanding regarding two of its components (the physical and digital objects). However, it claims that the DT is just an intelligent digital model of a physical asset, with little to no emphasis on the interaction between the two, its requirements, and limitations. Some works [23], [24], however, do make observations about the twinning rate (i.e. the rate of synchronization between the two objects), and mention that it is a requirement that depends on the DT's use case.
- The third definition completely ignores the bi-directional communication requirement of a DT, essentially confusing the DT with a *digital shadow*, which would more accurately fit that description.
- The fourth definition focuses entirely on the components of the DT, but it does not hint towards the capabilities of a DT, making the definition too generic.
- The fifth definition shifts its attention to the services provided by the DT, but not on its structure and technologies that enable said services.

To put the five definitions into a better perspective, we will work through a hypothetical example. Consider the DT of an autonomous car, where the virtual representation of the car is able to continuously communicate with the physical asset and become aware at all times of its state and environment in order to make appropriate control decisions. The use-case of autonomous driving imposes some strict requirements on the DT, the most obvious of which are: ultra-low latency communication between the real and virtual twins, large data storage capacity, high processing power to reduce data-to-insight delays, and high-fidelity virtual rendering of the car and its environment.

Now, seeing this example through the lenses of the five definitions, we would find that some of the above scenario's very important aspects are omitted. The first and third definitions claim that the DT only mirrors the life of its twin, so they do not envision the other half of the feedback loop between the two entities, where the DT itself can control the car based on its real-time data. The second definition comes close to describing our DT, except that it makes no mention of the DT's requirements that might differ from use-case to use-case: a DT of an autonomous car will need a higher rate of synchronization than the DT of an industrial water boiler, for instance. The fourth definition makes no mention of the DT's use-case at all, even though it is a deciding factor in the choice of enabling technologies and other requirements (a DT for lifetime monitoring of a car would not need a bi-directional communication medium, unlike a DT for autonomous driving). Lastly, the fifth definition focuses entirely on the use-case and the services the DT can provide, but the use-case's requirements and the DT components are only implied via the definitions of the services themselves, and not explicitly stated as DT characteristics.

It is thus clear that there is a need for a comprehensive definition of the DT. The definition needs to be specific enough that it identifies the components of a DT, how they interact, and what services it should provide, but also generic enough that it can describe DTs across multiple industrial domains and use cases.

As such, in this work, and many hereafter, we will refer to the Digital Twin as a self-adapting, self-regulating, self-monitoring, and self-diagnosing system-of-systems with the following properties: (1) it is characterized by a symbiotic relationship between a physical entity and its virtual representation, (2) its fidelity, rate of synchronization, and choice of enabling technologies are tailored to its envisioned use cases, and (3) it supports services that add operational and business value to the physical entity.

We believe that this alternative provides a better understanding of the DT concept, as it gives a precise indication of what the DT is (i.e., a system-of-systems), what its components are (i.e., physical and digital entities), how they interact (symbiotic relationship, i.e., a mutually beneficial two-way interaction), how their interaction is leveraged (i.e., to offer services that bring operational and business value), how accurate and synchronized the virtual asset should be, and what technologies should be used to build it (i.e., use case-dependent). Looking back on the DT example for autonomous driving, it is now clear to see which are the DT's components (the car and its environment are the physical asset, while their virtual model is the digital asset), that they interact through a bi-directional communication medium (one for collecting data from the real space, and another for delivering insights and commands from the virtual twin), that the DT is supposed to, in our case, assist the car in driving autonomously, and that this use-case implies some specific restrictions (low-latency, high security, etc.).

The fundamental characteristics of a DT, which are the motors that actually bring operational and business value to the physical entity, lie centrally in the DT philosophy. The "self-X" constructs distinguish a true DT from digital models and shadows, and emphasize the usefulness of a DT in I4.0. These traits are explained below:

- *Self-adapting* - a DT automatically reacts to changes in its real twin's environment and configuration, but it

TABLE III
THE VARIOUS DEFINITIONS OF DIGITAL TWINS FOUND IN THE LITERATURE.

Definition no.	Digital Twin is defined as...	References
1	"an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin."	[25]–[29]
2	a virtual representation of a physical asset, that continuously consumes data from the physical asset, processes it, then provides intelligent feedback to its real counterpart.	[23], [30]–[33] [24], [34]–[38]
3	an accurate digital representation of a physical asset, offering monitoring capabilities throughout the whole lifetime of its real twin.	[39]–[43] [44]–[48] [49]–[54]
4	the tuple formed by the following components: physical asset, virtual asset, and a bi-directional communication medium between the two.	[26], [55]–[57]
5	a collection of various services (e.g. monitoring, optimisation, predictive maintenance, etc.).	[58], [59]

should do so in a way that continually ensures operational excellence (i.e., as measured via use case-appropriate performance measures).
- *Self-regulating* - the changes a DT undergoes while adapting to its real twin's environment should not exceed the physical twin's own limitations for the sake of maximising its performance measures (e.g., productivity, throughput, etc.).
- *Self-monitoring* - the DT is always aware of its real twin's environment and configuration, by means of monitoring the parameters that are relevant to its use cases.
- *Self-diagnosing* - the DT should be able to assess its own health and know, based on its current and historical conditions, when and why it is no longer able to maintain optimal operations.

As such, a DT's services should enable it to be self-adapting, self-regulating, self-monitoring, and self-diagnosing, or, in fewer words, *self-evolving*.

III. MARKET POTENTIALS AND TRENDS

Academic research on the topic of DT has positioned it thus far as a central player in the race to I4.0. The widely-praised potential of the paradigm presents attractive opportunities and challenges that, once overcome, promise to bring benefits that far outweigh the costs. However, the issue of costs is more prominent in the industry than it is in the academia. While the DT is a versatile technology that can be successfully applied to various domains businesses still remain reluctant to implement the DT. That is because the Return On Investment (ROI) on a DT is difficult to quantify, since it is not a product that directly brings revenue, but rather a technology that aims to reduce and optimize costs. Nevertheless, this section will detail how the leaders in the DT market have leveraged its aptitudes, and whether their results predict a good omen for the future of the DT.

IBM [60], one of the top DT solutions providers, valued the DT market at USD 3.1 billion in 2020 [61], and predicted that the technology would see significant adoption and economic growth in the following years. Although they do admit that the creation of a DT is not always a sound financial investment, IBM's case studies show encouraging returns and cost optimisations for DT implementations in manufacturing and smart buildings. For example, ASTRI [62] used DTs to validate software packages before their deployment on the physical twin, reducing 30% of development costs and expediting deployment by 40%. University of California San Francisco [63] implemented DTs for a branch of the Mission Bay Hospital which helped engineers to reduce the diagnosis and repair process of the building's pipes from 2-3 days to just a few hours.

Another big player on the DT market is Ansys [64], who praise the DT as the bridge between equipment development and equipment operations, allowing manufacturers to monitor the behaviour of their product throughout its whole lifetime. Mecuris [65] have used Ansys products to develop a DT for tailor-made orthoses and prostheses development to reduce product testing costs. Similarly, Jet Towers [66] implemented DTs of modular wireless towers to reduce installation and design time by 80%.

General Electric [67] lead the DT market in the power systems industry, where their solution claims to reduce start-up time by 50% and maintenance costs by 10%, deliver up to \$5 million additional MWhr, and save costs on outages of up to \$150 million per year. In the telecommunications industry, Spirent [68] are taking the stage as the leading DT solutions provider for 5G networks. To optimise network design, testing, and deployment, Spirent propose leveraging the DT for use cases such as: cellular Vehicle-to-Everything (V2X) virtual drive testing, private 5G networks for smart factories, and testing and design for Communications Service Providers. Another Spirent report [69] praises the DT for its Predictive Maintenance (PdM) aptitudes in I4.0's smart factories, claiming to reduce machine breakdown by up to 70% and save up to 25% of maintenance costs [70].

A Markets and Markets report [71] highlights attractive growth opportunities in the DT market and stresses on the increasing need for PdM and business optimisation. The report also states that the market in North America recorded as high as \$1.32 billion, the largest share of the overall DT market in 2019, and it is projected to reach \$16.94 billion by 2026. The paper forecasts that the global DT economy is expected to grow from \$3.2 billion in 2020 to \$48.27 billion by 2026 with a Compound Annual Growth Rate of 58%. Another report by the Institution of Engineering and Technology [72] echos the idea that the DT market is on the rise, although it also mentions that industry-agnostic adoption at the time of publication amounted to only 5% of enterprises. Nevertheless, the authors are optimistic that the DT should pave the way to I4.0.

IV. Digital Twin: Enabling Technologies

Although it is often referred to as a piece of technology in and of itself, the DT can be more accurately thought of as a system-of-systems, a meld of several enabling technologies that construct an intelligent virtual representation of a physical entity and support a continuous two-way feedback loop between the twins. At the same time, the enabling technologies themselves can take many forms depending on the DT's use case. For example, although it is known that a communication medium is needed between the real and digital twins, the choice of the specific communication protocol is entirely dependent on the communication requirements of the DT's application. These being said, this section will explore the most common enabling technologies of the DT and provide insight into how researchers from various industries have chosen algorithms and frameworks that were fitting to their use cases.

A. Machine Learning

One of the advantages of DT is that it brings awareness (or intelligence, or understanding) to a physical asset that would otherwise lack it. Of course, we are not referring to the human understanding of "awareness" [73], but rather a new kind of specialized intelligence that is able to understand significant amounts of numerical data and draw domain-specific conclusions from it faster than a human expert could. Thus, the DT should be able to infer meaningful and actionable information from the data that is generated by its physical twin and its environment. In this scenario, ML techniques represent the foundation, or the brain, of a DT.

Across the reviewed literature, researchers have employed the whole array of ML algorithms types in their DT implementations: traditional ML [74], Deep Learning (DL) [75], supervised ML [76], unsupervised ML [77], classification ML [78], regression ML [79], Reinforcement Learning (RL) [80], etc.

The applications and choices of ML models encountered in this review are various and they depend on the use cases and services of the proposed DTs. However, since ML algorithms are ultimately used to solve optimization problems, one common approach is to employ data-driven models to minimise or maximise a given process parameter. For example, in [39], where the DT of a Mobile Edge Computing system had been implemented, a Deep Neural Network (DNN) was used to maximize energy consumption efficiency across the network based on features like user association and resource allocation. Similarly, the authors in [40] used Genetic Algorithms (GA) to predict the circumstances that would favour most devastating forest fires, such that they could be proactively prevented. In [55], four ML algorithms (Random Forest, AdaBoost, LightGBM, and XGBoost) were able to learn from the equipment's sensor data and optimise production yield in the petrochemical industry. The same approach is especially common in literature focused on RL, where the algorithm learns by trying to maximise a reward function. The reward that these models attempt to maximise could be product quality outcome [23] or other arbitrary mathematical reward functions [58].

Besides objective function optimisation, another application of ML within DTs is to make predictions about the future behaviour of the physical asset. In this context, Artificial Neural Networks (ANNs) have been used in [30] to predict future samples of the active power component based on historical time series data. However, ML models, and in particular DL methods, are generally perceived as black-boxes [81]. This is because they do not offer sufficient transparency into what is motivating their predictions. On the other hand, in DT applications, transparency is desirable, and often required (e.g., in applications such as fault identification and urgency classification [41], or anomaly detection and root cause analysis [82]). Thus, researchers have looked for ways of integrating both physics-based and data-driven models into the DT. On this note, the authors in [42] combined these two approaches to enable a prognosis service that predicts the future parameters of a physical asset, even though said parameters evolved at different time scales. As such, physics-based models were used to preprocess data coming from multiple time-scale data streams, while the ML models, Mixture of Experts and Gaussian Processes (ME-GP), combined the extracted information to predict future bahaviours of each time series parameter.

Another use case of ML in DT implementations is application security. Indeed, the authors in [56] proposed a DT for remote surgery services, and used neural networks to protect the crucial connection between the physical and virtual worlds, which has stringent requirements for availability and latency, by detecting and preventing Denial of Service (DoS) attacks. Whereas in other works, ML is used to bring intelligence to the virtual representation of a physical asset, the study conducted in [43] proposed Deep Convolutional Neural Networks (DCNNs) to create the digital replicas of fibrous materials from real and synthetic images, and this constitutes an example of ML being used to build DTs.

On the note of synthetic data creation, DTs can also be used to generate artificial training data for ML models [76]. Of course, for such models to be able to generalise well on real data, the distribution of the synthetic data they were trained with has to closely resemble the distribution of the real data from the test set [31]. This requires extremely accurate, and thus complex, simulation engines. A workaround for this challenge is offered by TL, where the ML model trained with artificial data can be adapted to perform good predictions on a real test set. TL requires that the distributions of artificial and real data be somewhat similar, such that only a small amount of real data is needed to make the model generalise well once deployed in production [44].

Another important use case of ML in DT implementations is remote control assistance. In scenarios such as remote surgery [83], [84] or space station maintenance [85], the DT can help bridge the distance between the operators and the physical twin. In the latter paper in particular, the authors proposed the Hierarchical Attention Single-Shot Detector Network (HA-SSD) for astronaut gesture recognition. The system is based on the popular MobileNet architecture [86] for fast and computationally inexpensive feature extractions, which could be easily deployed on chips with low processing power. Such a system is ideal for space station DTs where cameras and surveillance equipment can detect and monitor faces, human postures, gestures and body language.

Table IV summarizes the findings of integrating ML into DT. It can be noted that most of the efforts towards DT implementation come from the manufacturing industry. Concurrently, the versatility of the technology makes it a promising tool for other domains as well, such as civil engineering or robotics. It is actually the vast array of existing and up-and-coming ML and DL algorithms that grants the DT its versatility. At the same time, the DT's reliance on data-driven analytics imposes some challenges: (1) traditional ML models are actually built upon a sequence of carefully engineered functional blocks that are tailored to increase efficiency on the task at hand. Thus, designing such a pipeline can be a resource-expensive task; (2) on the other hand, end-to-end DL techniques remove some of that complexity, but they require significant amounts of data for training and tuning, while also offering no transparency into their predictions; (3) finally, on the note of training data, generative ML models can be used to create artificial data to compensate for the lack of real data. However this could also induce bias in predictions if the two distributions (i.e., real and synthetic) are not aligned.

B. Cloud, Fog, and Edge Computing

Depending on its use-case, DT can be used to mirror systems across the whole spectrum of complexity, from unitary elements, such as the movement axis of the Computerized Numerical Control (CNC) machine tool [87], to an entire fleet of aircraft [88]. The virtualisation of composite heterogeneous machines or services always requires heavy computational prowess. This demand, coupled with the DT's characteristic of real-virtual synchronisation, often calling for almost real-time responsiveness, illuminates a need for distributed and parallel computing. For this purpose and many others, cloud, fog, and edge computing are frequently encountered in DT-related literature. As such, this subsection will review how researchers have integrated distributed computing into their DT implementations, with an emphasis on the reason why this enabling technology was mandatory for the works' use-cases.

Table V highlights an overview of the papers reviewed in this subsection. It is noteworthy that our search indicated that distributed computing and DT have been conjoined in works mostly pertaining to the manufacturing sector. Even papers focusing on DTs for logistics are mainly created to help the logistics departments of the manufacturing industry, again showing that there is an overwhelming focus on DT development in this area.

The unison of cloud computing and DT creates a prosperous environment for complex simulations, multi-variable analysis, DL-based analytics, and Big Data storage. In this type of system, the cloud platform acts as the data warehouse and also provides heavy-processing capabilities, while the DT deals with synchronising the physical and virtual assets [25], [32], [45]. Additionally, a cloud platform allows the harmonious connection and hosting of the virtual counterparts of the heterogeneous subsystems that form a complex DT [33]. In the healthcare industry, the cloud represents a shared information platform between the medical service provider and the patients [26], while in the manufacturing domain it can serve as a common medium where enterprises can share data regarding the failure modes and maintenance needs of similar equipment to support DT-enabled Predictive Maintenance [89].

In applications that imply a great amount of data consumption and processing, even the cloud can become overwhelmed. To prevent this from happening, Hu et al. [90] reduce the cloud workload by using the MTConnect protocol and a new Knowledge Resource Centre to manage all communications with the cloud-hosted DT. Another approach to avoid over-dependence on the cloud is to use more forms of distributed computing (i.e, cloud, fog, and edge) to manage different layers of complex logistics and manufacturing systems [27], [34].

C. Internet of Things

As previously mentioned, the research communities of academia and the industry recognise the DT as a system formed by three functional blocks: the physical asset, its virtual counterpart, and the communication medium that binds them together. Any DT proposal that misses or does not envision the inclusion of any one of these three components is therefore not a real DT. In this section, the focus will fall on the role of the two-way connection between the digital and real twins, and the recent literature works that detail how this connection benefits the implementation of the DT. Table VI provides an overview of the articles discussed in this section, as well as their target domain and main contributions.

In this context, the Internet of Things and the Industrial Internet of Things are the main enabling technologies that can perfectly fit in-between the digital and real twins to converge virtuality and reality. These paradigms are at the center of I4.0 due to their ability to aggregate data from multiple heterogeneous data sources via disparate communication mediums to facilitate data mining and alaytics through distributed computing frameworks.

The main appeal of these technologies is represented by the IIoT devices, like smart sensors, RFID tags, and smart wearables, that are useful and cheap data sources [35] which can paint meaningful virtual reflections of reality that the

TABLE IV
OVERVIEW OF REVIEWED LITERATURE INTEGRATING ML INTO DIGITAL TWIN.

Domain	ML Algorithm	Reference	Use and advantages of Machine Learning
Manufacturing	Random Forests, AdaBoost, LightGBM, XGBoost	[55]	The four ML algorithms are used to improve the effectiveness and yield of productions in the petrochemical industry. In this comparison, the authors tackle latency issues in ML responsiveness, time lag issues, and frequency unification across time series data. The models are tested on real Big Data from the petrochemical industry.
	DCNN	[43]	Deep Convolutional Neural Networks are used to analyse uCT scans of reinforcement materials and classify their pixels accurately to create their digital material twins. The DCNN obtains better results than traditional ML.
	DCNN	[76]	The DT is used to generate automatically labeled virtual images to construct synthetic datasets for DCNN training. The model is adapted to classify real images via TL.
	SSAE-based DFDD	[31]	The DT produces artificial data to train a Stacked Sparse Autoencoder (SSAE) to learn the features with the highest weight on fault diagnosis and life prediction. Data coming from the real twin is used to retrain the model, which has integrated an Adaptation Layer to mitigate the differences between real and virtual data. The resulting model is called Digital Twin-assisted Fault Diagnosis using Deep Transfer Learning (DFDD).
	LSTM	[44]	A Long Short Term Memory (LSTM) network is trained with artificial data to detect anomalies in virtual space. It is retrained with few hours-worth of real data to detect anomalies in the real asset.
Networking	DNN	[39]	DNNs are used to optimize energy consumption efficiency based on various Mobile Edge Computing network parameters.
	ANN	[56]	Neural Networks are used to detect DoS attacks on the DT of a remote surgery environment.
Robotics	Natural DQN, DDQN with PER	[23]	Deep RL (Natural Deep Q Learning, Double Q Networks with Prioritized Experience Replay) algorithms were used to learn from both synthetic and real data to test various scheduling strategies in a manufacturing robot's processes to reduce down time costs, time, and other resources
	PPO-based DRL	[58]	Proximal Policy Optimisation-based (PPO) Deep Reinforcement Learning (DRL) was trained with virtual data from the DT of a robotic arm. The physical twin learned to complete given tasks thanks to its training in the digital space.
Civil Engineering	Quadratic Discriminant	[41]	The DT's underlying physics-based models generated synthetic failure data which the Quadratic Discriminant then classified in various urgency levels.
	ME-GP	[42]	Physics-based modeling, Mixture of Experts and Gaussian Processes were used to predict future machine states by analysing multiple time-scale time series data.
Electrical Engineering	ANN	[30]	Artificial Neural Networks are used to predict the time series samples of the active power component sensor based on historical data.
Fire Protection Engineering	GA	[40]	Genetic Algorithms are used to predict the environmental parameters that would favor devastatic fires, such that they could be proactively prevented.
Space Industry	HA-SSD and MobileNet	[85]	Gesture recognition models, such as HA-SSD, are proposed to remotely control physical robots on-board spacecraft.

cloud-based DT can interpret and analyse in order to reduce manufacturing uncertainty and complexity in fixed-position assembly islands [57], optimise the functioning of power equipment switchgear [24], provide PdM for automotive brake pads [46], and visualise in real time the stress endured by metal shelving brackets via Augmented Reality [47]. Other use-cases benefit from these technologies as well, since smart sensors and wearables can also be integrated in mobile equipment that people carry, urban infrastructure, and interior appliances. The richness of heterogeneous data that the IoT sensors bring can be used to virtualise and visualise cities, allowing structural simulations for hazards prevention [48], and to remotely manage safety issues in the workplace [28].

