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A Comprehensive Review of AI-Powered Digital Twin Technologies

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Abstract:

Digital twin (DT) technologies have rapidly evolved as a cornerstone of modern cyber-physical systems, enabling real-time monitoring, simulation, and optimization of physical assets through their virtual counterparts. The integration of Artificial Intelligence (AI) into digital twins has further enhanced their capabilities, transforming them from passive replicas into intelligent, adaptive systems capable of decision-making and predictive analytics. This review provides a comprehensive examination of AI-powered digital twin technologies, covering their foundational concepts, system architectures, enabling AI techniques (e.g., machine learning, deep learning, reinforcement learning), and diverse applications across industries such as manufacturing, healthcare, energy, and smart cities. The paper also highlights the key benefits of AI integration, including improved accuracy, autonomy, and scalability, while addressing current challenges such as data quality, interoperability, model complexity, and real-time responsiveness. Finally, we outline emerging trends and propose future research directions aimed at advancing intelligent digital twin systems for next-generation applications. This review serves as a valuable resource for researchers, practitioners, and stakeholders seeking to understand and leverage AI-driven digital twin innovations.

1. Introduction

Digital twins are virtual replicas of real-world systems that accurately reflect the system's behavior, with the goal of achieving functionalities like automatic fault diagnosis or run-time monitoring. A Digital Twin (DT) can represent an object, such as a smart building, or a process, such as a production process. Following the definition of Jones et al. [1], a DT is characterized by a physical-to- virtual connection, the data stream that replicates the real-world system. Additionally, the inverse, a virtual-to-physical connection, closes the loop between virtual and physical space, allowing the physical system to benefit from the output of the digital twin. A digital twin should have the ability to process various kinds of data, including real-time data, for providing real-time monitoring of the physical system it represents - this is essential for immediate detection of the original system's behavior, its critical events or anomalies, and response to them.

Artificial Intelligence (AI) and Machine Learning (ML) solutions have become an important part of research in many disciplines in recent years. AI has been shown to outperform humans in several different tasks, such as reconstructing brain circuits [2], playing strategy games [3], and predicting protein structure [4]. Due to the wide applicability of AI solutions, different systems can benefit from the integration of an AI component for predictive functionality.

Since both AI and DT systems require data to function, it is a logical step to integrate them. Integrations of AI and DT, creating an AI-DT system, have been proposed in different application domains, where the AI component makes predictions based on data stemming from the DT. As some examples, Fahim et al. [5] describe a digital twin of a wind turbine using machine learning to forecast the system's energy production. Xiong et al. [6] propose a solution for predictive maintenance of an aircraft engine,

combining a DT of the engine with an LSTM model [7] serving as the ML component. In all such contributions, the Digital Twin derives significant advantages from the application of ML techniques, and through the utilization of vast historical data and pertinent AI algorithms, attains the capability to enhance the accuracy of its predictions. This is achieved by making use of the analytical power of ML, which in turn leverages information and patterns embedded in the historical data to refine predictions, leading to more precise and reliable DT outputs.

This study systematically searches and investigates the literature on the intersection of digital twins and artificial intelligence. After the search, relevant studies are referred to give an overview of the state of the art. The results provide researchers with a summary of the related work, serving as foundational knowledge for future work in the field. Based on this, we identify a number of relevant insights and gaps within current research, suggesting directions for future work.

In recent research, some literature reviews on artificial intelligence and digital twins have been conducted [8–10]. However, although similar in the overarching topic, the focus, search scope of these reviews, and thereby identified research gaps, differ substantially from our review.

Kritzinger et al. [11] define three levels of integration for digital twins: *Digital models*, which have a manual information flow between the physical and the virtual system in both directions; *Digital shadows*, which automate the physical-to-virtual data flow, but still have a manual virtual-to-physical feedback loop; *Digital twins* are the most advanced level of system integration, providing a bidirectional automated data flow between real-world system and digital twin. In this paper, we follow these definitions for digital model, digital shadow, and digital twin.

This paper is structured as follows: Section 2 provides the background for this work and characterizes related literature reviews. Section 3 describes the methodology employed for our literature review, describing the search process and the research questions investigated. Section 4 presents the results of the literature search, characterizing the state of the art, and general findings regarding past research in the field of AI in digital twins. Further, results specific to the research questions are presented. Section 5 identifies research gaps and discusses the findings. Lastly, Section 6 concludes the paper, summarizing the contributions.

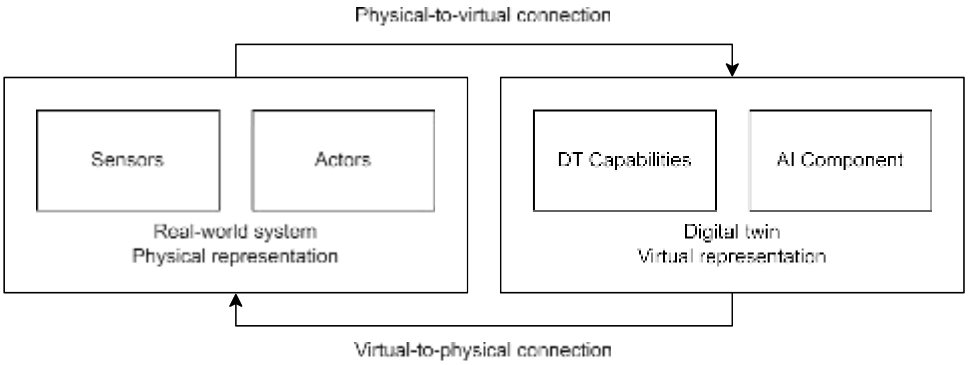
2. Background

Jones et al. [1] have conducted a systematic literature review on digital twins, identifying characteristics of a digital twin and highlighting gaps in the research field. The authors do not explicitly mention machine learning or artificial intelligence, however, concepts such as predictive maintenance and advanced control systems are emphasized as components of a digital twin. Semeraro et al. [12] have performed a review on the paradigm of digital twins, with a focus on the definition of a digital twin and its application domains, based on text mining techniques. While their research focuses on the components of a digital twin, artificial intelligence is not acknowledged in the article.

