Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

REVIEW AND CLASSIFICATION OF CHALLENGES IN DIGITAL TWIN IMPLEMENTATION FOR SIMULATION-BASED INDUSTRIAL APPLICATIONS

Alexander Wuttke[1], Bhakti Stephan Onggo[2] and Markus Rabe[1]

[1]Dept. of IT in Production and Logistics, TU Dortmund University, Dortmund, GERMANY
[2]CORMSIS, University of Southampton Business School, Southampton, UK.

ABSTRACT

Digital Twins (DTs) play an increasingly important role in connecting physical objects to their digital counterparts, with simulation playing a key role in deriving valuable insights. Despite their potential, DT implementation remains complex and adoption in industrial operations is limited. This paper investigates the challenges of DT implementation in simulation-based industrial applications through systematically reviewing 124 publications from 2021 to 2024. The findings reveal that while nearly half of the publications tested prototypes, most are limited to laboratory settings and lack critical features such as cybersecurity or real-time capabilities. Discrete Event Simulation and numerical simulation emerge as the dominantly utilized simulation techniques in DTs. From the analysis, 33 challenges are identified and the classification of them into nine dimensions is proposed. Finally, further research opportunities are outlined.

1 INTRODUCTION

Digital Twins (DTs) have gained significant attention in both research and industry due to their ability to digitally represent real-world physical objects. By leveraging sensor data and other sources, DTs enable monitoring, analysis, and optimization of physical systems. Simulation plays a central role in DTs by utilizing models to provide valuable insights to the physical objects (Onggo and Currie 2024).

Despite their growing popularity, especially within the scientific community, the adoption of DTs in operational business settings within producing industries remains limited (Tao et al., 2024). This highlights a gap between scientific DT frameworks and their practical implementation, as real-world deployment is often hindered by challenges that complicate the translation of concepts into functional systems.

The implementation of DTs has been reviewed in several prior studies. While some reviews lack formal systematical methodologies, recent comprehensive analyses have provided valuable insights. For instance, Tao et al. (2024) examined challenges associated with DTs in industrial applications, while Taylor et al. (2023) focused specifically on simulation-related challenges within DTs. There are also several formal SLRs that have previously addressed challenges related to the implementation of DTs in industry. However, some of these reviews were conducted several years ago and did not account for newer developments. Moreover, other reviews take broader perspectives that extend beyond implementation challenges, including the study of Semeraro et al. (2021), who examine various aspects of DT technology without delving deeply into the practical difficulties associated with their implementation. Similarly, studies like Botín-Sanabria et al. (2022) provide general overviews of DTs but are not limited to industrial applications. Additionally, there are domain-specific reviews that concentrate on particular industries or applications, for instance, by Errandonea et al. (2020) who focused on maintenance applications.

Despite these contributions, there remains a limited focus on challenges specific to simulation-based industrial applications within DTs. Given the increasing reliance on simulation for industrial operations, addressing these challenges is essential to advance both research and practical adoption. This paper aims to fill this gap by systematically reviewing literature at the intersection of DTs, simulation, and industrial applications with regard to associated implementation challenges. Additionally, it investigates the current stages of research regarding DT development, ranging from purely conceptual studies to prototypes. Furthermore, this paper examines the use of simulation techniques in DTs to offer guidance to the simulation community on key areas of focus. To achieve these objectives, three research questions (RQs) are examined. Among them, **RQ1** serves as the primary RQ, while **RQ2** and **RQ3** function as secondary RQs:

- **RQ1:** What are the key challenges in DT implementation for simulation-based industrial applications?
- **RQ2:** What is the distribution of research across different stages of DT implementation for simulation-based industrial applications?
- **RQ3:** Which simulation techniques are used in DTs in industrial applications?

This paper is organized as follows. Section 2 provides an introduction to DTs and distinguishes them from related concepts while introducing simulation techniques. Section 3 details a systematic literature review (SLR) conducted to identify reported challenges. These challenges are further explained in Section 4 and a classification for them in dimensions is proposed. The findings and implications are discussed in Section 5, followed by conclusions and future research opportunities presented in Section 6.

2 DIGITAL TWINS FOR SIMULATION-BASED INDUSTRIAL APPLICATIONS

2.1 Digital Twins in Industrial Applications

According to Matta and Lugaresi (2024), one of the most significant definitions of DTs is provided by Grieves and Vickers (2017), who describe DTs as virtual representations of physical objects in the real world with a bi-directional flow of data between the two. DTs can be distinguished from related concepts by examining the directionality of data flow. For instance, an unidirectional flow of data from the physical object to its digital counterpart is referred to as a Digital Shadow (Kritzinger et al. 2018).

Interest in DTs for the industrial domain is increasingly widespread and their utilization is promising. However, significant challenges must be addressed to enhance their maturity and enable large-scale adoption in industry (Tao et al. 2024). Although the basic understanding of DTs is relatively straightforward, implementing them as fully functional systems is a complex undertaking. This complexity arises from the need to integrate multiple tasks, services, and features into a cohesive framework. Key components include data collection and pre-processing from sensors and other sources, efficient storage and management of these data, their application in simulations and models, as well as advanced analytics to extract actionable insights. These processes must be executed reliably, securely, and often at real time to meet the demanding requirements of industrial applications.

Some authors argue that simulation is a mandatory component of DTs (Negri et al. 2017). However, this view is not universally accepted and is either absent or not explicitly emphasized in other definitions, such as the one provided by Grieves and Vickers (2017). Regardless of whether simulation is deemed mandatory, it undeniably plays a significant role in DTs and continues to be a key focus for further research.

