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When is a Simulation a Digital Twin? A Systematic Literature Review

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Abstract

This paper presents a systematic literature review to analyze the connection between the capabilities of Digital Twin (DT) and simulation; it also reviews industrial applications of DT and its different definitions. After a systematic search of several databases and a careful selection based on established criteria, 120 journal academic publications regarding practical implementations of DT were selected and classified according to the capabilities of DT and/or simulation that they implemented. Based on the results of the SLR classification and analysis, the challenges in this area that are preventing the widespread adoption of a fully capable DT are presented. This work also identifies the current limitations and reasons behind some misconception of DT. There is still a disconnection between the DT concepts and applications, as people continue to construct DTs that are basically simulation models. Furthermore, those that build a DT only make use of a portion of its capabilities.

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Keywords: Digital Twin; Simulation; Capability

1. Introduction

Digital Twin (DT), usually described as a virtual representation of a physical product or system connected with bi-directional data, has been a topic of increasing interest over the past five years by both academia and industry [1,2]. For instance, companies such as IBM, Siemens, and GE are already adopting DT technologies [3]. This growth is driven by Industry 4.0 and advances in technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), wireless sensor networks, Machine Learning (ML), and big data, providing opportunities to integrate physical and virtual environments [4]. As a consequence of this growing interest, many works have been published about DT and its applications, leading to a dilution of the concept of DT, which is engendering a misunderstanding of the application of DT and its benefits.

It is widely acknowledged that the concept of DT was first introduced by Michael Grieves in collaboration with John Vickers from NASA [5]. Grieves defines a DT model as one that is composed of three elements: physical space, virtual space, and the data flow that connects the physical space to the virtual space and vice versa. Several papers regarding DT have been published since Grieves presented the concept, including nine systematic literature reviews (SLR). For instance, [2] conducted a comprehensive review focusing on analysing DT in terms of its concepts, technologies, and industrial applications, and presented recommendations related to the different lifecycle phases of the DT. [6] analyzed 22 papers with an emphasis on examining the status of DT applications in the construction industry. Similarly, [7] also performed a SLR in the construction industry but with the goal of identifying the countries or regions that are active drivers of DT adoption and assessing its impacts. They found that the majority of the developed countries, such as the UK, US, Australia, and Italy have the highest number of researchers contributing to the driving forces for the adoption of DT in the construction industry. [8] conducted a SLR to investigate the temporal evolution of research fronts and emerging research trends in the field of physical internet and DT in supply chain management. [9] identified categories of barriers to DT implementation and

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provided a conceptual model that prescribes how these categories in the process industry affect each other. On the other hand, [10] reviewed DT from an engineering and business innovation perspectives and identified future perspectives for DT. [11] reviewed papers related to DT in product design and development, classifying them into conceptual design, detailed design, design verification, and redesign. [12] reviewed the DT's technologies and implementation challenges in several domains and applications in engineering and beyond. [13] provided a detailed explanation of how the DT reported in the manufacturing literature are structured and how they function.

Overall, these existing SLRs focus on providing an overview of established definitions of DT, classifying the DT in terms of its application, components and technologies, suggesting further research, and highlighting the current gap in the literature in specific application areas. Although such reviews are extensive and detailed, no SLR or other study in the literature has looked at the relationship between DT and simulation. Note that this is a natural relationship, as these two techniques have some similar capabilities and objectives. In fact, several papers reviewed herein build simulations and call them DT, but it is unclear if these simulations have the full capabilities usually associated with DT. This work investigates the connection between simulation and DT, uses classification to delineate the differences and similarities, and adds a discussion of a future agenda for researchers and practitioners.

Clarifying the differences between the capabilities of DT and simulation is necessary to achieve consistency in DT implementations. For instance, [14] provided an outline of some distinctions between a model and a DT, however numerous simulation-based applications continue to be referred to as DTs. According to [15], simulation is a component of a DT, but it is not implied that every simulation is a DT. Simulation and DT are distinct technologies with unique benefits that can provide important insights to a problem; therefore, they should be classified accordingly, and it is crucial to clarify their differences to prevent misunderstandings. Thus, through an in-depth SLR, this paper intends to:

- Identify whether the current literature is truly applying DT or if it is using simulation in place of DT
- Highlight the main differences in capability between DT and simulation
- Classify the DT applications according to its capabilities and provide a summary of technology and industrial application fields
- Identify the implementation challenges of simulation-based DT and recommend future research directions.

This work is structured as follows. Section 2 presents background information on concepts of the DT and simulation capabilities. Section 3 presents the SLR methodology. Section 4 describes the findings on the capability classification. Section 5 presents the results from the concepts, technology, and industry classification. Section 6 provides a discussion about the challenges preventing a widespread adoption of a fully capable DT and provides our insights on how to address these issues. Finally, a conclusion is provided in Section 7.