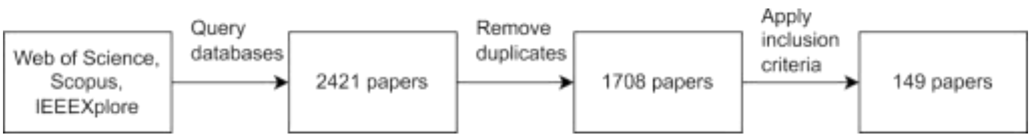
Schmid and Winkler [8] have performed a literature review on the combination of AI methods and digital twins of production systems. They review common challenges encountered in related work and propose a framework combining human interaction and automated components utilizing AI in a production system. A systematic literature review on the role of artificial intelligence, machine learning, and big data within digital twins has been carried out by Rathore et al. [9]. The authors group the existing literature by application domain, characterizing the use-case of the analyzed studies, as well as the machine learning solution employed. Further, they focus on tools supporting the creation of digital twins, providing a reference architecture of their design. While Rathore et al. [9] focus on application domains and the tools supporting digital twin development, this paper is focused on the tasks of artificial intelligence within digital twins as well as the modeling approaches pursued in existing work.

Lim et al. [13] survey state-of-the-art digital twin techniques, sampling exclusively journal articles. Their review focuses on the lifecycle stages of a DT system, positioning past research work by lifecycle stage. Further, the authors identify the integration of big data and digital twins as a future perspective for DT research, stating that the combination can improve decision-making support and improve the quality of simulations within the DT. Bartsch et al. [10] have conducted a literature review on the application of artificial intelligence methods in digital twins for additive manufacturing. They survey a small set of papers specific to digital twins in additive manufacturing as well as a separate set of papers focusing on artificial intelligence in additive manufacturing. The authors state that there is a need for the integration of AI methods with digital twins, however, their analysis does not connect the two research areas.

The previously given definition of a digital twin by Kritzinger et al. [11] is aligned with the definition by Grieves [14], who first mentioned digital twins. Grieves states that a digital twin requires a physical system, a virtual counterpart, and a two-way connection between them. Additionally, his definition highlights the real-time application scenario as paramount, as digital twins provide the most value when applied in a real environment, making an impact on a live system, rather than being applied in a lab setting on synthetic data. Fig. 1 shows a schematic model of a digital twin, adapted from Grieves [15], with the addition of an AI component, showing the bidirectional information flow between the DT and the real-world system. The real-world system, which is the physical representation, contains sensors such as a temperature sensor and actors, which are active components that the DT can control, such as a ventilation system. The AI component is a part of the digital twin, which is a virtual representation of the physical system. The AI component fulfills predictive tasks, such as performing a forecast based on real-time temperature data. The digital twin has additional capabilities, such as data analysis, decision-making, and scenario simulation, which depend on the use case and are summarized in the figure as *DT Capabilities*. The physical and virtual representations are bidirectionally connected, where the virtual-to-physical connection represents a feedback loop from the digital twin, which sends feedback to the physical system based on its internal processing and decision-making, while the physical-to-virtual connection is the data stream supplying the DT based on measurements from the real-world system.



/ig. 1. Schematic model of a digital twin with an AI component.



/ig. 2. Literature search process.

In this paper, AI is used as an overarching term describing the research field, which encapsulates machine learning and deep learning (DL). Deep learning is a subfield of artificial intelligence, where, following the definition of LeCun et al. [16], computational models learn representations of data with multiple levels of abstraction. In practice, deep learning uses different types of neural networks in combination with non-linear activation functions to pursue different tasks, such as regression or classification. Reinforcement learning (RL) is a process where an agent learns to solve a problem by trial-and-error [17], which is typically encountered in optimization scenarios. AI algorithms are often black-box models which are not inherently understandable for the user. The field of explainable AI is concerned with the interpretation of AI models for human users.

Feedforward neural networks are the foundational model architecture of deep learning. They have been used in practice since the inception of the backpropagation algorithm [18], allowing them to learn complex, nonlinear problems. Convolutional neural networks (CNNs) [19] are a special type of neural networks, that subsample the input data with spatial or temporal convolutions, allowing them to capture more complex relations in, e.g., images. Long short-term memory networks (LSTMs) [7] correspond to recurrent neural network architectures, able to capture temporal dependencies within data, often used for forecasting tasks.

Traditional machine learning techniques rely on different techniques, that depend on the task to be solved. Random forest [20] is an approach that combines decision trees with bagging and random subspace sampling for classification or regression. The support vector machine (SVM) [21] is a traditional machine learning method relying on maximum-margin hyperplanes for classification, which can also be used for regression.

Reinforcement learning tackles optimization problems, where an agent that interacts with a defined environment must find an optimal solution to the given problem based on a cost function. RL can be combined with deep learning, which is called deep reinforcement learning (DRL). Deep Q Learning [22] is an approach used in deep reinforcement learning where a deep neural network receiving high dimensional data is used to train an RL agent.

3. Methodology

This paper follows the systematic literature review methodology, as specified in the guidelines by Kitchenham et al. [23]. The search process followed is visualized in Fig. 2. The literature search was conducted in the scientific databases IEEEXplore,[1] Scopus,[2] and Web of Science.[3] Scopus and Web of Science were selected, as they provide a large collection of articles from the field of computer and systems sciences. Both Scopus and Web of Science index the publishers Springer, ACM, Wiley, and Taylor & Francis; Due to this, the publishers have not been queried separately. IEEEXplore was included in the search since it is a more specific database focused on technology and engineering. Google Scholar was excluded from our search, as it indexes articles that are not peer-reviewed. Each database was searched with the same parameters, limiting the field to computer science, the publication year between 2002 and 2022 as well as the publication type to journal and conference papers. The publication year was limited until 2022 to guarantee that no newly published papers were indexed anymore, as the literature search was conducted in August 2023.

Table 1

Inclusion criteria.

Criterion	Description
Publication year: 2002–2022 full year	To limit publications between the year of the initial proposal of DT and the last
Language: English	To ensure comprehension
Journal or conference paper	To include high quality, peer-reviewed publications
Publication available as a pdf	To review the contents of the publication
Primary study	To restrict the search to original work
Main focus on the use of AI/ML methods within a digital twin	To limit the search to papers focusing on digital twins that employ AI/ML methods

Study depth	Completed research work

Table 2

Characteristics extracted from each relevant paper.

Characteristic	Exemplary values
ML algorithm	LSTM, kNN, CNN, SVM
Algorithm tested	Yes, No
ML task	Classification, Regression, Forecasting
Explainable	Yes, No
Feedback loop	Yes, No
DT represents	Object(s) or process(es) represented
Application domain	Manufacturing, Energy, Healthcare
Task of the AI-DT system	Defect detection, process optimization
Data source of the DT	Theoretical, Synthetic data, Real data
Conceptualization of the DT	Conceptual model, Workflow, Framework
Human in the loop	Yes (including responsibility), No

The choice of search parameters is elaborated in the description of the inclusion criteria in Table 1. The search string used for the query over title, abstract, and keywords is the following:

(‘‘Machine Learning’’ OR ‘‘Artificial Intelligence’’ OR ‘‘Deep Learning’’) AND
(‘‘Digital Twin’’ OR ‘‘Digital Shadow’’)

The string consists of two parts, which are linked with a logical AND operation. The first part ensures that a keyword related to artificial intelligence is present, which can be machine learning, artificial intelligence, or deep learning. The second part of the query limits the search to papers also containing either digital twin or digital shadow. This ensures that articles terming their solution a digital shadow are included in the analysis. Overall, the query employed is broad, including papers from any domain, that mention artificial intelligence and digital twins.

