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SURVEY

Digital Twin for Railway: A Comprehensive Survey

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ABSTRACT Digital transformation has been prioritized in the railway industry to bring automation to railway operations. Digital Twin (DT) technology has recently gained attention in the railway industry to fulfill this goal. Contemporary researchers argue that DT can be advantageous in Railway manufacturing logistics to planning and scheduling. Although underlying technologies of DT, e.g., modelling, computer vision, and the Internet of Things, have been studied for various railway industry applications, the DT has been least explored in the context of railways. Thus, in this paper, we aim to understand the state-of-the-art of DT for railway (DTR), for advanced railway systems. Besides, this survey clarifies how DT can serve the railway twin system designers and developers. As DTR is still in its early adoption stage, there is hardly any clear direction to identify the technologies for specific DTR applications. Therefore, based on our findings we present a taxonomy for DTR for designers and developers. Finally, we describe potential challenges, pitfalls, and opportunities in DTR for future researchers.

INDEX TERMS Digital twin, railway, modelling, structural health monitoring, artificial intelligence, safety.

I. INTRODUCTION

Digital Twin (DT) technology has become increasingly prevalent in recent years, revolutionizing the way in which various sectors operate. DT is defined as the virtual clone of a physical living or nonliving entity that can exchange data and feedback between the real and digital world [1]. In addition, DT is an outcome of the aggregation of technologies like the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI) [2]. DT has invaded various fields such as industrial decision-making, virtual learning, well-being, and healthcare diagnosis due to its potential and unique characteristics [3]. In addition to its inherent benefits, the recent standardization [4] efforts within the digital transformation framework, have rendered DT an increasingly demanding technology for manufacturers and other stakeholders.

DTs have been rigorously examined for a variety of applications within industrial systems. For example, in [5], researchers developed a DT model for a shop floor, focusing on tool wear prediction and system variables' forecast. P. Aivaliotis et al. in [6], introduced an advanced physics-based modeling technique designed to harness the potential of the DT paradigm in predictive maintenance scenarios. Expanding the horizon of applications, a notable contribution in [7] unveiled a DT-driven framework to address anomaly detection. This approach not only ensures efficient and reliable anomaly detection in automation but also addresses prevailing challenges. It prioritizes real-time health surveillance of industrial setups, facilitating immediate anomaly recognition and prediction. Furthermore, the utility of Digital Twins extends to production systems as highlighted in [8], where they are employed to streamline and enhance both the planning and optimizing phases.

In recent times, the railway transportation industry -as any industrial sector- has shifted away from conventional computer-based systems towards virtual platforms, leveraging the capabilities of digital transformation technology. Despite being one of the rapidly used facilities by commuters, DT in the railway industry is still in progress. A Digital Twin for Railway (DTR) has been described in the literature as

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a collection of observational state (insight), predictive state (foresight), and actuation state (oversight) [9].

DTR employs numerous technologies, but the diverse methods of leveraging these technologies to enhance DTR's potential remain underexplored. For example, research has delved into using IoT devices [10] to monitor railway infrastructure components such as tracks and signals. However, to implement monitoring applications, DTR may define alternative ways to use IoT devices in conjunction with other technologies such as computer vision (CV) and virtual reality (VR) to enable predictive maintenance and minimize downtime. Furthermore, the full potential of DT-enabled railways can be realized only when researchers and developers gain a comprehensive understanding of how diverse DTR technologies can be integrated and applied in multifaceted ways; as well as to identify the key challenges and opportunities that arise within the railway transportation industry [9].

For that reason, we aim to investigate the current progress and trends in the adoption of technologies within the context of DTR, with the intention of identifying the associated challenges and gaps.

The rest of the sections are organized as follows. In Section II, we present a meta-review of related DTR surveys, to understand the need for this survey over existing work. Section III outlines the methods used to conduct this survey, detailing the paper collection and information extraction process, and research questions. Section IV finds how DT has served the railway systems over the past years; Section V finds the emerging technologies and techniques or strategies to apply in railway applications; while Section VI, in its first part addresses challenges and research gaps, while the second part briefly discusses the study limitations. Finally, we conclude this research in Section VII.

II. EXISTING SURVEYS

Despite several scopes of DTR to advance the railway, few surveys have been conducted on the topic. Addressing maintenance, the authors in [11] elucidated the challenges and advantages of DT for railways, employing Machine Learning (ML) within the DT framework. Additionally, Condition-Based Maintenance (CBM) in the scope of DTR was explored in [12] and [13]. The former paper illustrated the application of DT in forecasting and wellness management paradigms, while the latter showcased emerging technologies for assessing railway tunnel conditions. The introduction of DT for tunnels represents an enhancement over traditional digital model representations. Furthermore, Doubell et al. in [14] leveraged DT to meet the evolving requirements of railway infrastructure data management. Nonetheless, this survey focuses on examining the ongoing advancements and trends in adopting technologies within the DTR framework, aiming to identify the inherent challenges and gaps.

The majority of existing surveys largely center on infrastructure maintenance and management. Yet, DTRs offer potential benefits in health inspection [15], visualization [16], automation [17], and safety monitoring [18]. A more encompassing survey addressing a wider array of applications would help identify trends, challenges, and gaps in DTR systems. Given the varied approaches in current surveys, there's a pressing need for a universal framework to support diverse applications and tackle existing challenges. Accordingly, our methodology, detailed in the subsequent section, extends from infrastructure maintenance to visualization.

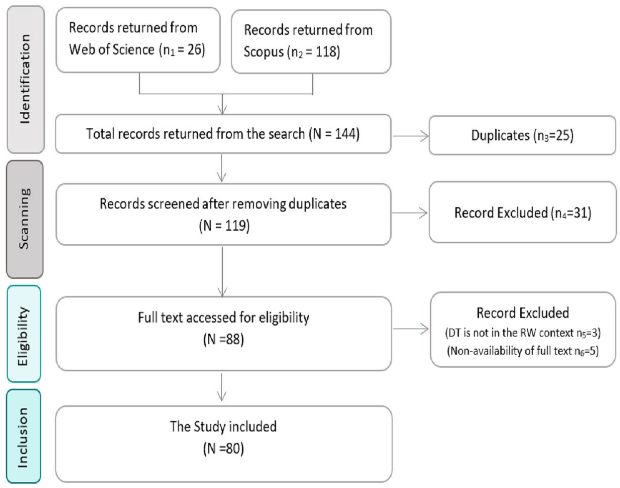


FIGURE 1. Paper selection flowchart based on PRISMA. N: Total number of papers. n_i: Partial number of papers.

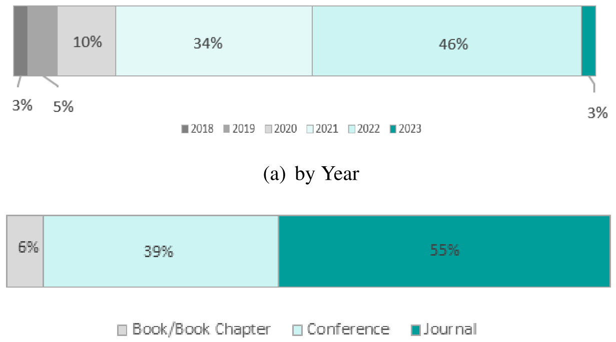
III. METHODOLOGY

We utilize the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [19] method, to narrow down the pool of relevant literature. The eligibility of the paper has been identified by conducting a thorough search of relevant databases using specific search terms and publication years, and then subjecting the resulting papers to four main phases of PRISMA, as illustrated in Figure 1. The search yielded 144 publications, which were subsequently classified based on their publisher, year of publication, and type. Duplicate publications were removed during the initial scanning phase, and non-relevant papers were excluded after further examination of their abstracts and full text. Finally, 80 papers were identified as meeting the criteria for inclusion in this study.

Initially, we formulate research questions (RQs) and conduct a thorough search for relevant literature. Then, we select the relevant papers based on pre-determined inclusion and exclusion criteria. Finally, the relevant information has been then extracted from the chosen papers employing a set of pre-defined concepts, as proposed by Petersen et al. [20] for systematic reviews. In the following parts, we detail the steps of the methodology used in this research.

A. RESEARCH QUESTIONS

The railway industry has garnered considerable attention in recent times due to the need for a comprehensive Intelligent



(a) by Year

(b) by Type

FIGURE 2. **Classification of selected papers.**

Transportation System (ITS) [21] and the requirement for sustainable, accurate, and efficient monitoring of rail inspections and maintenance [22]. However, traditional approaches still present a challenge as they are susceptible to human errors and lack the ability to provide swift and direct solutions for defects and faults. This has led to an increasing need for predictive models that harness the capabilities of IoT and emerging technologies such as Cyber-Physical Systems (CPS) to usher in the DT paradigm for railways. This survey addresses three RQs stemming from the need to demystify the "Railway-Digital Twin" engagement in literature, hence identifying the opportunities and future recommendations, as well as pointing out the challenges and limitations. The RQs are as follows:

- **RQ_1: What contributions has Digital Twin technology made to the Railway System?**
- **RQ_2:** What are the emerging technologies for Railway Digital Twins and how are they employed?
- **RQ_3:** To what extent has Digital Twin achieved its functionality in Railway and what are the research gaps?

B. PAPER COLLECTION

The search query for this study has been formulated based on the primary focus of "Digital Twin" and "Railway" in combination.

The query is then applied to Web of Science and Scopus repositories with a restricted search to "Title, abstract, or keyword." After scanning the publications, the most relevant ones covering the period from 2018 to January 2023 inclusive were selected. The search returns 144 papers, which are then reduced to 80 articles by removing duplicates and non-relevant research through a thorough screening process. Two inclusion eligibility criteria are established: (a) the paper should be available in English and (b) the DT should be in a railway context.

