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SURVEY

Data Integration for Digital Twins in Industrial Automation: A Systematic Literature Review

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ABSTRACT The domain of industrial automation faces challenges, such as shortened product life cycles, shortage of skilled labor, and increased complexity. Addressing these issues necessitates innovative solutions, one of which is the Digital Twin, being a virtual counterpart of a physical asset. Central to the quality of a Digital Twin is the data it harnesses. While current Digital Twins primarily draw data from their corresponding physical assets, future interconnected production environments promise an influx of additional data from external devices. However, it remains uncertain how existing Digital Twins incorporate and leverage such data. In this systematic literature review, drawing from a pool of 1107 unique publications, we analyzed 141 works to shed light on data utilization in industrial Digital Twins. We categorized these publications based on Digital Twin types and classified them according to various criteria regarding different characteristics of data. Our findings reveal that the majority of Digital Twins predominantly rely on structured data sourced directly from their associated assets, often employing proprietary integration methods. Facing the trends towards agile and interconnected production ecosystems, as well as an increasing amount of unstructured data, we assert that current Digital Twins are not equipped to meet forthcoming demands in the industrial domain. Consequently, we propose necessary adaptations to fully unleash the potential of Digital Twins and outline future research fields, including automated data integration and evaluation.

INDEX TERMS Data integration, digital twin, Industrial Internet of Things, literature review.

I. INTRODUCTION

The industrial sector faces challenges such as shorter production cycles, a shortage of skilled workers, increased complexity of production systems, and growing competition, leading to greater pressure for effective and efficient automation engineering and plant operation [1]. This necessitates a continuously improving level of innovation in production. To meet these challenges, innovative concepts have been pursued to make future production more flexible, efficient, and secure [2].

In this context, a key concept that is gaining increasing significance is the Digital Twin. Across multiple references, a Digital Twin can roughly be described as a virtual representation of an asset being synchronized with the asset and able to fulfill a given Use Case [3], [4]. The Digital Twin is located in the Information Technology (IT) world and is likely distributed across edge and cloud environments. It is used to provide additional information about the asset. One aspect of a Digital Twin is to utilize software to predict, simulate, or optimize asset behavior according to the given requirements [5]. In industrial Use Cases, the quality of the Digital Twin, and therefore its added value, depends on the data provided from the asset and the information extracted from it [6].

Moreover, its quality depends on the (simulation) models provided by the Digital Twin and executed during production, generating insights beyond directly measurable data. These

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insights cover aspects such as predictive diagnostics, current energy consumption, and the carbon footprint, as well as collision analyzes, lifespan expectations, and many more. These insights are valuable for predictive maintenance, production optimization, energy savings etc. [7]

To gain the insights mentioned above, the (simulation) models must be executed simultaneously during the operation of the asset and supplied with relevant live data. Besides the sensors of the asset itself, a possible source of such data are the heterogeneous and diverse systems in an interconnected production network. Such production networks are intensively promoted by concepts such as Smart Manufacturing [8], Industry 4.0 [9], and the Internet of Things (IoT) [10].

Consequently, an increase in available sensors and data, along with the enhanced interconnectivity of various assets, is anticipated [11]. It is projected that by the year 2027, the volume of data generated worldwide per year will exceed 280 Zettabytes (ZB) [12] with IoT-based devices presumably generating approximately 41% of this data in 2025 (79 ZB of 181 ZB) [13]. To utilize this vast and divers amount of data, it is necessary to enable an easy and flexible integration of data and appropriate processing within the Digital Twin.

Based on the expectation of future connectivity and the resulting amount of data, this study aims to conduct a systematic literature review (SLR) to examine how data is integrated into and how it is currently used by the Digital Twin. Based on these results, it should be evaluated whether the functionalities of Digital Twins as described in the current literature are suitable for the anticipated future of industrial automation, and what possible challenges the Digital Twin and field of industrial automation may face in terms of data utilization and integration in the future.

The objective of this study is to investigate and address the following formulated research questions based on a SLR:

1) **What kind of data is relied on in implementations of Digital Twins in current literature?**
2) **Where does this data come from and how is it used?**
3) **Are current Digital Twins suited for future, increasingly flexible and connected production environments?**

The remainder of the paper is structured as follows: Section II defines and describes key concepts relevant to this work to establish a common understanding of the subject matter. This is especially necessary for the concept of Digital Twins, as a vast variety of definitions exist in the literature. Section III presents related studies and their key findings. Section IV outlines the methodology and categorizes the publications used for this SLR. The results are presented in Section V, and their significance for industry and research is discussed in Section VI, along with the potential limitations of the SLR. Section VII summarizes the findings and provides an overview of open research areas in the field of data integration for Digital Twins in industrial automation.

II. BASICS AND DEFINITIONS

This SLR is based on several concepts and their interactions, including the Digital Twin, the IoT, and Industry 4.0. These concepts represent broad subject areas, and no overarching or unified definition has yet been found and accepted. Therefore, the following sections explain how concepts are understood in the context of this study, to create a common basis for understanding.

A. DIGITAL TWIN IN INDUSTRIAL AUTOMATION

The idea of a Digital Twin was first mentioned in an industrial presentation as an information based representation of a physical asset providing the asset condition throughout the entire lifecycle. This was called the *conceptual ideal for Product Lifecycle Management*, which originated from the product lifecycle domain, and the term "Digital Twin" was not explicitly mentioned. [15]

The first definition of the Digital Twin for technical systems was presented by NASA as an "*integrated multi-physics, multi-scale, probabilistic simulation of a [...] system, that uses the best available physical models, sensor updates, [...] to mirror the life of its flying twin.*" [16]. Since then, numerous other definitions of the Digital Twin have emerged, adding different aspects to the concept or specifically expanding/defining it for certain subdomains [17].

Common in most definitions is, a physical asset conveying (real-time) information about its own state to its Digital Twin, typically measured via sensors of the asset itself. The Digital Twin, in turn, uses sophisticated algorithms and simulation models to gather additional information and enhance the control and behavior of the asset. Therefore, the control signals are sent from the Digital Twin to the physical asset. Especially in industrial contexts, for reasons related to reliability, intellectual property, or security, a separation between Operational Technology (OT) and IT is recommended [14] (see Fig. 1). To minimize production downtimes, the OT network needs to be highly available and fast to enable real time control of the machines, for example for safety functionalities. In contrast, the IT network covers a non-critical infrastructure. Typically, this covers hard-/software for data analysis or monitoring services, which do not have real-time claims and do not disrupt the production or plant safety functionalities in the case of an outage. Although some aspects of a Digital Twin certainly may also be in the OT network, for simplification, we assume the Digital Twin to be in the IT network, functioning as an extension of the already working asset. If the IT network is operating normally, the Digital Twin can be used to enhance asset control. However, in case of an IT outage, the asset continues to work with default settings from the classic automation control.

The depth and level of detail in the definitions of the Digital Twin vary significantly [17]. To provide a common understanding of the Digital Twin as referred to in this work, two definitions are presented. A detailed definition describes the functionalities, components, and relationships of a Digital

Twin [18]. Although this detailed definition provides a common understanding, it is not suitable to categorize the literature for the SLR because of its high specificity. For this purpose, a second and more abstract definition of Digital Twins from [19] is used. Both definitions and their interrelationship are briefly explained in the following subsections.

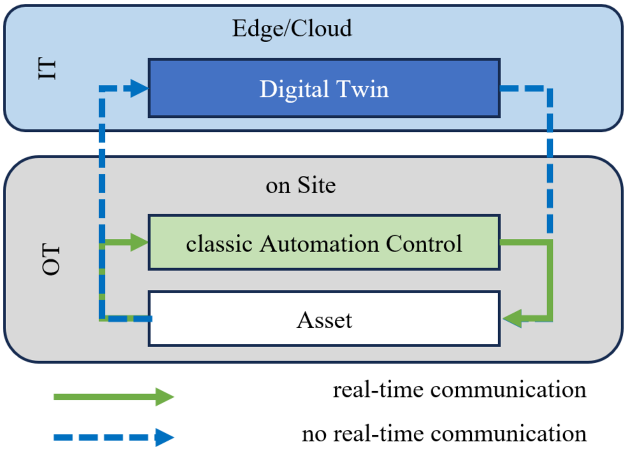

FIGURE 1. Positioning and interaction of the Digital Twin within classic automation components. (simplified from [14]).

1) ABSTRACT DIGITAL TWIN DEFINITION

According to this more abstract definition [19], three variants of *Digital Representations* of a physical asset exist. *Digital Model*, *Digital Shadow*, and *Digital Twin*. The term *Digital Representation* is intended to address all three variants as a collective term. The three variants are schematically illustrated on the left-hand side of Fig. 2. They differ in the degree of automation in the exchange of data and information between the physical asset and its Digital Representation. In the *Digital Model* (the Digital Representation with the lowest automation level), the transfer of data from the physical to the digital, and vice versa, is executed manually. In the *Digital Shadow*, data transfer from the physical asset to the Digital Representation is automated. Consequently, the Digital Representation is frequently or continuously updated about the current state of the physical asset and can provide corresponding improvements in asset control. However, these suggestions need to be manually transferred back to the physical asset. In the *Digital Twin*, both directions of the data transfer are automated. The *Digital Twin* frequently obtains information on the current state of the physical asset and reacts accordingly by adjusting and correcting the control of the physical asset.

The variants of Digital Representations defined in [19] provide an abstract categorization that is widely applicable. However, a precise understanding of the inner components of a Digital Representation and their interactions is not given because only the interfaces are defined. Therefore the inner structure is modeled as a kind of black box. To better understand the functionality and structure of Digital Twins we refer to the following detailed definition.

2) DETAILED DEFINITION OF THE DIGITAL TWIN

In [18], the Digital Twin is described as the representation of a physical asset in the digital world. The Digital Twin, illustrated on the right, in Fig. 2 - is a collaboration of various (software) components, likely distributed deployed and working together to enable the diverse functionalities of the Digital Twin. In addition to a Digital Twin, [18] introduces an extended version, the *intelligent Digital Twin (iDT)*. As shown in Fig. 2 by background highlighting, the Digital Twin in the context of [18] is equivalent to the Digital Shadow in the categorization of [19], as it has no feedback interface. Only the iDT is equivalent to a Digital Twin as defined in [19].

As mentioned, an iDT consists of a series of interacting components, with the most important components for this contribution, briefly explained below. For a detailed description of all components, refer to [18].

The iDTs interfaces include a Data Acquisition Interface (DAQ) and a Feedback Interface (FI), enabling interaction in both directions with the physical asset. The DAQ receives data from the physical asset and the FI sends corresponding control signals or parameterizations to improve the control and behavior of the physical asset. The behavior of the physical asset can be verified using sensor signals and (simulation) models in the Digital Twin. This includes geometry, topology, and circuit diagram models, but also behavior models for simulating the physical behavior of the asset etc. The data received via the DAQ is stored as Operation Data, making it available for later analysis by the iDT. These can be conducted using the intelligent algorithms of the iDT.