The search resulted in a total of 2421 papers from the combined search of the databases, which was reduced to 1708 studies after removing duplicates. These articles were filtered based on the inclusion criteria listed in Table 1, with two authors assessing each paper to increase objectivity. The paper inclusion process was done in an iterative way until reaching consensus among the authors. Studies that were considered immature by the authors were excluded, as we are focusing on completed research work. This resulted in a final set of 149 articles, which fulfilled the inclusion criteria and are therefore relevant to the topic of artificial intelligence in digital twins.

This paper investigates the following research questions:

- **RQ1:** How can an artificial intelligence component improve the processing functionality of a digital twin regarding its tasks?
- **RQ2:** Which modeling approaches are used for digital twins employing artificial intelligence in the literature?
- **RQ3:** Are digital twins with artificial intelligence components demonstrating a bidirectional connection between physical and virtual representations?

The first research question (RQ1) is concerned with the overall integration of AI within digital twins regarding the functionality of the twin. The goal of this question is to investigate, which tasks the AI component fulfills and which types of algorithms are commonly implemented to improve the processing functionality. (RQ2) focuses on the modeling approach of digital twins with an AI component, aiming to extract which model-based representations are typically chosen. The last research question (RQ3) examines whether the proposed digital twins implement the characteristic bidirectional connections between virtual and physical systems.

To address the research questions, multiple characteristics were extracted from each of the relevant articles, as shown in Table 2. The characteristics are divided into two categories, one focusing on the AI component and its ML algorithms, the second describing the digital twin and its properties. Table 2 describes each characteristic with example values, while an exhaustive list of values is presented in Section 4.

ML algorithm describes the algorithm or a set of algorithms that were used in a paper. In the case of neural networks, different architectures of the same network type were summarized with the network type, such as LSTM, CNN, or Neural Network. The characteristic *Algorithm tested* can take the values Yes and No, describing whether the paper demonstrated an evaluation of the method, meaning that its performance was tested on a dataset. The *ML task* is divided into the elementary problem types that are

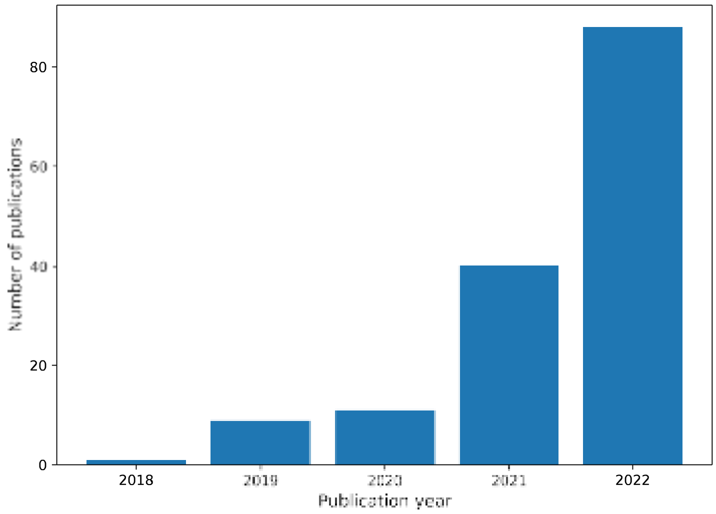


Fig. 3. Histogram of publication years.

encountered in machine learning, such as classification, numeric regression, forecasting of sequential data, or outlier detection. We further categorize each ML algorithm as either *Explainable* or *Non-Explainable* based on its inherent explainability.

The characteristic *Feedback loop* states whether a given research study demonstrates that its proposal for a digital twin has a feedback loop to the physical system. This characteristic takes the value No for the studies that only show a visionary concept of a feedback loop. The object or process that is represented by the digital twin is described with the characteristic *DT represents*, which can also take multiple values when a paper proposes DTs of multiple objects or processes. The *Application domain* characterizes the business domain that the digital twin was applied in. The characteristic *Task of the AI-DT system* shows which task the system was built for, which could be, for example, automatic path planning or anomaly detection. This characteristic is based on the application domain and provides detail from a business-oriented point of view, different from the technically-focused *ML task*. The type of data that the system is using is described by *Data source of the DT*, which can take the values *Theoretical*, where the proposed AI-DT system is not tested with any data, *Synthetic data*, which is artificially generated data, *Real data*, which is historic data stemming from a real system, or *Live data*, which is streamed, real-time data from a real system.

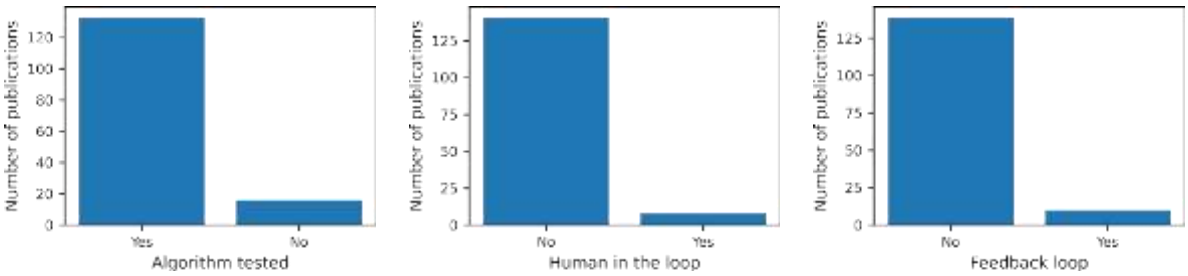
Conceptualization of the DT describes the modeling approach that was used to present the proposed digital twin, and it includes the following approaches: *Schematic model*, a high-level schematic diagram of the DT system, which does not follow any modeling languages; *Workflow*, a textual or graphical description of a temporally ordered procedure for the usage of the model; *Framework*, a combination of a workflow and a schematic model; *System architecture*, an overview of the components of the system showing their interactions and structure; *Conceptual model*, a structured diagram of system concepts with clear relations and cardinalities between them following a modeling language such as Unified Modeling Language (UML), Business Process Modeling Notation (BPMN), or other. To extract this characteristic, the proposed models were classified based on the definitions given in this paragraph. When differing definitions for modeling approaches are used in the papers, we follow the definitions given in this paragraph. Lastly, the characteristic *Human in the loop* states whether a human plays an active role within the AI-DT system, and if there is one, which role the human takes on.