The majority of the collected articles were published in 2022 (Figure 2 (a)), and most of them are journal papers (Figure 2(b)), with a larger portion originating from the Scopus database (Table 1). The distribution of papers by type over the years of publication is depicted in Figure 3. It is evident that no publication activities occurred before 2020, except for journal articles,[1] on the subject of DT with railways.

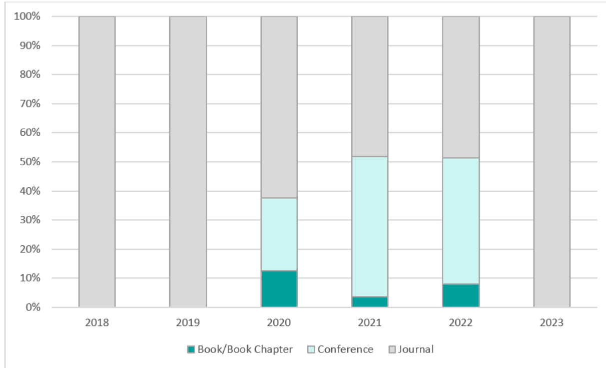


FIGURE 3. **Papers distribution by type over the years of publication.**

TABLE 1. **Number of papers by publisher by database.**

Publisher	Scopus	WoS	Total by Publisher
Springer	14	4	18
IEEE	13	3	16
Elsevier	7	4	11
MDPI	6	5	11
Taylor & Francis	2	1	3
Other Publishers	16	5	21
Total Publications	**58**	**22**	**80**

C. INFORMATION EXTRACTION

A multi-phase approach has been employed to extract information on the topic of DTR. The initial step involves analyzing the abstracts of relevant publications to identify the main ideas and classify them based on the problem addressed and the specific research field of interest. The keywords are then added to the classification sheet. Next, a full-text reading has been conducted to identify the tools, technologies, and applications related to DTR. Based on the frequent terms a word cloud has been generated using the "Google Drive Word Cloud" tool to visualize the most common terms, excluding "Digital Twin" and "Railway", which were ubiquitous across all eligible publications. After that, the common terms have been unified under a single term, such as various types of bridges as "Bridge."

The extracted information has been utilized to find the RQ_1 by analyzing correlation and progression over the years.

IV. RQ_1: WHAT CONTRIBUTIONS HAS DIGITAL TWIN TECHNOLOGY MADE TO THE RAILWAY SYSTEM?

In this section, we detail our findings under the RQ_1 which aims to find the potentials of DTR in literature to serve various purposes of the railway. To answer this question,

[1]The scope of this survey is limited to the publications available until January 2023.

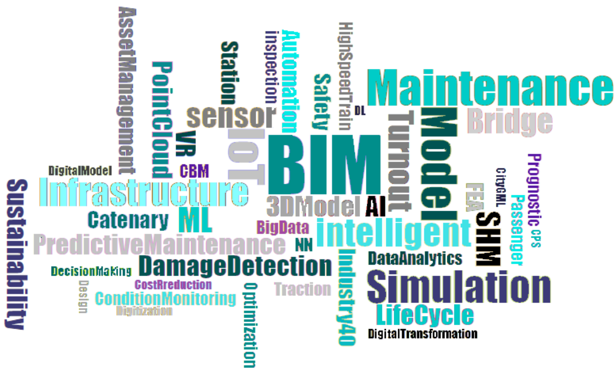


FIGURE 4. Most frequent terms.

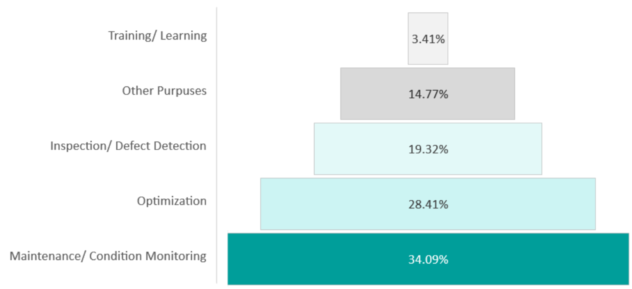


FIGURE 5. Main fields of interest for DTR.

we employed the information extraction process discussed in the above section. The Word Cloud generated from the information has been illustrated in Figure 4. In addition, we demonstrate the progression of DT in the railway system in Figure 5. Finally, we generated a heatmap from the information to demonstrate the relation between the key terms and railway over the past few years (Figure 6).

A. FREQUENT TERMS

The Word Cloud presented in Figure 4 illustrates the prominent DTR terms in the literature from 2018 to January 2023 to highlight the areas of research focus. This figure also points out the areas where further efforts and attention may be required. The size of the words represents the frequency and significance of using these terms in literature. From the figure, it appears that the most significant field within DTR publications is modelling techniques, followed by IoT and intelligence. For instance, Building Information Model (BIM) was observed to outweigh any other modelling techniques in this context. In fact, depending on the level of development (LOD), BIM has been considered a version of DT in several studies. In terms of application, maintenance has been found to be the major area of interest, followed by Structural Health Monitoring (SHM), predictive maintenance, and damage detection. In terms of focused railway parts, we found the bridge, infrastructure, and turnout, are some commonly studied railway components.

To understand the relation between the key terms and railway over the past few years, we generated a heatmap using the information extracted from relevant studies. Figure 6 depicts the relation of DTR with the most frequent terms on three essential levels: technology (VR, AI, and IoT), modelling (BIM and simulation), and purpose (condition monitoring, SHM, maintenance, predictive maintenance, and sustainability). For this part, we have grouped machine learning (ML), deep learning (DL), federated learning (FL), and neural networks (NN) under the umbrella term AI, while IoT devices, sensors, and actuators were aggregated under the term IoT.

The generated heatmap highlights that most of the technical terms have been used extensively since 2021, with the exception of modelling with BIM and IoT, because those terms have been studied earlier in the context of DTR from the outset of its evolution [23]. In contrast, terms such as VR, predictive maintenance, and sustainability have received limited exploration in the literature.

B. PROGRESSION OF DT

This section explores the purposes and corresponding percentage of use of DTR to achieve those purposes within the literature.

The imperative to replace the labor-intensive and extensive procedures used for maintenance and condition monitoring has elevated the appeal of this category for research [24]. This fact is revealed in Figure 5 where the most common interest in DTR is occupied by the ''Maintenance/ Condition Monitoring'' accounting for 34.09% of the research focus. So, it can be observed that DTR models have been primarily utilized for monitoring the health of complex systems and identifying potential risks before their occurrence.

Secondly, ''Optimization'' has been found to occupy 28.41% of the research focus in DTR. It is apparent that the DTR paradigm has been employed to optimize system performance and identify ways to improve efficiency. This field encompasses various domains such as industrial, financial (cost and budget), structural, operational, planning, and modelling activities, Quality of Experience (QoE) of passenger services, life-cycle, and data management.

The third common application area of DTR is ''Inspection/ Defect Detection'' which accounts for 19.32% of the research focus. To a certain extent, this application domain overlaps with maintenance and monitoring. However, these studies are mainly focused on detecting defects and improving the inspection process.

The ''Other Purposes'' accounts for 14.77% of the research focus. The ''Other Purposes'' include tasks involving DT for sustainability, safety, security and privacy, cartography, scheduling, and guidance approaches for the railway.

Lastly, ''Training/Learning'' is the least common application area accounting for 3.41% of the research focus. From these statistics, we can conclude that DTR is still not well-exploited for these areas.

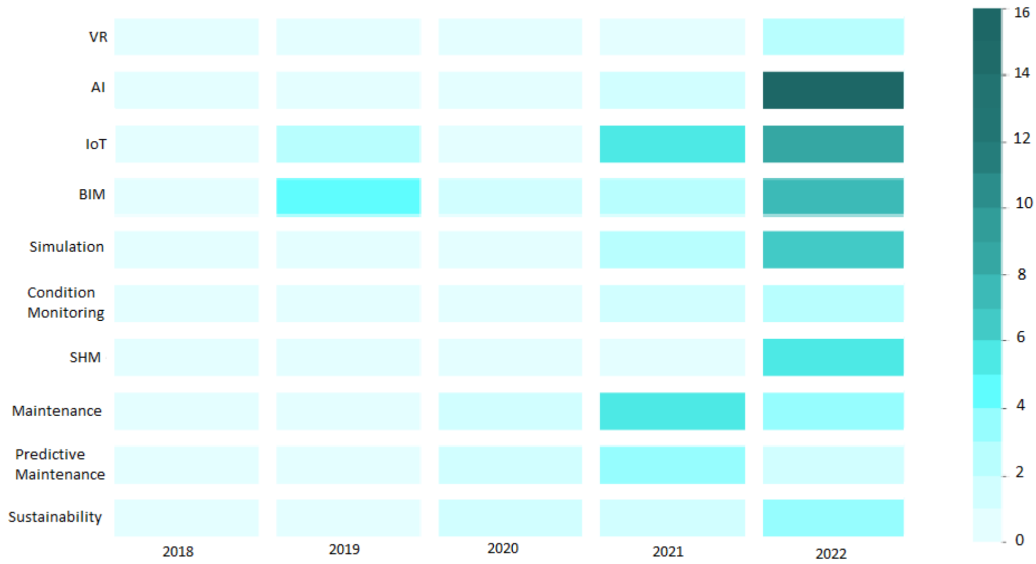


FIGURE 6. "Key term-Publication year" engagement.