To minimize misunderstandings, the following naming convention is used in this study. Because the abstract definition is better applicable to the various definitions in the analyzed literature, the terms defined there will be used throughout the rest of the work. Furthermore, the term “Digital Representation” is used if no explicit assignment to one of the three levels (Digital Model, Digital Shadow, Digital Twin) is intended.

Based on the abstract and detailed definitions of the Digital Twin concept presented above, a common understanding is established. As shown in the definitions, the integration of data from the physical asset is an integral part of enabling useful and correct functionality of the Digital Twin. Therefore, two increasingly relevant concepts for data integration and data availability are briefly described in the following two sections.

B. (INDUSTRIAL) INTERNET OF THINGS

The concept of the Internet of Things (IoT) involves connecting physical devices, machinery, and objects to the internet using IT technology, resulting in information about these assets being available in a machine-readable

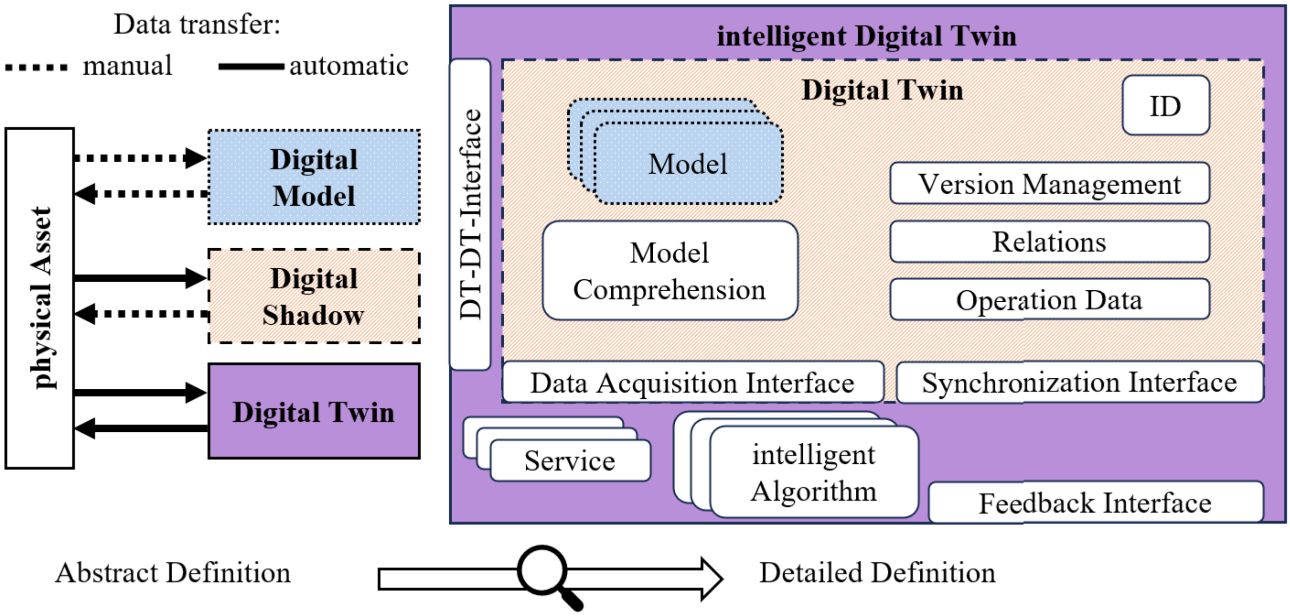

FIGURE 2. (Left) Abstract representation of the different stages of a Digital Representation [19]. (right) Detailed view of the corresponding concepts [18]. The concept of the "Digital Twin" in the detailed concept corresponds to the "Digital Shadow" of the abstract concept. The same applies to the "intelligent Digital Twin" in the detailed concept and the "Digital Twin" in the abstract concept. The parallelism is highlighted through the colors and contours of the respective blocks.

form for other components. In the industrial context, this concept enables the deployment of intelligent algorithms and software. This in turn enables process optimization, energy savings, predictive maintenance, increased security, and flexibility in assets [20].

The industrial application of the IoT, also known as the Industrial Internet of Things (IIoT), deepens these concepts specifically for industrial automation. The use of high-level algorithms and the integration of real-time data enables advanced analyzes and applications aimed at creating a more efficient and secure production environment. However, embedding IIoT concepts into a sensitive industrial OT environment requires additional work in the areas of safety and security.

C. INDUSTRY 4.0

The concept of Industry 4.0 was first used at the Hanover Fair 2011 [21] and refined as a set of recommendations by the Platform Industry 4.0 on behalf of the German Federal Government [9]. It outlines a comprehensive approach to modernize the manufacturing industry using emerging modern technologies to address future challenges. Among the various goals, the technological objectives of the initiative focus on standardizing Digital Representations and developing open standards to enable cross-company networking and the integration of value-added networks. This includes the following aspects:

- Machines, devices, and sensors are accessible from IT networks (e.g. the internet) thus enabling generic access mechanisms.
- Utilizing data analysis mechanisms and exchange approaches to harness the large volume of generated data for informed and optimized decisionmaking.
- Deploying autonomous and intelligent systems reacting independently to changing conditions and enabling optimal productivity.
- Comprehensive horizontal integration enables machine-to-machine interaction as well as vertical integration utilizing information across hierarchy levels to improve production processes.

A central component of this initiative is the socalled Asset Administration Shell (AAS), designed to provide life cycle information about physical assets by a comprehensive standardized software interface providing access to data and information which is structured in standardized submodels [22]. In essence, the concept of Industry 4.0 envisions the introduction of internet-based technologies into industrial engineering and production processes, enabling a new level of seamless and continuous interoperability of various hardware and software systems to make optimal decisions based on collected information [9]. Therefore, IT is broadly introduced into the OT environment.

After introducing the relevant concepts and building blocks for the SLR, in the next section, related studies on the topic of data integration in Digital Twins are described.

III. RELATED STUDIES

Because the concept of the Digital Twin has been the focus of several literature reviews in the past, this section provides a rough overview of related studies and their key aspects.

In [23], the authors analyze the role of the Digital Twin in the context of the IIoT, underlining enabling technologies and challenges. The scope extends beyond the manufacturing industry, covering topics such as smart cities and healthcare. Key findings from this study suggest that the data quality should be high for algorithm processing. Challenges arise in connectivity and communication failures, resulting in impacts on Digital Twin algorithms. For the Digital Twin, this results in a need to effectively compensate for any loss of the data streams. The study concludes that Artificial Intelligence (AI), in general algorithm development, and IoT are key enablers for Digital Twins.

The survey by [24] highlights the enabling technologies and challenges of Digital Twins. Relevant technologies include Machine Learning, Cloud/Fog/Edge Computing, and IoT. Challenges identified for the implementation of Digital Twins cover data ownership rights, data security, and the granularity and synchronization intervals between the Digital Twin and the asset, depending on the specific applications. In [25] the correlation betweem Digital Twins and AI, Machine Learning, and Big Data is examined. In addition to manufacturing, they cover areas such as power and energy, automotive and transportation, healthcare, as well as networks and communication. In aspects of manufacturing, they identify AI as crucial for detection, prediction, and optimization functionalities. This requires the Digital Twin to make dynamic decisions based on gathered data. They also highlight IoT as the source principle to harvest data from the environment of the physical asset. Therefore, IoT can act as another data source for AI algorithms. Challenges for AI usage in the Digital Twin include data collection due to the heterogeneous nature of data, processing capabilities due to the exploding amount of available data, and data analytics because of the application-specific usability of AI algorithms.

In [17], a comparison of various definitions for the Digital Twin is presented, describing implementation challenges due to a lack of consistent terminology and standardization for the Digital Twin and its technological maturity. The study also describes challenges in implementing data interfaces for Digital Twins due to variable requirements on the update frequency and exchange mechanism used in Digital Twins.

In [26], a literature review is conducted with a focus on multiple domains, with maintenance and digital manufacturing covering two-thirds of the overall publications analyzed. The review concludes that the availability of data due to company regulations and concerns about intellectual property is critical. The complexity of integrating diverse sources of data into Digital Twins is identified as a challenge for the implementation of Digital Twins.

There are numerous other reviews on Digital Twins [19], [27], [28], [29], [30] that convey a similar message, highlighting the following:

- Requirements on data to be integrated in the Digital Twin in the future.
- Requirements on Digital Twin itself to integrate data in the future.
- Future challenges regarding the usage of specific technologies in Digital Twins because of data characteristics.

Despite the high number of available reviews, there is no literature on the current state of Digital Twins in manufacturing with context to data. Neither on what data is used in Digital Twin applications nor on how this Data is integrated to date. Therefore, this review focuses on identifying what data is used in current Digital Twin applications, where this data originates, and what the challenges are when applying current Digital Twin concepts to future productions scenarios.

In the next section the used methodology for the SLR is described.

IV. RESEARCH METHOD

A SLR aims to use a systematic approach to evaluate the existing literature to minimize possible biases and errors in the methodology. The methodology used for this SLR is adapted from [31], which was developed for literature studies in the Software Engineering domain. Because our SLR is neither completely allocated in the Software Engineering Domain nor a pure systematic mapping study, the method was applied if useful and modified if beneficial. The resulting methodology consists of five steps, as shown in Fig. 3.

1) **Definition of Research Question:**
   Based on the motivation for the SLR, research questions are defined, serving as the starting point for the SLR. A detailed description of the research questions is provided in IV-A.
2) **Conducting the Search:**
   In this step, the search for relevant primary literature is carried out based on search strings in scientific databases. The selection of search terms, choice of search strings, and used databases are described in IV-B.
3) **Screening of Papers for Inclusion/Exclusion:**
   The inclusion and exclusion criteria are defined for the found titles. The initially found quantity of literature is narrowed down to literature relevant to the SLR. The inclusion and exclusion criteria, as well as the results of the process, are presented in IV-C.
4) **Screening of Papers:**
   In this step, the remaining literature is analyzed in a sample manner. Based on the findings, a further filtering process is conducted in IV-C.
5) **Data Extraction and Mapping Process:**
   In this step, the actual data extraction and evaluation of the final remaining literature is performed. For this purpose, a classification schema was developed, which is presented in IV-D.