2. Background

Traditional simulation and DT models share the same ability to replicate a physical system in a virtual environment, but they are not the same [14]. The use of simulation combined with a DT is very common, which creates an immense misconception about classifying a simulation model as a DT and vice versa [16]. Several organizations use the term 'Digital Twin' synonymously to a simulation model and several software and consulting companies are creating and selling simulation software claiming it is a DT [17].

There are several applications where a traditional simulation serves a valuable purpose, but to call a simulation a DT is not accurate. Besides having the capabilities to model and simulate the physical system in a virtual environment, a DT presents continuous bilateral communication, it measures the changes in the physical system by sensors, and predictions are constantly being shared with the physical system for real-time decision making [18]. In this section, we use the extant literature to identify the key capabilities of simulation and DT. We will use them to classify the works reviewed herein as either simulation and/or DT, based on the capabilities that they have.

2.1.1. Digital Twin capabilities

There have been previous works focused on providing an architecture of DT and showing how the various DT components interact. Most reviews assess the current definition of DT and provide new insights. On the journey to determine the definition and capabilities of DT, several previous related terms have existed, such as: Digital Model and Digital Shadow [15]. Some researchers, such as [19,20], present DT concepts, definitions, and architecture. Others, such as [10,21], explore the trending technologies for industrial DT application.

Researchers have been trying to reach a consensus on a single and unified definition that sufficiently represents a DT. For instance, [22,23] consider DT of a product, whereas [24,25] consider DT of a process. To reach a consensus on a DT definition, the specifications of the fundamental requirements and capabilities for a DT are necessary and these requirements have changed over time because they are linked to advancements in the technologies, such as ML, and big data. The definitions of the levels of capability of a DT used in this research follow the description given by [18,26]. They propose a versatile structure for designing and implementing a general-purpose DT and call it the 4R framework. This 4R framework is composed of four levels: Representation (R1), Replication (R2), Reality (R3), and Relational (R4). A DT is classified into one of the 4R phases depending on its maturity and capability levels, which increase in each phase.

The first level, Representation, is characterized as the initial step of building a DT. It focuses on understanding the behavior of the physical system and creating a system for data collection and storage from the physical environment. The second level, Replication, focuses on duplicating the system in a virtual environment utilizing the architecture created in the representation phase. It uses the data collection system created in the representation step to replicate the physical system in a virtual environment. The DT is capable of reproducing the same outputs when given the same inputs from the physical system. The third level, Reality, is when the DT is used to investigate what-if scenarios with the goal of using the results obtained from the virtual runs into the physical system. The last level, Relational, reflects a DT with the capabilities of incorporating decision-making technologies by using AI or ML. In this step, the physical and virtual systems are connected and the data between them is bi-directional [18,26].

2.2. Simulation capabilities

The definitions of the level of capability of simulation used in this research follow the definitions provided by [27]. After combining the simulation definitions mentioned in the literature, we summarize the simulation capability into four levels. For simplicity and to make it comparable with the 4Rs of DT, we are going to define them as 4S: Modeling (S1), Analyzing (S2), Predicting (S3), and Prescribing (S4).

The first level of simulation capability, Modeling, entails a simulation model that can virtually represent a physical system using historical data that is collected and inputted into the simulation software. The system being modeled is understood and its behavior is converted into the model, which is verified and validated. The second level, Analyzing, is achieved when a simulation model can analyze the system being modeled. A design of experiments is developed to provide analysis of the system from varying the model inputs and structure. The third level, Predicting, is attained when a simulation model can predict the outcome of how the physical system will operate under new and different conditions. It can investigate alternative scenarios and measure the performance of a system. The last level, Prescribing, is achieved when a simulation model is used to evaluate the system and provide insight into its optimal operation or configuration. It uses the results from the simulation to optimize the physical system and prescribe an optimal solution to be applied right away [15,27]. Fig. 1 summarizes the 4Rs and 4Ss capabilities.

One of the issues facing the widespread adoption of DT is the lack of an agreed-upon language. In the world of simulation, the terminology has become standard. The definitions are clear, and the vocabulary used is well-known. Whereas in the world of DT, the engineering community is still in the process of forming this shared language, which is something that has happened organically for some topics such as simulation, but not for DT. At least, not yet. It is our intention that the classification approach presented in this paper will contribute toward creating a consensus about when a simulation model is a DT and when it is not.

3. Systematic Literature Review

This study is grounded in a SLR approach that focuses on minimizing bias by applying systematic methods that are documented in advance with a protocol [28]. To examine the extensive literature within the established scope, this study adapted the methods used by [2,9]. Moreover, a three-stage process was used to select the academic journal papers, eliminate publications that were not closely related, and analyze the content of the related papers. This three-step process is composed by: (a) literature search, (b) literature selection, (c) review process.