4. Results

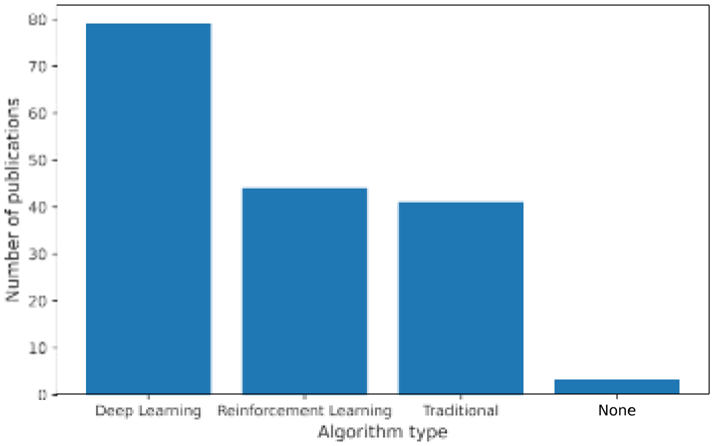
This section outlines the results of the literature search, aggregating the extracted characteristics from the final set of 149 relevant articles. For characteristics that can take multiple values for a single study, namely *ML algorithm*, *ML Task*, and *DT represents*, studies were counted once for each of the values, leading to a higher absolute number of occurrences than the total number of relevant papers when evaluating these characteristics. Fig. 3 shows the distribution of publication years of the found studies. The first relevant paper about AI-DT included in our analysis was published in 2018 [24], with the subsequent years showing an increase in popularity. In 2022, 88 relevant papers were published, more than double compared to 2021.

Fig. 4 highlights the imbalance in the distributions of the three *Yes*/*No* characteristics that we extracted from each paper. 133 papers (89.3%) evaluate their algorithms, while 16 papers only conduct theoretical research, not evaluating their proposals. This shows that research on AI in DTs is typically evaluated in practice and not only proposed on a theoretical basis, while theoretical papers proposing new concepts represent a smaller portion of the overall research.

141 studies (94.6%) do not describe a DT architecture that includes a human as a component of the system. Of the studies that include a human, different roles are taken on: in the domain of healthcare, Tai et al. [25] and Gupta et al. [26] propose a DT that has a doctor in the loop, which is a common use-case where expert knowledge is beneficial for system performance. Latif et al. [27] introduce a framework where a production manager receives recommendations from the DT to improve an assembly process.



/ig. 4. Imbalanced distribution of studies that tested their algorithms, had a human in the loop, and demonstrated a feedback loop from the virtual system to the physical system.



/ig. 5. Histogram of algorithm types.

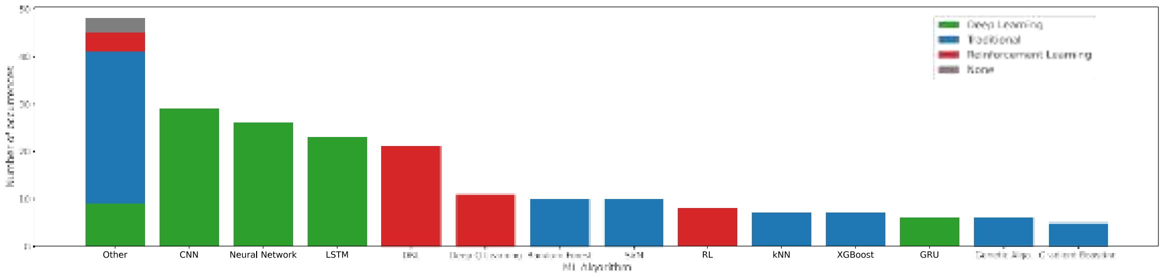
et al. [28] propose a theoretical model where a human operator collaborates with a robot in a production process. A similar proposal is made by Gallala et al. [29] where an operator works with a robot in a digital twin environment. Pires et al. [30] also introduce a model where an operator interacts with a digital twin of an assembly line with the goal of optimizing productivity. Barricelli et al. [31] propose a fitness digital twin, where a fitness coach, acting as a rule editor, interacts with the DT environment to support the decision-making process. Um et al. [24] utilize smart glasses, integrating the user with a virtual reality environment, serving as the DT.

A total of 138 articles (92.6%) do not clearly demonstrate a feedback loop from the virtual system to the physical system. Overall, only a few papers [32–34] clearly show the effect of their feedback loop, while some papers [35–37] show a visionary feedback loop but do not demonstrate a concrete application of their feedback loop. This highlights that many papers propose a digital twin that does not integrate a virtual-to-physical feedback loop. In these cases, the proposed models do not fulfill a key criterion of a digital twin.

4.1. Machine learning methods used in digital twins

To categorize the ML methods used by the relevant studies, every algorithm was labeled as either *Deep Learning*, *Reinforcement Learning* or *Traditional*. The histogram in Fig. 5 shows the number of publications utilizing each of the techniques. Studies that utilized algorithms from multiple categories were counted once for each category that was used. 3 studies (2.01%) only used preprocessing techniques such as PCA, which were classified as *None*. Deep learning is the most popular machine learning technique, with 79 papers (53.0%) integrating DL with a DT. 44 papers (29.5%) used an AI component based on reinforcement learning, while 41 papers (27.5%) employed traditional machine learning methods. This confirms the popularity of using deep learning approaches to solve complex problems, which has recently been seen in multiple domains [16]. Despite the popularity of deep learning, a considerable number of papers base their research on reinforcement learning and traditional ML methods. Reinforcement learning is designed to tackle different problems than deep learning, which is a possible explanation for their co-existence. Traditional ML methods are often [38–40] used alongside deep learning approaches to compare their performance for the given task of the AI component.