Concurrently, the IoT/IIoT brings more than just data to the DT system. In [91], the DT is built upon the traditional IoT framework, and it is split into two parts: one at the edge, and one in the cloud. Both essentially working also as the gateways that connect the two corresponding media of the IoT framework. Furthermore, while the IoT is a powerful enabling technology of the DT, the DT itself can also act as a supporting pillar for the IoT by providing a self-adaptive and self-integrating digital abstraction of the IoT devices to make the IoT framework resilient to dynamic changes [49], or by allowing virtual simulations of large sensor networks [50]. In the context of IIoT, equipping edge devices with ML solutions can be a challenging task due to the limited resources on the devices as well as the concerns about communications with the cloud (low latencies, raw data privacy). As such, the authors in [93] proposed building a DT of the Edge Network that was able to leverage Federated Learning (FL) to re-train aggregated models locally, on edge devices (thus avoiding raw data transmissions), as well as optimize communication efficiency using the DT's updated mirroring of the network. For additionally improved communication security for the previously reviewed framework, the authors in [94] proposed using the blockchain technology to store the aggregated model parameters of the edge devices on the Base Station, making the FL process even more robust to data privacy issues.

Another aspect that IoT contributes with into the DT development is that it provides a platform that can understand and translate data from multiple protocols. IoT devices are usually built with certain communication standards in mind, like MQTT, CoAP, MTConnect [90], OPC-UA [35], or 5G uRRLC [92], and IoT is a bridge that connects those standards with the higher-level abstraction that is the DT. The choice of IoT devices, communication protocols, and IoT platforms can influence a very important characteristic of the DT: the synchronization rate between the real and virtual twins. We have established before that this synchronization rate will depend on the use-case of the DT. For time-sensitive applica-

TABLE V
OVERVIEW OF REVIEWED LITERATURE INTEGRATING DISTRIBUTED COMPUTING INTO DIGITAL TWIN.

Domain	Distributed Computing	Reference	Use and advantages of distributed computing
Manufacturing	Cloud	[25]	The cloud performs heavy processing tasks while the DT provides the most recent state of the physical asset.
	Cloud	[33]	The cloud platform hosts the DT and allows the interconnection of its heterogeneous subsystems.
	Cloud	[89]	The cloud performs heavy processing tasks and provides a shared medium for multiple enterprises to pool maintenance data into.
	Cloud	[90]	The cloud provides computing power with timely responsiveness enabled by the MTConnect protocol for DT communications.
	Cloud, Edge	[27]	Edge computing pre-processes data and handles small tasks, while cloud computing deals with more demanding analytics.
Logistics	Cloud	[32]	The cloud performs heavy processing tasks while the DT provides the most recent state of the physical asset.
	Cloud, Fog, Edge	[34]	All distributed computing forms are used for timely layered management of complex logistics system.
Healthcare	Cloud	[26]	The cloud connects the medical services provider with the patient, for real time access to health analytics.
Automotive	Cloud	[45]	The cloud performs heavy processing tasks while the DT provides the most recent state of the physical asset.

TABLE VI
OVERVIEW OF REVIEWED LITERATURE INTEGRATING IOT/IIOT INTO DIGITAL TWIN.

Domain	Reference	Use and advantages of IoT/IIoT
Manufacturing	[35]	IoT devices used as a cheap alternative to legacy sensing equipment to feed data into the DT.
	[57]	IoT devices used to adapt the DT to the dynamic nature of the structure of fixed-position assembly islands.
	[24]	Industrial Internet used to synchronise the virtual and real assets, as well as carry Big Data.
	[91]	The IoT traditional framework serves as a reference for the development of the Digital Twin.
Any domain	[47]	IIoT devices provide data and connectivity to support DT and AR-based real-time monitoring.
	[49]	The DT serves as an enabling technology for the self-adaptive and self-integrating Elastic IoT.
	[50]	The DT is an enabling technology for IoT, to allow virtual simulations of large sensor networks.
	[92]	5G's uRLLC is used to connect the digital and real twins, providing reliability, efficiency, and low latency.
	[93], [94]	The DT is used together with Federated Learning to improve communication efficiency across a network of IIoT edge devices.
Automotive	[46]	The IoT platform, ThingWorx IoT, is used to facilitate real-time data acquisition and feedback between twins.
Smart City	[48]	IoT devices and platforms play a central role in transporting and unifying rich, heterogeneous data between twins.
Logistics	[28]	IoT devices used as an alternative to GPS for indoors location services, supporting a DT in achieving 96.5% accuracy in identifying anomalous behaviours in workers.

tions, ranging from remote healthcare to traffic management in smart cities, the communication link between the two entities should include secure uRLLC, while other use-cases where synchronization latency is not necessarily a problem, like rarely-used manufacturing equipment, this requirement is not so stringent.

D. Cyber-Physical Systems

With the advancement towards the digitisation of conventional physical systems, the term Cyber-Physical Systems has gained ample attention from the academia and industry. However, in the literature works surveyed in this paper, we have found that there are at least two definitions that fall under the span of the CPS abbreviation, and while they are quite similar in meaning, they still represent different concepts.

In the original vision of CPS, they represent the ubiquitous and holistic convergence between real complex systems of heterogeneous systems and their virtual intelligent control instances. The physical space is represented by an ecosystem of physical equipment, sensors, actuators, and human operators that labor together towards the same goal. The cyber elements are the virtual representations of the physical components and they offer a layer of intelligence that provides self-configuration, self-adaptation, and self-preservation to each physical instance, to ensure that the ecosystem is resilient to changes and failures that would affect its ability to reach its goals (this paradigm is sometimes referred to as Cyber-Physical Production Systems (CPPS) [95]). In other words, this definition of CPS envisions them as a system of inter-connected DTs so, in this sense, the DT is an enabling technology for CPS. This interpretation of CPS leaves a blurry boundary between CPS and DTs, as they boast similar features and advantages and represent the smooth convergence between reality and virtuality. To clear confusion, a study detailing a comparison and correlation between the two paradigms has been conducted in [36].

The second meaning of CPS is more down-to-earth. In the literature, CPS sometimes refers to physical systems with varying levels of complexity that are equipped with built-in sensors, actuators, networking and computation capabilities, and that are controlled digitally via computer-based algorithms. It is clear that such CPS, compared to the ones in the previous definition, require a lower level of intelligence and digitalization. However, they do represent an enabling technology for the DT, given that they are I4.0-ready physical equipment that are proficient in reliable data acquisition, process optimization with feedback inputs, and improved built-in monitoring and control capabilities. Such CPS are an asset for DTs to gather data securely from the physical processes and perform regulatory control operations at the edge.

In the works that reference the first definition of CPS, the authors rely on a generic architecture of CPS onto which they build the DT [59], [51]. As such, the DT makes use of the CPS-specific Service-Oriented Architecture (SOA) and act as Cyber-Physical System Nodes [29] in the virtual ecosystem, or it assures managerial independence of heterogeneous interconnected systems [37].

The articles that interpret CPS according to the second definition provided above use the computer-controlled system as the physical counterpart of a virtual twin. These works dive deeper into the implementation of adaptable DT simulations via Functional Mock-up Units [52] or GA for scheduling optimization [53]. Others use the CPS-integrated Manufacturing Execution System (MES) software as a downlink between the virtual twin and the physical CPS [38], or leverage the DT to facilitate, control, and monitor highly complex material flows [54].

Table VII summarizes the contributions and advantages of the literature works revised in this subsection. Again, the bulk of CPS-integrating DTs comes from the manufacturing industry, where significant efforts have been made to turn conventional factory equipment into CPS by populating them with sensors and connecting them to their virtual twins that generate intelligent insight. The SOA, which is a founding principle of CPS, serves as a decoupling strategy that allows DT services to interact independently and efficiently.

E. Virtual Reality and Augmented Reality (VR/AR)

The Digital Twin's goal of virtuality and reality convergence seems to perfectly align with the driver behind two developing technologies: Virtual Reality and Augmented Reality. Indeed, VR aims to improve Human-Machine Interactions (HMI) via 3D computer-generated simulations with which the user can intuitively interact through wearable electronic devices. In other words, VR can help immerge human operators into a digital environment. On the other hand, AR technologies make use of wearable devices render 3D digital images onto a real-world background. In essence, AR helps bring virtual information in a physical environment. This section will explore how researchers have leveraged these two cutting-edge technologies to drive forward the DT paradigm.

In the healthcare industry, Laaki et al. [56] created a DT of a remote surgery environment. The virtual representation of the medical equipment in a given location can be accessed via VR by health professionals from a remote location. In turn, wearable devices (head-mounted displays) allow the doctors to control a virtual robotic arm that operates on a dummy patient. The DT then synchronizes the real and virtual twins of the robotic arm, such that the user can directly and intuitively control the physical asset via its DT.

Besides immersive and remote control of the real twin, VR also enables human operators to interact with the virtual twins of industrial equipment as they normally would with the equipment itself, without interrupting the normal functioning of the real entities. As such, engineers can devise new deployable Circular Economy strategies to be implemented on the real twin once thoroughly tested in the virtual world [96], create high-quality artificial training sets for safety training in scenarios where real data acquisition is risky or costly [97], or have students and trainees learn how to operate the physical twin by immersively interacting with and practising on their DTs [98]–[100].

AR technologies can facilitate quick access to the DT interfaces of real entities by superimposing their virtual data and images onto the camera feed [101], when the camera is pointed at the physical twin itself [102]. This feature allows human operators to dynamically monitor DTs, without having to go out of their way and connect to the computer that hosts them.

According to one study [103], the VR/AR-enabled DT can address three current challenges in HMI development: high-fidelity virtual representations of physical assets, availability of both real and simulated data, and intuitive interfaces for human operators. However, for a complete merge between the real and virtual worlds, neither technology is enough by itself. Both technologies allow the user to interact with the virtual representation of a physical entity, but they do not allow the real and virtual surrounding environments to interact with each other. For such cases, Mixed Reality (MR) technologies combine the advantages of both VR and AR, to bring digital models in the physical world and simulate their processes under real circumstances [104]. Table VIII summarizes the main findings of this review, highlighting the main domains where VR/AR/MR technologies have enabled the DT to provide immersive HMI, training and monitoring.

F. Modeling Methodologies

While not an enabling technology in-and-of-itself, the umbrella of modeling methodologies covers a great range of frameworks and software meant to guide developers towards building a core component of the DT: the virtual representation of the physical entity. Similarly to the DT definitions, the modeling approaches also vary greatly across the literature, that some researchers concluded that there is no consensus on the subject [13], [105]. The challenge to overcome here sits in the interdisciplinary and use case-specific nature of the DT. It

TABLE VII
OVERVIEW OF REVIEWED LITERATURE INTEGRATING CPS INTO DIGITAL TWIN OR VICE-VERSA.

Domain	Reference	Use and advantages of CPS
Manufacturing	[59]	A four-layer CPS architecture is used to integrate a tri-model Digital Twin (Digital Model, Computational Model, and Graph-based Model)
	[51]	A five-layer CPS architecture (data store, pre-processing, model & algorithms, analysis, user interface) is used to integrate a Digital Twin.
	[29]	The Service Oriented Architecture of CPS is used to facilitate the integration of DT in CPPS.
	[37]	Digital Twins are used to virtually manage individual components' issues (data ownership, version management, etc.) in a System of Systems.
	[52]	Functional Mock-Up Units are used to standardize the connection between a CPS and its DT, allowing for facile integration of physical systems in CPS.
	[38]	The CPS-specific MES software controls the physical CPS and communicates with the Matlab-based virtual twin.
	[54]	The DT is built upon an add-on software and communication infrastructure setup that controls, monitors and connects a real material-handling system with a simulation-based decision support.
Logistics	[53]	The DT incorporates the predicted machine health into the production scheduling algorithm (Genetic Algorithm) to optimize logistics tasks to avoid failure and prolong machine lifetime.

TABLE VIII
OVERVIEW OF REVIEWED LITERATURE INTEGRATING VR/AR INTO DIGITAL TWIN.

Domain	**VR/AR**	**Reference**	**Use and advantages of VR/AR**
Manufacturing	VR	[96]	The VR-based DT is used as a safe testing environment for developing new disassembly processes without interfering with the real twin.
	VR	[98]	The VR-based DT of an industrial robotic cell is used to teach robotics students on how to operate the real twin.
	AR	[102]	AR is used to overlap digital information extracted from the DT onto a camera feed showing the real twin.
	VR, AR	[103]	Both VR and AR are proposed to enhance HMI via intuitive and immersive interfaces for human operators.
	VR, AR, MR	[104]	MR proposed to overlap the user's perception of the physical and digital twins, converging reality and virtuality.
Healthcare	VR	[56]	VR is used to integrate the medical professional into the DT of the patient and their environment via a head-mounted display.
Safety	VR	[97]	VR is leveraged to create artificial images of humans wearing safety equipment in order to train ML algorithms via TL.
Robotics	AR	[101]	AR is used to track the movements of a mobile robot via its DT. The virtual image of the robot and its trail are superimposed on a camera feed, allowing real-time tracking.
Gastronomic	VR, AR	[99]	VR- and AR-based DT of an ice cream machine is used for real-time monitoring and for training employees on how to maneuver the real asset.

is indeed difficult to create a one-size-fits-all architecture for such a versatile technology, given that its application scenario can impose significant alterations to that architecture. This is also part of the reason why the DT is also difficult to define. For example, it is not always the case that the physical twin is an actual, real object, characterized by a physical geometry. As such, proposed modeling methodologies that imply the existence of a physical object would not map well to use cases like the DT of processes. On this note, the authors in [106] proposed an architecture for the manufacturing industry that breaks down the DT into three constituents, namely product DT, process DT, and operation DT, with each component having a seemingly different architecture. A different modeling methodology, presented in [107], summarizes a manufacturing DT as the synchronization between 3D modeling and mechanism modeling.

Nevertheless, researchers in the field have come up with DT frameworks that abstract away from the use case-specific details of implementing. Instead, they take a step back in order to focus on the components one could reasonably expect to find in any DT, no matter the application scenario. The authors in [108] claim that a DT only requires two main components to be whole, which are: a virtual representation of the physical entity and an API. The authors also mention that the virtual model does not require to include the 3D geometry of the physical object, unless that is required by the DT's use case. In addition, other dimensions can be added to the DT, such as: data storage, access control, methods, events, and a human-machine interface. Similarly, other works [109] insist on the importance of creating an API-like middleware that allows the DT to connect to external systems. Riedelsheimer et al. [110] proposed a methodology for building DTs for already-built, complex, inter-disciplinary physical objects, with the aim to optimize the systems' sustainability throughout its lifetime.

With the goal of creating the DT of a smart factory able to manufacture customizable products, the authors introduced a planning and development framework that integrates several design and management frameworks, such as V-IoT, 8D-Model, Design Elements, SCRUM, etc.

A more common approach to modeling methodologies that can be found in the literature is the 5-dimensional DT initially proposed by Tao et al. [111]. According to this work, the five dimensions of the DT are: physical entity, virtual entity, communication, data, and services. This break-down of the paradigm allows for a decoupled architecture with orthogonal elements, making it easier to understand. For this reason, many researchers have based their modeling methodology proposals on Tao's work. Wang et al. [112] build on top of the 5D DT to introduce a System Design Digital Twin which aims at reducing the complexity of model-based system engineering by closing the gap between the physical and theoretical design processes. The authors in [113] proposed a DT information modeling method dubbed GHOST (Geometry, History, Object, Snapshot, Topology), representing an expansion of the data element of Tao's architecture. Its aim is to provide a flexible framework for combining multi-source heterogeneous information in complex DT systems. Wu et al. [114] presented a methodology for building 5D DT models that is supported by an improved version of the TRIZ function model. The TRIZ function model describes a complex system by breaking it down into various types of elements and relationships. In order to provide further nuance and fidelity to the model, the authors enhance TRIZ with behavioural logic via conditional flow control, rules, and interactions with the external environment. Finally, other existing architectures partially overlap with Tao's methodology. For example, Bazaz et al. [115] defined the DT as an interconnection of five layers: data store layer, primary processing layer, model and algorithms layer, analysis layer, and the user interface component. Judging by the description of each layer provided in the paper, Tao's data dimension corresponds to Bazaz's data storage layer, the communication element is similar to the primary processing layer, elements of the virtual entity dimension can be found in the models and algorithm layer, while Tao's services element, it can be argued, includes both the analysis and user interface layers.

Abstract modeling methodologies have seemingly slowly begun to converge in the DT-related literature around Tao's 5D model, depicted in Figure 5. However, the in-depth implementation details and technologies remain use case-specific. In [116], the authors took a closer look at the specific frameworks and software that can be used for DT development.

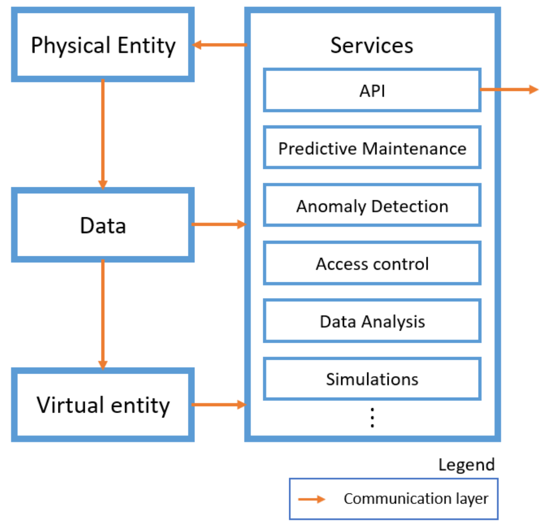

Fig. 5. Five-dimensional DT architecture.

V. Digital Twin: Use Cases and Services

As we have stated previously, the choice of enabling technologies for the DT will be highly dependent on the DT's envisioned applications and services. In this section, we will present how DT frameworks differ in their components from one application scenario to another, and it will become apparent how, even within the same use case, the DT structure can vary greatly. As such, this section will be divided into two central characteristics of the DT, as presented in the definition we provided in Section II, namely DT use cases and DT services. There are many potential DT services and use cases; however, within this section, we limit our survey and discussion to some typical examples in each category to demonstrate the concept and potential of the DT. This choice of DT services and use cases also align well with the specific case studies we present in Section VI.

A. Use Cases

1) Smart Factory and Industry 4.0: The current vision of I4.0 aims to cut the costs of production, build efficiency and give companies an increasingly versatile approach to production. Factory stations now have the ability to communicate directly with one another, eliminating the need to communicate via a central processing controller. This decentralisation through modularisation and the IoT increases flexibility, opportunity and efficiency. Rather than a centralised control unit delivering instructions to each machine to carry out linear sequential steps, individual machines now intercommunicate directly enabling the partly-finished product to be passed straight on to the next station. As everything is now processed locally, the production line is equipped to produce any number of unique products, which was not previously possible on single unit lines. By not having to communicate with a centralised unit, the production line can run more smoothly and efficiently. In addition to increased efficiency, the new security sensors built into the autonomous modular systems create a safe working environment for human operatives, ensuring robots halt if they encounter an obstruction. This has the added benefit of workers being able to touch a robot to stop its motion without the need to activate an isolator. The decentralization of manufacturing processes and the increasing demand for customization leads to a need for adaptive and intelligent production equipment. The DT aims to address this challenge.