2.2 Simulation in Digital Twins

Simulation is a well-established computational method for numerically analyzing models, with widespread applications across various industrial domains (Law 2015). Law (2015) categorizes simulation techniques into several types, including the two major approaches Discrete Event Simulation (DES) and continuous simulation, as well as further specialized techniques such as agent-based simulation, System Dynamics, and Monte Carlo Simulation (MCS). Moreover, numerical simulation (NS) plays a significant role by leveraging mathematical models to study physical systems, such as finite element analysis for structural evaluations and robotics trajectory planning (Allaire 2007).

Simulation has long been an essential method for analyzing and understanding complex problems prior to the emergence of DTs. Traditionally, simulation models were not designed to accommodate frequent updates to input data or dynamic changes in the states of real systems (Onggo and Currie 2024). Furthermore, while its primary application within the system lifecycle was historically focused on planning, simulation is now increasingly being applied during the operational phase when integrated into DTs (Taylor et al. 2023). Adapting simulation for DTs has long been recognized as an important research priority (Onggo et al. 2018) that has already proven to be valuable across various applications. For an introduction to DTs and their alignment with simulation, readers are encouraged to refer to Matta and Lugaresi (2024).

3 SYSTEMATIC LITERATURE REVIEW

To address **RQ1**, **RQ2**, and **RQ3**, a SLR is conducted following the guidelines outlined by Kitchenham and Charters (2007). The review protocol specifies searches in the digital libraries Scopus, IEEE Xplore, and ACM Digital Library. The scope is limited to conference papers and journal articles written in English that have undergone peer review to ensure quality. Other SLRs are excluded to prevent redundancy and ensure that this study contributes novel insights rather than reiterating findings from existing reviews.

The domain of the review is restricted to applications within producing industries, including internal logistics. Non-producing industries as well as logistics related to supply chains or package delivery are excluded. Furthermore, only studies adhering to the definition of DTs specified in Section 2.1 are considered for further analysis. Additionally, only studies that either explicitly utilize simulation or demonstrated a clear connection between DTs and simulation are included. The used search string is: *"digital twin*" AND "simulation*" AND (“industr*” OR “manufactur*” OR “production” OR “logistic*”) AND NOT ("review" OR "literature*").* To focus on recent developments in DT implementation, only research published between 2021 and 2024 is included.

Given the substantial number of publications identified through these criteria, the SLR focuses on the 50 most-cited papers per year per digital library with at least two citations. Due to insufficient results from ACM Digital Library under these conditions, a total of 556 publications are selected instead of the intended 600 publications. After removing duplicates and filtering for English-language conference papers and journal articles, 240 publications remain eligible for further screening. These remaining papers are evaluated based on their domain relevance, use of simulation, and adherence to the defined concept of DTs. This process resulted in a final selection of 124 publications deemed relevant for inclusion in this SLR. While relaxing filtration criteria would have broadened the scope of the examined literature body, focusing on recent high-quality research maintains a representative overview to reflect key challenges and trends.

In response to **RQ1**, challenges are identified when authors explicitly refer to them anywhere in their publication as challenges or implicitly described them as problems, limitations, open research questions, or other expressions indicative of unresolved issues. To ensure methodological rigor and avoid double-counting, challenges are only considered when they clearly represent the original perspective of the authors of the respective publication. References to challenges that are cited from other publications are excluded. A total of 33 distinct challenges are identified across all reviewed works. These challenges are proposed to be classified into nine dimensions. Table 1 presents an overview of these challenges along with their frequency across publications and their assigned dimensions. Figure 1 illustrates the share of publications mentioning at least one challenge within each dimension, while Figure 2 highlights the share of mentions for the ten most frequently cited challenges across all reviewed works. Further details regarding these dimensions and challenges are provided in Section 4.

To address **RQ2**, the publications are categorized based on the following stages of research regarding DT implementation:

- **Concept**: No implementation of a DT.
- **Emulation**: DT implemented, but physical object is computationally emulated.
- **Data Use-Case**: DT implemented, but data are previously recorded at a physical object.
- **Prototype**: DT implemented and actually connected to a physical object.
- **Operations**: Fully implemented DT used in ongoing industrial operations.

Table 1: Proposed classification dimensions and the identified challenges. Numbers in parentheses represent the number of publications mentioning the dimension or challenge.

Dimension	Challenges
Architecture (56)	Implementation Guidelines (21), Interfaces (20), Standardization (19), Adaptability (14), Hierarchy and Collaboration (11), Autonomy (7), Context-Awareness (5), Maintainability (2)
Technical Infrastructure (52)	Real-Time Capabilities (42), Cybersecurity (18)
Modeling (44)	Problem Modeling (39), Automated Modeling(7)
Data Infrastructure (39)	Data Collection (22), Data Integration (16), Data Storage (11), Data Quality (9), Data Management (6)
Quality Assurance (16)	Verification and Validation (11), Trustworthiness (4), Reliability (2)
Practicality (15)	Capabilities (4), Reporting (4), Definition (3), Understanding (3), Objectives (2), Collaboration (1)
Knowledge Utilization (13)	Knowledge Extraction (13), Knowledge Transfer (6), Knowledge Representation (3)
Tools (12)	Implementation Tools (7), Simulation Tools (6)
Finance (11)	Investment Costs (10), Business Models (2)

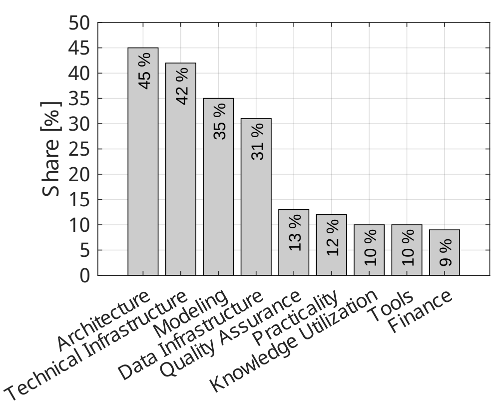

Figure 1: Share of publications citing at least one challenge from a dimension.