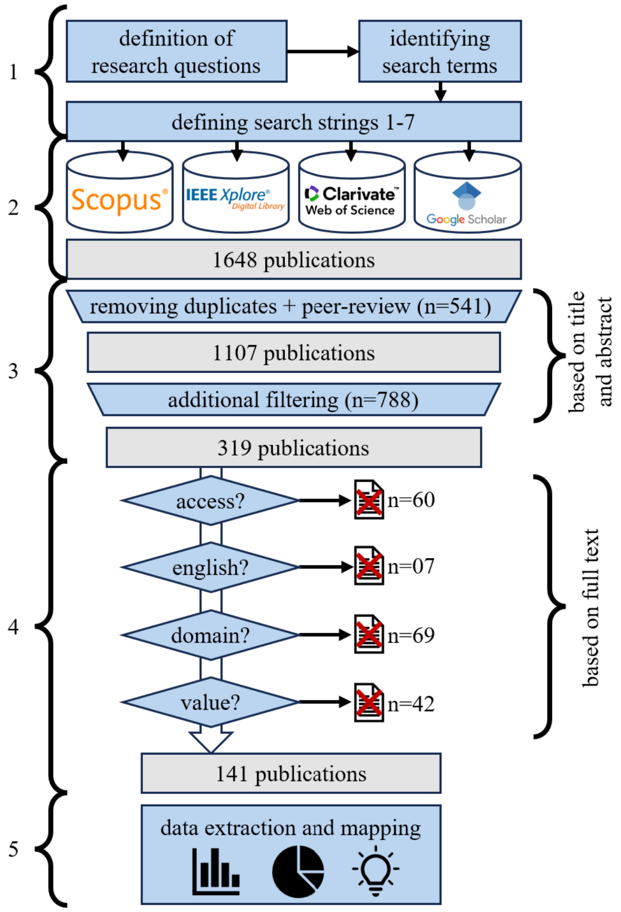

FIGURE 3. Process of the literature search and filtering process.

A. DEFINITION OF RESEARCH QUESTION

As indicated in Section I, the amount of available data is expected to increase significantly in the future. Additionally, the future networking capabilities of devices such as sensors (Sections II-B and II-C), imply that this data will not be isolated in separate data silos, but rather be actively exchanged among various actors in an interconnected production. The Digital Twin is one actor in such a production. An integral component of the Digital Twin is the integration and processing of data. Therefore, this study aims to investigate the following:

1. What data is integrated into the Digital Twin in present implementations?

2. Where does this data come from and how is it used in the context of the Digital Twin?

Answering these research questions provides insights into what data is/is not integrated in Digital Twins and to what extent this ratio aligns with future developments in industrial automation.

While the primary data source of the Digital Twin is its own physical counterpart (see II-A), whether it is asset data captured during operation or engineering artifacts from the engineering phase, much of the available data in the future will no longer be generated by an asset itself but by entities in the environment or even spatially distant assets. Against this backdrop, the third research question is as follows:

3. Are current Digital Twins suited for future, increasingly flexible and connected production environments?

Therefore, this study aims to assess the capability of the Digital Twin to interact with new available data sources.

The research questions presented form the basis for the SLR described in this paper. Based on this foundation, search terms are defined and used for literature search.

B. CONDUCTING THE SEARCH

The methodology presented in Table 1 is used to generate an objective set of search terms. In the initial step, the main themes of the SLR are defined, namely "Data in Digital Twins" to set focus on what data is used in the Digital Twin and "Synchronization of the Digital Twin" to focus on how the data gets from its point of creation to the Digital Twin. Based on these topics, relevant overarching terms are defined. Subsequently, sub terms are defined for these overarching terms. After this, a first test wise literature search is performed. The goal is not to find specific content for the SLR but rather to identify additional search terms from the literature. Relevant terms are added to the overarching or sub terms in Table 1. Synonyms are identified and the terms are clustered accordingly. Based on the clusters found, search strings for the literature search are defined. The search strings used for the literature search are presented in Table 2.

Each of the seven search strings included the term "Digital Twin" and a domain restriction to the industrial production using the terms "manufactur* OR industr*." The * operator is used to account for various spellings (e.g., industrial, industry, industries) in the search term. In addition to domain-specific terms, each of the seven search terms includes a theme-specific cluster derived from Table 1. The clusters consist of two-word groups linked through the cartesian product (×). For example, in the case of the first search string, every combination of the two-word groups is part of the search term (e.g., external data, independent data, outer data, environmental data, external feature, independent feature and so on).

Seven search strings are used for the literature search in three scientific databases (Scopus, IEEE, and Web of Science) and the Google Scholar search engine. A total, 1648 titles were found. These are filtered through the inclusion and exclusion criteria, as described in the following section.

C. IN-/EXCLUSION OF FOUND LITERATURE

To reduce the identified literature to titles that provide added value for answering the research questions, the following inclusion/exclusion criteria are applied:

1) **Remove Duplicates:**
   Because the results are compiled from four different sources, duplicates are removed.

TABLE 1. Search term table used for identifiying relevant search terms.

Main Topics	Data in Digital Twin	Synchronization of the Digital Twin
General Terms	time series data; data fusion; sensor fusion; external data; data identification; data filtering; data acquisition; data processing	communication; internet of things interfaces; data processing
Sub-Terms	data reduction; multi-sensor; combining sensor data; uncertainty reduction; direct fusion; indirect fusion; data integrity; data integration	internal synchronization; external synchronization; industrial internet of things; smart devices; device2device communication
Related Terms	acquisition: *addition, delivery* time series data: *runtime data, live data, historical data* sensor fusion: *multi sensor data fusion* external: *outer, exterior, independent, foreign* identification: *selection, classify, determine, find, analyze* filtering: *cleaning, processing, clarification* estimation: *guess, projection, rating* fusion: *integration, joining, combine, blend*	interface: *intersection, confluence* internal: *in-house, domestic, constitutional, enclosed, centralized* smart: *intelligent* communication: *connection, contact, link, transmission* synchronization: *integration*

2) **Include only Peer-Reviewed Literature:**
Only journal articles and conference papers are included in the list of publications to be analyzed. Book chapters, theses, project reports, etc., are excluded to ensure that only peer-reviewed literature is considered in the SLR.

Based on these two inclusion/exclusion criteria, 1107 titles remained. The following inclusion/exclusion criteria focus less on the meta-aspects of the publication and more on the publication content. Therefore, titles are further filtered based on their abstracts with respect to the following aspects:

3) **Domain Relevance:**
As defined in the search strings, only literature related to industrial manufacturing should be considered. Despite the restrictions in the search strings, publications from other domains were still included. Sometimes, the Digital Twin and its origin in manufacturing were mentioned in the abstract, but the paper dealt with an entirely different domain such as healthcare, building information modeling, aero-space, etc.
Therefore, a stricter theme filter containing relevant thematic terms was created. This led to a filter step with the criteria listed in Table 3.
4) **Filtering by Topic:**
As a result, 319 publications remained, which are further analyzed. The remaining full texts of the publications were then read, and further publications were excluded based on the following criteria:
    - Titles that were not accessible to the authors (60 titles)
    - Titles not written in English (7 titles)
    - Titles with topics from other domains not excluded in the previous filtering step (69 titles)
    - Titles that obviously cannot contribute to answering the research questions, as their thematic focus did not fit the research questions. (42 titles)

Ultimately, 141 publications remained, which were used in the final step of data extraction and mapping. The criteria used to evaluate the remaining publications are described in the following section.

D. DATA EXTRACTION AND MAPPING PROCESS

As described in Section IV-A, the SLR aims to shed light on the interaction between the Digital Twin and its usage of data. For this purpose, the following categorization criteria were chosen.

1) **Digital Twin Type:** This category assigns the Digital Representations described in the publications to one of the types of the abstract definition in [19]. The decision is based on the degree of automation of data and information exchange between the physical asset and Digital Representation. With this, it is determined whether the respective publication describes a Digital Model, a Digital Shadow, or a Digital Twin showing the level of autonomy in current Digital Representations.
2) **RAMI Level:** The manufacturing domain extends across multiple hierarchical levels. Digital Representations can be applied to individual sensors as well as entire manufacturing companies. Therefore, the requirements for Digital Representation can vary significantly. The hierarchy levels presented by Industry 4.0, and specified in IEC 62264/61512, were used as categorization criteria for the described Digital Representations. These levels are part of the Reference Architecture Model for Industrie 4.0 (RAMI 4.0) [9]. This categorization enables the analysis of the hierarchy levels in which Digital Representations are established. Possible values are product, field device, controller, station, plant, company, or the connected world.
3) **Data:** This is the most crucial category for this SLR, focusing on the characteristics of the data integrated by the Digital Representations. Five sub-aspects are examined:
    - The first sub-aspect investigates the sata sources that the Digital Twin integrates, distinguishing between internal and external data sources. Internal data sources refer to all data objects generated by the physical asset itself, whereas external data sources describes data generated from other devices [6].

TABLE 2. Used search strings.

#	Topic aspect of search string
ALL	Digital Twin AND (manufactur* OR industr*)
1	[(external | independent | outer | environmental) × (data | feature | information)]
2	[(data | feature | sensor | information) × (identification | selection | classification)]
3	[(data | feature | sensor | information) × (filtering | cleaning | processing)]
4	[(data | feature | sensor | information) × (fusion | integration | combination | blending)]
5	[(data | sensor) × (interface | confluence | intersection | connection)]
6	[(data | sensor) × (syncronization | exchange | linking | transmission | correlation)]
7	[(data | sensor) × communication]

- The Data Acquisition sub-aspect distinguishes whether the data is integrated through a specifically implemented method or through flexible and universal methods.
- The Data Type sub-aspect examines the type of integrated data, distinguishing between structured and unstructured data.
- The sub-aspect of Data Origin distinguishes in the context of the life cycle. Data can originate from the engineering of the physical asset or can be generated during the production phase.
- Finally, a distinction is made regarding the Data Purpose for which the data is used, differentiating between retention, monitoring, and feedback.

Further, we analyze if the found publications cover other relevant topics concerning the integration of data in combination with the Digital Twin, such as:

- usage of semantic technologies. Semantic covers the topic of making the context of data understandable for machines (e.g., by using machine-readable formats of units to tell a machine, that the number 42 is given in millimeters and not meters). When integrating data from multiple, heterogeneous sources the use of semantic technologies becomes a relevant concept.
- usage of machine learning technologies. Although machine learning (ML) is not the sole solution to data integration problems in Digital Twins, its potential for enhancing the quality of data integration is large.
- usage of real-time data. Depending on the system under consideration, feedback from the Digital Twin to the physical asset may require real-time processing and evaluating of gathered data.
- usage of edge computing concepts. In combination with the previous point, real-time data will inevitably lead to an increase in the required computational power for data processing. To guarantee a timely response of the Digital Twin, edge computing may be a compromise between computation power and timeliness.