Makarov et al. in [117] investigated the design concept of a DT, coining two new types of system and splitting the

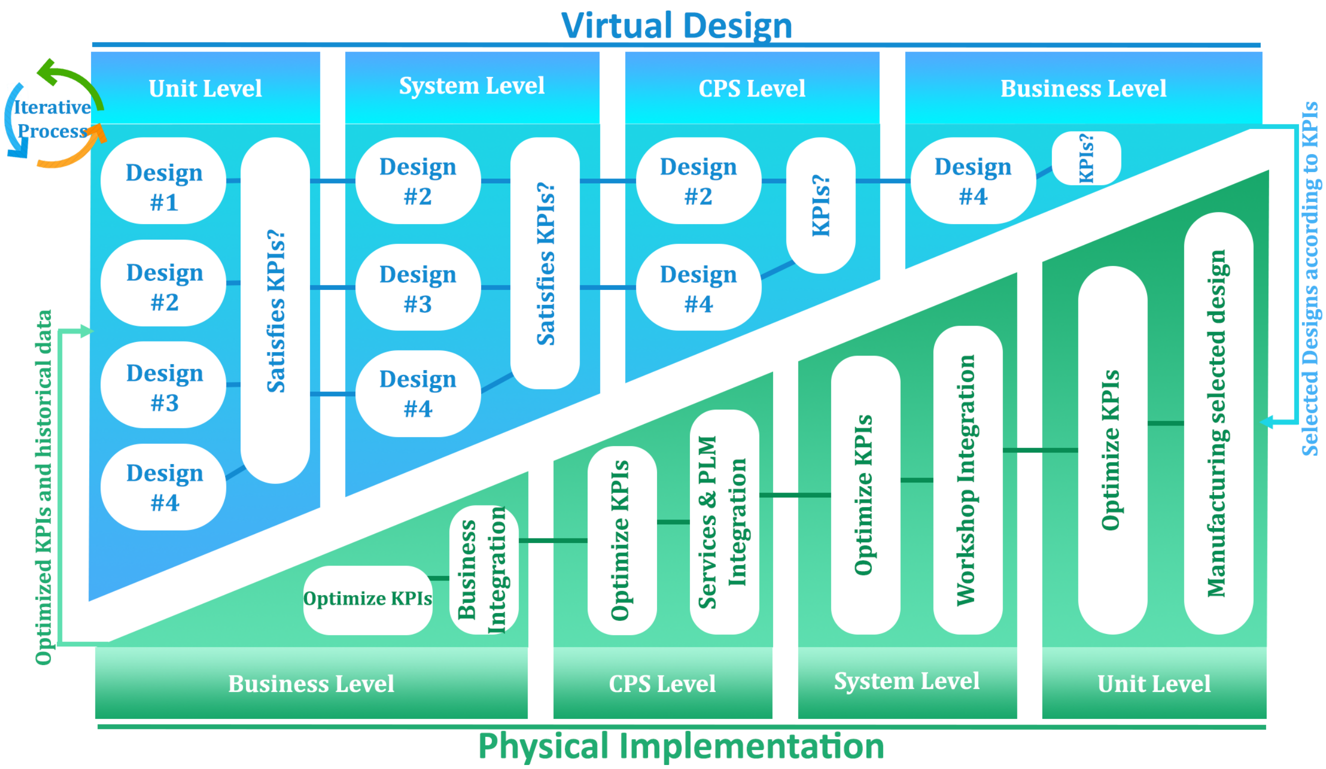

Fig. 6. Digital Twin framework for smart manufacturing.

definition of a DT into four parts. A pre-DT is defined as a virtual prototype for a system to reduce technical risks and root out design problems before development. Any issues with the system found on the virtual twin can be solved and corrected on the physical system. An adaptive DT uses a user interface, linking the two systems, allowing the virtual twin to understand the preferences from the human operators in different scenarios. Finally, an intelligent DT has all the characteristics mentioned before; however, it contains unsupervised ML for pattern detection in the physical system environment. The results found to reduce repair costs and increase quality control for a lowered amount of product defects.

Lee at al. in [118] proposed a DT framework for smart manufacturing. More specifically, the authors introduced a systematic integration of the DT in various levels of shop floor design: unit level, system level, CPS level, and business level. Figure 6 displays the workflow of the proposed architecture: shop floor designs are initially tested against unit level Key Performance Indicators (KPI) and are only selected for the subsequent level testing if they satisfy them. Consequently, a triage-based system filters out the designs that do not meet KPI requirements at each level during the virtual implementation of the shop floor. In the physical space, the selected designs are implemented gradually across all levels, and the real performance of the designs help optimize the KPIs in the virtual domain.

In [119], Preuveneers et al. proposed the use of safeguarding systems throughout the software of the DT system. These safeguarding systems, coined ”software circuit breakers”, are designed to handle local system errors to stop faults propagating through the levels of the DT, as these have the potential to be catastrophic. Such local failures can include:

- Missing sensor data
  - Failed transmissions
  - Disconnected sensors
- Broken Sensors
  - Hardware failures or disconnected actuators
  - Denial of service attacks

The results show that the addition of software circuit breakers in DT systems can station errors cascading into higher-level systems, and keeps the fault local to that physical station. The goal of this, however, is not directed at stopping the spread of errors, more to isolate them, as different errors hold different levels of severity.

In [120], J. Lee et al. investigated a DT-enabled predictive maintenance framework for a CNC machine tool system using DL. The authors outlined vital design characteristics and requirements for integration of DTs in a CPS. The rapid growth and requirements for IoT and ML mean data transfer latency has to be as low as possible. The authors suggest 5G will significantly contribute to the integration of ML and be the backbone of DT technology. They also indicate that all sensors should be developed into smart sensors for ease of plug and play and scalable networking.

G. A. Gericke et al. [121] investigated the efficiency and latency of communication and production rate of 500ml water bottles with a cyber-physical bottling plant. Using Open Platform Communication (OPC), they were able to give possible positions of bottle-necks in production. Using this, the DT can also detect drops in production rates. The authors conclude by pointing out the machines cannot rely on OPC as the only connection to the physical system due to the significant latency, ranging from 100ms to 500ms. They also found that as the system scales, more OPC connections will be needed, further slowing the system.

W. D. Lin et al. [122] carried out research on the design and implementation of a DT on a CPS. The authors suggested there are three layers of modules required to produce a DT system:

- Operation Layer – used for tracking all physical assets on the CPS
- Visualisation Layer – used for real-time simulation, taking the data gathered from the operation layer and provides a remote-monitoring function to allows companies to be continuously updated on current production status
- Intelligence Layer – This takes all the information from the previous two layers to create a historical data bank. This layer will use this data bank, along with real-time data, to perform efficiency and health monitoring.

The authors then took this design concept, implemented it onto a prototype Surface Mounted Technology production system, built of seven stations. This system worked and acted as a validation to their prosed three-layer DT design concept.

H. R. Hasan et al [123] investigates the use of blockchain technology as a way of optimising the DT format on a CPS. The problem outlined in this paper is with the development side of DTs. There is a need for monitoring the interaction between design teams and workflows, so each change made to the software can be accredited to a specific person, who can be held accountable. This employs transparent history monitoring, security and trust and ensures the trusted creation of virtual models. The blockchain platform used was Solidity - Ethereum smart contracts.

In [124] Kanak et al presents a blockchain-based model for distributed and collective DT environments which is becoming essential in new "Any 4.0" era. They proposed a novel approach to use security as a symmetric and asymmetric cryptographic tool to be implemented at a hardware level. The DT ecosystem proposed includes "X-by-design" and "X as-a-service" principles where "X" is security, accountability and integrity.

Similarly, the authors in [125] developed a simulation-based CPS DT for blockchain enabled Industrial Hemp Supply Chain (IHSC), which is utilized to improve the understanding of a complete process pf supply chain, assist in quality control verification and fast track the development of secure and automated supply chain system. They present the two-layer blockchain based data tracking, information sharing, and interoperability framework for the end-to-end IHSC which can greatly improve both security and efficiency.

In [126] a DT for an experimental assembly system based on a belt conveyor system and an automatized line for quality production check is proposed. They have created a DT for Bowden holder from a 3D printer, which is composed of some plastic components, fastener parts and a stepper motor. The assembly was positioned in a fixture with ultra-high frequency tags and IoT devices for identification of status and position. The inspection system included an industrial vision system for checking presence of parts, inspecting the dimensions and looking for errors before and after assembly operation.

Vachálek et al [127] presented a DT model of the production line based on the simulation tool called Plant Simulation, made by SIEMENS. This model was a detailed virtual copy of the physical process involved in assembling the hydraulic pistons. The goal was to extract the information about the number of times there has been movement, to the data storage and OPC data server of SIEMENS have been used to process this information transfer.

2) Infrastructure: Civil infrastructures are highly valuable assets, having vital societal roles and involving a large number of people at every stage of its complex working life from initial conceptual drawings, 3D numerical model, construction activities to operational service, as shown in Fig. 7. Thus, infrastructure management has been a subject of intense research activity, aiming to maximize their safety and service life while minimizing the building and maintenance costs. In the following subsection, recent works investigating DT-based paradigms unifying practical tools and expert knowledge with novel advanced technologies are reviewed. Furthermore, a DT application for Structural Health Monitoring developed by the authors will be described in Section VI.

a) Smart Building:

A building consists of a number of components spanning different domains from energy, ventilation, heating, air-condition, plumbing, mechanics, and so on. Thus, having effective building management is challenging, especially with a high-rise building or a commercial complex. Therefore, Lu et al. [128] have developed a smart O&M management tool using DT specialized in detecting anomalous behaviors. At first, a dynamic and distributed data integration component was built to integrate heterogeneous data from various daily-updated databases using corresponding object IDs. Secondly, intelligent anomaly detection functions were implemented using the BOCD to identify suspected change points, related time instants, locations, and even elaborate the causes of the change points.

Lu et al. [129] have developed a dynamic DT in order to improve asset maintenance and asset failure prediction in a campus of the University of Cambridge. The DT framework consists of five layers: (1) first, acquisition layer collecting data from multiple sources including Building Information Modelling (BIM), real-time IoT sensor data, asset registry, and asset tagging data and space management data; (2) second, transmission layer transmitting data collected from physical device in the first layer to a central database using WiFi, 5G, low-power wide-area networks, etc.; (3) the third layer is digital modeling, where different types of digital models could be developed for various requests in DTs; (4) fourth, the data/model integration layer provides real-time analysis, then assess up-to-date asset condition and maintenance status with the help of AI-based functions; (5) and lastly, the application layer with visual interface facilitates the interaction between DT and facility managers.

Thyssenkrupp, in collaboration with Microsoft [130], developed a DT framework for the elevator system in a high-

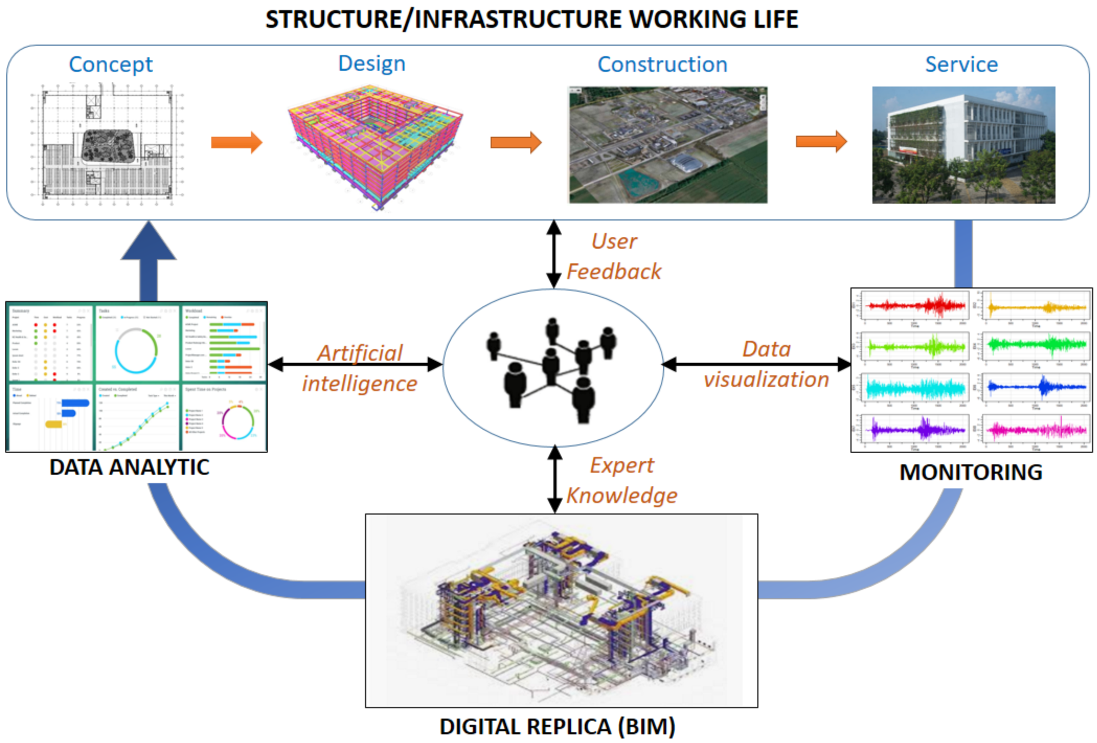

Fig. 7. Digital Twin in infrastructure

rise building in Rottweil, Germany. The new advanced elevator, which could move both vertically and horizontally, was equipped with IoT systems and deployed via the Azure DT framework. This DT is able to reduce the downtime of the elevator significantly, provides information related to elevator occupancy and usage to enhance the availability of the elevator, which serves more than 10,000 people per day. Moreover, the DT is reinforced by AI learning to optimize travel times of frequent users.

b) Smart Infrastructure:

Ganguli and Adhikar [131] thoroughly presented a DT for a Single Degree Of Freedom (SDOF) dynamic system, in which a double time-scale system was proposed the first time. Specifically, the fast time scale reflected the dynamic responses of the real system and the slow one for the DT, and it was found that such a multiple time-scales DT was able to capture effects of mass and stiffness evolution on the SDOF simultaneously. Ding et al. [132] proposed a DT for a steel bridge construction using BIM and IoT data from embedded sensors, able to dynamically monitor the construction processes and key related factors such as site resources, business processes, field workers, as well as their live interaction, thus ensuring a lean construction.

In order to develop a proactive maintenance system for bridge structures, Shim et al. [133] proposed twin models fusing entire lifecycle information from design, construction to operation, and maintenance. The first model was built from as-built documents using BIM, while the second model was generated with the help of the 3D scanning technique using Unmanned Aerial Vehicles and laser scanner. A maintenance-oriented digital process connecting two models was also elaborated to update the structure's status continuously.

Structural Health Monitoring (SHM) is an important topic in civil engineering, thus Wagg et al. [134] explored a SHM-oriented DT. Essentially, data-augmented modeling is implemented to compensate for the discrepancy between numerical models and physical counterparts, which involves two phases. First, the discrepancy is qualitatively and quantitatively measured from the physical entity. Second, bias-corrected models are calibrated based on the numerical model and measured discrepancy, yielding augmented outputs which closely approach the real behavior of the structure over its working life. Another concrete example of DT application in SHM is the work of Kaewunruen et al. [135] for railway turnout systems, which consists of many delicate and complex details and has a critical role in ensuring the safety of the railway system. The application is built by expanding the conventional 3D BIM models to 6D models, involving three geometric dimensions, time dimension, cost dimension and its sub-categories, and carbon footprint dimension. Moreover, not only actual operation information are investigated, but data from historical phases such as planning, design, pre-assembly to predicted future action, i.e., maintenance, demolition are also taken into account. A similar DT approach via 6D BIM is applied to the renovation management of the King's Cross station [136], aiming at a more resource-economic and environment-friendly model than traditional construction methods such as 2D paper drawings, or 3D static numerical models.

With regards to the offshore structures, Akselos [137] has developed a holistic DT framework coupling with parallel cloud computations, which can provide real-time risk-based decisions in response to time-varying uncertainty encountered by offshore structural engineering involving wave, wind, marine environment, and so on. As one of the leaders in the power plant industry, General Electric has been devising a sophisticated DT framework, a.k.a. Predix, [138] including a spectrum of aspects of the physical entity ranging from thermal, mechanical, material, electrical, economic, statistical, environmental. This DT is expected to perform a wide range of applications such as optimizing profitability, maximizing plant safety, accurately forecasting productivity, profiling customers, synchronizing operations of many machines on plants. For this purpose, various advanced technologies have been implemented in Predix: firstly, multimodal data analytics are required to automatically collect, update, and store a vast amount of heterogeneous data involving: parametric data (temperature, pressure), graphical data (infra imaging, camera), spectral data (spectroscopy), time-series data (sensors, accelerometers), text data (service records), historical data (maintenance database), and so on. Secondly, the company deploys a number of digital models encompassing physics-based models, i.e., thermodynamic model, combustion model, transient dynamic model, and data-driven models such as statistical process control, ML-based anomaly detection, and DL regression and classification. Finally, a knowledge network, called Expert Twin is explored to connect experts across the enterprise around the world for sharing data, knowledge, solution, and best practice.

c) Smart City:

In an attempt towards sustainable growth of the city as well as a better quality of life for citizens, Francisco et al. [139] investigated a DT paradigm for Smart City using spatio-temporal data. At first, a digital replica of the city is rebuilt in a virtual space using the Unity cross-platform; after that, the researcher can navigate across the virtual city via VR devices. In addition, an AR crowd-sourcing module allows for integrating feedback of citizens about real infrastructures into the platform parallelly. By doing so, the triangle interaction human-infrastructure-technology is captured, analyzed, and updated, serving to improve the sustainability and wellness of the city.

Ruohomaki et al. [140] explored a Smart city platform using DT for the city of Helsinki to enhance city management in various aspects, including urban landscape, energy consumption, environment. At the base of the platform is the 3D city models called CityGML integrating geographic information, geometry, topology, and appearance. Next, sensor data are linked to city models via an IoT platform called SenSorThings, composed of two main parts: sensors for observation and thing, i.e., API, for connection to the network. By doing so, the initial 3D model is transformed into a semantic ecosystem with high interoperability. Du et al. [141] presented a Proof of Concept of DT for Smart City's Information System at an individual level, namely, Cog-DT, to reduce the cognitive overload for residents and workers in the city. The first step of Cog-DT involves using VR technology to gather personal cognitive information such as neuroimaging, physiological, ergonomic. Then, the second step is to simulate human cognition in response to various information stimuli. Finally, an adaptive information system is implemented to display engineering information adjusted in a real-time fashion. In an attempt to improve the long-term performance of the O&M service of building and other infrastructure, Lu et al. [142] developed a 5-layer DT architecture and applied it to the West Cambridge site with more than 20 buildings and other facilities. The proposed DT architecture can be extended further up to a city-sized application. Their five main layers are data acquisition layer including sensor data, weather, energy, security, culture, policy data and so forth; transmission layer via the Internet, 4G/5G, HTTP; digital modeling layer with the help of BIM, energy simulation model, weather simulation model; data/model integration Layer powered by data analytics and AI; and finally service layer providing multiple services such as energy management, asset management, security management, etc. at different levels for different stakeholders. Lin et al. [143] explored a DT application for Smart City's underground parking garage using Wireless Sensor Networks (WSN) in conjunction with BIM technologies for improving environmental management. The WSN was composed of various sensors able to monitor gas, temperature, the humidity of the garage, whose data were later transferred to a central host with the help of communication routers. On the other hand, a BIM model of the garage is built by Autodesk Revit and Naviswork, providing a detailed digital representation. When coupling the BIM model with environmental data from sensors, the risk status, i.e., CO gas level, user comfort level, are lively represented and can be visually noticed with green/red color code.

3) Towards 5G/6G with Digital Twin: The future Industry 5.0 paradigm envisages removing any physical limitations and building in virtual connectivity and capabilities that will enable the seamless interaction between devices, humans and infrastructure [144]. Even though this digital transformation across various industries will enable applications that serve different purposes, they all have something in common: dependency on reliable and strong connectivity enabled by the underlying next generation network infrastructure (e.g., 5G/6G). The fifth generation networks is already a key component in I4.0, since, even in the DT technology, the connection of components and devices is of utmost importance and communication latency is expected to be less than a few milliseconds. In this context, the relationship between 5G/6G and DT can be seen from two different point of views. The first one, sees the 5G/6G network as an enabler for different DT applications, while the second one sees the DT as an enabler for 5G/6G by looking at the DT of the network itself. Both point of views are addressed in this section.

Communication technology is going to be the foundation of industrial IoT, hence in [145] authors have presented a detailed overview of 5G wireless transmissions and their application prospects according to cyber-physical-based manufacturing systems. Furthermore, a novel 5G-based industrial IoT architecture for smart manufacturing is proposed. In [146] authors have taken an industrial robotic arm as a use case and have performed an analysis of simulated robot with the effects of simulated network for CPPS. The key contribution of the study is the comparison and analysis of effects of using different kinds of network types in a Gazebo simulated robot. The three types of networks used between robot controller and robot are wired link, public LTE and the 5G uRLLC network. The results showed that 5G outperforms LTE and wired network in terms of productivity as well as the processing time increased by 50%.

Furthermore, 5G (and beyond) and the DT can revolutionize the cooperative vehicle infrastructure. The authors in [147] have explored the implications of 5G based communication to the intelligent V2X system called Providentia and proposed scene detection, fusion and object detection strategies. The vehicles in the Providentia system play two roles, first being the source of information about the current state of vehicle and its surroundings, second as a user of the DT system. All the communications in this infrastructure is realized through on-board 5G modems as well as 4G LTE. Similarly in [148] 5G communication networks, more specifically edge devices, are recommended for the real time data collection in DTs designed for traffic congestion avoidance. The proposed solution for road connectivity infrastructure involves real time situational information gathering, collection of driver history using ML algorithms, data lake, intelligent transport system, DTs and blockchain services for vehicles. The application domain of the DT technology is very vast, as the authors in [149] have optimized the services of mobile edge computing using DT and DL algorithms. Achieving ultra-reliable and low-latency in mobile edge computing can be challenging because of the possibility of losing the packets in case of deep fading channels. Thus, in order to optimize the offloading probability, a DT is developed in [149] which can evaluate the normalized energy consumption, reliability of user association schemes and delays. The DT will save the optimal option and store it in memory as a training data for DL algorithms. Tactile Internet or 5G will also revolutionize the traditional multi-modal applications. Research has been carried out to evolve the current state of the art media to multimodal media, where DTs can facilitate the high quality interactions, like touching and smelling the objects of remote environment [150]. Moreover, the DT and 5G/6G will also play a vital role in autonomous navigation systems [151] where autonomous ships can easily be commanded and decisions regarding navigations are made easy.