The SLR methodology employed in this study is illustrated in Fig. 2. Considering the main objective of investigating the current state of the art concerning DT and simulation levels of capability, two research questions were posed: (RQ1) Are simulation models that do not have any DT capabilities being referred to as DTs? and (RQ2) Do existing implementations of DT have all its capabilities?

RQ1 aims to investigate whether in the existing literature authors are creating DT or just applying simulation instead and calling it a DT. RQ1 becomes of fundamental importance because, as previously stated, simulation and DT are different technologies; therefore, they present different properties and capabilities. RQ2 aims to investigate if the existing DT applications present its full capabilities or if they are only reaching certain levels of it.

In the first step of the SLR methodology, two academic search engines were used to gather relevant literature: Engineering Village and Web of Science. These two database sources were used two ensure that an acceptable number of research papers were captured and used in this study, since they include high-quality publications in a variety of fields. An initial and comprehensive search was conducted using the keywords with appropriate Boolean operators to select publications with the term “digital twin” in the title and “simulation” in the abstract. Only papers in English and

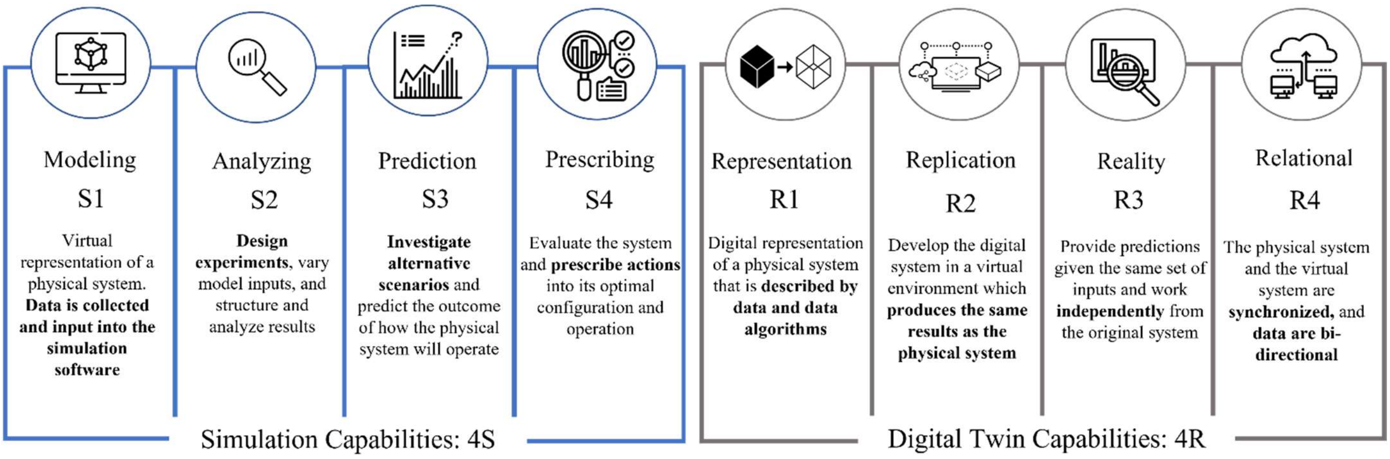


Fig. 1. Summary of simulation and DT levels of capability

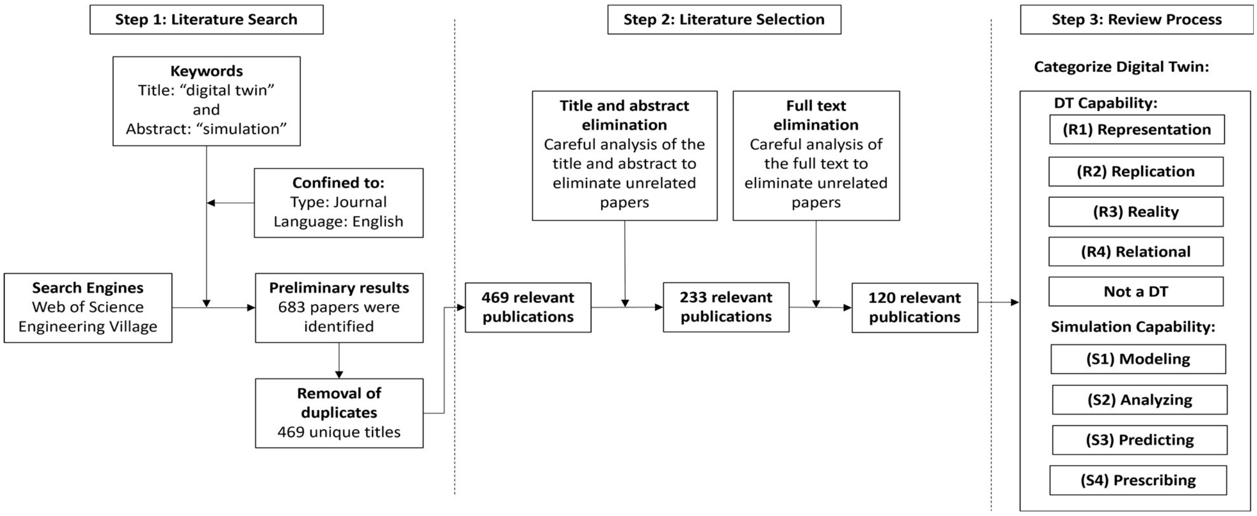


Fig. 2. Systematic literature review methodology

published in journals have been included in this analysis to enhance the quality of obtained data since they provide the most reputable and influential sources of knowledge.

After combining the papers obtained from each database, the total number of retrieved publications was 683. This number decreased to 469 after removing duplicates. Then, a detailed, critical, and comprehensive examination was carried out to identify and select the most appropriate publications for this research. This was executed in the second step of the SLR, which consisted in two parts: first reading the title and abstract of each paper and selecting the papers that were directly related to a practical application of DT and then reading the full paper to further eliminate any other unrelated papers. For the inclusion or exclusion criteria, only publications that focused on DT application and presented a case study in their full text were used in this research. Any papers outside the application range with no mention of DT implementation in their title or abstract, such as conceptual papers, literature reviews, frameworks, methodologies, surveys, theories, and mathematical models were excluded from this analysis. After analyzing the title and abstract, a total of 236 papers were discarded in this step, resulting in 233 potentially relevant publications for the full text analysis. During the full text review, 113 unrelated papers were excluded, resulting in 120 relevant publications to be analyzed and categorized.