In addition to the content-based analysis of the identified publications, we conducted a bibliometric analysis to explore several meta-aspects within the field of Digital Twins and data integration. The analysis focused on the following areas:

- The frequency of word occurrences in the titles and abstracts of the 141 publications. For this, we used the "wordcloud" Python module, limiting the maximum number of words to 80. This analysis aimed to highlight the topics and aspects that frequently appear in conjunction with Digital Twins, in the context of data integration.
- The relevance of various journals and conferences in the research field. We utilized VOSviewer to create a graph that displays the most relevant journals and conferences for this SLR based on citation counts and their interconnections.
- The distribution of publications by country, aiming to identify the regions most active in Digital Twin research related to data integration.
- The distribution of publications over time, to assess whether the intersection of Digital Twins and data is gaining increasing relevance within the scientific community.

The results of the literature review are subject of the next section.

V. SLR RESULTS

The full texts of 141 publications were analyzed. Based on the information obtained they were assigned to the categories presented in Section IV-D. Afterwards the results are used to answer the research questions stated at the beginning of this SLR. We start with a presentation of the results of the bibliometric analysis in Subsection V-A, covering the topics mentioned above. Afterwards we continue with the content based results in Subsections V-B. Based on these findings, we try to answer the research questions in Subsection V-C.

TABLE 3. Terms used in the additional filter step.

	Additional Filter
	Digital Twin
AND	data OR information
AND	manufact* OR industr* OR production
AND	integrati* OR identifi* OR select* OR external OR environment* OR surrounding OR synchron*
NOT	Building Information Modeling OR Gas OR Oil OR Blockchain

A. BIBLIOMETRIC BASED ANALYSIS

This Subsection is divided into four topics. In the first part (V-A1), the occurrences of topic-specific terminology are analyzed. Part two (V-A2) covers the most relevant journals, conferences, and their connections. In the third part (V-A3), we present the distribution of publications according to countries, whereas in the fourth part (V-A4), the popularity of the analyzed topic is revealed based on an analysis of the number of publications per year.

1) MOST FREQUENT TERMINOLOGY

The results of this analysis are shown in Fig. 4. Unsurprisingly, the most prevalent terms are *digital twin* and *data*. Additionally, *Industry* and *manufacturing* are highly common terms, although their frequency is likely influenced by the search strings used, as outlined in Table 2.

The next most frequent terms include *system*, *model*, *information*, and *process*. The prominence of the term *system* highlights the reliance of Digital Representations on a real-world system that can be modeled. This suggests that Digital Representations are more commonly developed in complex systems than in simple *components*. The frequent occurrence of the term *model* underscores its importance in Digital Representations. Combined with various formulations of the term *process*, this suggests that data processing through models is a fundamental aspect of Digital Representations, which is also crucial for another frequently mentioned term: *information*. There exist two types of information: The *information* provided by the *sensors* of the *physical system* to be used as input for the models, and the *information* generated by these models to enhance the overall understanding of the complete *cyber-physical* system.

In addition, the wordcloud reveals what the most common contributions of the analyzed publications are, namely *frameworks*, *architectures*, *concepts* and *implementations*.

FIGURE 4. Wordcloud representing the most frequently occuring words in the Titles and Abstracts of the analyzed 141 Publications.

2) JOURNAL AND CONFERENCE ACTIVITIES

The analysis of the 141 considered publications revealed several journals and conferences that prominently cover the topic of industrial Digital Twins and their relation to data integration. The results are shown in Fig. 5.

It can be observed that both *IEEE Access* and *Procedia CIRP* have a high number of cited articles, as well as a substantial number of citations to and from other journals and conferences. Although the edges in this graph are limited to the scholarly venues included within itself, it still provides an estimate of the interconnectedness of these publishers and the respective articles. The next most cited journals are *Systems* and the *International Journal of Computer Integrated Manufacturing*. Additionally, the following journals and conferences have a notable impact on the field of Digital Twins and data integration, according to the presented literature analysis:

- *IEEE Transactions on Industrial Informatics*
- *Journal of Manufacturing Systems*
- *IEEE Sensors Journal*
- *Journal of Intelligent Manufacturing*
- *Procedia Manufacturing*
- *IEEE Signal Processing Magazine*
- *Enterprise Information Systems*
- *Proceedings of the IEEE*
- *Processes*

While this list is likely not exhaustive, it may serve as a useful guide for important publishing venues in the area of Digital Twins in Manufacturing, with a particular focus on data integration.

3) RESEARCH ACTIVITY PER REGION

This subsection presents the regional distribution of the 141 analyzed publications. The results, shown in Fig. 6, indicate that a significant portion of the research on Digital Twins and Data Integration is conducted in Europe (92 publications), China (41 publications), and the USA (10 publications). Within Europe, Germany (27 publications), Italy (12 publications), and the United Kingdom (7 publications) notably contribute to this research area. Although there may be some bias due to population size, these countries share a common characteristic: They are major exporting nations whose economies rely on the exports of complex or large quantities of products. This may explain their strong interest in optimizing manufacturing processes, thus contributing to their higher research output in these areas.

4) PUBLICATIONS PER YEAR

The bibliometric analysis examines the distribution of publications over time, considering the publication dates of all 141 papers. Between 2016 and 2018, an average of five publications per year was observed. This was followed by a sharp increase, with the number of publications rising to 19 in 2019 and 29 in 2020. In 2021 and 2022, the number of publications reached 37 annually. By 2023, four publications had been recorded, although it should be noted that the literature review was conducted early in that year.

Given the overall trend of increasing publications across various research areas, a definitive statement on the growing popularity of Digital Twins in general may not be entirely

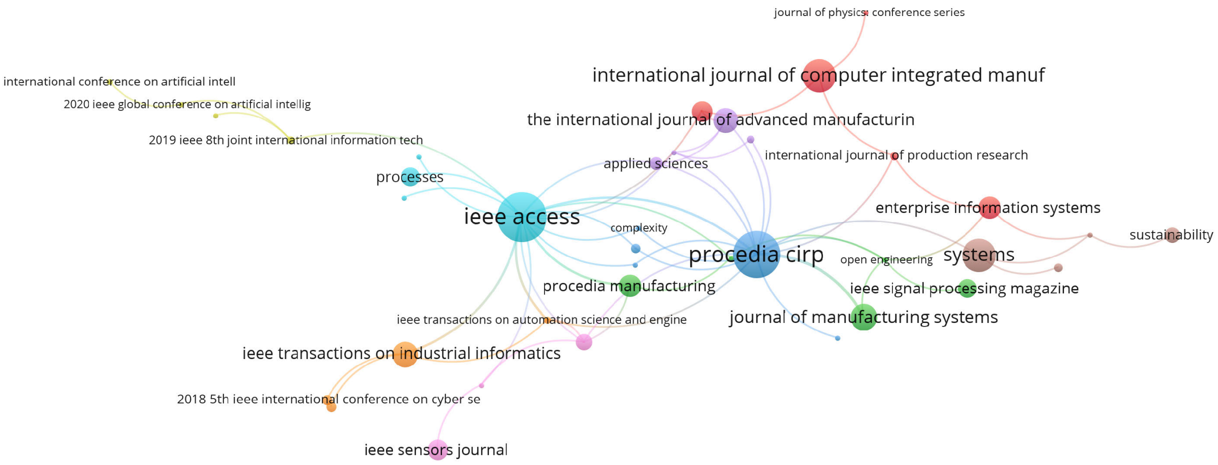

FIGURE 5. Resulting Graph representing the Journals and Conferences where the analyzed literature is published in. The individual sizes are determined by the total number of citations the respective publications recieved.

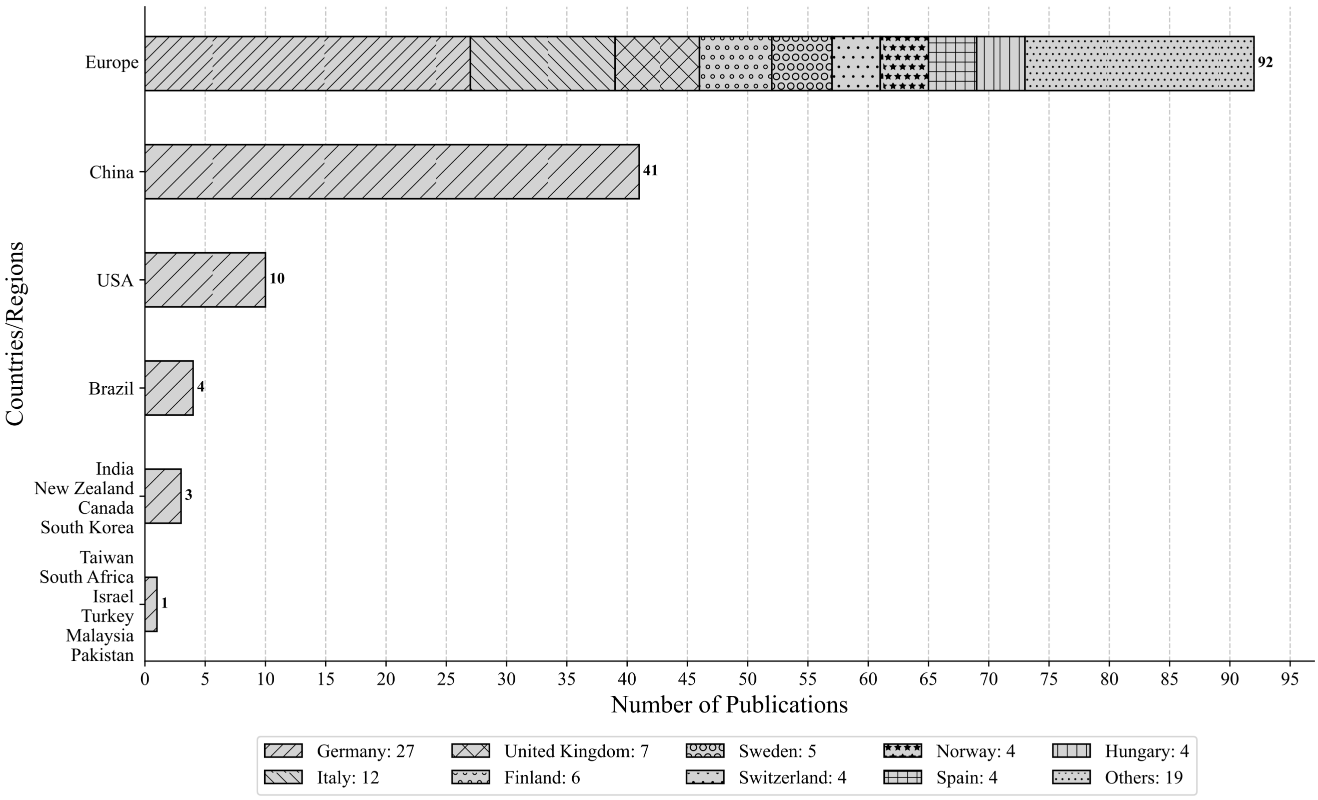

FIGURE 6. Distribution of the analyzed literature in respect to the locations of the authors institutions. (Each unique country was counted once per publication.)

reliable. Nevertheless, the rise in publications specifically focusing on the intersection of Digital Twins and data integration may indicate increasing interest in Digital Twins within manufacturing, particularly in relation to connecting the growing availability of data in these environments.