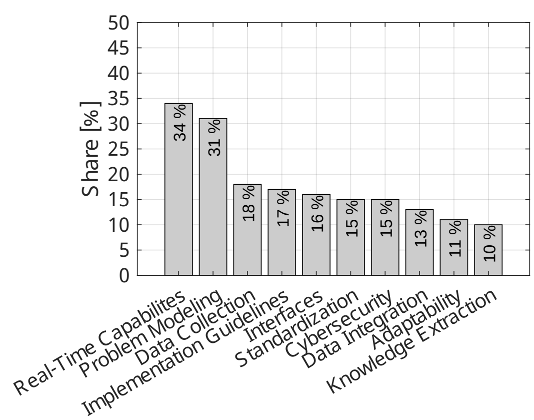

Figure 2: Share of publications citing one of the ten most cited challenges.

Papers that discussed DT implementation without proposing a concept or implementing a DT are excluded in the examination for **RQ2**. The findings are visualized in Figure 3 and discussed in Section 5.

For **RQ3**, the simulation techniques utilized or proposed within the reviewed publications were analyzed and recorded. These techniques are classified as described in Section 2.2. However, as shown in Figure 4, only DES, MCS, NS, and their combination (hybrid models) are reported in the analyzed publications. The implications of these findings are discussed in Section 5.

4 PROPOSED CLASSIFICATION: DIMENSIONS AND CHALLENGES

This section provides concise descriptions of the proposed classification dimensions and their associated challenges, highlighting key findings from the SLR as summarized in Table 1.

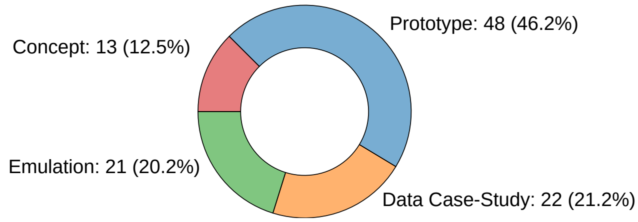

Figure 3: Stages of research in publications.

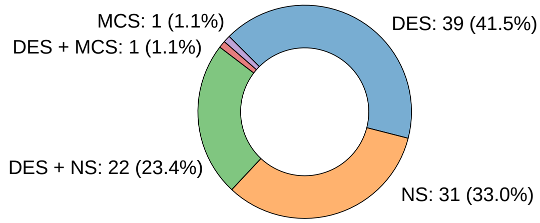

Figure 4: Simulation techniques in publications.

4.1 Architecture

The architecture dimension addresses challenges related to the internal structural design of DTs and their interoperability with other systems.

Implementation Guidelines: The lack of clear guidelines and blueprints is recognized as a major barrier to DT implementation. Glatt et al. (2021) emphasize that guidelines should be tested in industrial applications rather than relying solely on theoretical concepts. Limited guidance exists for selecting specific technologies (Jeong et al. 2022), integrating DTs into existing systems Rojek et al. (2021), integrating DTs into extended reality applications (Yang et al. 2022), or implementing simulation models within DTs (Santos et al. 2022).

Interfaces: The lack of interfaces is cited as a challenge at multiple levels, including between DTs and sensors, between modules within the DT such as a simulation tool interacting with data storage (Turner and Garn 2022), and between DTs and legacy systems such as enterprise resource planning (Bellavista et al. 2023). The lack of human-machine interfaces is also reported, including those needed to enable DTs to participate in the industrial metaverse (Cui et al. 2023). Interface challenges often relate closely to standardization issues.

Standardization: Insufficient standardization in the DT domain is widely reported as a barrier to further development, including DT components, data collection, and simulation utilization. The development of reference architectures has been proposed, e.g., by Hakiri et al. (2024), who emphasize their importance for interoperability and compatibility with other DTs and systems. Some authors suggest that existing standards, such as communication protocols, should be leveraged more extensively in current DT implementations.

Adaptability: Aligning DTs with constantly changing real objects is challenging. This includes updating simulation models within DTs to reflect changes accurately (D'Urso et al. 2024) and the flexible utilization of hardware and software resources. Autonomous adaptability without human intervention has been called for by Castañé et al. (2023), with context-awareness repeatedly cited as an enabler for achieving adaptability.

Hierarchy and Collaboration: Organizational concepts for collaboration among multiple DTs or between DTs and other systems are insufficiently researched, also within industrial Internet of Things networks. For example, concepts for production systems with multiple unit-level DTs and a superordinate DT to orchestrate them should be worked on (Zhang et al. 2024).

Autonomy: Developing autonomous DTs is essential to minimize human interaction in tasks such as monitoring, modeling, or adaptations. Autonomy allows decision-makers to focus on higher-level objectives while delegating operational work to DTs (Bellavista et al. 2023).

Context-Awareness: Context-awareness enables situational adaptability in complex scenarios and enhances results generated by DTs. It is also identified as a crucial enabler for autonomy since it allows flexible handling strategies without manual intervention (Bellavista et al. 2023).

Maintainability: Long-term usability requires designing DTs with maintainability in mind. This includes ensuring that software can be updated seamlessly over time without compromising functionality or reliability (Paasche and Groppe 2022).

4.2 Technical Infrastructure

The technical infrastructure dimension focuses on challenges related to ensuring the functionality, security, and efficiency of DTs in industrial applications.