C. SUMMARY OF RQ_1

In summary, the findings of our exploration of RQ_1 imply that DTR has been primarily utilized for maintenance and condition monitoring, followed by optimization and inspection/defect detection. However, there is still potential for DTR to be applied in other areas such as training/learning and sustainability, and further approaches for the railway. The integration of BIM and IoT has been prominent over the periods, whereas the integration of AI and VR is still in its incubation period.

V. RQ_2: WHAT ARE THE EMERGING TECHNOLOGIES FOR RAILWAY DIGITAL TWINS AND HOW ARE THEY EMPLOYED?

The realization of the DTR concept has been made possible through the integration of several state-of-the-art technologies. In order to address the first part of RQ_2, we conducted a comprehensive review of the existing literature, in which we summarized, compared, and contrasted current DTR studies across various applications. Figure 6 summarizes the evolving trends in technology and maintenance domains from 2018 to 2022 within the DTR sector, offering a brief overview of research directions.

Whilst to answer the second part of RQ_2, we sought to gain a better understanding of the techniques used in DTR applications and the scope of their integration. We follow the core features of DTR including representation, data, intelligence, and safety and security to organize our answers to RQ_2. Each of these components has been elaborated into two parts - 1) existing work, and 2) employed technologies.

A. THE REPRESENTATION

Representation is one of the key characteristics of DT [1]; it can take different forms, such as structural 3D modelling, or multi-modal interaction through VR, Augmented Reality (AR), and extended reality (XR) technologies.

Modelling has been studied since the early stages of DT's evolution. As shown in Figure 6, BIM has emerged as a popular modelling technique since 2019. Therefore, the papers listed in this section cover a wide range of topics, including infrastructure maintenance, simulation, operations and control, and health. The categories of DTR papers focusing on Modelling to achieve the specific goal are presented in the following sections. Another newly growing technology for representation focuses on multi-modal interaction and there are a few shreds of evidence in the literature, which will also be reviewed in this section.

1) MODELLING IN DTR FOR VARIOUS APPLICATIONS

The categories of DTR papers focusing on Modelling to achieve the specific goal are presented in the following sections. By organizing these papers into categories and summarizing them, we can better understand the various ways in which DT technology is being applied in the railway industry and the different modelling techniques that are being used to achieve specific goals.

i. Infrastructure Maintenance Using DTR
Modelling Techniques have been extensively studied in the context of infrastructure maintenance [25], [26], [27], [28], [29], [30], [31]. This section is focused on exploring the use of modelling technologies in literature in the context of railway infrastructure maintenance. The studies discussed in this section examine the various modelling technologies used to create DT. Table 2 summarizes the DT applications in railway infrastructure using modelling.

ii. Automation Using DTR
Several researchers have explored the use of modelling techniques to optimize the creation, maintenance, and

TABLE 2. Summary of papers on modelling for infrastructure maintenance using DTR.

Ref.	DT Application	Modelling Technology	Key Findings
[25]	Sustainability and vulnerability evaluation, monitoring	BIM, 6D	Use of DT technology can evaluate the sustainability and vulnerability of subway stations.
[26]	Maintenance, resilience, safety	BIM	DT can manage railway bridge maintenance and resilience.
[27]	Maintenance optimization, safety	Physical modelling	Use of physical modelling and advanced analytics can optimize maintenance for railway infrastructure.
[28]	Short-term production planning	BIM	Use of DT technology and multi-objective optimization for short-term production planning in a railway context.
[29]	Evaluation of railway station buildings	BIM	Use of 3D modelling for evaluating the condition and performance of railway station buildings.
[30]	Linear infrastructures lifecycle management	BIM	Design and development of a DT for the lifecycle management of linear infrastructures.
[31]	Audit for subway stations	BIM	Use of DT technology for auditing subway stations and identifying areas for improvement.

TABLE 3. Summary of papers on modelling for system automation in railway using DTR.

Ref.	DT Application	3D Modelling/ Simulation Technique	Key Findings
[32]	ERPSs	DT concept both at equipment and system level of ERPSs	DT capabilities ensure reliable and secure operations based on the performance of real physical system
[33]	Industrial equipment	LiDAR technologies	FL can optimize the creation, maintenance, and update of DTs with reduced data exchange
[34]	Railway switches	3D solid FEM	Numerical simulations of train-track interactions can determine the placement of sensors for the condition monitoring of railway switches
[35]	Train control and automation	NA	The adoption of AI and advanced communication technologies has brought up huge potential in terms of optimization, learning and adaptation, but also raised several dependability concerns
[36]	MVDC railway system	Real-time model	Offers a thorough insight into the modelling of every part of the MVDC railway system
[37]	Optimizing traction converter	FEM/FEA	Leverages DT to strategically position temperature sensors and power modules for proactive maintenance and breakdown causes identification.
[38]	Automating intermodal transportation	AnyLogics software (Agent-based software)	Uses a DT approach to Overcome the traditional techniques for the "road-rail-ship" transportation system .
[39]	Railway electric component	Multi-physics modelling	Developing of a hybrid, model-based condition monitoring of compound electronic and mechatronic systems in railway applications (e.g. safety-relevant electronic systems for train control).

Note: **ERPSs**: Electric Railway Power Systems, **EFA**: Finite Element Analysis, **EFM**: Finite Element Model, **LiDAR**: Light Detection and Ranging, **MVDC**: Medium-Voltage Direct Current

update of DTs [32], [33], [34], [35], [36]. This section aims to analyze recent research papers that explore the application of DTR in system automation. The summary of the review is presented in Table 3.

Besides, the application of Modelling for Automation has expanded to encompass various domains, including Automation and Digitalization, Automation in Industry, and Automation for Lifecycle Maintenance. These areas of application have been extensively examined, with comprehensive details provided in Table 4, Table 5, and Table 6, which present the purpose of applying modelling for automation, the techniques employed for modelling or simulation, the tested use cases, and the challenges encountered in realizing these applications.

iii. Modelling for Health Inspection in Railway using DT

Railway infrastructure is subject to significant wear and tear, making it essential to have an efficient health monitoring system to prevent accidents, maintain high levels of service, and reduce maintenance costs. DTR is emerging as a promising solution to support SHM. In this section, we discuss contemporary studies on modelling techniques for health monitoring in railway DT. Table 7 provides a summary of different modelling techniques that are being used in the context of DT health monitoring for railway systems.

Overall, the reviewed studies demonstrate the potential benefits of simulation and modelling in automating processes and services within the railway industry, particularly for system automation and lifecycle maintenance. DT-based health monitoring has also been studied in literature to replace manual inspection and solution planning stages through various modelling techniques. These techniques offer benefits such as reduced labor times and costs as well as precision monitoring in various applications of SHM such as load test data processing, operational condition monitoring, predictive maintenance, fault diagnosis, and damage assessment. As a conclusion, modelling technologies have promising potential for infrastructure management and maintenance through DTR in the railway industry.

2) MULTI-MODAL INTERACTION IN DTR FOR VARIOUS APPLICATIONS

The concept of Multi-modal Interaction (MMI) is an integral part of DTs as it provides the capability to represent and simulate the physical system in a virtual environment, and potentially interact with this virtual representation [1]. Despite the extensive use of MMI in literature, it has not yet

TABLE 4. Summary of papers on modelling for automation and digitalization using DTR.

Ref.	Purpose	3D Modelling/ Simulation Technique	Use Case	Challenges
[40]	Building the R4F, a theoretical model-based 6-layer DT platform, representing the full railway infrastructure subsystems integration.	6-layer model	Railway track	NA
[17]	Creating and producing ICS for railway framework within digitized environment	3D visualization AR	Freight railway station *(railway hump yard)*	Accuracy of the analytical form Lack of platforms
[41]	Illustrating the benefits of DT in railway to carry out a digital transformation and operation for railway upkeeping	Virtual simulation	Railway maintenance *Rolling stock, wheel,etc*	Big data management Data quality Security issues
[42]	Exploiting all the state-of-the-art technologies to build the DT for railway bridges to permit proactive and prognostic upkeeping.	3D geometry model C4D / PhDsoft	Railway bridge	Management of massive collected data *(Store, interpret, transfer, visualize)* Information privacy
[43]	Building DTs for a 9kV MVDC electric railway system	MATLAB	Electric Charging base	
[18]	Training members on train DT afore being in place to expert the conditions and to avoid critical and risky situation.	3D Model *(Unity3D)* VR *(eVRyLab)*	Railway locomotive *(ES64U2/Taurus 2)*	Reality identicalness *(interactivity)* HMD variety and compatibility Extensive level of details Lack of information VR limited accessibility *(glasses, anxiety, adaptation to new technologies)*
[44]	Exploiting recent connectivity techniques to empower automation for accurate monitoring and upkeeping of resources. Encompassing these techniques, DT is presented to support instant feedback.	3D geometry model *(Rihno/Grasshooper)* FEM-based *(numerical model)*	Railway bridges	Scheduling optimization Data management Data security and privacy Completeness of DT Real data acquisition
[45]	Leveraging DT to minimize laborers' in-duty injuries in tamping missions, and exploring the technical keys of automated railway track apparatus and its effect on the maintenance team count's reduction.	BIM	Railway track	NA
[46]	Introducing the DT for checking, monitoring, and upkeeping the bridges of railway infrastructure using big data, AI, and ML.	PhDC4D 3D model *(BrIM, point cloud, BIM, FEM)* DL classifier ML *(prognostication)*	Railway bridges	NA
[47]	Presenting a digital paradigm for the heritage bridges preservation taking advantage of digital technology in all stages.	HBrIM Laser scanning Photogrammetry Agisoft Metashape Pro. SCENE 2018 Point cloud and Revit	Railway bridge	Need for dynamic data

Notes: **BrIM**: Bridge Information Model, **FEM**: Finite Element Model, **HBrIM**: Heritage Bridge Information Model, **HMD**: Head-Mounted Display, **ICS**: Industrial Control System, **IFC**:Industry Foundation Classes, **MVDC**: Medium-voltage Direct Current, **Pro.**: Professional

been thoroughly investigated in many studies. This section presents the aspects of MMI in DTR applications.