In the 149 studies, a total of 217 ML algorithms were employed, with an average of 1.46 and a median of 1.0 algorithms per article. A total of 36 studies used more than one algorithm, showing that most articles do not make a comparison of different ML



/ig. 6. Histogram of ML algorithms. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

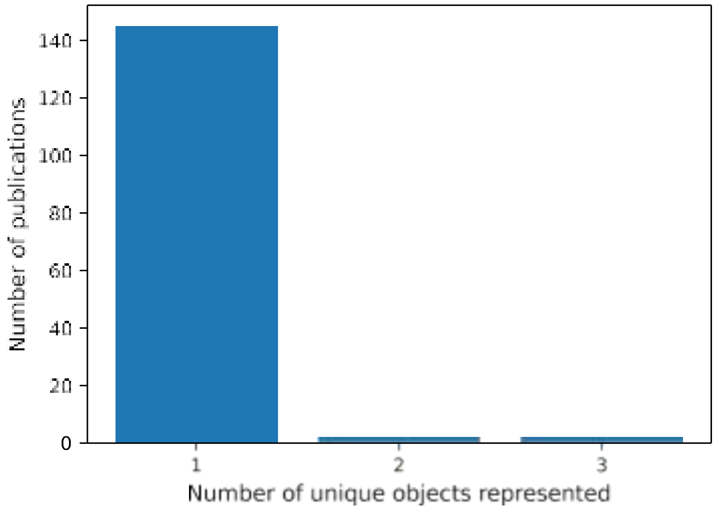
/ig. 7. AI algorithms by testing rate.

solutions. Fig. 6 shows the distribution of ML algorithms, colored by algorithm type. All algorithms that had less than 5 occurrences across all papers were grouped and labeled as *Other* to avoid a long-tailed distribution. Most of the algorithms in *Other* belong to traditional ML methods, with only a small number of other RL and DL methods. The most popular methods are three deep learning methods, namely convolutional neural networks (CNNs) (29 papers, 13.4%), feedforward neural networks (26 papers, 12.0%), and long short-term memory networks (LSTM) (23 papers, 10.6%). These are popular neural network architectures suited for different machine learning tasks. Multiple papers utilize deep reinforcement learning (DRL) (21 papers, 9.68%) and deep Q learning (11 papers, 5.07%). The two most popular traditional ML algorithms are random forest (10 papers, 4.61%), and the support vector machine (SVM) (10 papers, 4.61%). Fig. 7 gives detailed insights on the correlation between AI algorithms and their testing rate on a by-algorithm basis. All algorithms have a testing rate of 80.00% or above, with gradient boosting having the lowest testing rate. Further, Deep Q learning, GRU networks, genetic algorithms, XGBoost, and kNN have a testing rate of 100%. All other algorithms range between 85.71% and 92.31% testing rate. This confirms the statement that the majority of papers test their algorithms. When grouping and normalizing by ML algorithm type, all three groups (DL, RL, traditional) show a high percentage of papers that tested their approaches, between 90.00 and 93.33%. This demonstrates that most researchers proposing an AI-DT system also test their solution and show the performance of the AI component regarding its task with a quantitative analysis. Performance evaluation is task-dependent and individual to each study, therefore, a comparative analysis of algorithmic performance between studies is not conducted.

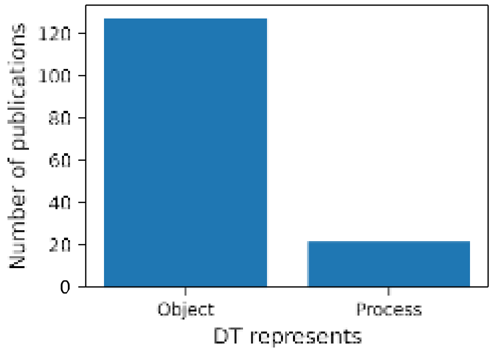
4.2. Objects represented by digital twins

The extracted characteristic *DT represents* demonstrates which object or process was virtually represented by a digital twin for each publication. As shown in Fig. 8, which does not differentiate between object and process, the majority of papers modeled a single unique type of object (145 studies, 97.3%). Two studies (1.34%) modeled two types of object: Li et al. [41] propose a digital twin system of vehicles and infrastructure for resource optimization. Miao and Zhang [42] use a DT of an unmanned aerial vehicle with a DT of a simulation environment to optimize path planning. Two articles modeled three types of objects: Li et al. [43] model an edge network that consists of mobile terminal users, an unmanned aerial vehicle, and resource devices. Wang et al. [44] model digital twins of humans, cars, and traffic with the goal of vehicle trajectory optimization. Overall, Fig. 8 underlines that most research in the field is focused on applying a digital twin of a single object type, which is not part of a larger system of systems where digital twins of multiple types of objects interact. Aggregating multiple digital twins, with communication between them, would allow for modeling more complex systems, than by modeling a single object.

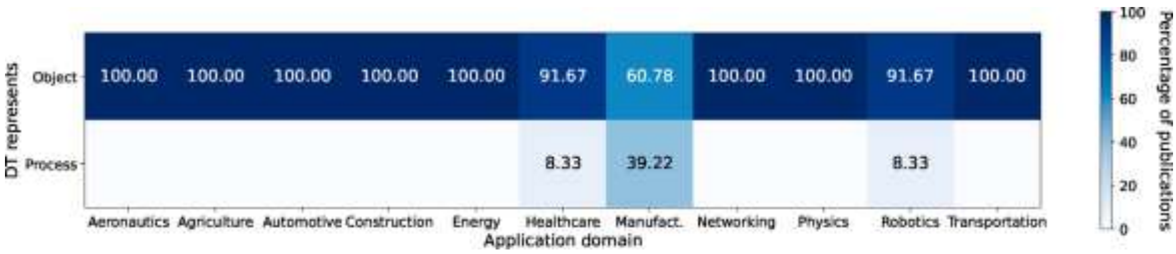
Fig. 9 shows that 127 publications (85.2%) model an object or multiple objects, while only 22 publications (14.8%) represent a process with their proposed digital twin. None of the publications model both a process and an object. Process modeling is common in the domain of manufacturing, which is highlighted in Fig. 10, which correlates the application domain and the represented object or process. Manufacturing models processes in 39.22% of the publications, while all other domains have either no publications modeling processes or 8.33%, in the case of healthcare and robotics, demonstrating that most domains focus on modeling objects. In healthcare, Chen et al. [45] model COVID-19 disease progression as a process, while in robotics Shi et al. [28] model a human– robot-collaboration process. A possible reason for this is that processes in these domains are typically not formally modeled and are, therefore, difficult to translate into a digital twin. In manufacturing, on the other hand, production processes, such as an assembly process, are well structured and have underlying process models, making a digital twin of such a process more feasible.



/ig. 8. Number of unique objects represented in each DT.