Smart manufacturing is one of the most important vertical industries identified by 5GPPP and with the maturing of network virtual functions and 5G, use of Virtual Network Functions (VNF) in smart manufacturing is gaining popularity in research community. To this context the authors of [152] have presented a use case in the manufacturing industry using the experience of a manufacturing company named Weidmuller Group. The manufacturing network services in the proposed use case are composed of different VNFs and it is developed using SDK and 5GTANGO lightweight Network Function Virtualization (NFV) prototyping platform. Similarly, in [153], an efficient solution is proposed, called MIGRATE, that implements virtual functions and virtual mobile devices to represent physical processing devices. MIGRATE ensures the successful and seamless transfer of software entities. Connectivity in the future is highly dependent on development of DT environments [154] that are actual representation of their physical counter parts. With the advent of future generation networks, it is expected from the DT technology to represent not only physical objects, but the biological world as well.

Fig. 8. The vision for DT-enabled next generation communications.

With the rapid advancements in smart technologies and applications like holographic projection, VR, AR as well as mission critical applications like remote surgery, that have strict Quality of Service (QoS) requirements, current networks including 5G will no longer be able to meet these expectations. Although the deployment of 5G networks is not yet completed at a large scale, many industry pioneers and technology leaders are looking ahead at defining the next generation networks, 6G. 6G envisions interactions between three worlds: the human world (e.g., senses, bodies, intelligence, etc.), the digital world (information, communication, computing, etc.); and the physical world (objects, organisms, processes, etc.) [155]. Furthermore, 6G envisions network speed of 100 to 1000 times faster than that of 5G for accommodating new service classes like further enhanced mobile broadband (FeMBB), ultra-massive machine type communication (umMTC), and enhanced ultra-reliable and low latency communication (eU-RLLC) [156] and latency less than 1ms for ensuring safety in mission critical communications and IIoT applications [157]. DT has great potential to provide for a digital environment where future generation networks like 6G can evolve. Integrating DT within mobile networks is gaining popularity in the industry from major tech companies like Ericsson, Huawei and Nokia [158]. In this context, DT has the capability to continuously monitor and analyze the performance of the network, predict any unanticipated failures and optimize the network performance by triggering intelligent decisions accordingly. Figure 8 illustrates a vision of the 6G DT that facilitates the live virtual replica of the whole or parts of the 6G network to perform continuous monitoring and assessment through a closed loop process between the physical entities and the digital counterparts. The 6G DT powered by AI will enable design and performance improvements and real time optimized operations enforced on the physical 6G network.

B. Services

1) Anomaly Detection: The Digital Twin has gained its significance in I4.0 by virtue of its intuitive and insightful role in integrating data analytics into traditional manufacturing facilities [15]. Through the analysis of run-time data incurred from the physical systems, DTs have enabled smart factories' engineers to know their facilities better. One of the many

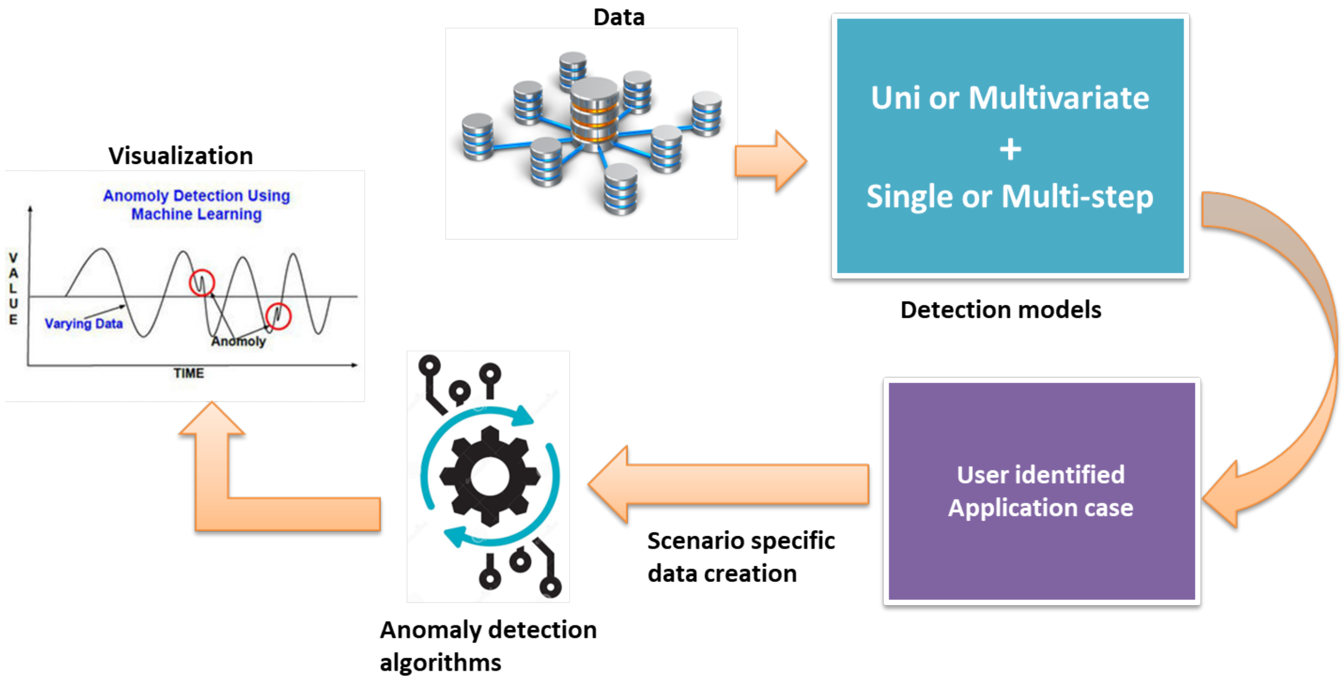

Fig. 9. DT application: Anomaly Detection Framework

strategies involved in analysing the data and discovering better insights is Diagnostic Analytics (DA), i.e., having a profound look at the data to observe and interpret the causes of events and behaviors. An effective and popular technique recognized for DA is anomaly detection [159]. Anomaly detection is a technique of fault diagnosis that detects sections of data disobeying the normal, expected behaviour [160], [161]. The DT-enabled anomaly detection has proven itself an asset for the Operation and Maintenance (O&M) phase of smart factories. As illustrated in the subsequent literature, it is clear that incorporation of anomaly detection in DT architectures has had a significant impact on the popularity of DTs in the I4.0 ecosystems.

The anomaly detection work flow followed by researchers in general is represented pictorially in Figure 9. Workflow of Anomaly detection application with most common key phases involved are shown in the Figure 9. It is observed that uni variate or multi-variate models with single or multi step detection models have significant effect on Anomaly detection applications performance. The primary sources of data for such anomaly detection applications are derived from industry run-time data from the connected IoT devices or historical data from database logs available. The DT models close to their physical counterparts in an industry may also simulate the data required along with the run-time and historical data available.Data set identification and creation based on the user specific applications is also determining factor to improve the performance of the anomaly detection application. Anomalies can be visualized with a right choice of algorithms based on standard machine learning models. The choice among supervised, unsupervised and semi supervised learning models is based on the availability of labelled data versus large data requirements for the training. The DT application can arrive at the next level PdM suggestions from the observations derived from the anomaly detection outcomes shown in Figure 9.

In [162], the authors proposed an IoT-enabled "Living Digital Twin" for additive manufacturing. The twin essentially rooted for assuring higher productivity by monitoring the system with analog sensors such as acoustic, vibration, magnetic, etc. The basic protocol might seem rudimentary due to the sensor-actuator action involved, but the twin had a significant contribution in the aspect of anomaly detection. The digital counterpart introduced the concept of a fingerprint library to detect anomalies. The fingerprints are the run-time values of asset parameters that compared with the instantaneous IoT data from the physical systems to detect potential anomalies.

A DT-enabled anomaly detection mechanism was proposed in [163] for built asset monitoring. The detection process asserted the need for cross-referencing the multiple data sources for building facilities information. Owing to the data inter-operability and re-usability aspects of the task, DT was accepted as a comprehensive solution for the data integration problem. Storing the data from heterogeneous sources into a single, integrated format eased the detection process, meant for every key asset in the building structure. The run-time data of the assets, acquired in various data forms, was encapsulated in a single data format that invariably assisted the detection process many-fold.

An extensive amount of research has been followed up in implementing anomaly detection with various ML algorithms. As a consequence, several research problems have been encountered by the researchers. Andrea et al. [164] implemented anomaly detection on industrial data with a semi-supervised learning approach. The dataset under study consisted of a major portion of unlabelled data (unsupervised learning) and a smaller portion of labelled data (supervised learning). The choice of hybrid dataset for the said study was influenced from the following facts: i) for the supervised approach, additional efforts need to be invested in labelling the data that is prone to be impractical for larger datasets, and ii) an unsupervised algorithm learns by the means of bulk statistics of majority behaviour, thus a smaller unlabelled dataset might result in an ambiguous output. A DT framework, by virtue of its simulation capabilities, generated the unlabelled portion of dataset with normal samples that simulated normal industrial operation. The latter half of the dataset comprised of anomalous samples derived from a real factory data. The article claims to have achieved a higher score in its performance indices for semi-supervised approach than the fully unsupervised approach (AUC scores 0.872 and 0.756 respectively). Maurizio et al. [165] proposed a reference model using DTs for risk assessment analysis in industrial process plants. They put forth a framework for a smart factory that would enhance its productivity while prioritizing the safety of human operators. The risk identification and assessment aspect of the model called for inclusion of an "Anomaly Detection and Prediction" tool in the twin. The tool was developed while being fairly inclusive of the twin-enabling technologies: i) development of a communication and control system with sensors-actuators at the edge and Programmable Logic Controllers (PLCs) at controller station, where the wireless sensor networks helped to gather the ground-level data to the twin, ii) development of ML models by employing the received data to analyse, predict the risk factors and educate the DT to invoke precautionary actions. Notably in [88], a framework was proposed for the monitoring and diagnostics of a fleet of aero-engines. The framework implemented anomaly detection for fault detection, isolation and identification. A physics-based model of a three-shaft turbofan engine was developed and simulated in-house. The simulation data for the said model and the signatures of potential component faults were generated by a DT. In order to simulate an entire fleet of engines, production scatter simulation was implemented by the twin that cloned multiple replicas of the engines with minimal random variation.

The capability of DTs to analyse temporal data in real time has proven to be a greater asset for targeting spurious events. This statement has been validated by Xie et al. [166] who have proposed a DT framework for crucial asset monitoring in a building facility. The multi-layered twin architecture mainly featured: i) the Digital Modelling layer that acquired time series data in real-time and stored simulation data as well as historical data, and ii) the Data/Integration layer that analysed the data at hand and took informed decisions. The said analysis was assisted by the Bayesian Online Change-point Detection (BOCD) algorithm that detected suspicious instances upon investigating the sudden variations in the time-series (change-points). The framework has been demonstrated in a DT demonstrator laboratory at the University of Cambridge. The experiment was conducted on two identical cooling pumps for vibration monitoring and the twin successfully identified anomalous vibrations. On the similar lines, a group of researchers put forth a blueprint for a unified DT for anomaly detection in Smart Manufacturing [167]. A novel aspect of the said architecture was a DT platform consisting multiple twins for every crucial process/entity. A demonstration on a CNC facility proved the significance of an anomaly detection scheme developed by framework. A range of limits is devised by the twin after thorough analysis of historical data. The instantaneous values are referred against this range and dubious instances, if any, are reported by the twin prior to unfortunate tool damage. Further protocol dictates switching the device state as "faulty", requesting for maintenance and reconfiguration of the facility topology until the device maintenance is completed. Through this article, the eminence of machine failure prediction by anomaly detection, reconfiguration and rescheduling has been emphasized.

From the literature discussed above, it is observed that DT proves its expertise in the field of anomaly detection owing to its varied capabilities. The various problems or limitations encountered in anomaly diagnostics such as the generation of a reference model for comparison based on past data, lack of simulation datasets, development of early prediction models for analysis in real-time etc. have been addressed efficiently by the DT. In conjunction with the enabling technologies, the DT showcases capabilities such as flexibility to include analytical tools in its core architecture [165], [166], [167], simulation of training dataset [164] and anomalous dataset [88] for better model training, compatibility with heterogeneous data and its pragmatic integration [163], real-time analytics [166], [167] and generation, preservation of signature copies of every entity in extensive sensor networks [162] to resolve the problems that are confronted with.

2) Predictive Maintenance: Another service that the Digital Twin promises to provide is Predictive Maintenance. The advantages in terms of cost, time, and resources that PdM can demonstrably bring to the industry have been long sought-after. Thus, significant research effort has already been invested into developing working architectures that can accurately predict a machine's failure (i.e., self-diagnosing). For example, Motaghare et al. [168] proposed a basic architecture that outlines the components of a PdM system's pipeline: data acquisition, data analysis & state detection, health assessment and prognosis, and maintenance actions & alerts. Although at a first glance these functional blocks might seem rudimentary, they in fact represent the founding pillars that support PdM services, and they are predominant in many framework proposals to this day. For example, the authors in [169] present a PdM architecture for nuclear infrastructure whose components greatly resemble the ones in the previously referenced work.

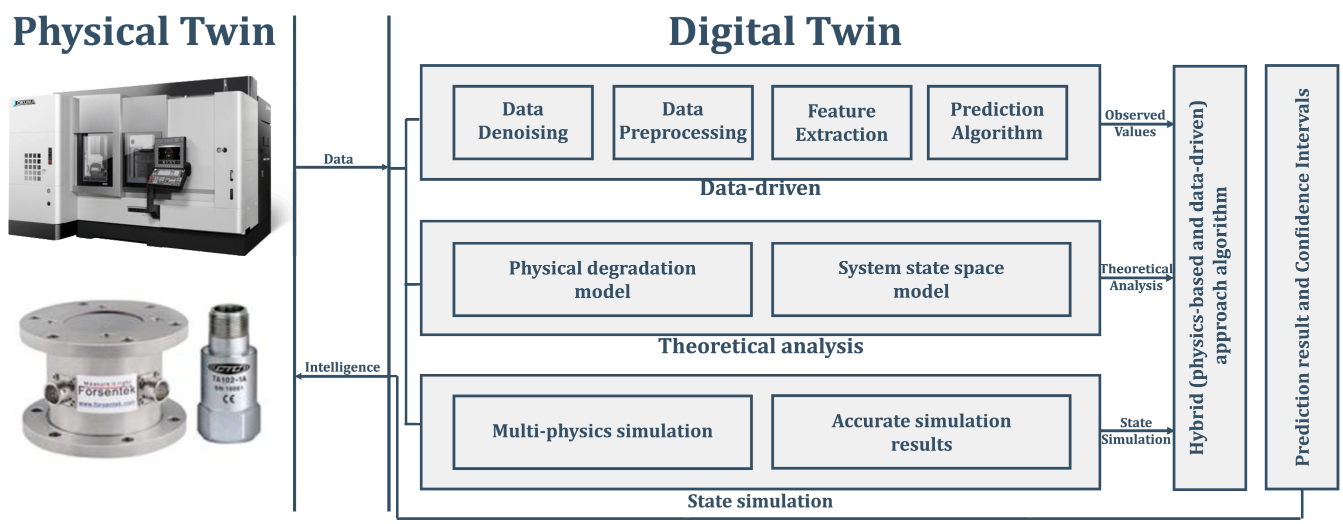

Fig. 10. DT-based PdM scheme using hybrid modeling.

Another PdM architecture that is rooted in the principles of the one presented by Motaghare et al. is Cheng et al.'s proposal in [170]. The paper introduces a solution for a bearing production line, and its framework is based on Edge-Cloud cooperation. In this architecture, the data pre-processing is done at the edge-level, and the processing-heavy tasks, like Remaining Useful Life (RUL) prediction, is delegated to the cloud. This type of structure is preferable when the ML algorithm used is actually a DL method. In that case, the training can be too computationally-intensive to perform at the edge, so instead it is deployed in the cloud. Indeed, for the estimation of the RUL parameter, the authors used a DL mixed algorithm, named in the paper ARIMA-LSTM model (Autoregressive Integrated Moving Average - Long Short Term Memory). In this system, ARIMA handles the prediction of the linear part of the time-series data, while LSTM predicts the non-linear components, which are then summed up to offer a final prediction. ARIMA is also employed in [171] as a technique of extracting the underlying trends in various data streams coming from sensors. The trends identified in heterogeneous time series data are then fed as features to a Principal Component Analysis (PCA) algorithm that extracts the most uncorrelated features to be fed into the RUL predictor. For remaining life estimation, the authors propose the use of a regression technique called the Support Vector Regression model. Cachada et al. [172] presented a complex and detailed architecture of an intelligent and PdM system that explores the interdependent modules that would constitute a functional block in a PdM framework. As such, the paper explains how different approaches are needed for the data acquisition block, depending on the type of input data: automated, semi-automated, or manually introduced by an operator; it also presents an offline data analysis scheme that also relies on the LSTM DL algorithm for prediction of machine state, a dynamic monitoring block that deals with visualisation and early detection of failures, and an intelligent decision support system for maintenance intervention that guides the operator through simple instructions and visualisations, in a way that reduces the need for technical knowledge, leaving room for focus on the maintenance task at hand. In this scheme, adjacent blocks communicate with each other in a sequential manner, but as-needed communication between non-adjacent blocks is also allowed for further automated optimisation.

As an overview of the proposed Predictive Maintenance frameworks in the literature up to date, it seems that they adopt the MIMOSA Open System Architecture for Condition-Based Maintenance (OSA-CBM) [173], either completely, or only the main parts of it.

For example, a variation of the OSA-CBM architecture is proposed in [174], where the integration of CPS, DT, and DL extensively rely on each other's advantages to reduce the need of human intervention usually required in a PdM scheme. In fact, the work suggests a great reliance on DL algorithms to completely remove manual feature engineering from the PdM architect's list of responsibilities. Instead, the introduced framework claims DL algorithms can single-handedly manage state detection (through automatic feature extraction), health assessment, RUL estimation, and advisory generation through closed feedback loop connections between different functional layers of the architecture. Such an implementation would undoubtedly require large amounts of resources in terms of storage space, computational power, and smart equipment.

Liang et al. in [175] proposed a layered architecture for a low latency deployment of a Convolutional Neural Network (CNN) – based prognosis system. The proposed scheme consists of three layers that share responsibilities effectively, keeping high-speed processing capabilities on the terminal and fog layers, close to the manufacturing equipment, and leaving the training of the CNN to the cloud layer. Drawing the line, it seems like the focus has shifted from the development of extremely intricate mathematical health prognosis models, which were tailored to be specific to the equipment, towards data-driven models which predominantly rely on ML and, of course, Big Data. The ability to reliably and quickly transport, store, and process huge amounts of data has opened new doors in the world of PdM, immensely facilitating the task. However, that is not to say PdM has become an easy job. The new approach presents other challenges in terms of time, resources, and sets of skills that are required to deliver accurate predictions of the RUL parameter.

A compromise between the complex, but transparent physics-based models and efficient, but opaque data-driven models, are hybrid models, where researchers have used both approaches simultaneously in order to leverage the advantages from both of them. In this context, Luo et al. [176] have proposed a DT-based PdM scheme that uses physics-based degradation and simulation models to generate theoretical baselines for the machine state, as well as data-centric models that consume real-time streams of data from the sensors installed in the machine. This work has been summarised in Figure 10, and the results of the hybrid model outperformed both physics-driven and data-driven models in predicting the tool wear of a CNC Machine Tool.

In order to achieve satisfying accuracy, PdM schemes that rely solely on Big Data more often than not require massive amounts of historical failure data. For example, Choi et al. [177] proposed a method for predicting the maintenance needs of an induction furnace with the help of neural networks. Due to the nature of the ML algorithms used, as well as the data-hungry aspect of PdM, the authors ended up using a data set that consisted of measurements across 24 months. Even then, the conclusion of the article admits that collecting data during faulty scenario was deemed nigh impossible, as running experiments with a failed induction furnace could have been fatally dangerous. As such, the solution to this problem, according to the researchers, was to place focus in their future work on *generating* and *simulating* erroneous data, instead of measuring it. In [168], Wang et al. introduced a two-part PdM scheme for the China's High-Speed Railway equipment using LSTM-RNN. As stated before, any DL approach requires tremendous amounts of data for training. Of course, there is plenty of data that can be generated by a nation-wide business like China's railway system, however it should be kept in mind that the work's target equipment, the Traction Power Supply System, is engineered to be sturdy enough to have as few failures as possible per year. As such, gathering historical failure data proved once again to be a prolonged challenge. In this direction, the authors proposed splitting the PdM framework into two: a *proactive maintenance* system, and a *predictive maintenance* system. The proactive maintenance system deals with analysing the failure modes of the physical asset to generate new failure data through stochastic modeling. The PdM system is then trained using solely simulated data, and the overall method is then validated using both simulated data and field data. While it turns out that the model performs predictably better on artificial test data rather than on real data, the performance is still very good and it shows promise in the direction of simulation-assisted PdM. Gugulothu et al. in [178] invented an innovative and practical approach to RUL estimation. Their work proves to be robust to noise, sensor inter-dependencies across time, as well as data unavailability, which are all issues that are very present in various data repositories in the industry. The proposed system uses "embeddings", or rather, hidden features extracted by a RNN encoder after it was fed a fixed window-sized signal input from different sensors, to extract the Health Index which will then be used to predict the RUL. The remaining life estimation is done by comparing the extracted Health Index with its previously seen values from the training data. The work delivers on its promises, providing a robust RUL estimator that can show good results, as long as enough training data is provided.