B. CONTENT BASED ANALYSIS

This section provides the content-based analysis of the 141 publications. The various subchapters correspond to the description in Section IV-D. First, the types of Digital Representations and the classification within the RAMI 4.0 hierarchy are presented. Following this, the data used is analyzed based on the presented categories from IV-D. Finally, investigations into the use of semantics, machine learning methods, real-time aspects, and edge computing are presented.

1) TYPES OF DIGITAL REPRESENTATIONS FOR ASSETS

With the definitions of a Digital Twin provided in Section II-A, the analyzed publications were assigned to the respective abstract definitions as per [19]. The distribution of the various types of Digital Representations is shown in Fig. 7. Digital Shadows [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101] represent the largest share (49.6%) of Digital Representations. In contrast, the Digital Twin [6], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131] was found least frequently (22.0%) in the publications. Slightly more often (28.4%) Digital Models [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171] have been described in the literature.

With these results, both the Digital Twins and the Digital Models are represented only half as often as Digital Shadows. This results in most Digital Representations in the analyzed literature only involving an automated integration of data from the physical asset to the Digital Representation. However, the insights gained through algorithms and models are still manually transferred back to the physical assets via appropriate human based interactions.

The most advanced type of Digital Representation, the Digital Twin, was identified only 31 times in the analyzed literature. Publications of this category address topics like using algorithms to enhance the sensory capabilities of the physical asset and use these insights in production [114], [120]. Other publications use the Digital Twin to improve the control of the physical asset [103], [105], [111], [124], [130] or optimize entire production processes [61], [107], [118], [119], [122]. Publications [127], [128] already mention concepts describing the automated creation of Digital Twins within production processes, thus automating developing Digital Twins themselves.

Some publications classified into the Digital Twin category do not explicitly describe the Digital Twins application but mention functionalities that align with the definition of the Digital Twin [54], [115], [116], [123]. Several publications concentrate on integrating data in the Digital Twin and analyzing the resulting benefits [6], [106], [108], [110], [121], [125], [129], [131].

After categorizing the literature into the different Types of Digital Representations in the next section the specific application areas are analyzed in more detail.

2) RAMI 4.0 LEVEL

Although the analyzed literature is already restricted to the domain of industrial manufacturing, numerous different levels of consideration still exist. In this context, Digital Representations can be created for a simple field device, a manufacturing station, or even an entire company. To gain an overview of the distribution of the systems under consideration, the identified literature was divided according to the hierarchy levels of the RAMI 4.0 model [9]. The results of this evaluation are shown in Fig. 8. Multiple assignments are possible in cases of ambiguity or multiple connections with hierarchical levels. Most publications describe a Digital Representation of a manufacturing production station (S) (61.0%) or a facility consisting of multiple production units (T) (44.7%). The next most frequent category identified was Digital Representations for products (28.4%), often being complex assets manufactured in small quantities (e.g., aircraft or ships). Digital Representations for less complex physical entities (Field Device (0.7%), control (7.8%)) are created rather seldom. This might be due to the effort required for implementing Digital Representations, not outweighing the generated value for less complex assets. Conversely, the situation is different for Digital Representations of large, highly complex entities (Enterprise (1.4%), Connected World (8.5%)). Although a Digital Representation of such entities would provide significant value, its implementation possibly is highly complex, again reducing the advantage of creating such a Digital Representation. The last category, "other" (14.2%) was added by the authors for publications describing a Digital Representation associated with a physical asset that does not allow a specific assignment to the remaining categories. E.g. publications discussing methodologies for the Digital Twin without explicitly focusing on concrete assets. However, the shown distribution of Digital Twins may also be influenced from the used search terms and filtering process.

In the following sections we analyze in detail the characteristics of the data used by Digital Representations as these are a fundamental part for their correct functioning.

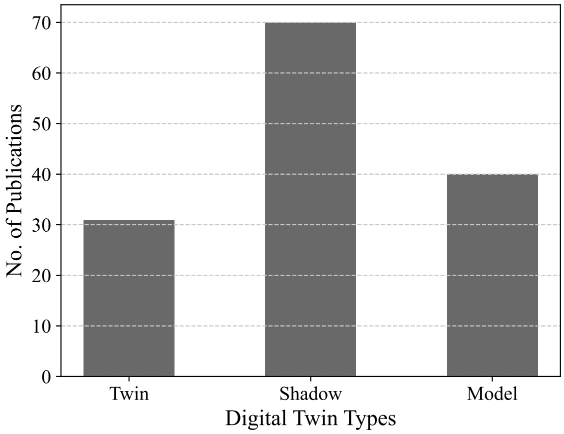

FIGURE 7. Allocation of the analyzed 141 publications to the three categories "Model", "Shadow" and "Twin" of a digital representation according to the abstract definition.

3) USED TYPES OF DATA SOURCES

In the future, production sites will be increasingly connected, and the data used by Digital Representations can be generated

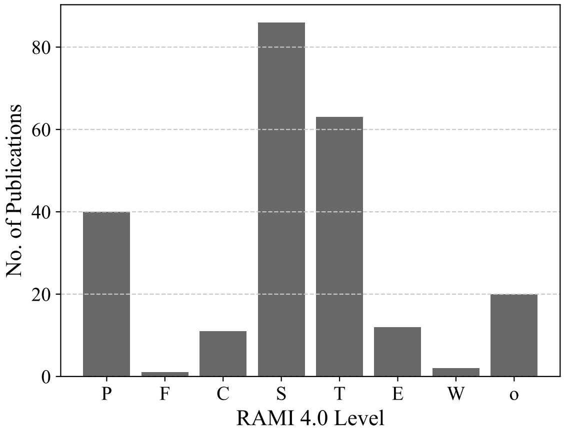

FIGURE 8. **Allocation of assets to the various RAMI 4.0 levels for the analyzed 141 publications (P=Product; F=Field Device; C=Control; S=Station; T=(Technical) Work Centers; E=Enterprise; W=Connected World; o=other).**

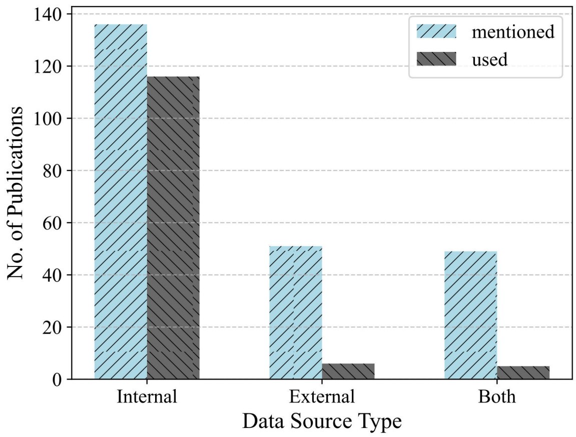

FIGURE 9. **Allocation of publications concerning the utilized categories of data sources - internal and external. Additionally, a distinction is made between mere mention and actual usage in the respective publication. Usage is also considered as a mention in this context.**

not only by the physical asset itself but also by external sensors. Therefore, we analyzed the data generated according to its origin. Fig. 9 shows the number of publications that use external or internal data sources. Additionally, we distinguish between mentioning internal/external data sources and explicitly using them in a corresponding prototype or concept (''using'' is also counted as a ''mentioning'' in the evaluation). As can be seen from the figure, internal data sources are mentioned by almost all publications (96.5%) and used almost equally often (82.3%). Since data is essential for the successful implementation of a Digital Representation, and the data generated by the asset itself (i.e. internal) represents an obvious data source, these results are indeed plausible. By contrast, external data sources are much less prevalent. About one-third of all publications mention external data sources (36.2%), while only six publications use them as Data Source for the Digital Representation (4.3%) [6], [45], [73], [87], [125], [129]. Despite the concepts like Big Data, Internet of Things, Industry 4.0, etc., promoting the increase in available data and easier accessibility, the use of external data in Digital Representations has received little attention so far. Publications considering both external and internal data sources are almost equally frequent as publications with external data sources solely (mention: 34.8%; use: 3.5%). This indicates than an exclusive focus on external data sources does rarely occur in current literature. As shown in Section V-B2 in industry, assets with Digital Representations are complex mechatronic systems or products equipped with their own sensors. These internal sensors depict the actual state of the asset very reliably. Neglecting these internal data sources and relying solely on external data sources would therefore be contra productive to the Digital Representations quality. Some publications mention integrating external data in the Digistal Twin but do not describe a corresponding prototype [61], [88], [102], [125], [140], [143]. The data is used for improving the production process [45], [51], [60], [74], [88], [96], [117], [120], [130], [143], [157] e.g., to better track products and mobile robots through external sensors or enhance predictions of the Digital Representations' simulation models [46], [55], [70], [96], [132], [137]. Additionally, various descriptions exist, on how external data can be integrated in [61], [69], [88], [125], [131], [140], [142], and [143] or exchanged between [92], [138] Digital Representations. Another approach uses external data sources to replace failing or faulty sensors [63], [73].

4) USED DATA ACQUISITION METHODS

To process data in Digital Representations, it is necessary to transmit it from their origin (internal or external) to the Digital Representation, respectively the hardware on which the models and algorithms are running on. There exist various possibilities for different communication paths and protocols for this purpose. Therefore, we analyzed whether Digital Representations rely on specific methods or employ a broad spectrum of acquisition methods. The results of the analysis are shown in Fig. 10. Many publications mention (92.9%) and exclusively utilize (80.1%) specific approaches for data integration. This distribution is similar to the results shown in Fig. 9. Combining these two aspects, it can be inferred that publications integrating solely internal data may do so via specific acquisition methods, whereas the integration of external data necessitates an expansion to universal acquisition methods. Approximately (70%) of publications which mention universal acquisition methods also mention external data sources. In addition there is a discrepancy between publications that mention universal data integration (30.5%) and those utilizing such integration methods (2.8%) [61], [90], [125], [141]. Further reasons for the limited use of universal acquisition methods could be the increasing efforts to implement and maintain universal data acquisition methods. Because it is not possible to simultaneously use specific and universal data acquisition methods the third bar only contains publications mentioning both types of

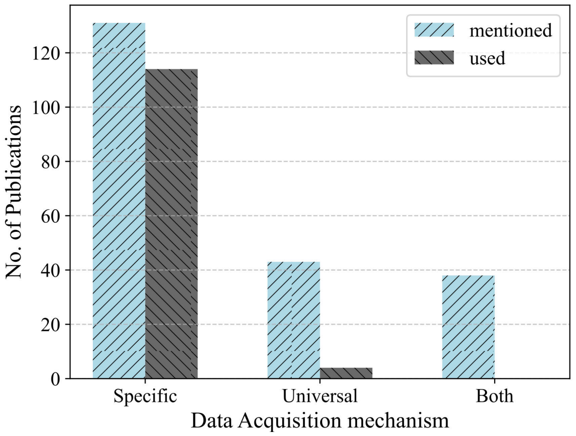

FIGURE 10. Allocation of publications concerning the data acquisition mechanism - specific and universal. Additionally, a distinction is made between mere mention and actual usage in the respective publication. Usage is also considered as a mention in this context.