In the final step of the SLR, once the set of publications was selected, we categorized them using two criteria. The primary classification criterion was to categorize the papers according to the levels of capability of DT, by observing the case studies reported by the authors and the definitions of each capability level (or R) presented in the 4R framework. The second criterion was to categorize the papers according to the levels of simulation (or S) defined in Section 2. Overall, the journals with most publications in the final set of 120 were: Journal of Manufacturing Systems (12), International Journal of Advanced Manufacturing Technology (9), and International Journal of Computer Integrated Manufacturing (8).

A breakdown of the papers by year of publication is shown in Fig. 3, along with the three steps of the SLR with the purpose of demonstrating how many papers were disregarded in each of these three steps. As can be observed, the development of DT was rather slow between 2009 and 2018. However, there was a significant increase in publications from 2019 to 2022, indicating a development in the use of DTs. Note that the relevant academic publications employed in this work (from step 3 of the SLR) only cover publications from 2018 to 2022, but they exhibit the same trends as the total number of publications first acquired in steps 1 and 2. Note that the year 2022 refers to documents published and indexed in the databases by March 29th, 2022, when the search was conducted.

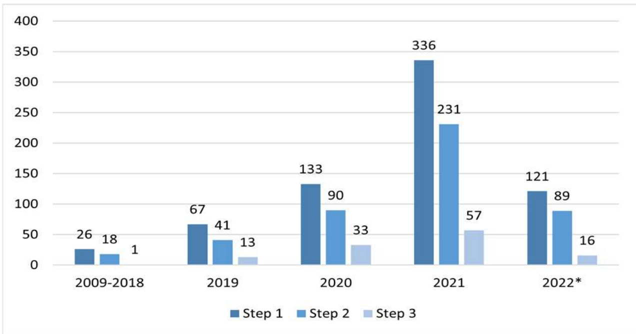
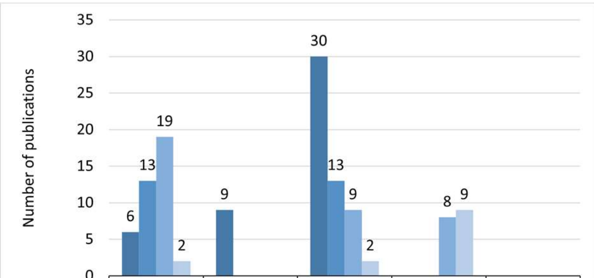


Fig. 3. Reviewed papers by year of publication

4. Capability classification

We conducted a classification of DT and simulation levels of capabilities for each paper selected through the SLR methodology described above. This classification provides information for understanding whether the current literature is truly applying DT or if it is using simulation in place of DT. Each publication was classified within the levels of 4Rs and 4Ss. As observed in Fig. 4, one third of the papers that claimed to do DT did not have any of the 4R capabilities, so cannot be called DT based on that definition (R0). Of the papers classified as doing DT (not R0), the most common level of DT capability achieved by the applications of DT in the literature was R2 (45%), while only 8% of the papers reached R1. The papers that reached R3 (14%) tend to be very sophisticated simulations. Note that most papers lie in the early stages of DT levels of capability, and there are no publications found that reached the R4 level. This indicates the infancy of DT implementations and the large gap still left to fill. These results validate our hypothesis that some researchers are calling their models a DT when it is merely a simulation model.