It can be noted that many works in the literature are researching ways to compensate for the low amount of historical failure data made available by their target monitored physical system. It becomes apparent that the quality of the data and, equally important, the quantity of data are extremely important boxes to check when developing failure prognosis solutions. Over the years, the focus has shifted from *model-based* PdM, where researchers came to the conclusion that developing a stochastic model for a complex system can be nigh impossible, towards *data-driven* approaches, where an algorithm can learn from tremendous amounts of historical failure data. And this shift in research direction can be justified. As an example of model-based PdM, where limited amounts of data is not considered a hard constraint, Wang et al. [179] proposed a fault prognosis system for wind turbine bearing by making use of analytical tools like the wavelet transform (for denoising and feature extraction), and Bayesian statistics for providing RUL predictions backed by 90% credible intervals, whose accuracy would increase over time. However the goal in I4.0 is to bring PdM to all equipment, including those that are too complex for statistical modeling, which is why the data-driven approach has gained significant traction. And this approach, as the name states, requires large amounts of data that is not always available, especially in old machinery where maintenance records have not been kept, or in equipment whose uptime is so crucial that no run-to-failure scenarios were allowed.

VI. Digital Twin: Case Studies

This section will take a closer look at DT applications and services by detailing three DT case studies that represent main research directions carried out at the London Digital Twin Research Centre[1]. The subsequent subsections will thus summarize the research goals, findings, challenges, and future directions for each case study in part.

A. A Look at the Tea Industry in India

An important case study that we carried out is from a multinational tea manufacturing company. It is a semi-automated manufacturing company involving machines and human beings to control them, who bring in several inaccuracies in their processes. The tea bag manufacturing machine operated daily on an average of 20 hours and 2 hours of rest period. Fig. 11 shows the snapshot of the different activities in the conveyor belt of the tea manufacturing company; starting with tea and herbs, dosage, blending, etc. Notably, there is a separate

[1]LDTRC website: https://dt.mdx.ac.uk/

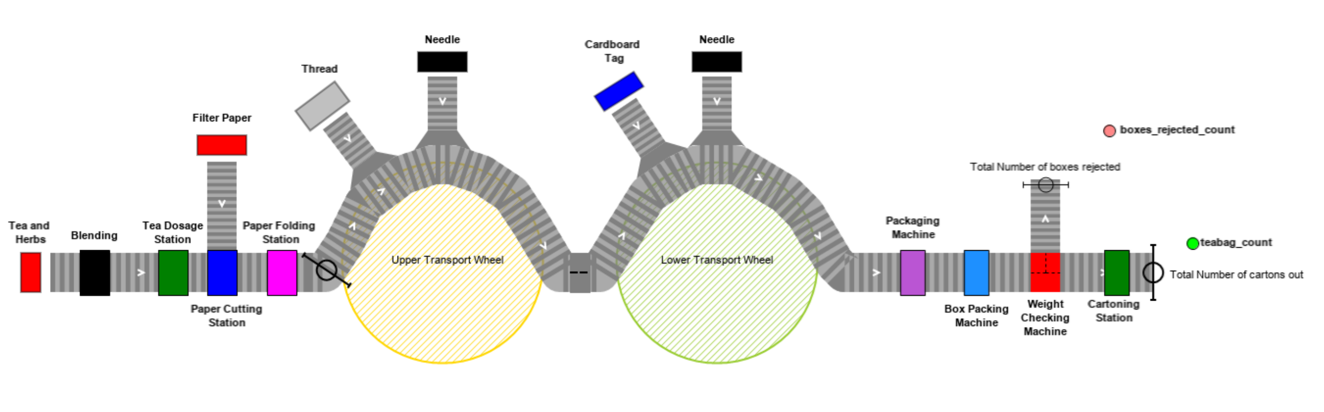

Fig. 11. Conveyor Belt Snapshot of a Tea Manufacturing Plant

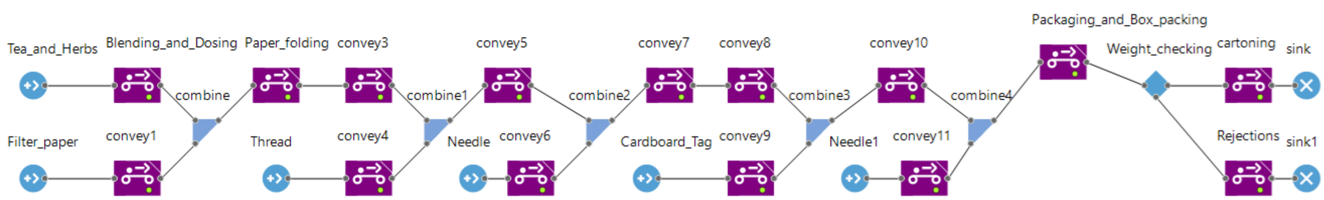

Fig. 12. Steps in the Process of Tea Manufacturing

placeholder for filter paper along with its cutting, folding, etc. There are two transport wheels: *upper* and *lower* where the operation of thread stitching and the cardboard using needle is being done. This different steps in the process can be clearly understood from the different steps in the process of the tea manufacturing, as shown in Fig. 12. There are several sequential steps and a relation between each step, right from adding tea and herbs, or filter paper to packaging, checking the weight of each box and also investigating rejections and possible reuse of the materials.

There were 6 to 8 downtimes per day over a 24 hour period, each lasting around 15 minutes. The activities during the downtime included: *change of product*, *loading new feed of raw materials*, *equipment/mechanical failure*, *misalignments of material feed*, *effect of new product on machine*, etc. Also, an accurate supervision of the facility during night shift is difficult. The tea-bag manufacturing process was studied in detail to detect and keep record on their anomalies, observe any patterns, identify prospects for twin modelling and predicting the maintenance needs of the machines. The seven major anomalies identified included: (1) Thread knot Anomaly; (2) Outer envelope print not centered; (3) No filter bag in the outer envelope; (4) Tag paper print not centered; (5) Outer envelope paper missing; (6) Faulty filter paper tube; (7) Filter paper slicing. Given the varying nature of the anomalies, they could be detected using multiple step dedicated anomaly detection technique, typically, an N-step approach.

One of the major concerns for a DT is the quality of data being fed. The lack of noise-free data being administered has severe consequences such as sub-standard performance of the twin [15]. This compels the DT to eliminate potential aberrations from the data in order to keep up with its performance. The demand for noise-free data has paved a way for anomaly detection algorithms that would filter spurious instances from datasets. The need for faster and more accurate results obliges the algorithm to have an equilibrium between the two performance parameters: accuracy and execution time. The service of anomaly detection integrated within a virtual twin demonstrates three of the DT's main characteristic traits enumerated in the definition we provided in Section II, namely: self-adapting, self-monitoring, and self-diagnosing. Through anomaly detection, the DT of the tea factory raises alarms whenever its external environment changes in a way that the DT is not able to recognize, allowing the operator or other pre-defined routines to handle the exceptional anomalies. At the same time, implementing anomaly detection implies the existence of a monitoring mechanism that continuously ingests data and checks for divergent behaviour within it. Lastly, anomalies can be a sign of degradation in some of the physical asset's systems, so they could trigger pre-defined maintenance pipelines to address these system health issues.

In order to validate this, a two-step anomaly detection technique was developed by Shetve et al. [180] and was evaluated for its data pre-processing capability.

The main drawback of the two-step approach was the diminishing accuracy with increasing outliers. Hence, the two-step approach could be generalized to "N-step approach". Each step would have its own technique that would be followed by another technique in a sequential manner. The N-step approach has been developed based on following key aspects:

1) Analysis of individual data instances
2) Evaluation of the relationship between neighboring points
3) Identification of the anomalies in dataset by the detection algorithm
4) Evaluation of the performance of N-Step

The techniques selected for each step are as follows: Step 1: DBSCAN (Density-Based Spatial Clustering with Applications in Noise) [181]; Step 2: Isolation Forest; Step 3: LOF (Local Outlier Factor) [182]; Step 4: KNN (K-Nearest Neighbour); Step 5: Hierarchical Classification based methods.

The reason for choosing the N-step approach in a particular way is as explained. DBSCAN would provide a very good separation of outliers from the overall data points, removing all false positives. Isolation Forest removes the few left over outliers that are located isolated from one another. Similarly, LOF and other following techniques would remove only the boundary located nodes; thereby removing the True negatives and false positives, if any and increasing the success ratio. A careful design of the N-step approach would result in higher accuracy/success ratio with a minimal increase in the computation time.

B. Festo Cyber-Physical Factory

Aside from anomaly detection, another important aspect of DTs in manufacturing, which is also the DT's original purpose, is continuous real-time monitoring of equipment and processes. It is important that smart factory workers have access to always-available digital factory status reports that are intuitive and remotely-accessible. This core feature of DTs enable equipment owners and factory executives to oversee the good functioning of their products and processes. Besides actual operators, the monitoring service can be used by the DT itself in order to maintain awareness, at all times, of its physical asset's current state and environment. This service enables a core principle of the DT, detailed in Section II, namely the ability to self-monitor.

On this premise, the work we conducted in [183] developed a DT framework of a real production line, in order to establish a continuous monitoring mechanism for the kinematics of the factory. The physical twin in question is the Festo Cyber-Physical Factory for I4.0 (CP-Lab) located at Middlesex University, a didactic model of an assembly line for mock mobile phones. The smart factory is composed of six functional stations, each equipped with a Human-Machine Interface, and two transport (or bridge) stations. Figure 13 depicts the physical twin on its left side, and it can be noted that it is composed of two islands, each equipped with four stations. On the first island, the first station is tasked with placing the back plastic cover of the mock mobile phone onto the carrier, which is then carried to the next islands via a conveyor belt. The second station is the manual station, where a human operator will place a Printed Circuit Board (PCB) onto the back cover. The third station visually inspects the product automatically, to verify that the PCB that was previously added corresponds to the correct order specifications. Lastly, a bridge station takes the carrier and passes it on to an Automated Guided Vehicle (AGV) that transports it towards the second island with its next four stations. The second island is also equipped with a bridge station that intercepts the AGV and sends the carrier to the island's second station, which places another plastic cover on top of the product. The next station applies a predefined pressure onto the product to seal the two plastic covers. Finally, the last component of the assembly line is the furnace, where the product is heated up to a user-defined temperature to complete the order.

The kinematic model of this assembly line, which initially only mirrored one station of the CP-Lab, was later migrated to the Unity game engine, where the whole structure and motion of the smart factory was modeled (right side of Figure 13). In addition, the virtual model captures streams of sensor data flowing from the CP-Lab via the TCP protocol. This led to the development of a DT-based PdM framework that includes a monitoring dashboard for the machine's sensors (temperature and power data) [184]. The framework makes use of real data coming from the CP-Lab, as well as configuration data stored on the DT, to better position the working regime, identify working stations, and assess the health of individual stations via data pertaining to the whole island. More specifically, the framework targets the health of the furnace station of the second island. Being that it is equipped with a powerful heating element, the malfunctioning of this station could potentially lead to a fire hazard, so it stands to reason that guaranteeing its good health is a necessity. For this reason, the furnace is also equipped with a "Safety Shutdown" mechanism, that will completely halt operations if the temperature inside its chamber surpasses 80°C, however, this system is also not infallible. As such, the framework captures temperature data from inside the furnace, as well as the power data pertaining to the whole second island, to predict if, or when, the Safety Shutdown mechanism will be triggered, in order to proactively prevent it. The DT provides the configuration data of the heating station (i.e., its real-time state) to help the framework extract the furnace's power consumption from the second island's power measurements. As such, in case the temperature sensor or element inside the heating chamber are faulty, the normal behaviour of the station can still be verified via its power data. The DT of the CP-Lab can increase productivity by preventing the unnecessary or anomalous triggering of the Safety Shutdown mechanism, as well as promote safety by predicting when the temperature inside the heating chamber of the Tunnel Furnace Station reaches critical levels.

C. Structural Health Monitoring for Vietnam bridges

In this subsection, the Digital Twin framework for SHM developed at London Digital Twin Research Centre, dubbed

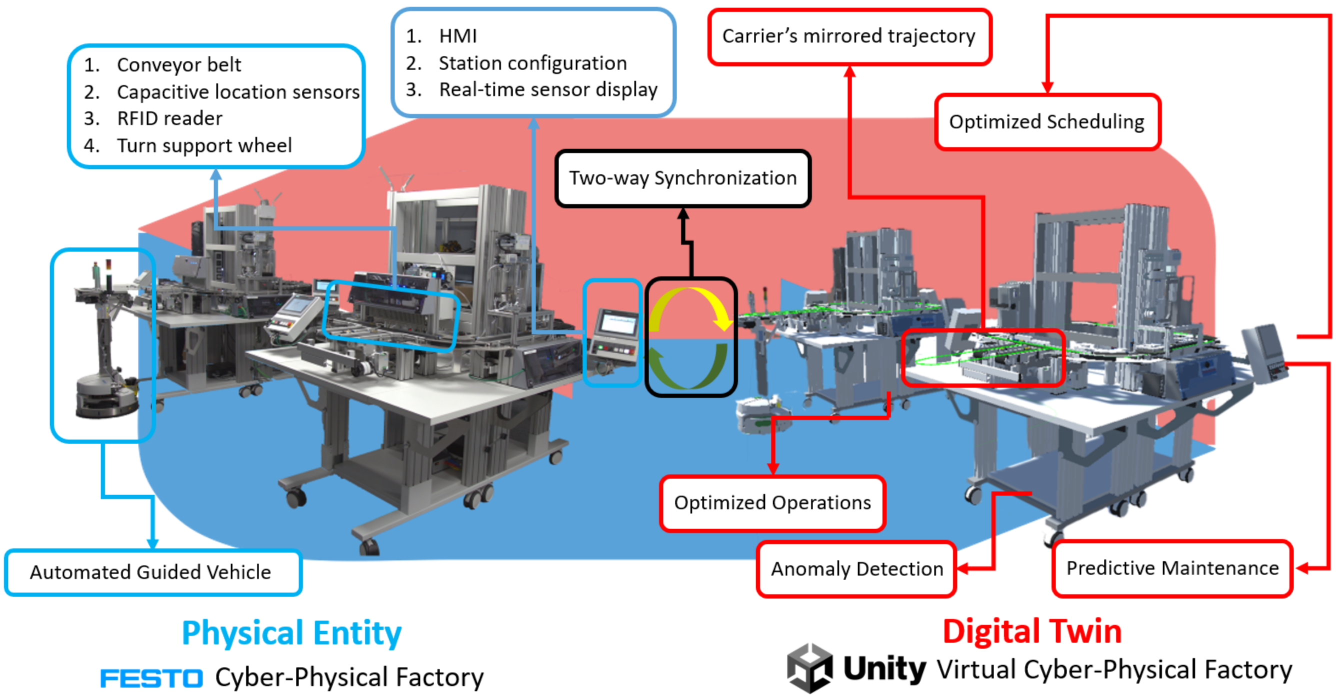

Fig. 13. Digital Twin in I4.0.

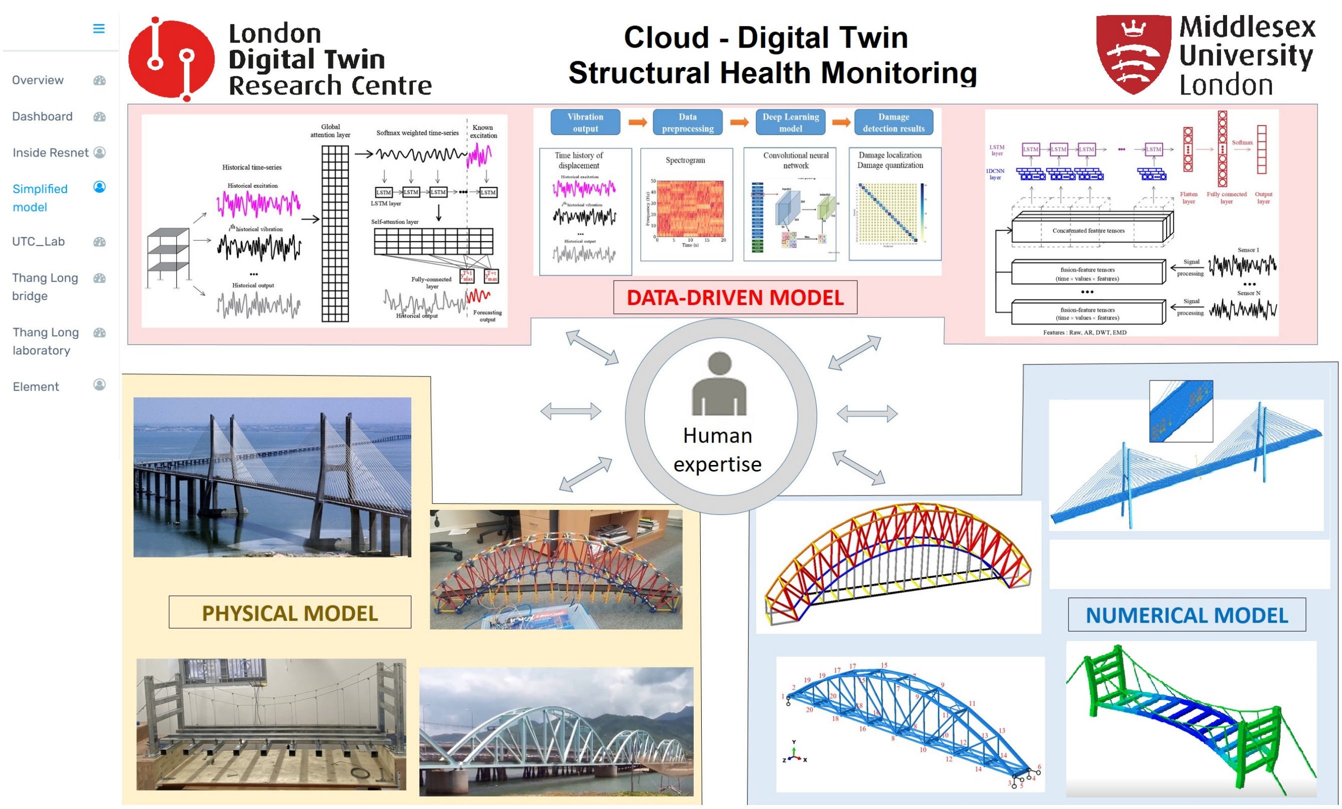

Fig. 14. Cloud Digital Twin Structural Health Monitoring web application

cDTSHM is presented, including its main components, case studies, and its application to bridges, mainly in Vietnam. The cDTSHM consists of four components: the real structures equipped with sensors along their body providing data related to their operational services, a fog layer with local computational servers preprocessing measured data, a cloud layer involving data storage services, and data analytic components leveraging both mathematical models and machine learning-based model, and a web application visualizing the data and computed results. The cDTSHM is developed with the help of the AWS cloud services; most of the programs are written in Python, the ML-based model is implemented using the DL library Pytorch, and the main input data for the framework are the vibration data from accelerometer sensors. Fig. 14 depicts the interface of the cDTSHM, including case studies carried out.

The first case study to demonstrate the applicability of the framework is a toy model of the Sydney Harbour bridge built by using K'nex interlocking plastic rods. Next, one manually excites the model by hand-shaking, where its vibration is recorded by using a set of accelerometer sensors MPU-6050 uniformly distributed across the model. The SHM database was empirically generated by hand-shaking the model; then vibration data were collected through an array of accelerometer sensors MPU-6050 and a microcontroller board Arduino Uno. The damaged states of the model were introduced by randomly removing one or two truss rods. After that, two data analytic algorithms, including a lite mathematical model and a ML-based model are developed to detect the structure status. Furthermore, the latter could spatially localize the damage's location and quantize the damage severity.

The second case study used to validate the correctness of the framework is a simplified laboratory model of a stayed-cable bridge whose physical and numerical models are shown in the corner of Fig. 14. The SHM procedure is realized similarly to the first example, but the experiment data, including excitation, vibration data, structure's deformation are controlled and measured more rigorously. The model is excited by introducing an impulse force of very short duration through an impact hammer; the structure's status is then assessed based on the loss level of prestressing strands which can be manually modified by alternating the anchor bolts tightness. As a result, the sDTSHM can provide highly accurate SHM results with much less CPU time while bypassing the cumbersome preprocessing modal analysis as in the conventional structural identification methods.

For the third case study, the performance of the SHM framework is tested with real data collected from the Z24 bridge in Switzerland [185]. For such a real structure, using a lite mathematical model or shallow ML cannot provide reliable SHM results. Thus, a highly modular architecture has been devised, allowing switching different DL algorithms and combining data from different sensors in a straightforward way [186]. The results demonstrate that the data analytic component of the cDTSHM outperforms competing methods with a structural damage detection result of 90.1% with low time complexity and budget memory storage.