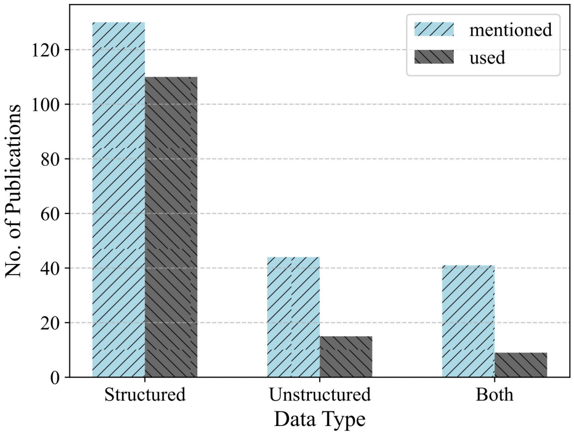

FIGURE 11. Allocation of publications concerning the daty type of used data - structured and unstructured. Additionally, a distinction is made between mere mention and actual usage in the respective publication. Usage is also considered as a mention in this context.

data acquisition and therefore distinguish between those in theory (27.0%). Publications support various communication protocols for the universal acquisition of data. For example in [125] HTTP, OPC UA, MQTT, and Modbus is used, whereas in [141], TCP, UDP, OPC UA, Modbus, CANOpen, and EtherNet/IP are supported. Reference [90] employs only HTTP and OPC UA. Many publications mention additional acquisition possibilities for horizontal integration, meaning a data exchange between assets at the same hierarchy level [6], [45], [48], [51], [69], [74], [90], [108], [120], [125], [127], [130] [141], [142], [143], [144], [145]. Few publications mention additional vertical acquisition methods across multiple hierarchy levels [71], [115], [127].

5) DATA TYPE

The increasing amount of generated data raises the need to process various types of data respectively interact with different types of databases. Today's mechatronic systems no longer generate solely 4-20 mA signals, but increasingly complex data structures. This includes imaging techniques, such as cameras, LiDAR, and radar. In the literature, a rough distinction is made between structured and unstructured data. As computing capacity becomes affordable and available, the maximum quantity/complexity of data that can be processed during operation by Digital Representation also increases. Fig. 11 illustrates how many publications integrate structured data, such as time-series temperature values, and/or unstructured data, for example images and videos. Structured data is mentioned in 130 publications (92.2%), and 110 (78.0%) use structured data in implementations or concepts. 44 publications (31.2%) mention unstructured data as a possible data input, whereas 15 publications (10.6%) use it. Similar patterns emerge for publications processing both structured and unstructured data (mention: 29.1%; use: 6.4%). This suggests that a purely unstructured data processing approach is rarely considered for Digital Representations in an industrial context. The most frequently mentioned applications for unstructured data include monitoring of production, often based on imaging techniques [6], [45], [73], [87], [96], [97], [114], [120], [140], [166], improving asset controls or production facilities [37], [40], [87], [96], [124], [130], [140], [143] or checking production quality [45], [51], [70], [95], [117], [157]. Other use cases involve supporting plant maintenance [45], [82] or using unstructured data from the engineering phase to enhance development efficiency [33], [136], [139]. The temporal development in the number of publications capable of processing unstructured data remains relatively constant during the observed time form 2016-2023. A possible explanation for this may be the signalbased and structured nature of automation systems, which is the focus of this study.

6) DATA ORIGIN

The Digital Representation of a physical asset is defined across all lifecycle phases. Therefore, data can be generated not only during the operating phase but also beforehand in the engineering phase. The lifecycle of industrial systems consists of more than just the engineering and production phases. However, because the lifecycle was not the focus of the SLR, the scope was limited to data generated before the actual operation (simplified as engineering) and data generated during operation. The results of the evaluation are shown in Fig. 12. A distribution similar to that of other subcategories can be observed. Nearly all publications (95.0%) mention data from the operational phase as the input for Digital Representations. In 107 publications (75.9%) this data is explicitly used in concepts or prototypes. 55 publications (39.0%) mention the benefits of data originating from engineering for Digital Representations. However, only 16 publications (11.3%) use this data. Because publications that use engineering data and those that use both engineering and operational data (mention: 35.5%; use: 6.4%) are similar,

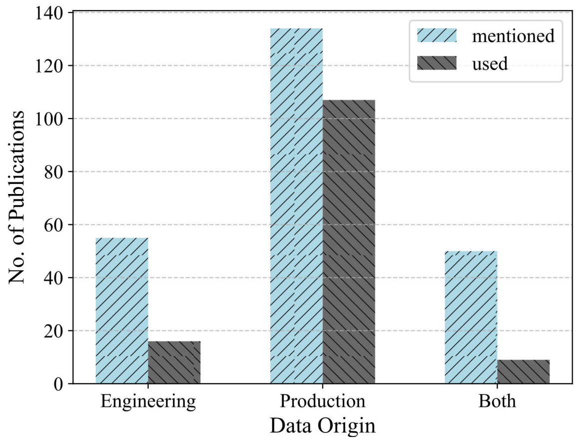

FIGURE 12. Allocation of publications concerning the origin of the data in respect to the Life Cycle of the Asset- engineering and production. Additionally, a distinction is made between mere mention and actual usage in the respective publication. Usage is also considered as a mention in this context.

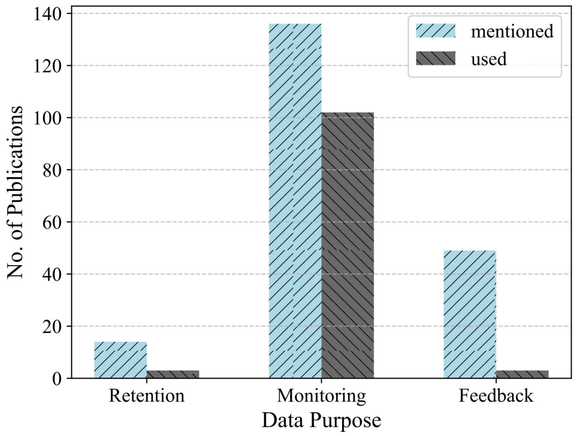

FIGURE 13. Allocation of publications concerning the purpose the collected data is used for - retention, monitoring and feedback. Additionally, a distinction is made between mere mention and actual usage in the respective publication. Usage is also considered as a mention in this context.

it can be inferred that solely integrating engineering data is hardly taking place in the literature. Several factors could explain this. A physical counterpart is usually an integral part of Digital Representations. Such a functional physical representation exists at the end of the engineering phase and during the operational phase. Also, the Digital Twin as a concept serves the idea to support the physical Asset itself and not only the engineering process of the asset. However, another aspect could be the limitations in the literature search imposed by the chosen search strings.

7) DATA PURPOSE

The main aspect of Digital Twin concepts is to use the collected data to enhance the behavior of the represented asset. To further analyze this usage, the purpose of the integrated data in Digital Representations was investigated. A distinction was made between mere data retention in the form of data storage, live monitoring of the physical assets' state, and use for improving the assets' performance. The results of the evaluation are shown in Fig. 13. Most publications use gathered data to enable live status tracking of the corresponding asset. A total of 136 publications (96.5%) mention this, while 102 publications (72.3%) use the data for monitoring in their prototypes or concepts. 52 publications (36.9%) mention the applicability of data for feedback reasons, and 3 publications (2.1%) indeed use the data to automatically provide feedback to the physical asset. The smallest number of publications mention (9.9%) or use (2.1%) data solely for storage reasons.

This distribution may be explained by correlation of the identified types of Digital Representation in the literature as discussed in Section V-B1. Digital Shadows, representing the largest portion of Digital Representations, are especially well fitted for monitoring because of their automatic data integration from physical assets. Similarly, the use case of feedback fits well with the definition of a Digital Twin with its additional automated information exchange with the physical asset. The low number of publications focusing solely on retention may be explained by the high implementation effort necessary to implement a Digital Representation. This effort is probably not worthwhile for sole data retention.

8) SEMANTIC TECHNOLOGIES

An important aspect to enable the efficient integration of data into Digital Representations is enabling machines to understand the context of the data provided. The Digital Representation must understand if a datapoint with a value of 42 represents a value in degrees Celsius, Meters, Volt, or Newton. Furthermore, it should be able to distinguish if the Temperature is representing e.g. the current ambient temperature or temperature of a sensor in a electrical motor. Semantics can help Digital Representations in establishing such capabilities by making the context of data machine readable. Therefore, this section covers if and for what reason semantics are used in the analyzed publications.

In total 35 of the 141 publications (24.8%) mention semantic technologies, while 15 (10.6%) use semantic technologies. A deeper analysis indicates, that 10 publications actually mention or use semantics for data mapping and integration mechanisms [66], [75], [76], [80], [106], [129], [131], [139], [145], [160]. Seven publications [34], [41], [56], [95], [126], [138], [162] use semantic technologies in a Digital Twin in combination with information modeling. Publications [38], [44], [48], [55] name semantics in the context of industrial standards and protocols, while [35], [52], [134], and [171] make use of semantic technologies in their presented concepts.

9) MACHINE LEARNING

When integrating data into Digital Representations, especially if the data is from multiple and heterogeneous sources, data preprocessing is inevitable. Once the data is available in the Digital Representation, information must be extracted from the data to fulfill a Digital Twins actual job, enhancing the monitoring and control of the represented asset. Machine learning methods can be applied to both tasks. Therefore, we analyzed the amount and tasks machine learning is used in industrial Digital Twin publications. In total, machine learning was mentioned in 65 publications (46.1%), of which 27 used machine learning methods (19.1%). The largest portion of publications mentions/uses machine learning with regard to data processing and analysis [40], [42], [46], [55], [89], [110], [129], [135], [166] and for predictive analysis of the physical asset state [38], [46], [54], [78], [136], [155], [163], [164]. Both of these clusters, therefore cover data processing for data that is already available in the Digital Representation. Publications [64], [66], [86] on the other hand utilize machine learning algorithms for the data preprocessing steps. Therefore, they first make the data available for the Digital Representation, which is a necessary step before any other use of the data. However, further use cases of machine learning methods in the analyzed publications cover process optimization [48], [88], [97], [117], [118], [170], quality control [62], [115], and decision support for human workers [56], [143].