With respect to the simulation capability classification, many papers (37%) achieved the capability level of modeling (S1), followed by 30% achieving the predicting level (S3), and 22% achieving the analyzing level (S2). Only a few publications (11%) create a fully capable model that can analyze results, predict outcomes, and prescribe optimal solutions. From looking at the combination of the 4Rs and 4Ss, the combination R2-S1 is the most common, followed by R0-S3. Analyses on these classifications are conducted in the following subsections. We proceed from highest to lowest levels of capability.



	R0 (33%)	R1 (8%)	R2 (45%)	R3 (14%)	R4 (0%)
S1 (37%)	6	9	30		
S2 (22%)	13		13		
S3 (30%)	19		9	8	
S4 (11%)	2		2	9	

Fig. 4. Combined analysis of 4Rs and 4Ss levels of capability

4.1. Relational classification (R4)

A DT is categorized into the Relational (R4) level of capability, in accordance with the 4Rs framework, when the physical and virtual systems are in sync and data is bidirectional. The available literature lacks significant DT applications that achieve the highest level of capability.

4.2. Reality classification (R3)

Only 14% of the articles utilized in this study were able to employ the R3 level of capability and the lack of autonomy experienced by these studies is what ties them. Although they each presented a DT that offers real-time data collection and produces optimization results, they are unable to develop solutions on their own and be self-learning. of these models achieved level S3, and nine achieved level S4.

4.2.1. Reality (R3) and Prescribing (S4)

The papers in this category achieved the Prescribing level of capability, which means they can assess data, predict outcomes, and make recommendations. The nine papers classified as R3S4 [29–37] are those that are closest to the 4R definition of a full-capability DT, using all levels of simulation capability. They developed DT models that collect real-time data and generate optimal outcomes. Some of them propose using different technologies to achieve this. For instance, virtual reality (VR) is used by [36] to connect historical and real-time data and analyze various scenarios and IoT is used to control and link processes between the physical and digital worlds.

4.2.2. Reality (R3) and Predicting (S3)

The eight articles classified as R3S3 present a DT that can assess data and predict outcomes under alternative scenarios, but they are unable to prescribe solutions. For instance, [38–42] presented a DT model that reflects and monitors its physical counterpart, clearly using real-time data collection, and dynamically providing optimal results. Although some authors [43–45] claim that their DT shows bidirectional data interaction, their case studies are not sufficiently detailed to support this assertion. Their DTs can predict behaviors but they are not always linked to their physical system.

4.3. Replication classification (R2)

The bulk of the publications (45%) used DT as a virtual replica at the R2 level. These studies presented a DT that can connect with real-time data and replicate the same outputs as the physical system, but they lack the ability to independently research alternate scenarios and find solutions to issues. Thirty of these papers attained level S1, thirteen did so at level S2, nine reached level S3, and two attained level S4.

4.3.1. Replication (R2) and Prescribing (S4)

Only two publications, classified as R2S4, made full use of simulation capabilities. Using their proposed DT, [46] replicate the system, link real-time data, and assign tasks to the actual scenario. The physical system is virtualized, inferences are drawn about it, future events are predicted, and the best course of action is suggested. Similarly, the simulation model-to-real process interface developed by [47] enabled the integration of both, transforming the virtual model into a representation of the real system and replicating the same outputs as the real system.

4.3.2. Replication (R2) and Predicting (S3)

Both the Predicting (S3) level of simulation capability and the Replication (R3) level of DT capability are attained by nine works. Although they developed models that can accurately simulate the behavior of the actual system and produce results that are identical to those of the real system, make prediction, and consider different scenarios, they did not incorporate any optimization techniques to enhance system performance. Some writers, like [48,49], connected historical data to be automatically entered into the virtual system, employing it as real-time data. On the other hand, real-time synchronization between the physical and the digital model was established by [50–53]. Several other authors provide the technologies used to establish these connections. For instance, [54,55] use a DT model that is continuously updated with real-time data gathered from sensors. IoT was used by [56] to gather and record real-time data from physical space and their model can imitate behaviors and anticipate the system with accuracy.