Afterwards, the cDTSHM framework is applied to the Nam O railway bridge located in central Vietnam. The bridge is 60 years old and constantly undergoes unfavorable factors involving the corrosive maritime environment, dynamic and heavy train loadings, etc. From the structural perspective, the structure's mode shapes and their high-order derivatives are sensitive to damages; therefore, a knowledge-enhanced deep 1D-CNN has been developed for automatically extracting modal characteristics from raw vibration data to accurately detect and quantify connection stiffness reductions. The realization steps and implementation details can be found in [187]. The results show that the framework could achieve accuracy up to 95% even with minor damage (5% of stiffness reduction) with faster convergence speed and more stable results than counterparts, including the Multi-Layer Perceptron and other DL architectures.

The four case studies illustrated in this subsection demonstrate that the enabling technologies supporting a DT will vary greatly, depending on the DT's use-case, as also mentioned in our definition, provided in Section II. Additionally, the cDTSHM framework has been developed to exhibit self-diagnosing and self-monitoring capabilities within several case studies of bridges.

VII. Lessons Learned, Research Challenges and Future Directions

The previous sections provided a comprehensive view of the DT, commencing with its definition, market potential, enabling technologies, frameworks and applications, and, finally, three case studies. Throughout the literature surveyed in this manuscript, as well as our own experience in developing DTs, we have learned important lessons and encountered significant challenges that will contour future directions for us and the research community. This section will delve into the most significant of these concepts, detailing the obstacles that the DT needs to overcome in order to realize its potential.

A. Investment costs

As mentioned in Section III, businesses still remain reluctant to implement the DT because of its envisioned development costs and difficult-to-quantify ROI. As a matter of fact, it is rather challenging to put a price on the DT because of its multi-disciplinary nature and use-case-specific particularities. Additionally, the DT is rarely a product that generates direct profit, since its core philosophy focuses primarily on saving costs. With the exception of DT solution providers and the healthcare industry, where the DT can indeed be a source of revenue, other entrepreneurs will need detailed and long-term plans of investment that emphasize the merits of DT development before diving into such expenditures.

One important aspect that must be factored into the costs when planning for DTs, is the ongoing maintenance requirements, such as: software updates that affect the DT, changes to the physical asset, etc. Considering the total life cycle of the DTs, one could anticipate that the maintenance and management cost might represent the largest proportion of the investment costs.

B. Social and ethical challenges

Digital Twin technology and applications are experiencing a shift from engineering/physics based domains, where closed equations are an appropriate modelling abstraction, to one where the problem domain is socio-technical, leading to the notion of Socio-Technical Digital Twins (STDT). Such a problem domain utilises systems that comprise complex interaction between humans, machines and the work environment

[188]. This class of system is characterised by heterogeneous networked agents, adaptive and goal oriented with respect to the environment and joint optimisation and evolution of both technical and social systems [189]. These properties are also those that are characterised by agent based systems and make such technologies ideal for representation of STDTs despite computational cost [189], [190]. Hence, STDTs generate new and different research challenges.

DTs of phenomena that include human interactions and behaviours acquire complexity simply due to the involvement of multiple disciplines. For example, DT models of cities for monitoring pandemic behaviour have included social geographers, economists, medical practitioners as well as computer scientists. Arriving at a shared understanding, common language and a way of working demands new methodological approaches as well as intuitive access to underpinning theory from different disciplines [191].

Moving away from closed equations to systems that model emergent behaviour presents expected validation challenges. Recognising that a STDT has purpose beyond prediction such as explanation is the first response [192]. STDTs can be used for discovering new questions, demonstrating trade-offs or experimentation with prevailing theories that lack empirical understanding. Hence they represent a move away from closed form analytical models. Models are a form of theory building [193] and as such they can only be invalidated so a more useful target is a form of *accredited* or *accepted* model based on standardised criteria and metrics [194]. As STDTs become more established, policy oriented domain-specific practice could lead to to libraries of accepted models, encoding existing knowledge, that do not need to change and are much less volatile. Given the emergent properties of STDTs, such models need to be defined at both micro, meso and macro levels. Building libraries of STDT models is reminiscent of component based development practice and its inherent challenges [195].

Validation of a model for STDT is closely related to abstraction concerns and in particular the challenges that arise from establishing an appropriate framing structure. The complexity, multi-level and range of modelling required to represent a socio-technical problem domain within a DT require choices to be made in determining the scope and detail of the environment to be modelled. This choice we can refer to it as a *conceptual problem frame*. For example, Barat et al. [191] in their city DT of Pune, for modelling the COVID-19 pandemic, observe that existing agent based systems for pandemic modelling do not show sufficient granularity of types of people and their movements within the city, raising concerns of model completeness.

Perhaps the most striking challenge that needs to be addressed is that arising from STDTs that include ML or other algorithmic decision making. Ethical concerns come to the fore when (1) conclusions drawn from inference are probable and therefore an epistemic limitation; (2) traceability between the input data and conclusion is not accessible and open to critique; (2) conclusions are dependent upon the quality of data; or (4) the actions based on conclusions are discriminatory even if well-founded [196]. Underpinnning these epistemically-based ethical issues is the encoding of value systems such as privacy, transparency, security and so on. Understanding value sensitive concerns and related approaches that explore more fundamentally the nature of social requirements and (unintended social impacts) of software remains an ongoing project in software engineering [197] and requires study in the context of STDTs.

C. Fidelity and rate of synchronization

A common misconception about the DT is that the virtual twin should reflect the physical twin in its entirety, and that it should gather and process all of its data in almost real-time. However, these feats are not currently feasible, and certainly not always necessary. As specified in our definition of the DT, provided in Section II, the virtual representation's fidelity and rate of synchronization are specific to the DT's use-cases. For instance, for ambitious, nation-wide project like the U.S. Air Force's DT for weapon system development, the required fidelity and responsiveness might impose prohibitive costs [198]. On the other hand, for the purposes of traffic relief, a DT that stores the coordinates and synchronization rates of traffic lights, as well as the real-time traffic density, might arguably perform almost as well as a DT that completely 3D models the city's infrastructure. As such, the DT's granularity and twinning rate requirements can be more, or less, lenient, depending on its applications. The more stringent demands for real-time, granular mirroring could be encountered in the healthcare industry, for scenarios where the DT is used to facilitate remote surgery.

D. Standardisation efforts

One of the most important features that could accelerate the adoption of DTs within various industries is their modularity. This could enable the rapid reproduction of DT processes and their components. However, this dynamic environment could become very complex, with different digital twins custom built for different purposes, specific equipment type, specific manufacturers, etc., these represent factors that could inhibit the adoption and implementation of DTs across multiple industries. These complexities could be eliminated through standardisation.

Recently, one of the subcommittees (SC 41[2]) of the Joint International Organization for Standardization (ISO) and International Electrotechnical Commission (IEC) Technical Committee (JTC 1)[3] has widened its scope and terms of references to include DT, looking now into standardization in the area of IoT and DTs, including their related technologies.

The ISO 23247-1[4] standard for DT framework for manufacturing is currently under development. The first part of the standard provides general principles and defines the requirements for developing DTs in manufacturing.

Similarly, the National Institute of Standards and Technology (NIST) in an attempt to standardize the DT technology,

[2]SC 41: https://bit.ly/3tf0hSM
[3]JTC 1: https://jtc1info.org/
[4]ISO 23247-1 Digital Twin Framework for Manufacturing: https://www.iso.org/standard/75066.html

have released a draft NISTIR 8356 [199] covering the definition, common low-level operations, usage scenarios, and use-cases examples.

Another initiative that has as a primary objective to influence the requirements for DT standards is the Digital Twin Consortium[5]. The consortium consists of members from industry, government, and academia that form a global ecosystem aiming to accelerate the development, adoption, interoperability, and security of DTs.

One proposed solution by Harper et al. [200] could be to define a set of standardised Application Process Interfaces (APIs) that could evolve over time. The advantage of this approach is that different DTs could be developed using different software and processes as long as they support the defined set of APIs.

Microsoft developed the Digital Twin Definition Language[6] (DTDL) that is used in their commercial services, such as IoT Hub, IoT Central and Azure Digital Twins. However, DTDL does not resource discovery and access and deals with resource description only.

Consequently, the current lack of standardised approaches when modelling digital twins open up new challenges when dealing with their interoperability in order to maximize the interconnectivity.

E. Data ownership and governance

Apart from standardisation, another closely related challenge is the data ownership and governance, that brings a new question, specifically: *Who owns the DT information?* One can anticipate that with the advancements in technologies, the industry is moving towards a connected data ecosystem of DTs with potential different owners of the physical assets as well as the DTs. Additionally, the potential existence of an ecosystem of DTs implies the need for a shared communication framework for standardized data exchange between multiple heterogeneous data sources. This scenario brings technical, financial and legal aspects challenges that need to be clarified.

One solution would be to adopt the Industrial Data Space (IDS)[7] concept that has been introduced in [201] to cater for all these issues within the I4.0 framework. The IDS concept represents a virtual data space that enforces data ownership within a distributed environment, based on open standards and existing technologies as well as common governance models for data economy. As DTs are seen as part of I4.0, the IDS model could be the answer for DTs data ownership and governance. In parallel, an effort for constructing an Information Management Framework (IMF) for the National Digital Twin is carried out in [202], where the goal is to create a common national information resource that can sustain a country-wide DT.

F. Data security

There are two ways to approach the discussion on security issues in DTs. The first one addresses the security of the DT itself, starting from the physical servers that host the DTs up until the safety and integrity of the software and data communication links that animate the DT. The second approach is about how the DT itself can provide security to its real twin, as an additional valuable offering. This section will touch on both of these aspects of security within DTs.

One of the central components of a DT is the communication medium that enables the symbiotic relationship between the physical and virtual twins. This link effectively transports all the data between the two entities, so it stands to reason that it needs to guarantee impeccable data security. Every time data flows to, and from, the real twin, or in-between the servers hosting the DT itself, the risk of losing important information is high, which calls for increased attention to preserving data integrity [203]. This communication medium becomes a potential area of weakness in front of data corruption and theft, and it can create disturbances for businesses. As such, data security principles, like privacy, authentication, integrity, and traceability, need to be taken into account during DT development. Some important measures that provide security features are data encryption, access privileges, source code automated scanning, penetration testing, and routine checkups [204]. Emerging approaches to deal with these issues include using blockchain technologies to ensure data privacy in the communication between DT systems-of-systems [94]. Yaqoob et al. [205] conducted an extensive research on how blockchain has been integrated in the DTs across literature to also ensure trust and transparency in various use cases.

Given that the DT is still an emerging technology, the related literature still lacks a consensus on its security requirements. As we have discovered throughout this research work, the use case and services envisioned for the DT can dictate the architecture of the virtual twin. According to Gehrmann et al. in [206], security measures should also be at the forefront of the DT architects' minds since they can have a significant impact on the final DT model's structure as well. The authors also introduced the idea of using the DT as an enabler of security in the communication between the physical twin and other cloud-based services, of which DTs might make use. In their work, all external communication with the physical twin would be carried out exclusively via the virtual model, through a synchronization gateway that filters all traffic to the real twin, effectively isolating it from bad agents. A similar approach was taken in [207], where the authors proposed using the DT to filter out incoming commands to a smart inverter and ensure that only the non-malicious ones are carried out.

G. Artificial General Intelligence, beyond human performance

In Section II of this manuscript, we have described the DT as a self-adapting, self-regulating, self-monitoring, and self-diagnosing system-of-systems, a definition which places it under the span of another, broader category of human ambitions: Artificial Intelligence. In fact, the idea of self-improving artificial systems was part of the original proposal made by McCarthy et al. in 1955 for the Darthmouth Summer Research Project on AI, a project which is also sometimes dubbed as the birthplace of AI [208]. Since then, significant

[5]Digital Twin Consortium: https://www.digitaltwinconsortium.org
[6]Digital Twin Definition Language: https://bit.ly/3jJ3EOV
[7]Industrial Data Space: https://internationaldataspaces.org

progress has been carried out towards realizing the objectives laid out in said proposal, and the term “AI” has now become so popular that some voices have raised concerns about the implications of integrating AI into our society [209]. However, as Shevlin et al. emphasize in [210], there is an important distinction to be made between the original meaning assigned to AI by McCarthy et al. in 1955, and AI as it is understood and marketed today. McCarthy’s proposal identified AI as a machine that behaves “in ways that would be called intelligent if a human were so behaving”, whereas nowadays, AI is sometimes used to refer to systems that reach or surpass human performance in specific tasks [211], [212]. The former interpretation corresponds to what is today understood as Artificial General Intelligence (AGI), while the latter is an appropriate example of Artificial Narrow Intelligence (ANI) [210].

However, although there is a great overlap between the DT and AGI, there are some differences that stand out and can make the DT an even more challenging task than AGI. First, the versatility of the DT paradigm across industries implies that it will, by definition, have a specialized kind of intelligence that cannot be generalized to other domains, but trains and excels in every possible task that pertains to the physical twin’s use cases, including hypothetical scenarios. In order for the DT to become truly self-evolving, just like humans and animals are, it needs to be able to implement a level of *creativity* that can make maximal use of its physical twin’s unique features (i.e., learn to become as resourceful with its physical structure as an animal is with its body). This implies that, just like there is a need for standardized benchmarks for validating human AGI, or animal intelligence-mimicking AGI [210], there is also a requirement for performance measures and benchmarks that can accurately evaluate the DT for each industry and application. Validation metrics aside, while current AI systems can definitely learn to perform tasks even beyond human-level performance, they also lack comprehension, and therefore cannot offer transparency into their “reasoning” [213]. This lack of transparency invokes skepticism, and can even impede development of DTs or AIs due to lack of trust.

VIII. Conclusions

This paper took an in-depth look at the existing and expanding Digital Twin-related literature, and we drew some lessons that will help the researchers in this field consolidate their understanding of the DT and choose future directions that need further development. In Section II, we took a look at the variety of DT definitions that the papers reviewed in this manuscript provided and we clustered them together according to their similarity; then, we introduced a new, comprehensive definition for the DT that covers important aspects that the others might have missed. In Section III, we evaluated the current level of adoption of the DT in the industry, and how this paradigm is currently valued by various leading businesses in this field. Section IV then dove into the technical aspects of the DT, namely its enabling technologies, and how they are being used to support the DT in delivering business value across various industries. Consequently, in Section V, we described how the previously presented technologies help the DT in providing a handful of services, ranging from smart manufacturing to new generation communication technologies. Section VI offered a closer look at three DT case studies in order to present how the technology can be leveraged and what requirements and limitations appear, based on the use case. Finally, Section VII summarized the lessons we have learned throughout this review, in order to point out interesting new challenges to be addressed in the research community.

Overall, the DT finds itself accelerating in full force towards I4.0, and its endless perceived potential makes it a central and evermore popular player in the race. Its enabling technologies are continuously evolving, and each step towards their improvement brings us closer to making true DTs a reality. As the DT attracts research interest, the number of attempts at developing it contour some common and persisting obstacles. In the era of AI, the focus falls on the data, and the DT finds itself in the middle of an information loop: it needs to be fed carefully considered data to power its complex ML algorithms, and then it further allows a better understanding of that data via its interactive and predictive feats. With some challenging puzzles in the way, the DT is steadily heading towards the automation of industrial processes.

References

[1] L. Laura, O. Clayton, S. Jeremy, and S. Kate, “How covid-19 has pushed companies over the technology tipping point and transformed business forever,” *McKinsey & Company*, vol. 5, 2020.

[2] S. Blackburn, L. LaBerge, C. O’Toole, and J. Schneider, “Digital strategy in a time of crisis,” *McKinsey Digital, April*, vol. 22, 2020.

[3] U. Cisco, “Cisco annual internet report (2018–2023) white paper,” *Online](accessed September 12th, 2021) https://www. cisco. com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/whitepaper-c11-741490. html*, 2020.

[4] M. Grieves and J. Vickers, “Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems,” in *Transdisciplinary perspectives on complex systems*, pp. 85–113, Springer, 2017.

[5] M. E. Rose and J. R. Kitchin, “pybliometrics: Scriptable bibliometrics using a python interface to scopus,” *SoftwareX*, vol. 10, p. 100263, 2019.

[6] B. R. Barricelli, E. Casiraghi, and D. Fogli, “A survey on digital twin: definitions, characteristics, applications, and design implications,” *IEEE access*, vol. 7, pp. 167653–167671, 2019.

[7] R. Minerva, G. M. Lee, and N. Crespi, “Digital twin in the iot context: a survey on technical features, scenarios, and architectural models,” *Proceedings of the IEEE*, vol. 108, no. 10, pp. 1785–1824, 2020.

[8] A. Löcklin, M. Müller, T. Jung, N. Jazdi, D. White, and M. Weyrich, “Digital twin for verification and validation of industrial automation systems–a survey,” in *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, vol. 1, pp. 851–858, IEEE, 2020.

[9] F. Biesinger, B. Kraß, and M. Weyrich, “A survey on the necessity for a digital twin of production in the automotive industry,” in *2019 23rd International Conference on Mechatronics Technology (ICMT)*, pp. 1–8, IEEE, 2019.

[10] Y. He, J. Guo, and X. Zheng, “From surveillance to digital twin: Challenges and recent advances of signal processing for industrial internet of things,” *IEEE Signal Processing Magazine*, vol. 35, no. 5, pp. 120–129, 2018.

[11] F. Pires, A. Cachada, J. Barbosa, A. P. Moreira, and P. Leitão, “Digital twin in industry 4.0: Technologies, applications and challenges,” in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, vol. 1, pp. 721–726, IEEE, 2019.

[12] A. Rasheed, O. San, and T. Kvamsdal, “Digital twin: Values, challenges and enablers from a modeling perspective,” *Ieee Access*, vol. 8, pp. 21980–22012, 2020.

[13] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, 2019.

[14] Z. Huang, Y. Shen, J. Li, M. Fey, and C. Brecher, "A survey on ai-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics," *Sensors*, vol. 21, no. 19, 2021.

[15] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE access*, vol. 8, pp. 108952–108971, 2020.

[16] NASA, "Apollo expeditions to the moon: Chapter 13." https://www.hq.nasa.gov/office/pao/History/SP-350/ch-13-1.html. (Accessed on 22/06/2021).

[17] K. Dröder, P. Bobka, T. Germann, F. Gabriel, and F. Dietrich, "A machine learning-enhanced digital twin approach for human-robot-collaboration," *Procedia Cirp*, vol. 76, pp. 187–192, 2018.

[18] M. Xia, H. Shao, D. Williams, S. Lu, L. Shu, and C. W. de Silva, "Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning," *Reliability Engineering & System Safety*, vol. 215, p. 107938, 2021.

[19] Q. Qi, D. Zhao, T. W. Liao, and F. Tao, "Modeling of cyber-physical systems and digital twin based on edge computing, fog computing and cloud computing towards smart manufacturing," in *International Manufacturing Science and Engineering Conference*, vol. 51357, p. V001T05A018, American Society of Mechanical Engineers, 2018.

[20] V. Souza, R. Cruz, W. Silva, S. Lins, and V. Lucena, "A digital twin architecture based on the industrial internet of things technologies," in *2019 IEEE International Conference on Consumer Electronics (ICCE)*, pp. 1–2, 2019.

[21] J. Leng, H. Zhang, D. Yan, Q. Liu, X. Chen, and D. Zhang, "Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop," *Journal of ambient intelligence and humanized computing*, vol. 10, no. 3, pp. 1155–1166, 2019.

[22] S. Aheleroff, X. Xu, R. Y. Zhong, and Y. Lu, "Digital twin as a service (dtaas) in industry 4.0: an architecture reference model," *Advanced Engineering Informatics*, vol. 47, p. 101225, 2021.

[23] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, and R. Harik, "A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence," *Journal of Manufacturing Systems*, vol. 58, pp. 210–230, 2021.

[24] P. Wang and M. Luo, "A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing," *Journal of Manufacturing Systems*, vol. 58, pp. 16–32, 2021.

[25] W. Xu, J. Cui, L. Li, B. Yao, S. Tian, and Z. Zhou, "Digital twin-based industrial cloud robotics: framework, control approach and implementation," *Journal of Manufacturing Systems*, vol. 58, pp. 196–209, 2021.

[26] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, and M. J. Deen, "A novel cloud-based framework for the elderly healthcare services using digital twin," *IEEE Access*, vol. 7, pp. 49088–49101, 2019.

[27] C. Liu, L. Le Roux, C. Körner, O. Tabaste, F. Lacan, and S. Bigot, "Digital twin-enabled collaborative data management for metal additive manufacturing systems," *Journal of Manufacturing Systems*, 2020.

[28] Z. Zhao, L. Shen, C. Yang, W. Wu, M. Zhang, and G. Q. Huang, "Iot and digital twin enabled smart tracking for safety management," *Computers & Operations Research*, vol. 128, p. 105183, 2021.