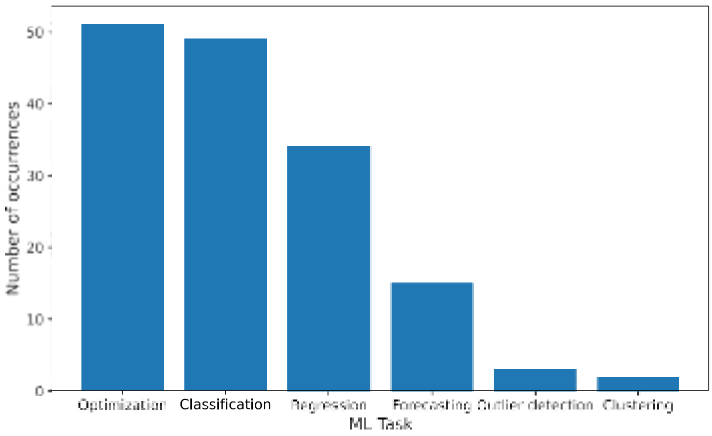
/ig. 9. Number of publications modeling objects and processes.



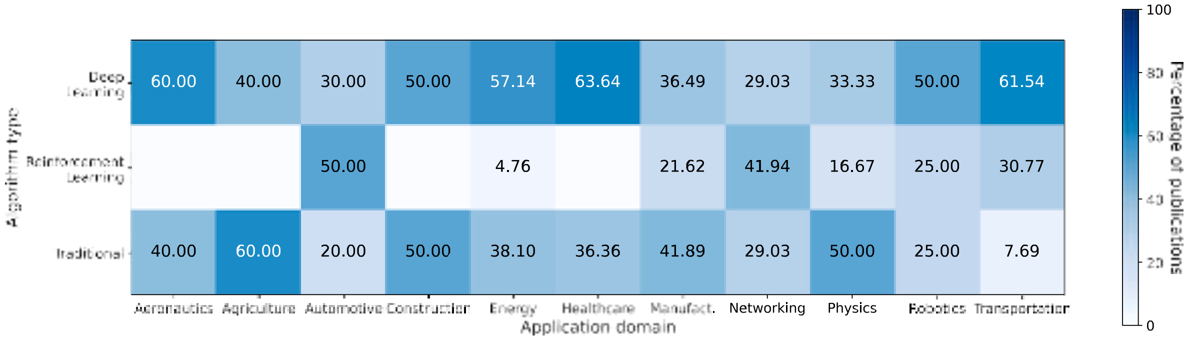
/ig. 10. Publications modeling objects and processes by domain.

4.3. Tasks of AI-DT systems

The tasks of the AI component, and with it, the ML method, can differ depending on the use-case of the DT. Fig. 11 shows the underlying ML tasks that were identified based on the results of the literature search. Papers that pursued multiple tasks within their DT, such as Fahim et al. [5] and Chhetri et al. [46], were counted once for each task, leading to a total of 155 tasks from 149 unique papers. The most common tasks are optimization (51 times, 32.9%), classification (49 times, 31.6%), and regression (34 times, 21.9%). Less common are forecasting (15 times, 9.7%), outlier detection (3 times, 1.9%), and clustering (2 times, 1.3%). Additionally, one article [47], which is not included in the histogram, did not pursue any specific ML task and instead proposed a theoretical architecture for a network digital twin in which multiple different ML tasks can be carried out. It can be argued that clustering and outlier detection are uncommonly seen tasks as they belong to the domain of unsupervised learning, while the other tasks belong to supervised learning and reinforcement learning. This shows that most applications of AI within DT work on



/ig. 11. Distribution of ML tasks.



/ig. 12. Types of ML algorithms implemented by application domain.

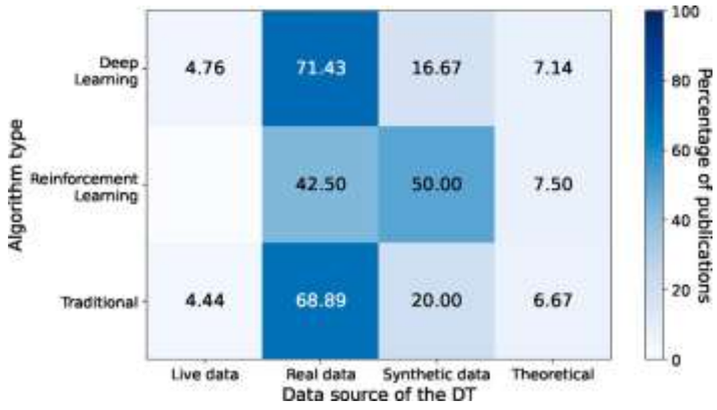
supervised learning with labeled data or reinforcement learning in an agent-environment scenario. Most optimization tasks are solved with reinforcement learning, while classification, regression, and forecasting belong to supervised learning. The task *classification* was assigned to studies that performed classification on tabular data, images, text, or temporal data, regardless of the input data type, which offers an explanation for the high number of studies working on classification.

The task of the ML component is connected to the overall task of the AI-DT system. This overall task varies depending on the use case, and the domain. In the relevant papers, a total of 98 unique tasks were identified, with the most common being anomaly detection (12 papers, 8.05%), network performance optimization (9 papers, 6.04%), and production process optimization (7 papers, 4.70%). These findings prove that digital twin systems that integrate an AI component have a wide range of application cases in different scenarios.

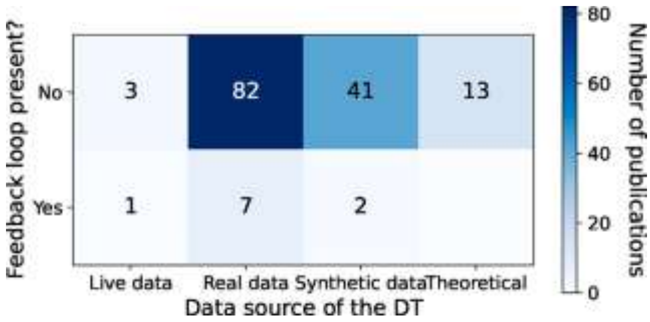
4.4. Application cases of deep learning, reinforcement learning, and traditional machine learning

Fig. 12 shows the relation between algorithm type and application domain. The heatmap shows percentages that are normalized by the number of papers per application domain. Reinforcement learning methods are primarily applied in a subset of all domains, namely automotive, networking, transportation, robotics, manufacturing, and physics. This demonstrates that different domains are facing different problem types, which require different types of ML algorithms. Aeronautics and agriculture are some of the domains where none of the articles applied reinforcement learning. The applicability of reinforcement learning highly depends on the problem being tackled and the cost of negative outcomes. Both automotive and networking commonly employ reinforcement learning, with over 40% of the papers relying on the technique. This can be explained by the simulation capabilities of a digital twin, which allow for solving complex optimization problems such as automatic path planning for cars or network resource optimization. In agriculture, manufacturing, and physics, traditional ML approaches are the most dominant solutions, while deep learning is more common for most other domains.