Real-Time Capabilities: Ensuring real-time capabilities is the most frequently stated challenge for DTs. Issues that hinder real-time performance can arise across various components, including latency in distributed or cloud computing environments (González-Herbón et al. 2024), Internet of Things networks despite advancements like 5G technologies (Hakiri et al. 2024), applying verification and validation (V&V) techniques (Martínez-Gutiérrez et al. 2021), data storage and access inefficiencies (Suhail et al. 2022), data analytics limitations (Friederich et al. 2022), and cybersecurity measures affecting system responsiveness (de Azambuja et al. 2024). Long simulation times and mathematical optimization tasks are also challenging to execute in real time due to computational demands, as noted by several authors. Furthermore, high numbers of scenarios and simulation runs also make real-time calculations difficult (Psarommatis 2021).

Cybersecurity: Cybersecurity is a widely discussed challenge in the analyzed literature, especially when DTs operate within systems of interconnected DTs, collaborate with offsite counterparts, or rely on grid or cloud technologies (Martínez-Gutiérrez et al. 2021). Alcaraz and Lopez (2022) highlight the critical importance of cybersecurity for DTs in automated manufacturing to prevent the disruption of entire production lines or when handling sensitive data to prevent exposing confidential data.

4.3 Modeling

The modeling dimension focuses on creating and managing accurate models for DTs, encompassing simulation, optimization, and data models for various industrial applications.

Problem Modeling: Problem-specific modeling in DTs is reported as an ongoing challenge. This mainly concerns the simulation, optimization, and data models used. Beyond common challenges like deciding what to model and determining the appropriate level of detail, there are unique challenges specific to DTs, e.g., how to model the physical object along its lifecycle (Pang et al. 2021). High-fidelity models of complex processes, including modeling human interaction, remain difficult to achieve (Cui et al. 2023). Real-time performance requirements further exacerbate these challenges.

Automated Modeling: Due to dynamic environments such as reconfigurable manufacturing systems, structural changes of models should be automated and the level of detail should be adjusted according to the current context (Lugaresi and Matta 2021). Semi-automatic modeling has also been suggested as beneficial in certain scenarios (Friederich et al. 2022). Beyond model structures, automating scenario generation for existing models is proposed as another area requiring attention (Jeong et al. 2022).

4.4 Data Infrastructure

The dimension of data infrastructure encompasses all aspects with regard to data in DTs.

Data Collection: Collecting heterogeneous and sufficient data in industrial applications is reported to be time-consuming and costly. Preventing redundant or unnecessary data collection is an important challenge (Jia et al. 2023), as is ensuring timely availability of data for DT processing (Santos et al. 2022). Advances in sensor technology are needed to improve data collection efficiency (Tavares et al. 2024).

Data Integration: Integrating data from heterogeneous sources, such as sensors, digital systems, and market data, is described as a significant challenge. Differences in data formats, update rates, and other inconsistencies exacerbate this issue (Castañé et al. 2023). Multi-modal data types, such as images, audio, logs, documents, and time series, add further complexity to integration efforts (Friederich et al. 2022).

Data Storage: The extensive volume of collected data presents challenges for storage. Beyond managing sheer size, the data must be stored quickly while remaining efficiently accessible to avoid slowing down other DT processes (González-Herbón et al. 2024).

Data Quality: High-quality datasets are essential for DT functionality but face practical challenges. Sensor data are often prone to noise caused by environmental factors (Chakraborty et al. 2021). Ensuring appropriate preprocessing methods that balance time constraints with quality requirements remains a challenge.

Data Management: Collaborative data management across different partners is a challenge but is often hindered by privacy constraints that limit sharing between companies (Mortlock et al. 2022). Effective data governance frameworks for DTs remain underdeveloped and require further attention (Ren et al. 2023).

4.5 Quality Assurance

The quality assurance dimension focuses on ensuring that DTs function as intended, meet required standards, and deliver reliable outputs in industrial applications.

Verification and Validation: Cleophas et al. (2022) highlight a general lack of V&V techniques in the domain of DTs, which poses significant challenges for ensuring their accuracy. Specific issues include validating data and models used within DTs, as noted by Friederich et al. (2022), as well as introducing methods to validate the outputs generated by DTs (Suhail et al. 2023). A well-executed V&V process not only improves the accuracy of DTs but also fosters trustworthiness and reliability (D'Urso et al. 2024).

Trustworthiness: Sasikumar et al. (2023) emphasize that enhancing the trustworthiness of DTs is vital for increasing their acceptance within companies and among customers of DT-related products. Trustworthiness begins at the data level, requiring high-quality inputs (Suhail et al. 2022), and extends to all models utilized within DT systems to ensure accurate representation and functionality.

Reliability: Building reliable DTs is a challenge that depends on consistently utilizing high-quality data, ensuring real-time responsiveness, and delivering dependable results (Donato et al. 2024).

4.6 Practicality

The practicality dimension addresses practical challenges in DT implementation, focusing on functional capabilities, communication, understanding, and collaboration within real-world contexts.

Capabilities: Expanding the use of artificial intelligence and machine learning algorithms within DTs is proposed to enhance their capabilities (Liu et al. 2021). Additionally, integrating smart contracts into DT systems remains an open challenge (Suhail et al. 2022).

Reporting: Rojek et al. (2021) highlight the need for better coordination and communication within the scientific community regarding DT research. Glatt et al. (2021) criticize the lack of reporting on DTs that are actively used in industry operations. Additionally, investigating the discrepancy between companies' awareness of DTs and their actual adoption levels remains an open challenge (Hakiri et al. 2024).

Definition: The existence of numerous definitions and interpretations of DTs is identified as a significant roadblock to progress (Cleophas et al. 2022). These inconsistencies can lead to misconceptions that hinder effective implementation and understanding.

Understanding: DTs rely on a combination of heterogeneous technologies and methods, making it challenging to understand each component thoroughly (Pang et al. 2021). Skill gaps among engineers and stakeholders further exacerbate this issue, as noted by de Azambuja et al. (2024). Training personnel to use complex DT systems poses additional challenges, particularly when they lack proficiency in IT technologies (Cleophas et al. 2022).