[29] C. Liu, P. Jiang, and W. Jiang, "Web-based digital twin modeling and remote control of cyber-physical production systems," *Robotics and computer-integrated manufacturing*, vol. 64, p. 101956, 2020.

[30] X. He, Q. Ai, R. C. Qiu, and D. Zhang, "Preliminary exploration on digital twin for power systems: Challenges, framework, and applications," *arXiv preprint arXiv:1909.06977*, 2019.

[31] Y. Xu, Y. Sun, X. Liu, and Y. Zheng, "A digital-twin-assisted fault diagnosis using deep transfer learning," *IEEE Access*, vol. 7, pp. 19990–19999, 2019.

[32] W. Hofmann and F. Branding, "Implementation of an iot-and cloud-based digital twin for real-time decision support in port operations," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 2104–2109, 2019.

[33] L. López-Estrada, M. Fajardo-Pruna, S. Gualoto-Condor, J. Ríos, and A. Vizán, "Creation of a micro cutting machine tool digital-twin using a cloud-based model-based plm platform: first results," *Procedia manufacturing*, vol. 41, pp. 137–144, 2019.

[34] Y. Pan, T. Qu, N. Wu, M. Khalgui, and G. Huang, "Digital twin based real-time production logistics synchronization system in a multi-level computing architecture," *Journal of Manufacturing Systems*, vol. 58, pp. 246–260, 2021.

[35] E. Hinchy, N. P. O'Dowd, and C. T. McCarthy, "Using open-source microcontrollers to enable digital twin communication for smart manufacturing," *Procedia Manufacturing*, vol. 38, pp. 1213–1219, 2019.

[36] F. Tao, Q. Qi, L. Wang, and A. Nee, "Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: Correlation and comparison," *Engineering*, vol. 5, no. 4, pp. 653–661, 2019.

[37] M. Borth, J. Verriet, and G. Muller, "Digital twin strategies for sos 4 challenges and 4 architecture setups for digital twins of sos," in *2019 14th annual conference system of systems engineering (SoSE)*, pp. 164–169, IEEE, 2019.

[38] E. Negri, S. Berardi, L. Fumagalli, and M. Macchi, "Mes-integrated digital twin frameworks," *Journal of Manufacturing Systems*, vol. 56, pp. 58–71, 2020.

[39] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, "Deep learning for hybrid 5g services in mobile edge computing systems: Learn from a digital twin," *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4692–4707, 2019.

[40] T. Zohdi, "A machine-learning framework for rapid adaptive digital-twin based fire-propagation simulation in complex environments," *Computer Methods in Applied Mechanics and Engineering*, vol. 363, p. 112907, 2020.

[41] T. Ritto and F. Rochinha, "Digital twin, physics-based model, and machine learning applied to damage detection in structures," *Mechanical Systems and Signal Processing*, vol. 155, p. 107614, 2021.

[42] S. Chakraborty and S. Adhikari, "Machine learning based digital twin for dynamical systems with multiple time-scales," *Computers & Structures*, vol. 243, p. 106410, 2021.

[43] M. A. Ali, Q. Guan, R. Umer, W. J. Cantwell, and T. Zhang, "Deep learning based semantic segmentation of μct images for creating digital material twins of fibrous reinforcements," *Composites Part A: Applied Science and Manufacturing*, vol. 139, p. 106131, 2020.

[44] B. Maschler, D. Braun, N. Jazdi, and M. Weyrich, "Transfer learning as an enabler of the intelligent digital twin," *Procedia CIRP*, vol. 100, pp. 127–132, 2021.

[45] Z. Wang, X. Liao, X. Zhao, K. Han, P. Tiwari, M. J. Barth, and G. Wu, "A digital twin paradigm: Vehicle-to-cloud based advanced driver assistance systems," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, pp. 1–6, IEEE, 2020.

[46] P. Rajesh, N. Manikandan, C. Ramshankar, T. Vishwanathan, and C. Sathishkumar, "Digital twin of an automotive brake pad for predictive maintenance," *Procedia Computer Science*, vol. 165, pp. 18–24, 2019.

[47] R. Revetria, F. Tonelli, L. Damiani, M. Demartini, F. Bisio, and N. Peruzzo, "A real-time mechanical structures monitoring system based on digital twin, iot and augmented reality," in *2019 Spring Simulation Conference (SpringSim)*, pp. 1–10, IEEE, 2019.

[48] G. White, A. Zink, L. Codecá, and S. Clarke, "A digital twin smart city for citizen feedback," *Cities*, vol. 110, p. 103064, 2021.

[49] A. Burger, C. Cichiwskyj, S. Schmeißer, and G. Schiele, "The elastic internet of things-a platform for self-integrating and self-adaptive iot-systems with support for embedded adaptive hardware," *Future Generation Computer Systems*, vol. 113, pp. 607–619, 2020.

[50] E. Y. Song, M. Burns, A. Pandey, and T. Roth, "Ieee 1451 smart sensor digital twin federation for iot/cps research," in *2019 IEEE Sensors Applications Symposium (SAS)*, pp. 1–6, IEEE, 2019.

[51] S. M. Bazaz, M. Lohtander, and J. Varis, "5-dimensional definition for a manufacturing digital twin," *Procedia Manufacturing*, vol. 38, pp. 1705–1712, 2019.

[52] E. Negri, L. Fumagalli, C. Cimino, and M. Macchi, "Fmu-supported simulation for cps digital twin," *Procedia manufacturing*, vol. 28, pp. 201–206, 2019.

[53] E. Negri, H. D. Ardakani, L. Cattaneo, J. Singh, M. Macchi, and J. Lee, "A digital twin-based scheduling framework including equipment health index and genetic algorithms," *IFAC-PapersOnLine*, vol. 52, no. 10, pp. 43–48, 2019.

[54] M. Glatt, C. Sinnwell, L. Yi, S. Donohoe, B. Ravani, and J. C. Aurich, "Modeling and implementation of a digital twin of material flows based on physics simulation," *Journal of Manufacturing Systems*, vol. 58, pp. 231–245, 2021.

[55] Q. Min, Y. Lu, Z. Liu, C. Su, and B. Wang, "Machine learning based digital twin framework for production optimization in petrochemical industry," *International Journal of Information Management*, vol. 49, pp. 502–519, 2019.

[56] H. Laaki, Y. Miche, and K. Tammi, "Prototyping a digital twin for real time remote control over mobile networks: Application of remote surgery," *IEEE Access*, vol. 7, pp. 20325–20336, 2019.

[57] D. Guo, R. Y. Zhong, P. Lin, Z. Lyu, Y. Rong, and G. Q. Huang, "Digital twin-enabled graduation intelligent manufacturing system for fixed-position assembly islands," *Robotics and Computer-Integrated Manufacturing*, vol. 63, p. 101917, 2020.

[58] M. Matulis and C. Harvey, "A robot arm digital twin utilising reinforcement learning," *Computers & Graphics*, vol. 95, pp. 106–114, 2021.

[59] P. Zheng and A. S. Sivabalan, "A generic tri-model-based approach for product-level digital twin development in a smart manufacturing environment," *Robotics and Computer-Integrated Manufacturing*, vol. 64, p. 101958, 2020.

[60] IBM, "What is a digital twin?." https://www.ibm.com/topics/what-is-a-digital-twin#:~:text=A%20digital%20twin%20is%20a, Types. (Accessed on 22/06/2021).

[61] A. Mehra, "Digital twin market worth $48.2 billion by 2026." https://www.marketsandmarkets.com/PressReleases/digital-twin.asp. (Accessed on 22/06/2021).

[62] IBM, "Hong kong applied science and technology research institute company limited." https://www.ibm.com/case-studies/hong-kong-astri-engineering-rhapsody. (Accessed on 22/06/2021).

[63] IBM, "Profile: Ucsf health and maximo lead the way on smart medical buildings." https://www.ibm.com/blogs/internet-of-things/iot-ucsf-health-and-maximo-smart-medical-buildings/. (Accessed on 22/06/2021).

[64] Ansys, "Digital twins: Making the vision achievable — ansys white paper." https://www.ansys.com/resource-center/white-paper/digital-twins-making-vision-achievable. (Accessed on 22/06/2021).

[65] F. Glas, "Virtual quality assurance in the digital orthopaedic workshop of the future — ansys case study." https://www.ansys.com/resource-center/case-study/mecuris-virtual-quality-assurance-digital-orthopaedic-workshop-future. (Accessed on 22/06/2021).

[66] R. Damian, "Ansys + jet towers." https://www.ansys.com/content/dam/product/3d-design/aim/case-study-jet-towers.pdf. (Accessed on 22/06/2021).

[67] G. P. D. Solutions, "Ge digital twin." https://www.ge.com/digital/sites/default/files/download_assets/Digital-Twin-for-the-digital-power-plant-.pdf. (Accessed on 22/06/2021).

[68] Spirent, "5g network digital twin - spirent." https://www.spirent.com/assets/wp_simplifying-5g-with-the-network-digital-twin. (Accessed on 22/06/2021).

[69] R. Jamnadass, "Stl partners: The relationship between 5g and digital twins in industry 4.0 - spirent." https://www.spirent.com/assets/the-relationship-between-5g-and-digital-twins-in-industry-4-0. (Accessed on 22/06/2021).

[70] D. A. Institute, "Predictive maintenance." https://www2.deloitte.com/content/dam/Deloitte/de/Documents/deloitte-analytics/Deloitte_Predictive-Maintenance_PositionPaper.pdf. (Accessed on 22/06/2021).

[71] Markets and Markets, "Digital Twin Market by Technology, Type, Application, Industry — COVID-19 Impact Analysis." https://www.marketsandmarkets.com/Market-Reports/digital-twin-market-225269522.html. (Accessed on 22/06/2021).

[72] A. B. S. Evans, C. Savian and C. Cooper, "Digital twins for the built environment." https://www.theiet.org/media/4719/digital-twins-for-the-built-environment.pdf. (Accessed on 22/06/2021).

[73] M. Mitchell, "Why ai is harder than we think," *arXiv preprint arXiv:2104.12871*, 2021.

[74] M. S. Ibrahim, J. Fan, W. K. Yung, A. Prisacaru, W. van Driel, X. Fan, and G. Zhang, "Machine learning and digital twin driven diagnostics and prognostics of light-emitting diodes," *Laser & Photonics Reviews*, vol. 14, no. 12, p. 2000254, 2020.

[75] P. Franciosa, M. Sokolov, S. Sinha, T. Sun, and D. Ceglarek, "Deep learning enhanced digital twin for closed-loop in-process quality improvement," *CIRP Annals*, vol. 69, no. 1, pp. 369–372, 2020.

[76] K. Alexopoulos, N. Nikolakis, and G. Chryssolouris, "Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing," *International Journal of Computer Integrated Manufacturing*, vol. 33, no. 5, pp. 429–439, 2020.

[77] F. Xue, W. Lu, Z. Chen, and C. J. Webster, "From lidar point cloud towards digital twin city: Clustering city objects based on gestalt principles," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 167, pp. 418–431, 2020.

[78] M. H. Farhat, X. Chiementin, F. Chaari, F. Bolaers, and M. Haddar, "Digital twin-driven machine learning: ball bearings fault severity classification," *Measurement Science and Technology*, vol. 32, no. 4, p. 044006, 2021.

[79] M. Samnejad, M. Gharib Shirangi, and R. Ettehadi, "A digital twin of drilling fluids rheology for real-time rig operations," in *Offshore Technology Conference*, OnePetro, 2020.

[80] C. Cronrath, A. R. Aderiani, and B. Lennartson, "Enhancing digital twins through reinforcement learning," in *2019 IEEE 15th International Conference on Automation Science and Engineering (CASE)*, pp. 293–298, IEEE, 2019.

[81] S. E. Ahmed, O. San, K. Kara, R. Younis, and A. Rasheed, "Multi-fidelity computing for coupling full and reduced order models," *Plos one*, vol. 16, no. 2, p. e0246092, 2021.

[82] J. Gammerman, "Predictive maintenance with conformal and probabilistic prediction: A commercial case study." https://www.jamesgammerman.com/files/Thesis.pdf. MSc. Thesis, Dept. of Computer Science, RHUL, London, (Accessed on 08/05/2021).

[83] A. Jayakumar, B. Mathew, N. Uma, and P. Nedungadi, "Interactive gesture based cataract surgery simulation," in *2015 Fifth International Conference on Advances in Computing and Communications (ICACC)*, pp. 350–353, IEEE, 2015.

[84] H. F. Vargas and O. A. Vivas, "Gesture recognition system for surgical robot's manipulation," in *2014 XIX Symposium on Image, Signal Processing and Artificial Vision*, pp. 1–5, IEEE, 2014.

[85] G. Lingyun, Z. Lin, and W. Zhaokui, "Hierarchical attention-based astronaut gesture recognition: A dataset and cnn model," *IEEE Access*, vol. 8, pp. 68787–68798, 2020.

[86] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," *arXiv preprint arXiv:1704.04861*, 2017.

[87] K. Liu, L. Song, W. Han, Y. Cui, and Y. Wang, "Time-varying error prediction and compensation for movement axis of cnc machine tool based on digital twin," *IEEE Transactions on Industrial Informatics*, pp. 1–1, 2021.

[88] V. Zaccaria, M. Stenfelt, I. Aslanidou, and K. G. Kyprianidis, "Fleet monitoring and diagnostics framework based on digital twin of aero-engines," in *Turbo Expo: Power for Land, Sea, and Air*, vol. 51128, p. V006T05A021, American Society of Mechanical Engineers, 2018.

[89] S. Mi, Y. Feng, H. Zheng, Y. Wang, Y. Gao, and J. Tan, "Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework," *Journal of Manufacturing Systems*, vol. 58, pp. 329–345, 2021. Digital Twin towards Smart Manufacturing and Industry 4.0.

[90] L. Hu, N.-T. Nguyen, W. Tao, M. C. Leu, X. F. Liu, M. R. Shahriar, and S. N. Al Sunny, "Modeling of cloud-based digital twins for smart manufacturing with mt connect," *Procedia manufacturing*, vol. 26, pp. 1193–1203, 2018.

[91] Z. Jiang, Y. Guo, and Z. Wang, "Digital twin to improve the virtual-real integration of industrial iot," *Journal of Industrial Information Integration*, vol. 22, p. 100196, 2021.

[92] J. Tan, X. Sha, B. Dai, and T. Lu, "Wireless technology and protocol for iiot and digital twins," in *2020 ITU Kaleidoscope: Industry-Driven Digital Transformation (ITU K)*, pp. 1–8, IEEE, 2020.

[93] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning for digital twin edge networks in industrial iot," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5709–5718, 2021.

[94] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning and permissioned blockchain for digital twin edge networks," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2276–2288, 2021.

[95] O. Cardin, "Classification of cyber-physical production systems applications: Proposition of an analysis framework," *Computers in Industry*, vol. 104, pp. 11–21, 2019.

[96] R. Rocca, P. Rosa, C. Sassanelli, L. Fumagalli, and S. Terzi, "Integrating virtual reality and digital twin in circular economy practices: A laboratory application case," *Sustainability*, vol. 12, no. 6, p. 2286, 2020.

[97] M. di Benedetto, E. Meloni, G. Amato, F. Falchi, and C. Gennaro, "Learning safety equipment detection using virtual worlds," in *2019 International Conference on Content-Based Multimedia Indexing (CBMI)*, pp. 1–6, 2019.

[98] V. Kuts, T. Otto, T. Tähemaa, and Y. Bondarenko, "Digital twin based synchronised control and simulation of the industrial robotic cell using virtual reality," *Journal of Machine Engineering*, vol. 19, 2019.

[99] A. M. Karadeniz, İ. Arif, A. Kanak, and S. Ergün, "Digital twin of egastronomic things: a case study for ice cream machines," in *2019 IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1–4, IEEE, 2019.

[100] T. Kaarlela, S. Pieskä, and T. Pitkäaho, "Digital twin and virtual reality for safety training," in *2020 11th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, pp. 000115–000120, 2020.

[101] R. Williams, J. A. Erkoyuncu, T. Masood, *et al.*, "Augmented reality assisted calibration of digital twins of mobile robots," *IFAC-PapersOnLine*, vol. 53, no. 3, pp. 203–208, 2020.

[102] G. Schroeder, C. Steinmetz, C. E. Pereira, I. Muller, N. Garcia, D. Espindola, and R. Rodrigues, "Visualising the digital twin using web services and augmented reality," in *2016 IEEE 14th international conference on industrial informatics (INDIN)*, pp. 522–527, IEEE, 2016.

[103] X. Ma, F. Tao, M. Zhang, T. Wang, and Y. Zuo, "Digital twin enhanced human-machine interaction in product lifecycle," *Procedia Cirp*, vol. 83, pp. 789–793, 2019.

[104] S. Ke, F. Xiang, Z. Zhang, and Y. Zuo, "A enhanced interaction framework based on vr, ar and mr in digital twin," *Procedia Cirp*, vol. 83, pp. 753–758, 2019.

[105] M. Van Den Brand, L. Cleophas, R. Gunasekaran, B. Haverkort, D. A. M. Negrin, and H. M. Muctadir, "Models meet data: Challenges to create virtual entities for digital twins," in *2021 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C)*, pp. 225–228, IEEE, 2021.

[106] J. Bao, D. Guo, J. Li, and J. Zhang, "The modelling and operations for the digital twin in the context of manufacturing," *Enterprise Information Systems*, vol. 13, no. 4, pp. 534–556, 2019.

[107] H. Qin, H. Wang, Y. Zhang, and L. Lin, "Constructing digital twin for smart manufacturing," in *2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pp. 638–642, 2021.

[108] G. N. Schroeder, C. Steinmetz, R. N. Rodrigues, R. V. B. Henriques, A. Rettberg, and C. E. Pereira, "A methodology for digital twin modeling and deployment for industry 4.0," *Proceedings of the IEEE*, vol. 109, no. 4, pp. 556–567, 2021.

[109] G. N. Schroeder, C. Steinmetz, C. E. Pereira, and D. B. Espindola, "Digital twin data modeling with automationml and a communication methodology for data exchange," *IFAC-PapersOnLine*, vol. 49, no. 30, pp. 12–17, 2016.

[110] T. Riedelsheimer, S. Gogineni, and R. Stark, "Methodology to develop digital twins for energy efficient customizable iot-products," *Procedia CIRP*, vol. 98, pp. 258–263, 2021.

[111] F. Tao, M. Zhang, and A. Y. C. Nee, *Digital twin driven smart manufacturing*. Academic Press, 2019.

[112] H. Wang, H. Li, X. Wen, and G. Luo, "Unified modeling for digital twin of a knowledge-based system design," *Robotics and Computer-Integrated Manufacturing*, vol. 68, p. 102074, 2021.

[113] Y. Fan, J. Yang, J. Chen, P. Hu, X. Wang, J. Xu, and B. Zhou, "A digital-twin visualized architecture for flexible manufacturing system," *Journal of Manufacturing Systems*, vol. 60, pp. 176–201, 2021.

[114] C. Wu, Y. Zhou, M. V. P. Pessôa, Q. Peng, and R. Tan, "Conceptual digital twin modeling based on an integrated five-dimensional framework and triz function model," *Journal of manufacturing systems*, vol. 58, pp. 79–93, 2021.

[115] S. M. Bazaz, M. Lohtander, and J. Varis, "5-dimensional definition for a manufacturing digital twin," *Procedia Manufacturing*, vol. 38, pp. 1705–1712, 2019.

[116] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Nee, "Enabling technologies and tools for digital twin," *Journal of Manufacturing Systems*, vol. 58, pp. 3–21, 2021.

[117] V. Makarov, Y. B. Frolov, I. Parshina, and M. Ushakova, "The design concept of digital twin," in *2019 Twelfth International Conference" Management of large-scale system development"(MLSD)*, pp. 1–4, IEEE, 2019.

[118] J. Lee, M. Azamfar, and B. Bagheri, "A unified digital twin framework for shop floor design in industry 4.0 manufacturing systems," *Manufacturing Letters*, vol. 27, pp. 87–91, 2021.

[119] D. Preuveneers, W. Joosen, and E. Ilie-Zudor, "Robust digital twin compositions for industry 4.0 smart manufacturing systems," in *2018 IEEE 22nd International Enterprise Distributed Object Computing Workshop (EDOCW)*, pp. 69–78, IEEE, 2018.

[120] J. Lee, M. Azamfar, J. Singh, and S. Siahpour, "Integration of digital twin and deep learning in cyber-physical systems: towards smart manufacturing," *IET Collaborative Intelligent Manufacturing*, vol. 2, no. 1, pp. 34–36, 2020.

[121] G. A. Gericke, R. B. Kuriakose, H. J. Vermaak, and O. Mardsen, "Design of digital twins for optimization of a water bottling plant," in *IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society*, vol. 1, pp. 5204–5210, IEEE, 2019.

[122] W. Lin and M. Y. Low, "Concept and implementation of a cyber-pbysical digital twin for a smt line," in *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pp. 1455–1459, IEEE, 2019.