While safety in fully automated vehicles may not be well-suited for heavy freight railways, VR devices and 3D modelling tools can greatly impact remote training eliminating the need for real apparatus or in-person trainers. For example, VR apparatus such as head-mounted displays (HMD) and 3D representation tools like unity3D and toolkits like Hurricane VR have been used to provide a safe and full virtual experience for trainees [18]. In addition to preparing trainees, the virtual experience also contributes to monitoring and decision-making. For instance, a virtual 3D environment has been proposed to emulate real-life geodetic monitoring, accompanied by a VR application applied for remote railway tunnel observation [59]. XR was also employed in guiding commuters in railway stations to find their destination using the DT and the A* algorithm to provide the optimal route, as demonstrated in [60].

To recapitulate, MMI in DTR remains relatively under-explored, yet it holds significant potential and promises numerous benefits.

3) TECHNIQUES OF REPRESENTATION

This section represents details of tools, and strategies used in literature for representation through DTR. First, we present the modelling techniques for numerous applications and second, we present the technique for Multi-modal Interaction.

i. Modelling Techniques for DT Maintenance of Railway Infrastructure
   In this section, we provide an overview of different modelling types and categories used for infrastructure maintenance and optimization using DT in railway in literature.

   - **BIM** is considered a hybrid modelling type as it integrates various data sources, including geometrical, spatial, and non-spatial data. BIM can aid in asset management visualization, including predicting maintenance needs and identifying potential failures. For example, a BIM model has been proposed in the literature to analyze the location and condition of assets [26]. To realize the BIM, Revit software was used in several studies. BIM can be

TABLE 5. Summary of papers on modelling for automation in industry using DTR.

Ref.	Purpose	3D Modelling/ Simulation Technique	Use Case	Challenges
[10]	Involving DT for production to mimic assembly line for complicated systems aiming improvement of all manufacturing phases.	Digital shadow: *IoT, CPS, BI* Digital model: *DES simulation (TPS)* *Optimization (Python)*	Railway axle	NA
[48]	Introducing a novel method to enable HSR to leverage Industry 4.0 techniques in terms of maintenance.*(Maintenance 4.0)*	Virtual System/ FEM 3D visualization *(CREO Parametric)* Simulation *(MATLAB)*	Railway vehicle Operation status of bogie *(Y237B)*	NA
[49]	Exhibiting the advantages of engaging DT in early-stage construction of decision-making and performance assessment taking railway as an application.	Parametric analytical model *(Markovian rep.)*	Railway axle	Non-stop varying external parameters Continuous evolution to avoid machine deterioration
[16]	Stepping from BIM *(digital model)* to DT *(digital copy)* paradigm for the manufacturing industry to address all phases mainly the operation and upkeeping. railway infrastructure LC was considered within this framework.	3D environment	Railway Station: Old tunnel protection Critical cases support Station servicing	DT is still in its early stages
[50]	Designing a unified digital model as DT for traction substation of two types of current (ac/dc) to support decision-making for equipment selection and evaluation	ETAR software Newton-Raphson	Railway power supply system	NA
[51]	Discussing digital modelling activities used in the railway industry, and introducing models aggregation to attain more substantial outcomes in achieving DT.	Formal Methods	Railway System	Heterogeneity (e.g. natures, objectives, subjects)
[52]	Building a locomotive cooling tower DT enabling the assessment and examination of suggested updates prior to their physical implementation.	Model-based approach MATLAB(2019)	Train cooling tower	NA

Notes:**BI**: Business Intelligence, **HSR**: High Speed Railway, **LC**: life-cycle, **Rep.**: representation, **TPS**: Tecnomatix Plant Simulation

TABLE 6. Summary of papers on modelling for automation for lifecycle maintenance using DTR.

Ref.	Purpose	3D Modelling/ Simulation Technique	Use Case	Challenges
[25]	Developing and engaging DT for LCA and exhibiting its effects on optimization and sustainability in several fields.	6D BIM *(Revit 2021 + NavisWorks 2021)*	Railway bridge	- Environment factors - Material durability
[26]	Presenting a 6D BIM to manage the life span of railway switches and crossings system.	6D BIM *(BIM level3)* *(Revit + NavisWorks)*	Railway turnouts	Availability of data sources
[31]	Presenting a subway station LCA evaluation through DT concept	BIM-based simulation *(Revit + NavisWorks)*	Subway station	LOD selection *(LOD300 is used)* Structural modifications *(manual eval.)* Structural deviations *(human error, on-site deviation)* Defect data form
[53]	Initiating bridges' DT structure to tackle enormous data understanding, processing, and managing problems to elicit necessary inputs for SHM objectives.	BIM real-time sensors Data-centric engineering	Railway bridge	Datasets heterogeneity
[54]	Aiming preliminary stages of railway design in the industry where modeling has been addressed as an essential part of the railway manufacturing lifecycle.	BIM Photogrammetry Generative and parametric modelling	Railway track	NA

Notes: **LCA**: Life-cycle Assessment.**LOD**: Level of Development/Details

seen in other sections in this study for achieving other goals in railway.

- **3D modelling** is a physical modelling type as it represents the physical properties and characteristics of railway infrastructure assets. The 3D models can be used to optimize track geometry, track maintenance and inspection, and design new infrastructure [29]. For example, a 3D model of the track can help identify areas of uneven wear and tear, leading to more targeted maintenance.
- **6D modelling** adds real-time monitoring and control to asset management by incorporating time and cost dimensions [25]. This modelling type provides insights into asset behaviour and enables predictive maintenance. For instance, a 6D model can help predict when a train may need maintenance based on real-time data about its speed, weight, and usage. However, it presents challenges in data acquisition, system complexity, and data management.
- **Physics-based modelling** is a numerical modelling type that simulates physical phenomena and provides detailed insights into asset behaviour and failure modes. This modelling type is useful for rolling stock maintenance and identifying potential failures

TABLE 7. Summary of papers on modelling for health inspection in railway using DT.

Ref.	Modelling Technique	DT Application	Key Findings
[55]	BIM tools and the IoT paradigm *(including sensors, actuators, and personal computers)* enabled by the ASHVIN IoT platform.	Automated pipeline for load test data processing of HS railway bridges	Automation can significantly benefit stakeholders by reducing labor times and costs.
[56]	MBS Model	Model-Based Operational Condition Monitoring of Crossing Panels	A framework using a digital twin, measured accelerations, climate data, scanned running surface geometry, and an MBS model can assess the status and predict future maintenance needs for a material asset.
[57]	MBS Model	Predictive maintenance for wheels and rails	The study showcases the capabilities of the MBS-based damage modelling for predictive maintenance purposes, as well as its potential to pave the way for DTRs assets.
[15]	High-dimensional Structures	Fault diagnosis of railway point machine	A digital twin can identify the possible root causes of malfunctions, leading to accurate and real-time monitoring and diagnosis of faults in railway point machines.
[58]	Peridynamics	Fatigue damage assessment of complex railway turnout crossings	A novel approach built on peridynamics and "crack on mid-plane" can investigate fatigue failures over a crossing nose from a fracture mechanics perspective.

Notes: **MBS**: Multi-Body Simulation

in infrastructure [27]. To illustrate, a physics-based model can help predict how a bridge will perform under different weather conditions, leading to more targeted maintenance and repair efforts. However, it presents challenges in data availability, model validation, and computing power.

ii. Modelling Technique for System Automation in Railway using DT
In the context of DTR, we elaborate on the 3D modelling/Simulation Techniques as follows accompanied with its application.
- **Numerical Simulation:** Numerical simulation is a technique used to model and analyze complex systems by solving mathematical equations using numerical methods [61]. It encompasses a wide range of numerical techniques used to simulate the behavior of physical systems. One of the primary techniques is the Finite Element Model (FEM) [34] which employs mathematical models to simulate the behavior of physical systems (e.g. behavior of the bearings while train crossing [62]). In addition to FEM, another approach known as numerical Reduced-Order Modeling (ROM) used to optimize the model by approximating the behavior of complex systems with a lower-dimensional one (e.g. thermal characteristics analysis for traction motors in railways [63]).
- **Real-time Simulation:** Real-time simulation is a technique used to simulate physical systems in real time, which means that the simulation runs at the same speed as the actual system. In the context of railway operations, real-time simulation can be used to model and simulate the behavior of the railway system in real-time, including train operations [36], track conditions, and signal and control systems. We can benefit from real-time simulation to optimize train scheduling by adjusting schedules in real-time based on real-world conditions, such as delays or changes in the track condition.

iii. Modelling Techniques for DT Health Inspection in Railway
Various modelling techniques have the potential to improve the effectiveness of railway health inspection through the integration of digital technologies. However, each technique has its own limitations and challenges that must be addressed in order to fully realize its potential as presented in this section.
- **BIM+ASHVIN**: ASHVIN project is part of the H2020 European project. The framework of ASHVIN project is related to Assistants for Healthy, Safe, and Productive Virtual Construction, Design, Operation & Maintenance, using Digital Twins [55]. BIM tools and IoT paradigm (including sensors, actuators, and personal computers) enabled by the ASHVIN platform can be used for data processing and condition monitoring of railway infrastructure [55]. However, the challenge lies in integrating different systems and technologies, as well as ensuring data security and privacy.
- **Multi-Body Simulation (MBS) Model:** MBS is a computational technique used to analyze the dynamics of systems consisting of multiple interconnected rigid or flexible bodies [64]. It can be used for predictive maintenance of wheels and rails in railways. MBS models simulate the motion and interaction of different components of a railway vehicle, which can then be used to predict the wear and tear of wheels and rails [34]. The scope of this technology is to enable predictive maintenance of railway vehicles and infrastructure, which can reduce maintenance costs and increase the lifespan of the assets [36]. The challenge lies in creating accurate MBS models that can reflect real-world conditions and in ensuring that the models are regularly updated with new data.
- **High-dimensional Structures (HDS):** These technologies can be used for fault diagnosis of railway point machines, in [15] three-dimensional and

five-dimensional structures were used to identify possible root causes of malfunctions in railway point machines. Also, it can be utilized to promote intelligent railway construction [65]. The scope of this technology is to improve the accuracy of fault diagnosis, reduce the time and cost of maintenance, and enhance operation management and services. The challenge lies in integrating these technologies with existing systems and ensuring that the data are accurately collected and analyzed.