Objectives: The objectives of DT implementations are reported as vague or insufficiently defined, which can hinder their adoption and effectiveness (Chakraborty et al. 2021). To address this, Cleophas et al. (2022) suggest more transparent communication of the unique selling points of DTs to stakeholders.

Collaboration: Competitive thinking among companies often prevents collaboration, which can hinder constructive advancements in DT development and implementation (Mortlock et al. 2022).

4.7 Knowledge Utilization

The knowledge utilization dimension addresses challenges related to creating, organizing, sharing, and maintaining knowledge within DT systems to ensure efficient decision-making and continuous improvement.

Knowledge Extraction: Extracting valuable knowledge embedded in the data and models within DTs poses notable challenges. Integrating machine learning techniques for enhanced knowledge extraction has been suggested as a potential solution (Leng et al. 2021), alongside advanced knowledge mining methods (Li et al. 2022). Furthermore, while problems such as machine failures are often detectable, identifying their root causes remains difficult.

Knowledge Transfer: Leveraging knowledge of existing DTs to create new ones or adopting this knowledge across systems is reported as an open challenge (Cleophas et al. 2022). Additionally, transferring knowledge across domains and throughout different lifecycle stages remains a hurdle (Zheng et al. 2024).

Knowledge Representation: Visualizing extracted knowledge effectively is an ongoing challenge. When humans are involved in utilizing DT-generated insights, ensuring that the presentation is explainable and comprehensible becomes especially critical to support decision-making processes (Castañé et al. 2023).

4.8 Tools

The tools dimension addresses challenges related to the availability and suitability of tools for implementing DTs, including simulation tools.

Implementation Tools: A lack of tools for DT implementation is widely reported in the literature (Tao et al. 2024). Even when tools are available, their functionalities often fail to meet all requirements (Glatt et al. 2021). Generic solutions frequently lack sufficient personalization options that can be implemented with minimal effort (Castañé et al. 2023).

Simulation Tools: It is reported that simulation tools can face interoperability issues within DT systems or when interacting with other simulation tools (Michael et al. 2022). Additionally, many available simulation tools struggle to incorporate real-time input data from physical objects, which limits their effectiveness in dynamic industrial environments (Turner and Garn 2022).

4.9 Finance

The finance dimension focuses on challenges related to the financial aspects of DT implementation, including its costs and opportunities to monetize DTs.

Investment Costs: Implementing DTs can demand significant financial investments, driven by costs for, e.g., industrial-grade sensors, hardware for high performance computing, and enabling technologies such as product lifecycle management or enterprise resource planning systems. Utilizing simulation to generate data that would otherwise be difficult or costly to obtain remains an ongoing challenge.

Business Models: Developing new DT-based business models is an open challenge. They are essential for fostering broader adoption of DTs and fully exploiting their financial potential (Hakiri et al. 2024).

5 DISCUSSION OF FINDINGS

In the following, selected challenges, the stages of research, and the utilized simulation techniques are discussed and limitations of this study are pointed out.

The most frequently mentioned challenge according to the SLR is identified as the real-time capabilities of DTs. The authors of this paper share this view and see real-time capabilities as the most challenging aspect in DT implementation. The interlinking of many, often complex processes results in high computational resource requirements. Depending on the required time tolerance for results, current hardware and software technologies often fall short of enabling DTs with an extensive range of functions, requiring prioritization of functions based on time constraints. Addressing this challenge will require advancements in computational performance and optimization of software tailored for real-time applications.

Missing implementation guidelines are a frequently cited challenge, although novel guidelines are widely proposed within the reviewed literature. Their effectiveness remains unclear due to varying system complexities and domain-specific requirements. This suggests either existing guidelines fail to meet practical needs or DT implementations require customized approaches that standardization cannot easily address.

There are some challenges that are underrepresented in current literature but deserve greater attention according to the authors' perspective. Reliability has only been reported twice as a challenge, however, ensuring consistent functionality is essential for widespread adoption in industrial contexts where downtime or system failures can result in significant financial losses or safety risks. Additionally, there are challenges absent from the reviewed literature but equally critical. For instance, an unclear return of investment may cause industrial companies to hesitate in adopting DTs without clear evidence demonstrating cost-effectiveness relative to traditional approaches or alternative technologies.

The analyzed publications proposing DTs mostly go beyond conceptual stages, with 88% introducing actual implementations as shown in Figure 3. Research that is either using an emulation for the physical object or a data case-study focus more on the digital representation of DTs and consider the challenges in establishing a working bi-directional data flow less detailed. Nearly half of the publications that propose a DT have tested it with a prototype, which shows that research is already well advanced. However, these prototypes predominantly focus on limited functionalities, operate within controlled laboratory environments, and often omit critical aspects such as cybersecurity. Furthermore, many prototypes lack proper implementation of data linkage between the virtual representation and the physical object. This reduces them to digital shadows rather than fully functioning DTs. Prototypes were mostly developed for single DTs, whereas collaborative DTs remain at less advanced stages. Strikingly, none of the analyzed publications tested their DTs in real industrial operations. This fact underscores their insufficient maturity level for practical application and hampers the ability to thoroughly investigate implementation challenges within industrial settings. Some publications of the reviewed literature already identified this concern as a challenge.

Figure 4 shows DES as the most common simulation technique for DTs, appearing in 66% of publications. It is primarily used for planning and scheduling tasks on tactical or operational horizons as well as pathfinding for robots. Interestingly, DES is often referred to generically as *simulation*. NS follows at 56%, primarily applied for finite element analysis or complex robot trajectory planning. Combining DES and NS appears promising and has been implemented in nearly a quarter of reviewed studies, where DES serves as a framework and NS addresses subcomponents. Given that DTs are usually employed to analyze the physical processes of real-world machines within a time-logical context, the authors consider the integration of DES and NS a logical progression. This approach could gain increased attention in the future, particularly regarding aspects such as (standardized) interfaces between the specific models, streamlined integration into simulation software, and synchronization mechanisms.