Fig. 13 visualizes the differences between deep learning, reinforcement learning, and traditional approaches, regarding the data source of the DT. The graph shows percentages of publications normalized by the ML algorithm type. Both traditional approaches and DL show a similar distribution, with data stemming from a real system being the most common data source, followed by synthetic data, and a small percentage of theoretical approaches and approaches relying on live data. RL shows different results,



/ig. 13. Types of AI algorithms and data source of the DT.



/ig. 14. Relation of the data source of the DT and presence of a feedback loop.

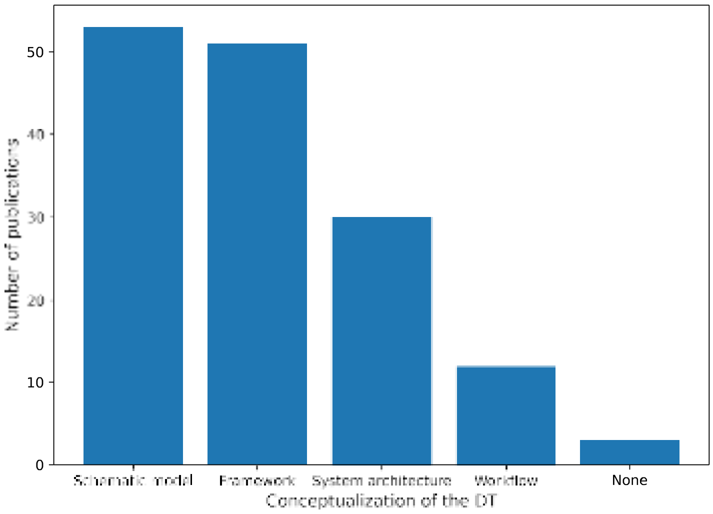
papers utilizing live data, a lower percentage of papers using real data, and a higher percentage using synthetic data. This can be attributed to the fact that RL does not rely on datasets, but requires an environment to operate, which is often synthetically created, rather than using the specification of a real system. Overall, RL relies on less real-world data than DL and traditional approaches, showing that the application cases of RL in digital twins are less mature.

Of the 149 relevant papers, only one paper [48] proposes a digital twin operating with live data that shows both a physical- to-virtual and a virtual-to-physical connection, demonstrating a clear feedback loop. The authors propose a digital twin for iron reverse flotation, a chemical production process. They train their AI component based on historical data and integrate their model with real-time data from a live system, observing changes in productivity after switching to the digital twin-based system. Their feedback loop dynamically adapts the dosage used in the production system, optimizing real-time productivity. In total, 7.38% of the studies (11 papers) present a feedback loop from the digital twin to the physical system. Additionally, only 2.68% (4 papers) of the analyzed publications work with live data stemming from a real system, which allows for online training of an AI component and decision-making based on real-time data. Recalling the criteria that define a digital twin, as given by Grieves [14], real-time data, and a bidirectional data flow between virtual and physical systems are essential parts of a digital twin. Fig. 14 clearly demonstrates a gap in current research where solutions are termed ‘‘digital twin’’, but do not fulfill the requirements for a digital twin.

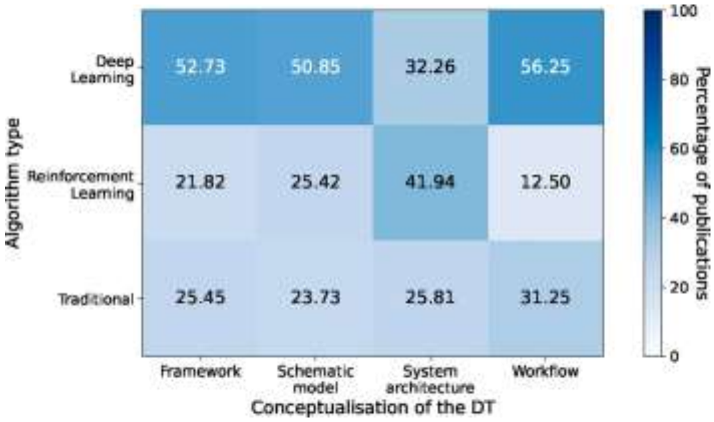
4.5. Conceptualization approaches for digital twins

Every paper included in our analysis was categorized by the conceptualization approach of the digital twin proposed. When no clear model was shown, this category takes the value *None*, which was the case for 3 studies (2.01%), as shown in Fig. 15. 53 articles (35.6%) show a schematic model of a digital twin, which is a model on a high abstraction level. The second most common approach is a framework, which was used by 51 papers (34.2%). System architectures, which are more detailed models, were proposed in 30 publications (20.1%), while 12 papers (8.05%) conceptualized their DT with a workflow. In the criteria we used, *conceptual model* was another possibility for conceptualization approaches, however, none of the found papers showed a conceptual model. Overall, it can be stated that most of the models shown in the literature on AI-DT systems are immature, providing a shallow overview of the system, often only schematically describing the proposed solution.

Fig. 16 presents the relation between algorithm types and the conceptualization approach of the digital twin. The plot is normalized by the conceptualization approach to show the relative differences between them. Deep learning is the most common approach, with between 50.85% and 53.33% for all types of conceptualization except for system architectures. System architectures



/ig. 15. Conceptualization approaches of the DTs.



/ig. 16. Conceptualization of digital twins relating to types of AI algorithms.

show the highest percentage of studies utilizing reinforcement learning, with 43.33%. Workflows show a significantly lower percentage of papers using reinforcement learning, with only 13.33%. A possible reason is that reinforcement learning requires a clear specification of an environment, an actor, and a reward system, which aligns with the requirements to design a system architecture, while a workflow can be less specific. Workflows show considerably more usage of traditional ML algorithms (33.33%) than the other approaches of conceptualization (23.33%–25.45%), which can be attributed to the fact that workflows have a relatively lower number of papers implementing reinforcement learning.