4.3.3. Replication (R2) and Analyzing (S2)

Both the Replication (R2) level of DT capability and the Analyzing (S2) level of simulation capability are attained by thirteen studies. The models used by these authors can examine the system under different parameter settings and provide analysis of the results, but they are unable to predict outcomes or make recommendations. Some authors [57–59] only demonstrate how they linked real-time data to their DT to replicate the system. For instance, real-time data is integrated with VSM by [60], but managers handle the analysis and discussion. [61] focus on how to digitally describe the system by using the data fusion approach. [62] propose the use of ML and AI in their DT methodology indicating they would reach a higher level of the DT capability, but their case study only provided one way connection of real-time data. [63–69], connect PLC and sensors to develop the virtual model but it is dependent on the original system to function.

4.3.4. Replication (R2) and Modeling (S1)

The majority of the studies that fell under the R2 level (30) just executed the first simulation capability, S1. Instead of conducting experiments or making optimized predictions, these authors just concentrate on creating a virtual model that accurately represents what occurs in a physical system. Most of these authors [70–77], develop a DT model architecture that uses real-time data, replicating the real system into a virtual world with no experimentation or analysis. Some authors [78–89] focus on employing sensors to establish a real-time connection between the two. Others provide alternative approaches to this connectivity. For instance, [90] integrate the simulation program and robotic arms layouts using augmented reality, whereas [91] uses VR to synchronize the digital replica with the physical system. Other authors, such as [92–96], focus on validating and verifying their DT models. Some authors [97,98] mention to have bidirectional connectivity between the virtual and physical, but their case study shows otherwise.

4.4. Representation classification (R1)

Only 9 of the publications (8%) employed in this study achieved the R1 level, adopting the DT as a virtual representation. These DT models share the trait of digitally representing and comprehending the behavior of physical systems. Even though these papers presented a case study of a DT that offers real-time data collection, they fall short in terms of analyzing different scenarios, producing optimization results, or achieving autonomy. Regarding the levels of simulation capability, all of these articles achieved level S1.

4.4.1. Representation (R1) and Modeling (S1)

Both the Representation (R1) level of DT capability and the Modeling (S1) level of simulation capability are attained by nine studies. The presented models used represent the physical system in a virtual world, but they are unable to examine multiple scenarios, provide analysis, predict outcomes, or make recommendations. Some authors [99–103], concentrate on offering the real-time data connection but don't offer any analysis or experiment outcomes. Others [104–107] focus on developing a cloud platform for data collection and storage.

4.5. Not a Digital Twin (R0)

After the Replication category, the R0 group has the second-highest number of articles presented. The authors in the R0 (33%) group simply create a simulation model and call them a DT. Their models do not offer any real-time data collection or bidirectional data connections. Instead, they use historical data as input. Six of these papers attained level S1, thirteen did level S2, nineteen got to level S3, and two reached level S4.

4.5.1. Not a DT (R0) and Prescribing (S4)

Only two publications, classified as R0S4, demonstrated that their models fully used all the simulation capabilities. [108,109] do not synchronize real-time data to their models, which makes it purely a simulation. They present a complete simulation model that can analyse alternative scenarios, predict outcomes, and prescribe optimization solutions.

4.5.2. Not a DT (R0) and Predicting (S3)

The S3 level of simulation capability is attained by nineteen articles. Although the authors in this category describe their model as a DT, the virtual model created has more characteristics of a very detailed simulation model of the object with no real-time connection. Some authors [110–126] attempt to obtain real-time data from the system but then use it as historical data. According to [127], the DT must produce predictions using real-time data, what-if analyses, and/or ML, but it's unclear whether they accomplished that. Even though [128] provided a DT composed by a virtual model using discrete event simulation (DES), an AI tool to provide accurate input data to the model, and a DT interface using dashboards, they do not appear to use real-time data at all.

4.5.3. Not a DT (R0) and Analyzing (S2)

Thirteen papers have reached the S2 level of simulation capability. Even though these authors [129–136] simulate, experiment with different parameters, and evaluate performance, they make no mention of gathering real-time data and connecting it to the virtual environment. Some studies [137,138] created a platform for simulation-optimization and carried out several experiments, employing sensors to gather data, but there is no direct connection to the virtual space. Other authors [139,140], use DES and call it a DT. They collect real-time data but do not automatically connect it to the simulation software. [141] use Monte Carlo simulation and DES to create scenarios and implement the results later in the real system.

4.5.4. Not a DT (R0) and Modeling (S1)

Six papers' simulation capability is limited to the S1 level. Some works [142–145], develop a digital representation of the physical system but do not provide any type of real-time synchronization between the virtual and physical spaces. For instance, [146] describe a simulation model of a griding process using Markov chains. [147] mention that their model has a direct data connection from the physical to the virtual, but they are not clear presenting how that information flows.