Several implications can be derived for simulation itself. Producing trustworthy and reliable simulation results requires enhancing simulation model robustness to account for input parameters that may be less controlled or lower quality compared to other simulation studies where inputs are handpicked. Additionally, simulations must often meet stringent real-time requirements imposed by DTs, which is particularly challenging when dealing with complex models or if there is an extensive number of scenarios to analyze.

The chosen SLR methodology has limitations, including publication bias favoring positive results over challenges and search criteria that skew toward technical reports on DT implementations rather than studies exploring broader issues like financial or organizational challenges. Additionally, most identified challenges arise from research in academic contexts rather than real-world industrial applications.

6 CONCLUSION AND OUTLOOK

Despite significant interest and extensive research efforts, the implementation of DTs for industrial applications continues to present substantial challenges. Through a SLR, this paper has identified 33 distinct challenges and proposed their classification into nine dimensions, whereas the challenges may overlap and are not necessarily mutually exclusive within or across dimensions. Among these challenges, ensuring real-time capabilities emerges as the most critical challenge, which is particularly problematic for complex DTs that must seamlessly integrate processes such as data collection, preprocessing, model analysis, and knowledge generation. These tasks must be performed while simultaneously meeting requirements for trustworthiness, reliability, and cybersecurity, while each of them represents a challenge in its own.

Although research has produced numerous prototypes of DTs, they often remain limited in terms of functionality. Furthermore, these prototypes are predominantly tested within controlled laboratory environments rather than being applied in real-world industrial operations. None of the analyzed publications reported on DTs being used in everyday industrial settings, highlighting a notable gap between research-focused prototype development and widespread adoption by industrial companies. This discrepancy underscores the need for further exploration into why DTs have not yet achieved broader implementation outside academia.

Simulation plays a pivotal role within DT workflows but is largely restricted to DES, NS, or a combination of both. Enhancing these simulation techniques and their associated tools to better align with DT workflows presents an ongoing opportunity for advancement within the simulation community.

Future efforts should prioritize testing DTs in operational industrial environments with reporting on outcomes and challenges. To bridge the gap between prototype development and real-world application, direct engagement with industrial companies is essential. Companies that have successfully implemented DTs or those that faced difficulties or failed attempts should be interviewed explicitly about their experiences and the challenges they encountered during deployment, which would provide valuable guidance for researchers and practitioners seeking to overcome challenges to widespread adoption of DTs in industrial applications.

REFERENCES

Alcaraz, C., and J. Lopez. 2022. “Digital Twin: A Comprehensive Survey of Security Threats”. *IEEE Communications Surveys and Tutorials* 24(3):1475–1503.

Allaire, G. 2007. *Numerical Analysis and Optimization*. Oxford: Oxford University Press.

Bellavista, P., N. Bicocchi, M. Fogli, C. Giannelli, M. Mamei, and M. Picone. 2023. “Requirements and Design Patterns for Adaptive, Autonomous, and Context-Aware Digital Twins in Industry 4.0 Digital Factories”. *Computers in Industry* 149:103918.

Botín-Sanabria, D. M., A.-S. Mihaita, R. E. Peimbert-García, M. A. Ramírez-Moreno, R. A. Ramírez-Mendoza, and J. d. J. Lozoya-Santos. 2022. “Digital Twin Technology Challenges and Applications: A Comprehensive Review”. *Remote Sensing* 14(6):1335.

Castañé, G., A. Dolgui, N. Kousi, B. Meyers, S. Thevenin, E. Vyhmeister *et al*. 2023. “The ASSISTANT Project: AI for High Level Decisions in Manufacturing”. *International Journal of Production Research* 61(7):2288–2306.

Chakraborty, S., S. Adhikari, and R. Ganguli. 2021. “The Role of Surrogate Models in the Development of Digital Twins of Dynamic Systems”. *Applied Mathematical Modelling* 90:662–681.

Cleophas, L., T. Godfrey, D. E. Khelladi, D. Lehner, B. Combemale, M. van den Brand, *et al*. 2022. “A Community-Sourced View on Engineering Digital Twins: A Report from the EDT.Community”. In *Proceedings of the 25th International Conference on Model Driven Engineering Languages and Systems*, edited by T. Kühn and V. Sousa, 481–485. New York, NY: Association for Computing Machinery.

Cui, Y., W. Yuan, Z. Zhang, J. Mu, and X. Li. 2023. “On the Physical Layer of Digital Twin: An Integrated Sensing and Communications Perspective”. *IEEE Journal on Selected Areas in Communications* 41(11):3474–3490.

de Azambuja, A. J. G., T. Giese, K. Schützer, R. Anderl, B. Schleich, and V. Rosa Almeida. 2024. "Digital Twins in Industry 4.0 – Opportunities and Challenges Related to Cyber Security". *Procedia CIRP* 121:25–30.

Donato, L., C. Galletti, and A. Parente. 2024. "Self-Updating Digital Twin of a Hydrogen-Powered Furnace Using Data Assimilation". *Applied Thermal Engineering* 236:121431.

D'Urso, D., F. Chiacchio, S. Cavalieri, S. Gambadoro, and S. M. Khodayee. 2024. "Predictive Maintenance of Standalone Steel Industrial Components Powered by a Dynamic Reliability Digital Twin Model with Artificial Intelligence". *Reliability Engineering and System Safety* 243:109859.