- **Peridynamics:** Peridynamics can be used for fatigue damage assessment of complex railway turnout crossings. It is a non-local continuum mechanics theory that can be used to simulate material behavior under extreme conditions as leveraged in [58] for crossing nose. The scope of this technology is to improve the safety of railway crossings and reduce the likelihood of catastrophic failures. The challenge lies in creating accurate models that can reflect real-world conditions and ensuring that the data are regularly updated with new information.

In a nutshell, different modelling types can aid in the creation and maintenance of a comprehensive DT for railway infrastructure. The application of numerical simulation (e.g., 3D solid FEM), and real-time simulation foster system understanding. The successful integration of these techniques into a comprehensive DT system will require collaboration between industry experts, technology providers, and researchers to address the technical, operational, and economic challenges involved.

iv. Techniques for Multi-modal Interaction

- **Virtual Reality:** Amongst virtual technologies, VR can be identified as the most prevalent. The technology's scope is to create an immersive digital environment with the intermediate of HMD, allowing users to interact with 3D representations, sound, and other sensory inputs, providing a feeling of being present in the virtual space as witnessed in [18] for train pre-operation health and safety training, for DTR management and control [66], and for permanent monitoring system [59]. Besides the lack of continuous real-time data, the challenge associated with equipment, including availability, cost, and long-term acceptability, further contributes to the existing obstacles.
- **Augmented Reality:** the technology that superimposes digital content onto the real-world environment, typically using displays such as smartphone and tablet screens or AR head-up displays (HUD). For example, AR can assist in providing specific details to improve surveillance and management of foundation pits in subway stations [67] during the construction and upkeeping phases. The main challenges are set in the complexity of designing intuitive and user-friendly interfaces and the difficulties of integration with existing systems.
- **Extended Reality:** is an umbrella term that encompasses all immersive technologies that blend digital and physical environments, providing a more engaging and realistic experience for the user. XR capabilities were harnessed in [60] to achieve the DTR that aims to guide pedestrians to their optimal paths within the station. The challenge pertains to the availability of real-time data for timely and continuous updates.

In terms of virtual representation, game engines have played a significant role. Out of all the platforms, **Unity3D** the cross-platform game engine, was the sole platform used in the literature [15], [18], [59], [67], [68], [69] to develop and implement the researchers' DTR prototypes.

In summary, the virtual experience afforded by DT augments the capabilities of systems, facilitating system automation and informed decision-making. By enabling a deeper understanding of the system and its surroundings, DTs contribute to improved performance and safety.

B. DATA

Recently, data collection has been discussed broadly [70] as a turning point in building modern industrial systems. DT can follow a data-driven or knowledge-driven approach. In the railway industry, DTs have the potential to improve the management of railway assets, operations, and maintenance by providing real-time data insights and predictive analytics. However, some limitations should be carefully considered before implementation when deciding between the two approaches. Therefore, in this section, we present a review of studies focused on Data Collection and Information Management.

1) EXISTING WORK ON DATA COLLECTION FOR DTR

IoT sensors and devices have been employed in DTR to capture and analyze data about trains, tracks, signals, and other vital components. The data collected through these sensors undergo processing and analysis with advanced analytics and ML algorithms, which results in the creation of a DT capable of accurately simulating the behavior of the physical system [27].

By leveraging IoT-generated data to build digital twins, railway companies can optimize their operations, minimize downtime, and enhance safety and security through CBM [71]. For example, in the context of predictive upkeep that serves the SIA H2020 project, [72] proposed an IoT data collection approach to support DT creation.

In [73], the authors utilized UbiBot and DS18B20 to acquire weather condition data affecting railway turnouts and safety. UbiBot is a wireless temperature and humidity monitoring system that leverages IoT and features a cloud-based platform providing real-time alerts and customizable reports. DS18B20, on the other hand, is a digital temperature sensor that yields accurate readings while requiring minimal wiring.

The authors employed both sensors to provide reliable and accurate readings for the railway switches and crossing DT. Additionally, IoT possibilities were employed to support the DT model for bridges in [42] and [44]. In [67], IoT was an essential technology employed to develop the excavation pit BIM-based surveillance platform.

In [55], DT was achieved with ASHVIN IoT platform support for railway bridge load testing concerns. Lastly, in [74], IoT supported the Computer Simulation Technology (CST) for empirical testing aimed at observing the H2S high-speed railways (HSR) embankment. Within the DT paradigm, IoT sensors play a crucial role in defining the connection between the physical and virtual space [75].

Harvesting useful data requires guessing the best placement of the sensors within the system. For this purpose, the authors in [34] and [76] presented DT for turnouts to explore the best location of the sensors (strain and stress) for adequate feedback and optimal inspection.

2) EXISTING WORK FOR INFORMATION MANAGEMENT USING DTR

Table 8 summarizes the articles that propose DTR from a data-driven or knowledge-driven perspective for information management.

DT can be useful for railway infrastructure management by integrating data from various sources and enabling features, such as sustainable decision-making. However, to fully leverage the potential of DTR, developers need to consider the spatiotemporal and interaction relationships among railway features and integrate data throughout the asset's whole lifecycle. The studies also highlight the need for standardized data formats and further research to fill existing gaps in the implementation of DTs in transportation infrastructure.

3) TOOLS/ TECHNIQUES USED FOR HANDLING DATA USING DTR

i. Tools for Data Collection

The data collection tools proposed or used in DTR studies are various ranging from scanning techniques to sensors and platforms. In this section, we discuss the major techniques employed in the literature.

- **Light Detection and Ranging (LiDAR) Technologies:** is a remote sensing technology that uses laser light to measure distances and create precise 3D maps of objects and environments [33]. LiDAR can be used to efficiently model existing railway infrastructure, including tracks, tunnels, bridges, and other structures. This information can be used for monitoring and predictive maintenance of the railway system due to its ability to capture anomalies such as deviations or misalignments.
- **Point Cloud scanning:** is a 3D scanning technique used to capture the shape and position of objects by collecting large sets of data points named Point Cloud Data (PCD). The PCD can be applied to generate railway masts [82], catenary arches [83], or the Overhead Line Equipment (OLE) elements [24]. This technique provides an efficient approach to developing infrastructure models for DTRs.
- **Fiber Bragg Gratings (FBG) sensors:** in [84], monitoring and data collection for the DT model were achieved by using FBG sensors. FBGs are optical sensors commonly used in structural monitoring applications such as monitoring the strain, temperature, or pressure of structures (i.e. bridges). Any shift in the FBG wavelength signals a change in structure and an alert for maintenance.
- **Accelerometer sensors:** is a type of sensor used to measure the acceleration of a moving object and can be used to detect changes in motion and orientation. It is considered a main source of data used by [56] to develop a railway crossings DT targeting evaluation and upkeeping forecasting, and in [85] for track line assessment based on the rail stress-strain evaluation.
- **ASHVIN IoT platform:** It can enable data acquisition from sensors and actuators installed in railway infrastructure, which can then be processed and analyzed by BIM tools to monitor the condition of the infrastructure as leveraged in [68].

ii. Techniques Used for Information Management Using DTR

The techniques used in the literature for information management using DTR are summarized below:

- **Knowledge integrated data modelling:** This technique can be used to explicitly describe the spatiotemporal and interaction relationships among railway features through a conceptual knowledge graph [77]. This can help in understanding the complex relationships among different railway features and their interactions with each other, which can aid in decision-making and optimization.
- **Data integration from multiple sources and Big Data:**
  Railway infrastructure produces vast data from sources like sensors [69]. Using big data techniques, this data can be analyzed for performance, maintenance, and safety insights [70], allowing early identification and prevention of potential issues.
- **Standardized 3D format:** CityGML is a standardized 3D format for city modelling that can be used to create a digital twin of the railway infrastructure in a 3D environment [78]. This can help in visualizing the infrastructure, identifying potential issues, and optimizing the layout and design of the infrastructure [79].
- **Data Driven Framework:** A data-driven DT can be created using machine learning and other AI techniques to learn from the data generated by the railway infrastructure. This can help in predicting potential issues, optimizing maintenance schedules, and improving overall performance [86] and [87].

TABLE 8. Summary of papers on information management for DTR.