10) REAL-TIME DATA

To efficiently use the Digital Twins computational resources to enhance the asset behavior and control, it must a) be able of send control signals in a timely manner, so new control signals are not already outdated when they arrive at the asset, and b) be able to compute real-time data about the physical asset. Therefore, we analyzed if and to what extent the usage of real-time data is considered in industrial applications of Digital Representation. We found that of 103 publications (73.0%) mentioning real-time as a relevant topic, 64 (45.4%) use real-time concepts or prototypes. Taking a deeper look we found that the vast majority used real-time data to monitor the current state of the asset [36], [39], [46], [50], [54], [56], [62], [67], [70], [83], [85], [90], [91], [92], [93], [94], [96], [97], [98], [101], [104], [107], [109], [110], [112], [113], [117], [122], [130], [136], [143], [158], [166], [170]. The following publications cover methods to enable the integration and processing of a high volume of real-time data [37], [42], [61], [69], [75], [78], [79], [90], [125], [127], [135], [137], [139] or providing feedback to the physical asset in real-time [52], [64], [67], [89], [99], [119], [120]. However, many publications also mention challenges in real-time data processing because of the latencies and computational needs for computing industrial amounts of real-time data. Therefore, [138], [148] cover edge computing and IoT in the context of real-time data processing. More niche topics are represented by real-time localization and tracking [45], [81], [88] and visualization for user purposes [137], [148]. However, it should be noted that the term "real-time" is interpreted differently throughout the publications. The timespan referred to as real-time varies from < 1 ms to over several seconds throughout the publications.

11) EDGE COMPUTING

As mentioned in the previous section the vast amount of data produced in industrial applications presents challenges in terms of data processing. Although cloud computing offers high performance capabilities, the introduced latency may not be suitable for use in industrial automation. Therefore, edge computing may be a potential compromise between availability/timeliness and computing power for such tasks. In total, 21 publications (14.9%) adress the topic of edge computing and 14 (9.9%) use it explicitly. Among the various use cases for edge computing, [49], [64], [66], [88], [115], [127], [138], [144] apply or mention it for performance improvements in latency and processing contexts. Another five publications [43], [87], [125], [137], [140] use edge computing to increase connectivity and aggregate or handle multiple data strams in IoT based scenarios. Several publications explicitly mention the advantage of edge computings against cloud computing concerning resource optimization [47], [66], [87], [88], [125], [144], for example to reduce stress on the cloud instance or bandwidth usage. Another cluster ([64], [66]) covers the reduction in data to cloud transfer related security concerns. The last aspect identified ([64], [125]) covers decentralization as a use case for edge computation in Digital Representations.

C. DATA INTEGRATION IN THE DIGITAL TWIN

The purpose of this study is to examine what data Digital Representations in industrial automation processes use, how they acquire this data, and whether today's concepts and implementations of Digital Twins are suitable for deployment in connected and flexible production environments. To achieve this, three Research Questions were stated during the SLR (see Section IV-A). In the following sections the research questions are answered by referring to the results of the previous sections.

1) RESEARCH QUESTION 1 AND 2

Here we aim to answer the question of what data Digital Representations use (RQ1), where the data originates from, and how it is used in industrial automation (RQ2). As indicated in the preceding subchapters, common characteristics are found in the analyzed literature:

- The data processed in Digital Representations is primarily generated by the physical assets themselves (V-B3), providing insights into the current state of the asset (V-B7).
- Specialized acquisition mechanisms, tailored for every specific Digital Representation, are mostly used to integrate the data (V-B4).
- Most integrated data is structured. In cases where unstructured data is integrated, it typically consists of complex engineering data, such as 3D geometry models,

or streaming data in the form of videos, LiDAR, or radar scans (V-B5).

- A significant amount of integrated data in the Digital Representation is generated during the operational phase of the asset (V-B6) and used to monitor its current state (V-B7). This is highlighted by the prevalence of Digital Shadows (V-B1), which specifically facilitate the automated transport of data from the asset to the Digital Representation, but miss the autonomous application of enhancement/feedback strategies.
- Although potentially crucial for the correct integration of data, espacially if it originates from heterogeneous sources and enters the system at runtime, semantics were mentioned in less than one third of the identified publications (V-B8).
- Machine learning methods seem to be important enablers in using multiple heterougeneous data sources in Digital Twins. They are used in Digital Twins for both, making data available via preprocessing, and for gathering new information via data processing. Further, machine learning has various applications in Digital Twins, such as process optimization, quality control, and decision support (V-B9).
- The importance of real-time capabilities in Digital Twins is shown by the large number of publications that mention this topic (V-B10). However, there seems to be a wide interpretation freedom in which requirements must be met for a Digital Twin to be real-time capable. One requirement covers the computing capabilities of the Digital Twin. In this context, edge computing may be used to enhance the computational power in Digital Representations. (V-B11) With only one tenth of the publications using edge computing, local computing ressources currently seem to be sufficient.

To summarize, the current usage of data in Digital Representations for the industrial domain is one-sided. Although some studies show more flexible and universally applicable data integration methods, most of the current implementations and concepts of Digital Representations seem to be specifically adapted to their respective assets. Potential reasons for these rather specific scenarios may include aspects such as retrofitting Digital Representations of already existing assets. This retrofitting involves creating a Digital Representation, which, in the first step, uses the available data interfaces provided by the asset. Any further extension of a Digital Representation - for example by adding a more flexible integration mechanism and therefore external data - would foremost increase development efforts without directly generating value for the asset, since the usability of such external data must be newly evaluated for every asset. With the findings from the first and second research questions in mind, the next section attempts to answer the third research question, asking whether current implementations and concepts of the Digital Twin are suited for future interconnected production environments.

2) RESEARCH QUESTION 3

In the preceding section, we explored the current state of the art in the data integration of Digital Twins. The third research question asks whether these existing procedures are sufficient to enable Digital Twins to operate effectively under the evolving conditions brought about by paradigms such as IIoT and Industry 4.0. As outlined in Sections II-B and II-C, these paradigms are expected to induce changes in production scenarios, manifesting in the following ways:

- The growing interconnection of devices has lead to increased data availability. This data is not uniformly formatted for all the potential data receivers. Consequently, receivers must possess the capability to handle multiple protocols and process variable data structures according to their requirements.
- A variety of communication protocols has grown due to different data sources. Certain communication protocols are better suited for transferring specific data based on characteristics such as size, update frequency, and structure. Additionally, the challenges in realizing a universally accepted protocol across the industry further contribute to the need for an expanding number of communication protocols.
- Data dynamics will increase because of the more frequent entry and exit of data sources in production scenarios. Shorter plant lifecycles and more frequent restructuring of production sites imply that manually connecting data sources to the Digital Twins may become economically unfeasible in the future. Therefore, they should be able to autonomously incorporate and process new data sources on their own.

Comparing these expected changes in future production environments with the current capabilities and implementations of Digital Twins, a deficit becomes apparent in existing implementations. Current Digital Twins mainly apply specific data integration methods, rely on processing internally generated data, and have limited processing capabilities for unstructured data. Furthermore, neither much data is semantically annotated nor are Digital Twins capable of processing such data. In addition, there is a lack of scalability in today's Digital Twin implementations. These characteristics do not align with demands for future production scenarios. With an increasing dynamic in the amount and availability of data sources and data types, the computational and communication needs of Digital Twins change during the operation phase. Integrating multiple data sources raises further challenges. Multiple sensors may provide information on the same subject, leading to questions such as which sensor should take precedence and how to handle conflicting values. While current Digital Twins may function adequately, they are unlikely to fully unleash the full potential of the available information in their environment in future production scenarios.

After answering the research questions, the next sections discusses the findings of the study.

VI. DISCUSSION

In this section, the research findings highlighted in the previous section will be summarized and discussed within an expanded context. However, before this summary, the strengths and limitations of the work will be further elaborated.

A. VALIDITY OF THE SYSTEMATIC LITERATURE REVIEW

The aim of the study was to investigate how Digital Twins integrate data in the current literature. Simultaneously, this study aims to provide insight into wheter these existing approaches align with future developments in the field of industrial manufacturing. To conduct this study, care was taken to employ a structured approach as described in [31]. In contrast to this method, the terms for the search strings were defined based on a search term table. To obtain a broad and comprehensive set of search terms, an initial screening of potential literature was conducted to identify suggestions for additional search terms. because this step broadens the literature search space and opens additional search directions, we consider this deviation of the procedure positive on the study's quality.

In the course of the study, following the inclusion and exclusion steps, 1107 publications were identified. As the 1107 publications on the one hand still included many publications from less relevant domains and on the other hand, a full analysis would have exceeded the authors' capacity, an additional filtration step was implemented (see Table 3). Since the assumptions made here were subjective and based on the authors' existing knowledge, it cannot be ruled out that relevant literature for the study was excluded. However, based on the results from Section V, which clearly indicate preferences in the context of data properties within the Digital Twin, it is assumed that the general statements remain valid. However, the clarity of the results may have been affected by the additional filtration steps.

While the study attempted to focus on the domain of industrial manufacturing, the diversity of the represented technical systems remains high. Of course, the structure and focus of Digital Representations vary according to the requirements of these different technical systems. This diversity complicates the clear categorization in the literature. To address this issue, an abstract definition [19] of the Digital Twin was used, which has broad applicability to various definitions of Digital Twins found in the literature. In addition to Digital Twins, the available data for technical systems at different hierarchical levels also varies. An attempt was made to categorize their diverse characteristics as uniformly as possible using broadly applicable categories of data characteristics (origin, type, source, acquisition, and usage).

Additionally, we analyzed publications regarding their usage of semantics, machine learning methods, real-time capabilities, and edge computing. The 141 publications comprised only a fraction of the overall available literature on each of these four areas. However, in the field of Digital Twins combined with data integration, the findings represent a relevant mass of publications. Overall, the authors believe that the validity of the statements persists, even though their significance may be weaker. With a total of 1107 uniquely identified publications, 319 roughly screened, and 141 fully analyzed publications, it is assumed that the present study effectively covers the existing literature regarding the Digital Twin in industrial manufacturing, with a focus on data integration.

B. DEFINITION OF THE DIGITAL TWIN

As demonstrated at the beginning of the present study, a clear definition of the Digital Twin within a domain, such as industrial manufacturing, has not yet been established. Instead, there exist a multitude of definitions that:

- vary in applicability to different technical systems.
- differ in their level of detail.
- use the identical terminology for different concepts.

Given the unlikely prospect of finding a universally accepted and equally applicable definition for all technical systems in industrial production, we consider it highly relevant for future work to precisely specify what definition of the Digital Twin is referred to. The large number of varying use cases for Digital Twins with their respective requirements and needed functionalities will otherwise inevitably lead to misunderstandings in scientific communication. As a result, further research on Digital Twins will be hindered, and communication will become more complicated.