Errandonea, I., S. Beltrán, and S. Arrizabalaga. 2020. "Digital Twin for Maintenance: A Literature Review". *Computers in Industry* 123:103316.

Friederich, J., D. P. Francis, S. Lazarova-Molnar, and N. Mohamed. 2022. "A Framework for Data-Driven Digital Twins for Smart Manufacturing". *Computers in Industry* 136:103586.

Glatt, M., C. Sinnwell, L. Yi, S. Donohoe, B. Ravani, and J. C. Aurich. 2021. "Modeling and Implementation of a Digital Twin of Material Flows Based on Physics Simulation". *Journal of Manufacturing Systems* 58:231–245.

González-Herbón, R., G. González-Mateos, J. R. Rodríguez-Ossorio, M. Domínguez, S. Alonso, and J. J. Fuertes. 2024. "An Approach to Develop Digital Twins in Industry". *Sensors* 24(3):998.

Grieves, M., and J. Vickers. 2017. "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems". In *Transdisciplinary Perspectives on Complex Systems*, edited by F.-J. Kahlen, S. Flumerfelt, and A. Alves, 85–113. Cham: Springer International Publishing.

Hakiri, A., A. Gokhale, S. B. Yahia, and N. Mellouli. 2024. "A Comprehensive Survey on Digital Twin for Future Networks and Emerging Internet of Things Industry". *Computer Networks* 244:110350.

Jeong, D.-Y., M.-S. Baek, T.-B. Lim, Y.-W. Kim, S.-H. Kim, Y.-T. Lee, *et al*. 2022. "Digital Twin: Technology Evolution Stages and Implementation Layers with Technology Elements". *IEEE Access* 10:52609–52620.

Jia, P., X. Wang, and X. Shen. 2023. "Accurate and Efficient Digital Twin Construction Using Concurrent End-to-End Synchronization and Multi-Attribute Data Resampling". *IEEE Internet of Things Journal* 10(6):4857–4870.

Kitchenham, B., and S. M. Charters. 2007. *Guidelines for Performing Systematic Literature Reviews in Software Engineering*. EBSE Technical Report.

Kritzinger, W., M. Karner, G. Traar, J. Henjes, and W. Sihn. 2018. "Digital Twin in Manufacturing: A Categorical Literature Review and Classification". *IFAC-PapersOnLine* 51(11):1016–1022.

Law, A. 2015. *Simulation Modeling and Analysis*. 5th ed. New York City, NY: McGraw-Hill Education.

Leng, J., M. Zhou, Y. Xiao, H. Zhang, Q. Liu, W. Shen, *et al*. 2021. "Digital Twins-Based Remote Semi-Physical Commissioning of Flow-Type Smart Manufacturing Systems". *Journal of Cleaner Production* 306:127278.

Li, J., G. Zhou, and C. Zhang. 2022. "A Twin Data and Knowledge-Driven Intelligent Process Planning Framework of Aviation Parts". *International Journal of Production Research* 60(17):5217–5234.

Liu, Q., J. Leng, D. Yan, D. Zhang, L. Wei, A. Yu, *et al*. 2021. "Digital Twin-Based Designing of the Configuration, Motion, Control, and Optimization Model of a Flow-Type Smart Manufacturing System". *Journal of Manufacturing Systems* 58:52–64.

Lugaresi, G., and A. Matta. 2021. "Automated Manufacturing System Discovery and Digital Twin Generation". *Journal of Manufacturing Systems* 59:51–66.

Martínez-Gutiérrez, A., J. Díez-González, R. Ferrero-Guillén, P. Verde, R. Álvarez, and H. Perez. 2021. "Digital Twin for Automatic Transportation in Industry 4.0". *Sensors* 21(10):3344.

Matta, A., and G. Lugaresi. 2024. "An Introduction to Digital Twins". In *2024 Winter Simulation Conference (WSC)*, 1281–1295 https://doi.org/10.1109/WSC63780.2024.10838793.

Michael, J., J. Pfeiffer, B. Rumpe, and A. Wortmann. 2022. "Integration Challenges for Digital Twin Systems-of-Systems". In *Proceedings of the 10th IEEE/ACM International Workshop on Software Engineering for Systems-of-Systems and Software Ecosystems*, 9–12. New York, NY: Association for Computing Machinery.

Mortlock, T., D. Muthirayan, S.-Y. Yu, P. P. Khargonekar, and M. Abdullah Al Faruque. 2022. "Graph Learning for Cognitive Digital Twins in Manufacturing Systems". *IEEE Transactions on Emerging Topics in Computing* 10(1):34–45.

Negri, E., L. Fumagalli, and M. Macchi. 2017. "A Review of the Roles of Digital Twin in CPS-Based Production Systems". *Procedia Manufacturing* 11:939–948.

Onggo, B. S., and C. S. M. Currie. 2024. "Extending Simulation Modeling Methodology for Digital Twin Applications". In *2024 Winter Simulation Conference (WSC)*, 3058–3069 https://doi.org/10.1109/WSC63780.2024.10838633.

Onggo, B. S., N. Mustafee, A. Smart, A. A. Juan, and O. Molloy. 2018. "Symbiotic Simulation System: Hybrid Systems Model Meets Big Data Analytics". In *2018 Winter Simulation Conference (WSC)*, 1358–1369 https://doi.org/10.1109/WSC.2018.8632407.

Paasche, S., and S. Groppe. 2022. "Enhancing Data Quality and Process Optimization for Smart Manufacturing Lines in Industry 4.0 Scenarios". In *Proceedings of the International Workshop on Big Data in Emergent Distributed Environments*. June 12th, Philadelphia, PA, USA, 1-7.