5. DT Terminology and Supportive Technologies

Although the notion of DT is defined in several scholarly publications, the bigger goal of having a universal definition of DT has not yet been met. Instead, this trend simply expands the scope by adding more definitions, leading to confusion in the field that encourages the usage of alternative technologies under the DT term. Although each new concept is logically justified, none of them has been shown to be more suitable than others and most researchers have failed to make a distinction between DT and simulation models. Numerous concepts are proposed without certain crucial components, which contributes to the definition's ambiguity and prolongs the quest for a comprehensive and agreed-upon definition. To find some association between the definition of DT used by each author and the level of capability of their application of DT, the source of the definition of DT used in each of the academic papers within this work was compiled. Some authors offer a list of numerous definitions, while others only offer one, and yet others offer none at all. To clarify, the DT definition gathered was the definition that was first mentioned in each work.

The top four sources of DT definitions utilized in the papers within the 120 pertinent publications are displayed in Fig. 5 (a). As it can be observed, DT was not defined in 32 papers (26%). The majority of the publications used definitions from Grieves et al. [5,148,149] (17%), Tao et al. [150–153](10%), and Glaessgen et al.[154] (6%). The other 41% of the publications displayed inconsistent use of a singular definition (1-3 times per manuscript). Numerous terms were found for how a DT is referred to in the literature. 69% papers referred to it as "Digital Twin", whereas 31% of the remaining scholarly articles referred to DT under a different designation, such as DT-assisted, DT-based, DT-driven, DT-enabled, DT-emulator, DT job shop based, DT simulation, and data driven DT. Finally, we consider the industry sectors in which the DT applications considered in the SLR were applied. Fig. 5 (b) illustrates the categorization of these papers according to the industry in which they are used. The manufacturing industry has the most studies, followed by energy and automotive.

For DT applications, numerous technologies—such as big data, IoT, edge computing, etc.—are integrated rather than used as standalone solutions. To help readers better understand the usage of these technologies in the creation of DT, the top nine software programs that academic papers most frequently mentioned when discussing the creation of DTs is provided in Fig. 6. Overall, the most popular software and user interfaces for DT applications include CAD (Computer-Aided Design), MATLAB, and Tecnomatix. While most publications mentioned a particular simulation software by name, they usually failed to mention the specific CAD software they employed; thus, we are grouping all the mentions of CAD into a single category. It's important to note that 33% of the publications reviewed in this study made no indication of the software that was employed. Additionally, 45 other software packages were referenced in the articles reviewed herein, but none of them were mentioned more than once or twice.

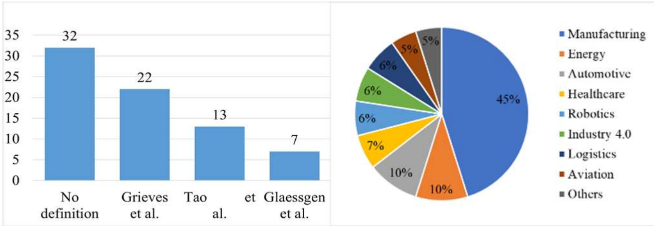


Fig. 5. (a) Top four sources of DT definitions; (b) Industry sectors

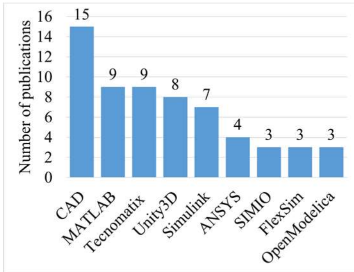


Fig. 6. Top nine supportive technologies for DT

6. Observations and Recommendations

Two main barriers were identified that limit a DT application from reaching a higher level of capability. First, our research has shown that there is still a disconnect between the DT application and concept, as people continue to claim that some traditional simulation models are DTs. Second, those that build a DT consistent with the most popular definitions only make use of a portion of its capabilities. In this section, we go over these issues and offer recommendations.

Some of the DT applications found in our analysis have been reporting their models as DTs even though they are essentially simulation models. Although some authors claim to use real-time data connections in their case studies, they actually use historical data, which illustrates the challenges related to real-time data transfer implementation. This study's findings reveal that there is still a disconnect between the theory and practice of DT even though several academics have already identified key DT components and attributes. Calling a simulation model with no real-time synchronization between the physical and virtual environment a DT might be accurate according to some definitions and incorrect according to others. It is crucial for a technology to have a unified definition to be distinguished from other technologies, and this has not been the case for DT.

The publishing culture concerning information data sharing also plays a role in this discrepancy between theory and practice of DT. We observed that many DT-related papers are vague about implementation details and do not offer details that could be used as a guide by other researchers. As a result of the lack of sufficient detail in the models presented in papers, the existing work cannot be replicated or improved upon by other researchers, which may cause redundant research, limiting the topic from being widely used. It is challenging to track the implementation process and determine how successful the current DT implementations are without the authors providing in-depth information about the implementation details. Such details may be outside the scope of traditional academic publications, but they could be added as supplements online. Changing the publishing culture to encourage more sharing of implementation details is necessary to form a systematic architecture of DT research.