Ref.	DT Application	Data or Information Management Technique	Key Findings
[77]	Railway Infrastructure	Data-model-knowledge Logical model Ontology model	A conceptual knowledge graph to represent the spatiotemporal relationship among railway characteristics, then constructing a conceptual, logical, and ontology model enabling a thorough understanding of the complex relationships among these features.
[78]	City Planning	Standardized 3D format based on CityGML	Data analytics embedded DT can be used to analyze and visualize urban data, such as building energy performance, air quality, and pedestrian movement.
[79]	Urban Planning	Uniform 3D format based on CityGML 3.0	Semantic segmentation for various transportation type using standards like OpenDrive, Geographic Data Files (GDF), and INSPIRE to avoid redundancy in DT representation.
[80]	Transportation Infrastructure	DT technology	Highlighted the effectiveness of data-driven DT in reflecting the performance of real-world products by simulating a virtual space.
[81]	Smart Infrastructure	Data as an engineering tool	A case study on railway assets show that data can be curated for the purpose of aiding sustainable decision-making.

- **Data as an engineering tool:** Data can be used as an engineering tool to model, simulate, and optimize the railway infrastructure [81]. This can help in identifying potential issues, optimizing layouts and designs, and improving overall performance and safety.

To summarize, the use of data technology in DTR management presents both opportunities and challenges. As a result, data-driven DTs can predict potential issues and improve overall performance, while sensors and monitoring systems can provide real-time data for decision-making and optimization.

C. INTELLIGENCE

The advent of equipping a digital representation with intelligence has been identified as the catalyst for the commencement of the DT era. Specifically, the incorporation of AI is deemed as one of the crucial features that have enabled the transformation of a static representation to an interactive and dynamic model. By facilitating diagnostics and prognostics, AI has elevated the capabilities of DTs, thereby enabling them to closely mimic real-world systems and interact with them in real-time. This section presents an overview of the diverse intelligent approaches employed in literature to address various tasks related to railway management and control, asset management, planning optimization, defect inspection, maintenance prediction, and delay prediction, among others. To this end, we have presented a summary of the different AI models adopted by researchers in Table 9, followed by a description of the techniques utilized to achieve their respective research objectives.

1) AI APPROACHES IN DTR

In this section, we will explore the potential of data-driven approaches based on DTs and AI techniques to improve various aspects of railway station management, bridges, tracks and their components, wheels, and overhead contact systems (OCS) as follows:

i. Railway Station

Several studies have utilized DTs to enhance diverse parts of the railway station and its management. For instance, Hong et al. in [67] proposed an intelligent approach to subway station foundation pit surveillance and management, which utilized multi-sensing technology, unmanned aerial vehicles (UAV), and CV, amongst others. Another study by Peng and Zheng [66] investigated the implementation of a DT-based shop floor management and control system. The study conducted an analogy of the system scheduling before and after the implementation, which revealed that the fuzzy rule NN exhibited superior performance to the traditional manufacturing method when the output volume surpassed a certain threshold. In [88], the authors introduced a real-time train delay prediction system for HSR networks using DT technology and DL algorithms. The efficacy of the proposed system is verified through a series of experiments, demonstrating its ability to ameliorate the efficiency and safety of HSR networks. Additionally, guiding pedestrians in rail stations to optimal routes using DT is proposed by Preece et al. [60], who utilized 3D scanning technology and Constrained Delaunay Triangulation (CDT) to construct a DT of the station. The A* pathfinding algorithm is then applied to compute the shortest path between two points within the created model. These systems' objectives are to improve the passenger experience and increase expediency within rail stations.

ii. Bridges

In recent years, SHM has gained significant attention for the continuous assessment of infrastructure assets' performance. In this regard, several studies have proposed the use of DTs coupled with AI techniques to enhance SHM's effectiveness. In their study, Eky Febrianto et al. [84] demonstrated the application of the statistical FEM (statFEM) to develop a DT of a self-sensing steel railway bridge. The study used FBG sensors for data acquisition and Bayesian learning to target long-range SHM. Likewise, in a study by Meixedo et al. in [86], an AI-based SHM methodology for instantaneous unsupervised damage detection for railway bridges was proposed, which utilized a hybrid approach involving Continuous Wavelet Transform

(CWT), Principal Component Analysis (PCA), and k-means clustering. The findings from both studies were promising, with successful detection of early damage scenarios even in minor cases, which could potentially reduce maintenance costs and improve safety levels.

iii. Tracks and their components
Rail tracks and their components were also a main part targeted by researchers within the literature. For example, in [68], a DT-based predictive maintenance model for turnout motors was proposed using Unity3D while the predictions were accomplished by involving a combination of Long-Short Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) models. In [40], the Rail for Future Platform (R4F) was presented, where track geometry is considered as the use case using the Vehicle and Track Interaction (VTI) model as a numerical model and Recurrent Neural Networks (RNN) to predict the lifetime of railway tracks. Similarly, Sresakoolchai and Kaewunruen [89] employed DL models and a BIM model to predict track geometry parameters. Moreover, in [90], an approach was proposed to build railway track geometric DTs (RailGDT) from airborne LiDAR data. The proposed method leverages the consistency of rail infrastructure to generate RailGDTs in a cost-effective and less arduous manner. These studies showcase how DT has the capabilities to revolutionize rail deviation and defect detection processes. Besides, they can help optimize the overall upkeep of railway systems, thereby promoting their sustainable evolution on a large scale.

iv. Rail Wheels
The field of continuous performance tracking has recently seen significant advances in the development of lifetime living models. In their work, Yang et al. [87] presented a framework for the development of such models, utilizing an AI-based DT to operate heavy freight cars. The authors applied ML models such as decision trees and Naive Bayes to two versions of the Wheel Impact Load Detector system (WILD), then employed Transfer Learning (TL) techniques to improve performance. The study aimed to enhance railway operation safety levels and reduce maintenance costs and downtime in the Canadian transportation sector. In the same way, the RailTwin conceptual framework is proposed in [9] to enable the DT with automation and actuation, transcending the classical structural modelling or information systems. This framework is enabled by AI subdomains such as DL, TL, Reinforcement Learning (RL), and explainable AI (XAI), allowing for the estimation of future states and decision-making beforehand. The authors demonstrated the effectiveness of the proposed framework with a use case for asset health inspection and surveillance. Consequently, these studies revealed that DT can play an important role in improving the efficiency and safety of transportation operations.

v. Overhead Contact System
The railway OCS is a critical component of railway infrastructure, its role is to provide a continuous electrical supply to the train. The integration of DT technology has been proposed as a promising approach for enhancing OCS management. Errandonea et al. [91] highlighted the challenges in incorporating IoT and edge computing systems and proposed new approaches for enhancing system interoperability. They also presented a four-stage methodology for developing edge-based AI solutions, which includes AI models selected based on multi-objective problems and implemented using XAI strategies taking the diagnostic of stagger amplitude as a use case. The study in [83] utilized terrestrial laser scanning and semantic segmentation techniques to generate accurate DTs for upkeeping, surveillance, and planning. A case study involving railway catenary arches was considered and a modified PointNet++ model was implemented. While Ariyachandra and Brilakis [82] and [24] proposed an automated method for detecting masts and overhead line equipment (cable, catenary) respectively using LiDAR data and the Random Sample Consensus (RANSAC) algorithm leveraging railway uniformity. Recent work by Patwardhan et al. [33] harnessed LiDAR technologies to optimize DT mechanisms in multi-faceted environments and proposed a decentralized approach for DT generation and updating using FL. The aforementioned studies aimed to upgrade OCS management and maintenance levels by leveraging DT.

2) AI TECHNIQUES FOR DTR

Several researchers have explored the application of DT by employing various AI methods for advancing decision-making, prediction, and detection. These studies have demonstrated the effectiveness of these techniques in terms of performance and accuracy. In this section, we aim to understand the mechanism of data-driven decision-making and predictive maintenance in railways through AI techniques. To achieve this, Table 9 summarizes the AI techniques employed in DTR across three primary domains such as ML, DL, CV, and a few remaining algorithms in the fields.

Building on the notable findings from earlier research, it's evident that DT plays a transformative role in multiple applications. For instance, in [82], a sophisticated methodology is showcased, achieving a remarkable 94% detection rate of railway masts using airborne LiDAR data by harnessing DT in PCD and IFC formats. In a related vein, [24] delivers a model-driven DT tailored for railway OLE, yielding an F1 score of 93.2% for OLE cables and 98.1% for other components across an 18 km domain, with an accuracy benchmark set at 3.82 cm RMSE. Diving deeper into infrastructure applications, [83] accentuates the pivotal role of contemporary DTs, particularly in legacy structures. By engaging mobile laser scanning with semantic

TABLE 9. Summary of papers on DTR for Intelligence sub-domain. *H:Heigh, L:Low, m_i: the i^{th} model, ANSYS: (Swanson) Analysis Systems, ANFIS: Adaptive neuro-fuzzy inference system, ARIMA: AutoregRessive Integrated Moving Average, BP: Back Propagation, CNN: Convolution Neural Network, CWT: Continuous Wavelet Transform, FCNN: Fully Convolutional Neural Network, FCN: Fully Connected Network, FE: Finite Element, GA-BP:Genetic Algorithm optimized Back Propagation, GRU: Gated Recurrent Unit, mIoU: mean Intersection-over-Union, LIME: Local Interpretable Model Agnostic Explanations algorithm, LSTM: Long Short Term Memory, MAE: Mean Average Error, MAPE: Mean Absolute Percentage Error, MSE: Mean Square Error, Namdam: Nesterov's Adaptive Moment Estimation, NARX: Nonlinear AutoRegressive network with exogenous inputs, OCS: Overhead Contact System, OLE: Overhead Line Equipment,PCA: Principal Component Analysis, PE: Polynomial Equation,Prob.: Problem, R^2: Coefficient of Determination, RANSAC: Random sample consensus, RMSE: Root Mean Square Error, RNN: Recurrent Neural Network, SIL: Silhouette Index, StatFEM: Statistical Finite Element Model, XR: Extended Reality.*