[123] H. R. Hasan, K. Salah, R. Jayaraman, M. Omar, I. Yaqoob, S. Pesic, T. Taylor, and D. Boscovic, "A blockchain-based approach for the creation of digital twins," *IEEE Access*, vol. 8, pp. 34113–34126, 2020.

[124] A. Kanak, N. Ugur, and S. Ergun, "A visionary model on blockchain-based accountability for secure and collaborative digital twin environments," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, pp. 3512–3517, IEEE, 2019.

[125] K. Wang, W. Xie, B. Wang, J. Pei, W. Wu, M. Baker, and Q. Zhou, "Simulation-based digital twin development for blockchain enabled end-to-end industrial hemp supply chain risk management," in *2020 Winter Simulation Conference (WSC)*, pp. 3200–3211, IEEE, 2020.

[126] K. Židek, J. Pitel', M. Adámek, P. Lazorík, and A. Hošovskỳ, "Digital twin of experimental smart manufacturing assembly system for industry 4.0 concept," *Sustainability*, vol. 12, no. 9, p. 3658, 2020.

[127] J. Vachálek, L. Bartalskỳ, O. Rovnỳ, D. Šišmišová, M. Morháč, and M. Lokšík, "The digital twin of an industrial production line within the industry 4.0 concept," in *2017 21st international conference on process control (PC)*, pp. 258–262, IEEE, 2017.

[128] Q. Lu, X. Xie, A. K. Parlikad, and J. M. Schooling, "Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance," *Automation in Construction*, vol. 118, p. 103277, 2020.

[129] V. Qiuchen Lu, A. K. Parlikad, P. Woodall, G. D. Ranasinghe, and J. Heaton, "Developing a dynamic digital twin at a building level: Using cambridge campus as case study," in *International Conference on Smart Infrastructure and Construction 2019 (ICSIC) Driving data-informed decision-making*, pp. 67–75, ICE Publishing, 2019.

[130] Á. Segura, H. V. Diez, I. Barandiaran, A. Arbelaiz, H. Álvarez, B. Simões, J. Posada, A. García-Alonso, and R. Ugarte, "Visual computing technologies to support the operator 4.0," *Computers & Industrial Engineering*, vol. 139, p. 105550, 2020.

[131] R. Ganguli and S. Adhikari, "The digital twin of discrete dynamic systems: Initial approaches and future challenges," *Applied Mathematical Modelling*, vol. 77, pp. 1110–1128, 2020.

[132] K. Ding, H. Shi, J. Hui, Y. Liu, B. Zhu, F. Zhang, and W. Cao, "Smart steel bridge construction enabled by bim and internet of things in industry 4.0: A framework," in *2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)*, pp. 1–5, IEEE, 2018.

[133] C.-S. Shim, N.-S. Dang, S. Lon, and C.-H. Jeon, "Development of a bridge maintenance system for prestressed concrete bridges using 3d digital twin model," *Structure and Infrastructure Engineering*, vol. 15, no. 10, pp. 1319–1332, 2019.

[134] T. Ritto and F. Rochinha, "Digital twin, physics-based model, and machine learning applied to damage detection in structures," *Mechanical Systems and Signal Processing*, vol. 155, p. 107614, 2021.

[135] S. Kaewunruen and Q. Lian, "Digital twin aided sustainability-based lifecycle management for railway turnout systems," *Journal of Cleaner Production*, vol. 228, pp. 1537–1551, 2019.

[136] S. Kaewunruen and N. Xu, "Digital twin for sustainability evaluation of railway station buildings," *Frontiers in Built Environment*, vol. 4, p. 77, 2018.

[137] M. Podskarbi and D. J. Knezevic, "Digital twin for operations-present applications and future digital thread," in *Offshore Technology Conference*, OnePetro, 2020.

[138] S.-K. Jo, D.-H. Park, H. Park, and S.-H. Kim, "Smart livestock farms using digital twin: Feasibility study," in *2018 International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 1461–1463, IEEE, 2018.

[139] A. Francisco, N. Mohammadi, and J. E. Taylor, "Smart city digital twin–enabled energy management: Toward real-time urban building energy benchmarking," *Journal of Management in Engineering*, vol. 36, no. 2, p. 04019045, 2020.

[140] T. Ruohomäki, E. Airaksinen, P. Huuska, O. Kesäniemi, M. Martikka, and J. Suomisto, "Smart city platform enabling digital twin," in *2018 International Conference on Intelligent Systems (IS)*, pp. 155–161, IEEE, 2018.

[141] J. Du, Q. Zhu, Y. Shi, Q. Wang, Y. Lin, and D. Zhao, "Cognition digital twins for personalized information systems of smart cities: Proof of concept," *Journal of Management in Engineering*, vol. 36, no. 2, p. 04019052, 2020.

[142] Q. Lu, A. K. Parlikad, P. Woodall, G. Don Ranasinghe, X. Xie, Z. Liang, E. Konstantinou, J. Heaton, and J. Schooling, "Developing a digital twin at building and city levels: Case study of west cambridge campus," *Journal of Management in Engineering*, vol. 36, no. 3, p. 05020004, 2020.

[143] Y.-C. Lin and W.-F. Cheung, "Developing wsn/bim-based environmental monitoring management system for parking garages in smart cities," *Journal of Management in Engineering*, vol. 36, no. 3, p. 04020012, 2020.

[144] V. V. Martynov, D. N. Shavaleeva, and A. A. Zaytseva, "Information technology as the basis for transformation into a digital society and industry 5.0," in *2019 International Conference "Quality Management, Transport and Information Security, Information Technologies" (IT QM IS)*, pp. 539–543, 2019.

[145] J. Cheng, W. Chen, F. Tao, and C.-L. Lin, "Industrial iot in 5g environment towards smart manufacturing," *Journal of Industrial Information Integration*, vol. 10, pp. 10–19, 2018.

[146] G. Szabó, S. Rácz, N. Reider, H. A. Munz, and J. Pető, "Digital twin: Network provisioning of mission critical communication in cyber physical production systems," in *2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, pp. 37–43, IEEE, 2019.

[147] G. Hinz, M. Büchel, F. Diehl, M. Schellmann, and A. Knoll, "Designing a far-reaching view for highway traffic scenarios with 5g-based intelligent infrastructure," in *8. Tagung Fahrerassistenz*, 2017.

[148] S. A. Kumar, R. Madhumathi, P. R. Chelliah, L. Tao, and S. Wang, "A novel digital twin-centric approach for driver intention prediction and traffic congestion avoidance," *Journal of Reliable Intelligent Environments*, vol. 4, no. 4, pp. 199–209, 2018.

[149] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, "Deep learning for hybrid 5g services in mobile edge computing systems: Learn from a digital twin," *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4692–4707, 2019.

[150] A. El Saddik, "Multimedia and the tactile internet," *IEEE MultiMedia*, vol. 27, no. 1, pp. 5–7, 2020.

[151] M. Höyhtyä, "Connectivity manager: Ensuring robust connections for autonomous ships," in *2019 2nd International Conference on Intelligent Autonomous Systems (ICoIAS)*, pp. 86–90, IEEE, 2019.

[152] S. Schneider, M. Peuster, D. Behnke, M. Müller, P.-B. Bök, and H. Karl, "Putting 5g into production: Realizing a smart manufacturing vertical scenario," in *2019 European Conference on Networks and Communications (EuCNC)*, pp. 305–309, IEEE, 2019.

[153] J. Santa, J. Ortiz, P. J. Fernandez, M. Luis, C. Gomes, J. Oliveira, D. Gomes, R. Sanchez-Iborra, S. Sargento, and A. F. Skarmeta, "Migrate: Mobile device virtualisation through state transfer," *IEEE Access*, vol. 8, pp. 25848–25862, 2020.

[154] H. Viswanathan and P. E. Mogensen, "Communications in the 6g era," *IEEE Access*, vol. 8, pp. 57063–57074, 2020.

[155] T. G. I. Association, "European vision for the 6g network ecosystem," *Online](accessed June 12th, 2021) https://5g-ppp.eu/wp-content/uploads/2021/06/WhitePaper-6G-Europe.pdf*, 2021.

[156] Z. Zhang, Y. Xiao, Z. Ma, M. Xiao, Z. Ding, X. Lei, G. K. Karagiannidis, and P. Fan, "6g wireless networks: Vision, requirements, architecture, and key technologies," *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 28–41, 2019.

[157] P. Yang, Y. Xiao, M. Xiao, and S. Li, "6g wireless communications: Vision and potential techniques," *IEEE Network*, vol. 33, no. 4, pp. 70–75, 2019.

[158] H. X. Nguyen, R. Trestian, D. To, and M. Tatipamula, "Digital twin for 5g and beyond," *IEEE Communications Magazine*, vol. 59, no. 2, pp. 10–15, 2021.

[159] H.-N. Dai, H. Wang, G. Xu, J. Wan, and M. Imran, "Big data analytics for manufacturing internet of things: opportunities, challenges and enabling technologies," *Enterprise Information Systems*, vol. 14, no. 9-10, pp. 1279–1303, 2020.

[160] J. Zhang, "Advancements of outlier detection: A survey," *ICST Transactions on Scalable Information Systems*, vol. 13, no. 1, pp. 1–26, 2013.

[161] V. Kotu and B. Deshpande, *Data science: concepts and practice, 2nd Edition*. Elsevier, 2019.

[162] S. R. Chhetri, S. Faezi, A. Canedo, and M. A. A. Faruque, "Quilt: quality inference from living digital twins in iot-enabled manufacturing systems," in *Proceedings of the International Conference on Internet of Things Design and Implementation*, pp. 237–248, 2019.

[163] Q. Lu, X. Xie, A. K. Parlikad, and J. M. Schooling, "Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance," *Automation in Construction*, vol. 118, p. 103277, 2020.

[164] A. Castellani, S. Schmitt, and S. Squartini, "Real-world anomaly detection by using digital twin systems and weakly supervised learning," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 7, pp. 4733–4742, 2020.

[165] M. Bevilacqua, E. Bottani, F. E. Ciarapica, F. Costantino, L. Di Donato, A. Ferraro, G. Mazzuto, A. Monteriù, G. Nardini, M. Ortenzi, *et al.*, "Digital twin reference model development to prevent operators' risk in process plants," *Sustainability*, vol. 12, no. 3, p. 1088, 2020.

[166] X. Xie, Q. Lu, A. K. Parlikad, and J. M. Schooling, "Digital twin enabled asset anomaly detection for building facility management," *IFAC-PapersOnLine*, vol. 53, no. 3, pp. 380–385, 2020.

[167] Y. Qamsane, C.-Y. Chen, E. C. Balta, B.-C. Kao, S. Mohan, J. Moyne, D. Tilbury, and K. Barton, "A unified digital twin framework for real-time monitoring and evaluation of smart manufacturing systems," in *2019 IEEE 15th International Conference on Automation Science and Engineering (CASE)*, pp. 1394–1401, IEEE, 2019.

[168] Q. Wang, S. Bu, and Z. He, "Achieving predictive and proactive maintenance for high-speed railway power equipment with lstm-rnn," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 10, pp. 6509–6517, 2020.

[169] H. A. Gohel, H. Upadhyay, L. Lagos, K. Cooper, and A. Sanzetenea, "Predictive maintenance architecture development for nuclear infrastructure using machine learning," *Nuclear Engineering and Technology*, vol. 52, no. 7, pp. 1436–1442, 2020.

[170] C. Cheng, B.-k. Zhang, and D. Gao, "A predictive maintenance solution for bearing production line based on edge-cloud cooperation," in *2019 Chinese Automation Congress (CAC)*, pp. 5885–5889, IEEE, 2019.

[171] F. Francis and M. Mohan, "Arima model based real time trend analysis for predictive maintenance," in *2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA)*, pp. 735–739, IEEE, 2019.

[172] A. Cachada, J. Barbosa, P. Leitño, C. A. Gcraldcs, L. Deusdado, J. Costa, C. Teixeira, J. Teixeira, A. H. Moreira, P. M. Moreira, *et al.*, "Maintenance 4.0: Intelligent and predictive maintenance system architecture," in *2018 IEEE 23rd international conference on emerging technologies and factory automation (ETFA)*, vol. 1, pp. 139–146, IEEE, 2018.

[173] MIMOSA, "Mimosa osa-cbm – mimosa." https://www.mimosa.org/mimosa-osa-cbm/. (Accessed on 10/08/2020).

[174] J. Lee, M. Azamfar, J. Singh, and S. Siahpour, "Integration of digital twin and deep learning in cyber-physical systems: towards smart manufacturing," *IET Collaborative Intelligent Manufacturing*, vol. 2, no. 1, pp. 34–36, 2020.

[175] Y. Liang, W. Li, X. Lu, and S. Wang, "Fog computing and convolutional neural network enabled prognosis for machining process optimization," *Journal of Manufacturing Systems*, vol. 52, pp. 32–42, 2019.

[176] W. Luo, T. Hu, Y. Ye, C. Zhang, and Y. Wei, "A hybrid predictive maintenance approach for cnc machine tool driven by digital twin," *Robotics and Computer-Integrated Manufacturing*, vol. 65, p. 101974, 2020.

[177] Y. Choi, H. Kwun, D. Kim, E. Lee, and H. Bae, "Method of predictive maintenance for induction furnace based on neural network," in *2020 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pp. 609–612, IEEE, 2020.

[178] N. Gugulothu, V. Tv, P. Malhotra, L. Vig, P. Agarwal, and G. Shroff, "Predicting remaining useful life using time series embeddings based on recurrent neural networks," *arXiv preprint arXiv:1709.01073*, 2017.

[179] J. Wang, Y. Liang, Y. Zheng, R. X. Gao, and F. Zhang, "An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples," *Renewable Energy*, vol. 145, pp. 642–650, 2020.

[180] D. Shetve, R. VaraPrasad, R. Trestian, H. X. Nguyen, and H. Venkataraman, "Cats: Cluster-aided two-step approach for anomaly detection in smart manufacturing," in *Advances in Computing and Network Communications*, pp. 103–115, Springer, 2021.

[181] A. Nowak-Brzezińska and T. Xieski, "Outlier mining using the dbscan algorithm," *Journal of Applied Computer Science*, vol. 25, no. 2, pp. 53–68, 2017.

[182] Z. Cheng, C. Zou, and J. Dong, "Outlier detection using isolation forest and local outlier factor," in *Proceedings of the conference on research in adaptive and convergent systems*, pp. 161–168, 2019.

[183] M. Raza, P. M. Kumar, D. V. Hung, W. Davis, H. Nguyen, and R. Trestian, "A digital twin framework for industry 4.0 enabling next-gen manufacturing," in *2020 9th International Conference on Industrial Technology and Management (ICITM)*, pp. 73–77, IEEE, 2020.

[184] S. Mihai, W. Davis, D. V. Hung, R. Trestian, M. Karamanoglu, B. Barn, R. Prasad, H. Venkataraman, and H. X. Nguyen, "A digital twin framework for predictive maintenance in industry 4.0," 2021.

[185] H. V. Dang, M. Raza, T. V. Nguyen, T. Bui-Tien, and H. X. Nguyen, "Deep learning-based detection of structural damage using time-series data," *Structure and Infrastructure Engineering*, pp. 1–20, 2020.

[186] H. V. Dang, H. Tran-Ngoc, T. V. Nguyen, T. Bui-Tien, G. De Roeck, and H. X. Nguyen, "Data-driven structural health monitoring using feature fusion and hybrid deep learning," *IEEE Transactions on Automation Science and Engineering*, 2020.

[187] H. V. Dang, M. Raza, H. Tran-Ngoc, T. Bui-Tien, and H. X. Nguyen, "Connection stiffness reduction analysis in steel bridge via deep cnn and modal experimental data," *Structural Engineering and Mechanics*, vol. 77, no. 4, pp. 495–508, 2021.

[188] E. Trist and F. Emery, *Socio-technical systems theory*. Oxford, UK: Pergamon, 1960.

[189] B. Heydari and M. J. Pennock, "Guiding the behavior of sociotechnical systems: The role of agent-based modeling," *Systems Engineering*, vol. 21, no. 3, pp. 210–226, 2018.

[190] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," *Proceedings of the national academy of sciences*, vol. 99, no. suppl 3, pp. 7280–7287, 2002.

[191] S. Barat, R. Parchure, S. Darak, V. Kulkarni, A. Paranjape, M. Gajrani, and A. Yadav, "An agent-based digital twin for exploring localized non-pharmaceutical interventions to control covid-19 pandemic," *Transactions of the Indian National Academy of Engineering*, vol. 6, no. 2, pp. 323–353, 2021.

[192] J. M. Epstein, "Why model?," *Journal of artificial societies and social simulation*, vol. 11, no. 4, p. 12, 2008.

[193] B. S. Barn and T. Clark, "Revisiting naur?s programming as theory building for enterprise architecture modelling," in *International Conference on Advanced Information Systems Engineering*, pp. 229–236, Springer, 2011.

[194] J. Oden, T. Belytschko, J. Fish, T. Hughes, C. Johnson, D. Keyes, A. Laub, L. Petzold, D. Srolovitz, and S. Yip, "Simulation-based engineering science: revolutionizing engineering science through simulation. report of the national science foundation blue ribbon panel on simulation-based engineering science," 2006.

[195] B. Barn, A. W. Brown, and J. Cheesman, "Methods and tools for component based development," in *Proceedings. Technology of Object-Oriented Languages. TOOLS 26 (Cat. No. 98EX176)*, pp. 385–395, IEEE, 1998.

[196] B. D. Mittelstadt, P. Allo, M. Taddeo, S. Wachter, and L. Floridi, "The ethics of algorithms: Mapping the debate," *Big Data & Society*, vol. 3, no. 2, p. 2053951716679679, 2016.

[197] B. Barn, R. Barn, and F. Raimondi, "On the role of value sensitive concerns in software engineering practice," in *2015 IEEE/ACM 37th IEEE International Conference on Software Engineering*, vol. 2, pp. 497–500, IEEE, 2015.

[198] T. D. West and M. Blackburn, "Is digital thread/digital twin affordable? a systemic assessment of the cost of dod's latest manhattan project," *Procedia computer science*, vol. 114, pp. 47–56, 2017.

[199] J. Voas, P. Mell, and V. Piroumian, "Considerations for digital twin technology and emerging standards," *NIST Internal or Interagency Report (NISTIR) 8356 (Draft)*, 2021.

[200] E. Harper, C. Ganz, and S. Malakuti, "Digital twin architecture and standards," *Industrial Internet Consortium Journal of Innovation*, 2021.

[201] C. Lange, "Industrial data space – digital sovereignty over data," 2016. Invited talk at the Taipei Tech Workshop of the Vienna Data Science Group.

[202] J. Hetherington and M. West, "The pathway towards an information management framework-a 'commons' for digital built britain," 2020.

[203] M. Dietz, B. Putz, and G. Pernul, "A distributed ledger approach to digital twin secure data sharing," in *IFIP Annual Conference on Data and Applications Security and Privacy*, pp. 281–300, Springer, 2019.

[204] M. Hearn and S. Rix, "Cybersecurity considerations for digital twin implementations," *IIC J. Innov*, pp. 107–113, 2019.

[205] I. Yaqoob, K. Salah, M. Uddin, R. Jayaraman, M. Omar, and M. Imran, "Blockchain for digital twins: Recent advances and future research challenges," *IEEE Network*, vol. 34, no. 5, pp. 290–298, 2020.

[206] C. Gehrmann and M. Gunnarsson, "A digital twin based industrial automation and control system security architecture," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 1, pp. 669–680, 2019.

[207] T. Hossen, M. Gursoy, and B. Mirafzal, "Digital twin for self-security of smart inverters," in *2021 IEEE Energy Conversion Congress and Exposition (ECCE)*, pp. 713–718, IEEE, 2021.

[208] J. McCarthy, M. L. Minsky, N. Rochester, and C. E. Shannon, "A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955," *AI magazine*, vol. 27, no. 4, pp. 12–12, 2006.

[209] P. K. McClure, ""you're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment," *Social Science Computer Review*, vol. 36, no. 2, pp. 139–156, 2018.

[210] H. Shevlin, K. Vold, M. Crosby, and M. Halina, "The limits of machine intelligence: Despite progress in machine intelligence, artificial general intelligence is still a major challenge," *EMBO reports*, vol. 20, no. 10, p. e49177, 2019.

[211] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. Van Den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, *et al.*, "Mastering the game of go with deep neural networks and tree search," *nature*, vol. 529, no. 7587, pp. 484–489, 2016.

[212] M. Campbell, A. J. Hoane Jr, and F.-h. Hsu, "Deep blue," *Artificial intelligence*, vol. 134, no. 1-2, pp. 57–83, 2002.

[213] G. Marcus and E. Davis, *Rebooting AI: Building artificial intelligence we can trust*. Vintage, 2019.

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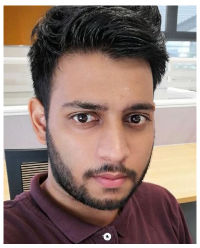

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