C. DATA IN DIGITAL TWINS - PRESENT AND FUTURE

While technical systems are currently undergoing a shift towards more flexible and modular manufacturing systems, a significant portion of existing production facilities remain monolithic, complex, and precisely coordinated units designed to serve a specific and static production purpose for an extended period. Consequently, the Digital Twins for such systems, found in the literature, are implemented in a similar specific and rigid manner. For monolithic technical systems operating as a closed unit, the identified dominant characteristics of data integration in Digital Twin are quite suitable:

- The use of internal data sources is sufficient if the production facility is not subject to external influences, and all necessary information is provided by the physical asset itself.
- The specific integration of data is more reliable and better suited when the data sources comply with this specific technology.
- Flexible data integration and processing methodologies unnecessarily drive-up costs for a technical system when upcoming data is already known in advance.

All of these assumptions apply to self-contained and monolithic production systems that dominate the industry today. Agreements can be made in the engineering phase, and a uniform implementation can be pursued.

However, the future of production is increasingly moving towards flexible, interconnected, and dynamic production units where individual actors are not known from the beginning but may be dynamically added, removed, or replaced during runtime. Thus, the number of relevant external factors will increase. Systems will need to interact with other systems whose specifications are not known at the time of engineering, let alone enter or leave production during reconfiguration or even at runtime. Digital Twins of such systems must meet these new requirements by considering information about the environment of their own systems. To achieve this, the data generated in this environment, being accessible in different protocols, must be integrated into the Digital Twin. Because of the different information required by different assets, their individual Digital Twins must process data received from the environment in varying ways.

Future flexible production will contain constantly changing production configurations, and therefore, available data sources. Manually integrating these volatile data sources is time consuming and probably neither feasible nor costeffective. Instead, the Digital Twins must be capable of autonomously discovering, evaluating, processing, and integrating new data sources for their own purposes.

For this purpose, it is essential that the Digital Twin is aware of the quality of the data it receives. This requires the use or development of machine-readable and (ideally) standardized data quality metrics. Examples of such quality attributes include accuracy, completeness, and timeliness of data. In the reviewed literature, descriptions of these metrics for the data were relatively rare. This is understandable, because these metrics are not urgently needed if sensors are specifically designed for the Digital Twin of a monolithic system. In such cases, the quality attributes of the data are intrinsically guaranteed by the choice of sensors. However, for future interconnectivity, it is crucial to explicitly disclose these quality factors, because automated networking will not be possible without them.

This realization is strengthened by examining the missing interconnectivity of today's industrial plants. The concepts of IoT and Industry 4.0 were first presented over 10 years ago, and an increasing number of centralized information gathering has been realized, for example in the form of process monitoring systems and dashboards. However, this is often achived through specific integration of the most relevant values for each asset. Often this results in so called Key Performance Indicators (KPIs) for single stations or complete production facilities being collected in a proprietary way. These KPIs are then either evaluated by humans or machines which in turn alarm humans if these KPIs do not match the expected values. Direct exchange of data between different stations inside a production facility is still very rare today. The centralized analysis of KPIs results in a *1 to n* constellation, where the data from *n* machines must be evaluated according to their relevance for one centralized monitoring application. However, if an interconnection between multiple machines is realized, this results in an *m to n* constellation, where all data from every machine/device *m* must be evaluated if useful for a specific application for machine *n*. Despite the high number of possible interconnections, the number of useful interconnections is probably very low. In production scenarios with multiple machines and even more generated data, evaluating such *m to n* constellations is neither manageable nor economically by humans. Therefore, the missing interconnectivity may be a result of missing automated evaluation methods to check whether data from an external source is valuable.

At this point, the strengths of semantically annotated data become apparent, as they enable machines to comprehend the data. As demonstrated in the survey, semantic technologies play a role in approximately one-third of the analyzed publications. However, to enable the automated interconnection of various data sources and sinks, it is crucial that this data is evaluated autonomously by machines. Building blocks for this are provided by semantic technologies as well as artificial intelligence methods, such as large language models or combinations of these approaches.

The idea of a fully interconnected production, where machines can exchange data freely via their Digital Twins, inevitably raises various security and safety concerns that must be addressed. Although these issues were not explicitly examined in the survey, several questions arise: How can it be ensured that correct data is not incorrectly integrated and that only correct data in general is integrated overall? What should an access management system look like to ensure that only authorized machines can read specific sensor data? What are the liability issues if property or personal damage occurs based on external data from the sensors of different vendors? How should data be stored? Resolving these questions and developing appropriate concepts is crucial for advancing the interconnectedness of Digital Twins.

In summary, the present SLR reveals a deficiency in the available implementations of the Digital Twin, whose characteristics still only align with the complex and monolithic production systems of the past. Despite previous explanations on the missing interconnectivity and its reasons, it is important to note that such implementations nontheless add value to the underlying asset. However, as depicted in Fig. 14, the relative percentage of value generated in this "old" way for the technical systems of the future will probably decrease, and a significant portion of the available value through interconnection of systems may not be realized in "old" Digital Twin implementations. Such implementations of Digital Twins for closed technical systems do not align with the necessary functionalities of open and connected production envisioned in the future.

VII. CONCLUSION AND RECOMMENDATIONS

The present study examines the role of data for Digital Twins with a focus on industrial automation. It explores what data is used and how this data is made available for the Digital Twin. In addition, it analyzes the role of

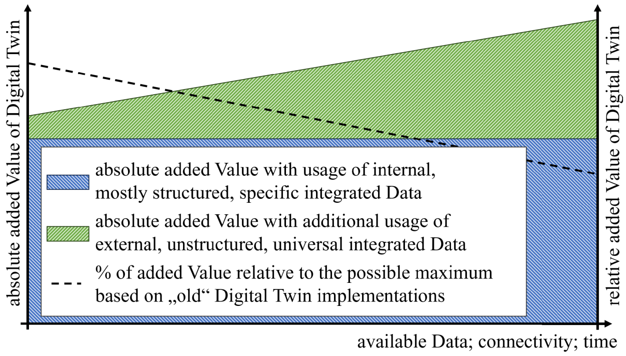

FIGURE 14. Estimated evolution of added Value of the Digital Twin in context of increasing available Data, connectivity. Although the absolute added Value of the Digital Twin based on existing technologies (internal, specific, structured) may remain constant, the added Value based on universal integration of external and unstructured Data will probably increase. Digital Twin implementations, solely based on "old" technologies will therefore have a gap to the total possible added Value as demonstrated by the dashed line.

Digital Twins in delivering added value to assets in the industrial production environment of the future, with flexible production, increasing connectivity of assets and availability of data. In a SLR starting with 1107 unique and peer-revied publications, 141 publications between 2016 and 2023 were deeply examined concerning data integration. It was found that a large number of publications derive data exclusively from internal sources, integrate these data specifically, and primarily focus on structured data. Based on the results of the presented SLR, several key aspects were identified and discussed in the following paragraphs. Namely:

1) Limitations in Digital Twins of the present
2) Requirements for Digital Twins of the future
3) Open research fields
4) Recommendations for Digital Twin providers and plant operators

Limitations in Digital Twins today - During the presented study it became clear that current implementations and concepts on Digital Twins are designed for already existing monolithic and self-contained assets (production units or products), resulting in several limitations. Without a flexible integration mechanism for external data, these Digital Twins are forced to rely solely on their as-is state as defined during their engineering. As a result, they can hardly adapt to changing requirements and circumstances, which will be more frequent in future production scenarios than ever. As Digital Twins are usually highly complex systems, any manual adaptations currently depend on human experts. The amount of adaptation required perhaps results in scenarios where manual adaptation may no longer be economically viable or may not even be appliable before the next adaptation is required already. This applies not only to the integration of external data, but also to the manual application of results generated by Digital Shadows. As shown in the SLR, most Digital Representations analyzed are indeed Digital Shadows. Their lack of automatic feedback to the asset as promoted by Digital Twins is also a neglected aspect in current implementations.

Requirements for Digital Twins - For Digital Twins to continue to add value in future production scenarios, they must fulfill several requirements. First, in addition to integrating data from their respective assets, Digital Twins must be able to explore their surrounding data space and integrate relevant data. This is the only way they can efficiently adapt to the frequently changing circumstances that they will encounter in future production. Because the relevance of data varies from asset to asset and from use case to use case, Digital Twins must also be able to automatically evaluate the relevance of potential data sources for themselves in their specific context. Therefore, Digital Twins must be able to handle and transform different data formats with their respective algorithms and implement multiple interfaces to communicate with varying data sources.

Open research fields - Due to their complex nature, implementing Digital Twins can be quite challenging. Sustaining their value requires the development of concepts and techniques to streamline manual adaptations or automate them entirely. Additionally, there is a need for approaches that facilitate flexible data integration, particularly in managing previously unknown or dynamically changing data and data sources, which remains a rather unexplored area to date. Ensuring that Digital Twins can effectively utilize data without pre-installing algorithms tailored for specific use cases is essential, particularly when handling unforeseen data (sources). To accommodate this, methods and concepts for automatic evaluation are vital, empowering Digital Twins to autonomously determine the relevance of the available data within their context. This includes approaches that enable machine-readable and standardized descriptions of data quality. Equally important are approaches to semantically describe the data. In our assessment, the gap lies less in the fundamental development of semantic data annotation methods, and more in the need for frameworks and tools that simplify this annotation and make it accessible to a wider audience. Another open research area involves the scalability of interconnected Digital Twins. Because the computational and network load of such highly interconnected and dynamic systems cannot be known during the engineering phase, future Digital Twins will need to incorporate flexible scaling mechanisms to handle potentially increasing data volumes, or to avoid wasting resources when data volumes decrease. In particular, when unstructured data is involved, the complexity of processing and amount of data to be transferred can vary rapidly. Finally, considering the heightened interconnectivity associated with Digital Twins, there is a pressing need for robust safety and security mechanisms to mitigate potential risks, as described in the previous section.

Recommendations for Digital twin providers and plant operators - Aligned with preceding discussions, it is essential for Digital Twin providers to provide forthcoming Digital Twins with enhanced flexibility. Neglecting this aspect may rapidly lead to maintenance overheads in changing production environments, surpassing the benefits that Digital Twins would normally generate. Moreover, there is a pressing necessity for Digital Twin providers and plant operators to adopt greater openness in terms of connectivity. Without access to data, the potential to leverage value across other assets significantly diminishes. We strongly encourage plant operators to explore the untapped potential of external data sources. Once embraced, the manifold benefits and various business cases of this approach have become apparent in various operational contexts. Without new concepts and developments in these areas, Digital Twins will continue to function within their encapsulated system boundaries but may not fully exploit their potential in interconnected production. In this case, connectivity, as described in concepts like the IoT or Industry 4.0, and the promised potential benefits will remain ideas and conceptual thoughts.

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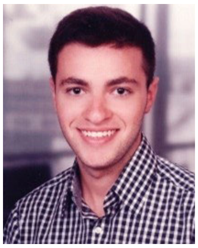

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