Ref.	Field of Interest	Technology	Railway Part/Task/Use Case	Algorithm/ Architecture	Performance Metrics & Results
[84]	Maintenance & Condition Monitoring	ML	- Railway bridge	- Bayesian	- Confidence Region: 95%
[91]	Maintenance & Condition Monitoring	ML	- Railway catenary *(Stagger amplitude of the Overhead wire)*	- H2O AutoML - Surrogate model	- RMSE: 4.46 mm
[86]	Inspection & Defect Detection	ML	Railway bridge	- Feature Extraction *(CWT+PCA)* -Clustering (k-means)	-SIL: Maximized at k=2
[40]	Optimization	ML	Railway track	RNN	
[68]	Maintenance & Condition Monitoring	DL	Switch machine	- LSTM (m_1) - ARIMA (m_2) - Agreggate of:(m_3) - LSTM - ARIMA - Entropy Weighted Method - Nadam	- RMSE: - H m_2 : 0.21 - L m_3: 0.196 - MAE: - H m_2:0.14 - L m_3: 0.13 - MAPE: - H m_2: 4.14% - L m_3: 3.84%
[67]	Maintenance & Condition Monitoring	DL	- Subway foundation pit	- BP - GA-BP - NARX - Elamn	- RMSE/ GA-BP outperformed the other algorithms
[89]	Maintenance & Condition Monitoring	DL	Railway track	- RNN - LSTM - GRU - Attention	- R^2: 0.95 - MAE: 0.56 mm
[83]	Maintenance & Condition Monitoring	DL & CV	Catenary arches	- PointNet++ *(+variation of it)* - SuperPoint Graph - PointTransformer	- mIoU: 71%
[9]	Maintenance & Condition Monitoring + Inspection & Defect Detection	DL	Railway assets $(brake, wheel, gate)$	- DL classifier - LIME	
[88]	Other Purposes	DL	Railway delay prediction	- FCNN+2xLSTM (m_1) - FCN+Transformer (m_2) - 3DCNN+LSTM (m_3) - Multimodal (m_4)	- RMSE: - H m_1 : 0.83 - L m_4: 0.68 - MAE: - H m_1:1.00 - L m_4: 0.82 - MAPE: - H m_3: 28.4% - L m_4: 21.8
[82]	Inspection & Defect Detection	CV	Railway masts	RANSAC	- Detection Rate: 93.83%
[24]	Optimization	CV	- OLE cable - OLE elements *(Catenary)*	RANSAC	- F1 Score: 93.2% - RMSE:- 3.4 cm - F1 Score: 98.1% - RMSE: 3.82 cm
[90]	Optimization	CV	- Railway rail - Railway trackbed	RANSAC	- F1 Score: 95% - RMSE:- 3.4 cm - F1 Score: 98% - RMSE: 2.7 cm
[87]	Maintenance & Condition Monitoring	TL	Railway wheel	- Decision Tree (m_1) - Naive Bayes (m_2) - Decision Tree with costMatrix (m_3) - Naive Bayes with costMatrix (m_4)	- Model Score: - H m_4: 352.22 - L m_3: 280.75 - False Positive Rate: - H $m_3, 4$: 0.14 - L m_2: 0.11 - Prob. Decision Rate: - H $m_1, 4$: 0.96 - L m_2: 0.92
[33]	Other Purposes	FL	Railway catenary*(OCS)*	- Classification *(PE)*	
[60]	Other Purposes	AI & XR	Railway station	A*	- Time: 0.16 second
[66]	Other Purposes	Fuzzy NN	Shop floor management and Control System *(scheduling system)*	ANFIS	- Manufacturing speed +50%

segmentation techniques, an accurate DT is synthesized from CAD models. Further refinement using the PointNet++ model led to a mean class IoU of 71%. Pursuing a similar trajectory, [89] pioneers a novel approach in railway track maintenance, channeling DL models and a 3D RNN for forecasting track geometry parameters in the imminent future. Augmenting this, a BIM DT facilitates co-simulation, yielding an average R^2 value of 0.95 and an MEA of 0.56 mm. These findings highlight the substantial positive effects of integrating DTs in diverse scenarios, affirming their capacity to enhance railway system effectiveness on multiple fronts.

D. SAFETY AND SECURITY

In this section, we review the research based on safety monitoring or security in the literature.

1) SAFETY MONITORING USING DTR

Table 10 provides a summary of a few studies that demonstrate the use of DT in various monitoring applications. It shows that the use of DT can bring about significant improvements in safety, and reliability.

These studies demonstrate the importance of incorporating advanced technology into railway operations, training, design, and maintenance processes. These innovative approaches hold the potential to improve safety in the railway industry, ultimately leading to improved outcomes for both employees and passengers alike.

2) DATA SECURITY AND PRIVACY IN DTR

Data authorization and authentication are crucial components for ensuring trust, security, and privacy in DTR [93]. Recent research highlighted the need to address emerging security and privacy technologies in the future. However, some studies have pointed out that data security and privacy remain challenging factors in this context, similar to any data-driven methodology.

For example, in [94], the authors proposed face recognition as a means of traveler identity authentication for supporting railway riders' station functionality and services. In [69], security levels were defined within the network structure for a proposed DT surveillance platform for HSR.

In the context of DTR, research has targeted data protection, confidentiality, and authentication. The research in [33] and [95] both focused on these issues.

FL provides a decentralized training method that can guarantee high levels of security and confidentiality for participants. In [33], FL was utilized to build a DT for railway catenary for maintenance planning.

Meanwhile, in [95], the authors introduced blockchain technology to address centralization dependency and security threats for trustworthy decision-making in manufacturing. The research framework was applied to different sectors of intelligent commuting, including railway prognostic upkeeping.

3) TECHNIQUES USED IN DT FOR SAFETY AND SECURITY

In this section, the techniques and strategies used to achieve safety and security in DTR are spread over Table 11 for Safety Monitoring and Table 12 for techniques and strategies for Security in DTR. The tables summarize the description of technologies, benefits, and challenges in brevity.

4) TAXONOMY OF DTR

To understand the categorization of the techniques, we have developed the DTR taxonomy (Figure 7) which delineates the foundational components and cutting-edge technologies underpinning the development and deployment of DTR. This architecture is structured around five core pillars: "Data", "Modeling", "AI", "Connected vehicles communication", "MMI", and "Security".

Data stands as the bedrock of any DT, aggregating inputs from diverse sources such as the IoT and historical records. These offer both instantaneous data feeds and past data insights. This collected data undergoes refinement through a spectrum of **Modeling** techniques, spanning from rudimentary data-centric methods to intricate mathematical modeling. The **AI** segment highlights the incorporation of ML strategies, encompassing techniques like DL and FL. These are crucial in amplifying the predictive precision and ensuring the agile responsiveness of the DTR system. Connected vehicles introduce the concept of real-time communication between vehicles, emphasizing **connected vehicle communication**. This refers to the real-time exchange of information between vehicles and infrastructure, facilitating safer, more efficient, and intelligent transportation operations within railway systems. **MMI** underscores the significance of a rich array of user interfaces and experiences. It captures senses ranging from the visual and auditory considering olfactory and gustatory dimensions as well. Additionally, innovations such as VR, AR, and haptic feedback pave the way for a more immersive engagement with the DTR environment. Concluding with **Security**, the emphasis is on pivotal measures that bolster the DTR system's resilience. From blockchain technologies that guarantee data's immutability to cybersecurity protocols that shield against potential external intrusions, the focus is on ensuring an impregnable and trustworthy system.

E. SUMMARY OF RQ_2

The above comprehensive section clarifies numerous technologies proposed and employed in the literature. It is evident from the summary of the studies and techniques that those technologies have been applied to activate the basic building blocks of DTR, as well as to support a wide range of railway operations. However, it can be noticed that several technologies are mutually inclusive. We concluded this section by DTR taxonomy (Figure 7) where we classified the core enabling technologies, techniques, and tools to fulfill DTR requirements.

TABLE 10. Summary of papers on safety monitoring using DTR.

Ref.	DT application	Used/Recommended Technique	Key findings
[42]	Inspection and maintenance of railway bridges	Digital Transformation, IoT, predictive maintenance, and DTs	Improved maintenance efficiency, accuracy, and reliability through real-time data analysis and predictive maintenance
[18]	Health and safety training for Austrian railway company	AR and VR immersive learning environments	Improved health and safety training through realistic simulations
[92]	Locomotive design and operational studies	Computer simulations, co-simulation, and parallel computing	Improved locomotive design and traction through multidisciplinary research

TABLE 11. Summary of techniques in dt for railway safety.

Technique	Description of Technique	Key Benefits	Challenges
Immersive learning environments	Using AR and VR to enable trainees to practice health and safety requirements step by step in a realistic work environment	Improved training outcomes, reduced safety incidents	The need for high-quality and up-to-date training content
Simulation and Co-Simulation	Using advanced simulation approaches to develop a realistic model of the asset, its validation and assessment	Improved design, optimized operations, reduced maintenance costs	The need for precise data for real simulation
Predictive maintenance approaches	Making use of a large amount of data available to improve the efficiency of maintenance processes	Provide more accurate and reliable anticipated diagnostics	The need for proper data and analytics tools to attain accurate predictions

TABLE 12. Summary of techniques for data security and privacy.