Pang, T. Y., J. D. Pelaez Restrepo, C.-T. Cheng, A. Yasin, H. Lim, and M. Miletic. 2021. “Developing a Digital Twin and Digital Thread Framework for an ‘Industry 4.0’ Shipyard”. *Applied Sciences* 11(3):1–23.

Psarommatis, F. 2021. “A Generic Methodology and a Digital Twin for Zero Defect Manufacturing (ZDM) Performance Mapping Towards Design for ZDM”. *Journal of Manufacturing Systems* 59:507–521.

Ren, Z., J. Shi, and M. Imran. 2023. “Data Evolution Governance for Ontology-Based Digital Twin Product Lifecycle Management”. *IEEE Transactions on Industrial Informatics* 19(2):1791–1802.

Rojek, I., D. Mikołajewski, and E. Dostatni. 2021. “Digital Twins in Product Lifecycle for Sustainability in Manufacturing and Maintenance”. *Applied Sciences* 11(1):1–19.

Santos, C. H. d., J. A. de Queiroz, F. Leal, and J. A. B. Montevechi. 2022. “Use of Simulation in the Industry 4.0 Context: Creation of a Digital Twin to Optimise Decision Making on Non-Automated Process”. *Journal of Simulation* 16(3):284–297.

Sasikumar, A., S. Vairavasundaram, K. Kotecha, V. Indragandhi, L. Ravi, G. Selvachandran *et al*. 2023. “Blockchain-Based Trust Mechanism for Digital Twin Empowered Industrial Internet of Things”. *Future Generation Computer Systems* 141:16–27.

Semeraro, C., M. Lezoche, H. Panetto, and M. Dassisti. 2021. “Digital Twin Paradigm: A Systematic Literature Review”. *Computers in Industry* 130:103469.

Suhail, S., M. Iqbal, and R. Jurdak. 2023. “The Perils of Leveraging Evil Digital Twins as Security-Enhancing Enablers”. *Communications of the ACM* 67(1):39–42.

Suhail, S., S. U. R. Malik, R. Jurdak, R. Hussain, R. Matulevičius, and D. Svetinovic. 2022. “Towards Situational Aware Cyber-Physical Systems: A Security-Enhancing Use Case of Blockchain-Based Digital Twins”. *Computers in Industry* 141:103699.

Tao, F., X. Sun, J. Cheng, Y. Zhu, W. Liu, Y. Wang, *et al*. 2024. “makeTwin: A Reference Architecture for Digital Twin Software Platform”. *Chinese Journal of Aeronautics* 37(1):1–18.

Tao, F., H. Zhang, and C. Zhang. 2024. “Advancements and Challenges of Digital Twins in Industry”. *Nature Computational Science* 4(3):169–177.

Tavares, S. M. O., J. A. Ribeiro, B. A. Ribeiro, and P. M. S. T. de Castro. 2024. “Aircraft Structural Design and Life-Cycle Assessment through Digital Twins”. *Designs* 8(2):29.

Taylor, S. J. E., C. M. Macal, A. Matta, M. Rabe, S. M. Sanchez, and G. Shao. 2023. “Enhancing Digital Twins with Advances in Simulation and Artificial Intelligence: Opportunities and Challenges”. In *2023 Winter Simulation Conference (WSC)*, 3296–3310 https://doi.org/10.1109/WSC60868.2023.10408011.

Turner, C. J., and W. Garn. 2022. “Next Generation DES Simulation: A Research Agenda for Human Centric Manufacturing Systems”. *Journal of Industrial Information Integration* 28:100354.

Yang, C., X. Tu, J. Autiosalo, R. Ala-Laurinaho, J. Mattila, P. Salminen *et al*. 2022. “Extended Reality Application Framework for a Digital-Twin-Based Smart Crane”. *Applied Sciences* 12(12):6030.

Zhang, Y., Y. Li, Y. Zhang, and R. Zong. 2024. “Numerical Analysis of the Behavior of Molten Pool and the Suppression Mechanism of Undercut Defect in TIG-MIG Hybrid Welding”. *International Journal of Heat and Mass Transfer* 218:124757.

Zheng, X., X. Hu, R. Arista, J. Lu, J. Sorvari, J. Lentes, *et al*. 2024. “A Semantic-Driven Tradespace Framework to Accelerate Aircraft Manufacturing System Design”. *Journal of Intelligent Manufacturing* 35(1):175–198.

AUTHOR BIOGRAPHIES

ALEXANDER WUTTKE is a PhD candidate and researcher at the department of IT in Production and Logistics at TU Dortmund University. He holds a M.Sc. in Mechanical Engineering from TU Dortmund University. His research interests are digital twins, condition-based maintenance, and simulation. His email address is alexander2.wuttke@tu-dortmund.de.

BHAKTI STEPHAN ONGGO is a Professor of Business Analytics at the University of Southampton. He is a member of the Centre for Operational Research Management Sciences and Information Systems (CORMSIS) and Centre for Healthcare Analytics. His research interests include simulation modeling methodology and its applications in digital twin, health care, disaster management and supply chain. His e-mail address is b.s.s.onggo@soton.ac.uk and his website is https://bsonggo.wordpress.com/.

MARKUS RABE is a full professor for IT in Production and Logistics at the TU Dortmund University. Until 2010 he had been with Fraunhofer IPK in Berlin as head of the corporate logistics and processes department, head of the central IT department, and a member of the institute direction circle. His research focus is on information systems for supply chains, production planning, and simulation. Markus Rabe is vice chair of the “Simulation in Production and Logistics” group of the simulation society ASIM, member of the editorial board of the Journal of Simulation, member of several conference program committees, has chaired the ASIM SPL conference in 1998, 2000, 2004, 2008, and 2015, Local Chair of the WSC’2012 in Berlin and Proceedings Chair of the WSC’2018. His e-mail address is markus.rabe@tu-dortmund.de.