Industrial applications of DT face a hurdle in collecting high-quality data despite it being a requirement, as gathering this data may depend on a variety of factors including the availability of resources to store high-dimensional data and processing capabilities to handle it. This becomes even more challenging to do if it has to happen in real time. Although the current literature may achieve real-time connectivity between physical and virtual spaces, the results from this study revealed that there are few works that implement information flows across the DT's entire lifecycle. Most of the researchers have been attempting to provide methods of tying these real-time data to a DT; however, their work only reaches as far as the R3 level. There hasn't been a paper where a DT achieved all the 4 levels of capability. Therefore, research on self-evolution and autonomy of the DT is needed. This would enable DT to learn and adapt in real-time.

The SLR reveals that most organizations are not prepared for to implement DTs. Furthermore, DT’s complexity varies based on the application sector, current technologies available, and the business objective. Sometimes the DT can be an integrated and complicated model requiring more research, specialist knowledge, cost analysis, and upkeep. Other times, it can be straightforward and practical, with well-defined parameters and expectations. Adding the complexity of a DT unnecessarily, where a traditional simulation is perfectly capable might be an inherent risk, which can cause issues related to security and cost. Inevitably, the creation and continuing maintenance costs for DTs at various levels of complexity will vary, making business cases and return on investment analyses more difficult. Each technology requires investments, therefore choosing the right one to utilize is critical for maximizing its efficiency.

Many of the reviewed papers suggest that industry already employs a wide range of software for routine activities and combining the current software with the DTs software is a challenging task. The data formats and the software tools used by various organizations are often different and these programs frequently do not work together, which causes delays in the adoption of DT. In addition, businesses are hesitant to allow a complete disclosure of data because there is no established protocol. Since a leak of real-time data can be extremely dangerous for a business, a binding legal regulation should be developed across businesses with specified standards for data sharing to have a successful DT operation. Also, platforms that integrate diverse data sources should be researched and the blockchain technology should be explored to build DTs to safeguard intellectual property. This allows data to be shared among several parties while still being connected together, accessible, and un-editable. Therefore, research on a high-fidelity connection between IoT devices is needed.

Another issue that was mentioned frequently in papers studied herein is that specific software skills will need to be added to the operations teams as organizations add smarter assets and address more complicated DTs. When a project has a short lifespan, DT can be costly and might not be an investment that businesses are ready to undertake. Similar to other technologies, DT also requires constant updates to reflect advancements in the fields of the technologies that it employs, such as IoT and ML. These technologies provide a DT the capability of updating itself with the incoming real-time data. Because DT depends on rapid evolving technologies, this investment in DT would need to be ongoing, which results in higher long-term costs. To prevent needless model complexity and lengthy runtime, it makes sense to model according to the appropriate granularity. Detailed research on this is necessary to aid the implementation of the autonomy property of the DT.

Several authors agree that there are several challenges that result from the absence of ML in DT applications currently in use. ML optimization problems can be highly complicated, potentially with a number of additional sub problems. Combining these sub problems into one and selecting the right tool to optimize the overall process is a challenge that requires knowledge of both the domain and ML. Also, a high degree of data quality must be present for the usage of ML to be successful. It can only rely on the data if it believes it to be accurate. Therefore, future research on integrating optimization features for the subcomponents of the DT is needed.

The proposed ways to facilitate the widespread adoption of a fully capable DT are: (1) clearly understand the benefits from adopting DT before investing in it, (2) assess if their business is ready to implement IoT technologies that will leverage DTs, (3) examine whether their goals may be achieved using less complex technology, including simulation, (4) develop metrics and indicators to track the development of DT before actually implementing it, and (5) create legal-binding regulations to have an effective DT operation across industries.

7. Conclusion

This paper investigated the connection between simulation and DT, using classification to delineate the differences and similarities in capabilities between them. It also included a discussion of a future agenda for researchers and practitioners. We believe this paper assists in clarifying the application of DT by presenting three main contributions: (1) a systematic literature review investigated whether the current literature is truly applying DT or if it is using simulation in place of DT, (2) simulation capabilities were defined as a 4S framework, and compared with the 4R framework for DT. These frameworks were used to classify the DT applications according to their capabilities, and (3) we concluded that there is still a disconnect between the DT concepts and applications, as people continue to construct DTs that are basically simulation models. Those that correctly build a DT only make use of a portion of its capabilities and none of them reached its full capability.

Our intention with the classification approach presented in this paper was to contribute toward creating a consensus about when a simulation model is a DT and when it is not. Because simulation and DT use similar technologies, it may be possible to transform simulations to DT. As future work, we intend to develop a framework to guide developers in building a DT directly from a fully capable simulation and demonstrate what techniques support this transformation.

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