Techniques/Strategies	Description	Key Benefits	Challenges
Face Recognition	AI technology that identifies and verifies identity of operators and passengers based on facial features	Enhanced security by ensuring authentication	Concerns over privacy violations, accuracy, and bias
Network-level Security	Protect against cyber attacks and unauthorized access within the railway system (V2V, V2Center, V2X)	Improved protection against cyber threats during data sharing, and increased trust in communication systems	Complex implementation in railway systems, network latency, can't prevent all types of attacks.
Federated learning	Decentralized ML approach allows multiple devices from controllers, operators, and passengers to collaborate in training a shared model without sharing data	Increased privacy and security by reducing communication. It can train non-easily transferable models	Slower convergence due to the limited data available on each device and communication issues.
Blockchain technology	Decentralized approach allows secure and transparent storage for railway history incidents and transfer of data without the need for intermediaries	Improved security, transparency, and efficiency by fostering trust	Limited scalability, regulatory uncertainty, and energy consumption concerns

Notes: **V2Center**: Vehicle-to-Center, **V2V**: Vehicle-to-Vehicle, **V2X**: Vehicle-to-Everything

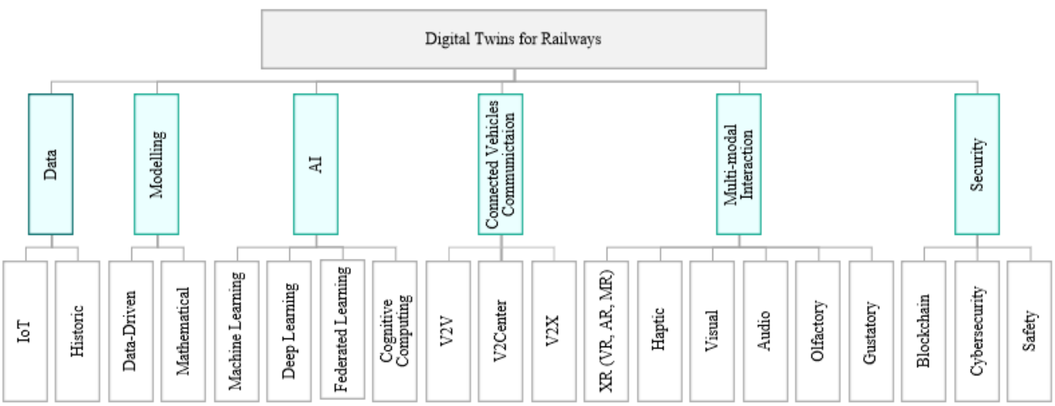


FIGURE 7. Taxonomy of DTR.

Several technologies in the taxonomy have been utilized in the literature, which is outlined in Table 11 and Table 12. The information presented in these tables answers how the technologies are employed to facilitate various DTR applications. Although Modeling, AI, and Data have already been studied in the literature for DTR, technologies including multimodal interaction, communication, and security have hardly been implemented and evaluated in the literature.

VI. RQ_3: TO WHAT EXTENT DIGITAL TWIN HAD ACHIEVED ITS FUNCTIONALITY IN RAILWAY AND WHAT ARE THE RESEARCH GAPS?

A. GAPS AND CHALLENGES

DTR has gained the attention of railway stakeholders and researchers due to being a shared platform to utilize various technologies for twining manual processes and conditional states. However, the adoption of DTR for heavy freights is still at its earliest stage and presents the following challenges and research gaps.

1) DATA AVAILABILITY

The railway industry produces enormous amounts of data. Therefore, to design and develop DTR, a seamless and continuous data stream is required. However, data distribution drift or acquiring data from outdated and sensor-lacking heavy freights has been a challenge for most studies [87]. Despite proposing transfer learning as a solution in contemporary research [87], the need for a continuous real-time data stream and access to railway industry data is essential to ensure the success of DTR.

To address the lack of availability of data, there is a need to ensure secured and authorized access to data. Furthermore, designing embedded systems or budget-friendly sensors to mount on freight bodies can be used in collecting data from various sources.

2) INTEGRATION AND SYNCHRONIZATION

To develop a full-fledged DTR, integration and synchronization of various parts of the railway system, such as control, scheduling, monitoring, and maintenance systems, are necessary. Different technologies have been proposed and evaluated for these systems in research; however, the successful implementation of DTR requires a comprehensive and standardized framework [9]. Besides, one of the main challenges is the propagation of data integration issues caused by the lack of standardization in data collection tools and formats of various parameters, including faulty images, environment states, and structural conditions. Moreover, the use of multiple sensors to collect diverse data types further complicates the analysis process. To address these challenges, it is essential to design a data standardization process or fusion techniques that can integrate data from diverse sources effectively.

3) BUILDING AI MODEL

As data (e.g. images) are rudimentary elements to create a reliable and efficient AI model, the development of an intelligent model (e.g. defect classifier) still needs to rely on manual data labeling (e.g. bounding box labeling) or historical data (e.g., particular defect images). However, for a massive industry like the railway, such a process is time-consuming and costly.

Several studies have shown evidence that DL can be applied to build classifiers with limited data [9]; however, these models have primarily been evaluated on smaller and particular datasets [77]. Thus, a less computationally expensive and reusable AI model architecture is needed to handle the diverse nature of data in the railway system. To mitigate the trade-off between limited data and efficient AI models, the Ensembling of transfer-learned models can be utilized for building reusable AI models. Moreover, to provide forecasting oversights in DTR based on the current and previous state, a relativity theory-based model is still required to be investigated.

4) CREATING VIRTUAL MODEL

Creating models of railway infrastructures is a complex task due to its moving nature. For example, modelling the controlling room for the training is intricate as it requires mapping exact components in 3D models in order to twin the manual monitoring or training process [18]. Creating models also requires redundant efforts. Furthermore, the research trend already demonstrates the adoption of immersive learning through cutting-edge technologies like VR, AR, or XR. This opens doors to accessing the QoE and usability of DTR use cases. Understanding the needs and requirements to improve the User Experience (UX) of DTR products is essential.

5) VIRTUAL MODEL INSPECTION

Although modeling has been emphasized in several studies, exploring the use of models for virtual inspection in shared persistent platforms like Metaverse is yet to be done. Developing a virtual model for the DTR using a shared, persistent, and consistent platform can aid in addressing the challenge of creating this model. For example, using the DTR as one of the cornerstones of the Metaverse can empower this development.

6) ENABLING FEEDBACK LOOPS

Enabling feedback loop is one of the crucial features to activate actuation, controlling, and interaction between virtual space and real space [1], [2], [3]. However, due to the unavailability of real-time data, and limited multi-modal interaction, the feedback loop in DTR has not been studied comprehensively in the literature. To facilitate the collection of real-time data and enable a feedback loop, the incorporation of multi-modal sensors such as haptics, and actuators such as controllers can be used.

The importance of emerging technologies such as immersive VR or XR to enable feedback loops in DTR has been recognized in the literature. However, there is still no specific approach to retrieve the outcome of DTR in a shared, consistent, and persistent platform.

7) SECURITY AND PRIVACY

As railway is one of the major transportation facilities worldwide, building DTR data security and privacy is a prime concern. However, Security at the communication level has not been fully realized through proper methodologies and

Challenges		Future Recommendation
Data		
	Accessing	Secured and authorized access to data
	Collecting	Designing budget-friendly sensors to mount on freight bodies
Training AI Model		Reusable AI model
Virtual Models		
	Creating	Utilization of Generative AI to generate 3D models from texts, or photos
	Retrieving	Using the shared, persistent, and consistent platform (e.g. Metaverse)
Enabling Feedback Loop		Utilization of multi-modal sensors, and actuators
Integration with existing systems		Generic framework with detailed design of components to incorporate relevant techniques

FIGURE 8. Challenges and future recommendations to desing and develop DTR.

evidence. Therefore, extensive evaluation of security in DTR is still required in the existing literature [95].

Based on our findings on challenges faced in designing and developing a DTR, we present the following future recommendations (Figure 8) that can benefit the railway industry in achieving a complete DTR.

B. LIMITATIONS

This survey has a few limitations that we would like to point out. Firstly, we were unable to fully elaborate on technologies included in the taxonomy, such as Haptics. This is due to the lack of enough contributions in literature and detailed information available to narrow down its characteristics and methods of implementation. Secondly, we suggest that future research should investigate the existing technologies with a specific framework and use case. Developing a generic framework with a detailed design of components to incorporate relevant techniques, such as Metaverse, Haptics, Reusable AI, and Blockchain, can help in integrating the DTR with existing systems. This can ensure seamless integration and improve the overall effectiveness of the DTR. We plan to address this limitation in the future by extending this survey. Moreover, using the snowballing technique in the future for paper inclusion eligibility may reflect a deeper topic coverage. We recognize that there may exist many DT-related papers that do not explicitly specify DT for railways as their main focus, but that are nonetheless related to topics such as predictive maintenance, AI, automation, etc. The railway systems may directly or indirectly benefit from such research papers. For the time being, such publications are not part of this survey since they do not focus on DT railway. Therefore, extending this work in the future to include such research papers will add a broader scope to the survey.

VII. CONCLUSION

In conclusion, DT technology has the potential to revolutionize the railway transportation industry by improving sustainability and efficiency. However, despite the growing interest in DT, its full potential in the railway domain has not yet been realized due to the lack of exploration of its underlying technologies. In this study, we present the DTR from the perspectives of representation, data, intelligence, and safety and security. Our aim is to bridge existing gaps by conducting an exhaustive literature review, introducing a DTR taxonomy grounded in cutting-edge technologies, and emphasizing challenges and unexplored research areas. This provides both industry and academia with a clear overview of the advancements in this field. We found several efforts have been made to realize the underlying technologies of DT for transforming the railway industry into an automated and digital transformation system. However, a comprehensive framework incorporating newly emerging technologies is still required to be designed. Besides, with a deeper understanding of how diverse DTR technologies can be integrated and applied, we obtained key challenges and opportunities in the railway transportation industry and maximized the potential of DT. We recommend future research to explore emerging technologies such as the Metaverse and Generative AI for further advancement of DTR.

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