4.6. Explainability of an AI-DT system

Model explainability in the context of AI-DT systems refers to the self-explanatory nature of a digital twin model, where more detailed models are more explainable, and higher-level models are less explainable. As seen in Fig. 15, most papers use high- level modeling approaches, that only provide little explainability. This aligns with the results regarding algorithmic explainability, showing that overall, most AI-DT systems do not consider explainability, either by model explainability or algorithmic explainability. Algorithmic explainability refers to an ML algorithm being a white-box algorithm, where predictions can be understood by a domain expert, while non-explainable algorithms, such as neural networks, are black-box solutions. Some algorithms can potentially be explainable, depending on the use case. Fig. 17 provides a histogram of the number of studies that have used explainable algorithms. We classified the algorithms as either *Explainable* or *Non-explainable*. Examples of explainable algorithms are decision

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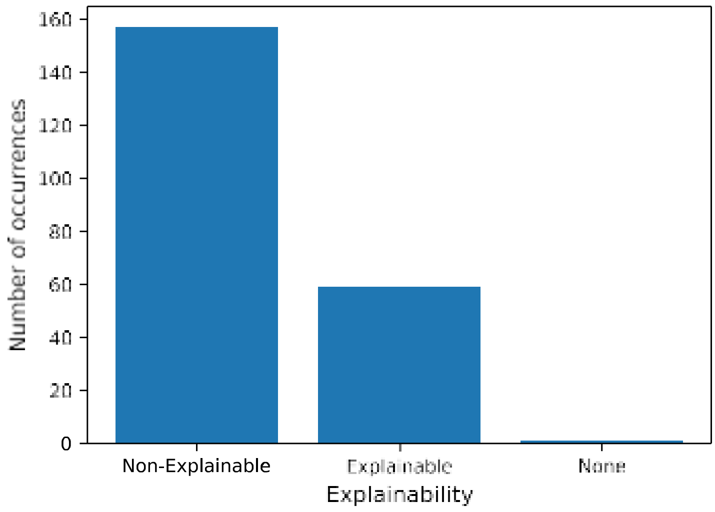

/ig. 17. Histogram of algorithm explainability across the proposed DTs.

trees or linear regression models, while non-explainable networks are for convolutional neural networks or recurrent neural networks. 59 (27.19%) of the used algorithms are explainable, while 157 (72.4%) are less explainable. This demonstrates that algorithmic explainability is an often overlooked factor which is crucial for a human operator to understand the predictions of the AI component.

5. Discussion

Low number of studies clearly demonstrating a feedback loop and using live data

We identified multiple gaps in the literature at the intersection of artificial intelligence and digital twins based on the results of this literature review. Firstly, most papers in the field do not define nor demonstrate a feedback loop, i.e. the virtual-to-physical connection, that utilizes the output of the digital twin. This is one of the main criteria that define a digital twin [14] since it allows the virtual system to not only simulate but also influence the real-world system. Additionally, most studies that were included in our search did not base their system on real-time data, which is another key capability of a digital twin. This is aligned with the findings of a recent systematic literature review by Wooley et al. [49], who investigate the difference between simulations and digital twins, while not specifically searching only for studies in the field of AI-DT. The authors state that an issue common to many studies is that traditional simulations are termed digital twins, despite not defining or demonstrating real-time data synchronization between virtual and physical systems. We made similar observations, with many articles showing a feedback loop in schematic diagrams, but not providing details on it. In our results, only one paper presents a digital twin with an AI component, that operates with live data and clearly demonstrates a feedback loop [48].

Low number of proposed digital twins with a human in the loop

A small subset of the analyzed papers integrated a human as a key part of the AI-DT system. It has been shown that human-in-the- loop machine learning can improve both model performance and explainability [50], two desirable traits for an AI-DT system. This is a possibility for future research work to expand upon, by either improving past research or proposing new model architectures that integrate a human. In the set of papers found in the literature search where a human interacted with the DT system, the human took different roles, such as operator, doctor, rule editor, or production manager. The current state of the art lacks a clear definition of possible roles for humans within an AI-DT system, which is applicable across different domains, providing human knowledge at different points in the system. Human-in-the-loop systems are key for Industry 5.0, which is often characterized as human-centric in the literature [51].

Lack of digital twins modeling multiple objects

The majority of papers included in our review propose a digital twin for a single type of object. We found a research gap, with only a small minority of analyzed studies combining digital twins of multiple object types. The next logical step is connecting multiple digital twins in a system of systems-based approach. Tao et al. [52] have suggested hierarchical levels of digital twins in manufacturing, where a system of systems is the highest level of abstraction. On top of the requirements for building digital twins, interoperability, data synchronicity, and communication [53] between the DTs need to be considered to design a system of systems with multiple DTs.

Processes are modeled almost exclusively in manufacturing

The digital twins in the surveyed papers typically model objects, with a smaller portion modeling processes. We found that processes are almost exclusively modeled in the domain of manufacturing. This is related to the emergence of Industry 4.0, which has accelerated the adoption of digital twins in the manufacturing sector. By modeling processes in other application domains with an AI-DT system, future work can address this gap. Some domains, however, may naturally be based on fewer processes and more objects and are, therefore, more inclined to replicate these objects. A prime example of this is construction, where the objects of interest are tunnels [54], buildings [55], or wind turbines [36]. Modeling the process of constructing a structure is less common, which also reflects in our data, although digital twins of the construction phase, that do not employ ML techniques, have been proposed [56].

Reinforcement learning is not used in some application domains

Reinforcement learning in digital twins has seen considerable attention in some domains, such as automotive, networking, and transportation, where the digital twin is used as a simulation environment for the RL agent. However, in other domains, namely aeronautics, agriculture, construction, and healthcare, none of the studies analyzed in our review make use of reinforcement learning. Due to its nature, reinforcement learning is suited to solve optimization problems that have different problem settings from classification or regression tasks. A digital twin can support a reinforcement learning solution by providing an accurate, low-cost simulation environment, while the RL benefits the DT by learning to solve an optimization problem.

Reinforcement learning-based studies do not work with live data

We found that none of the papers applying reinforcement learning within digital twins use real-time data for their digital twin. Additionally, past work based on RL methods uses synthetic data more often than real data. This confirms that digital twins using RL are often proposed in a lab setting with synthetic data. Considering the definitions of digital twin, digital shadow, and digital model given by Jones et al. [1], a digital twin without live data should instead be termed a digital model. A direction for future research is to investigate how well digital twins using RL integrate with a real-world, real-time data setting compared to the synthetic lab setting.

Most modeling approaches are high-level and do not follow modeling languages

Digital twins in the field of AI-DT are often modeled with schematic models, without following conventional modeling approaches. The majority of proposed models display a high-level overview of the digital twin, i.e., providing a shallow level of detail. More detailed models, such as a system architecture, are shown less commonly, while none of the found papers describe a conceptual model following a modeling language. This showcases the need for more detailed modeling approaches in the AI-DT community, by moving away from schematic models to detailed, in-depth models of the proposed system, which would contribute to a better understanding of the AI-DT system and the ability to increase the efficiency of its design, development, and maintenance.

Lack of model explainability and algorithmic explainability

Most of the articles taken into account in this review do not focus on explainability, both on a model level regarding the digital twin and on the algorithmic level of the AI component. Since digital twins are systems that are designed for real-world scenarios, making both explainability on a model level and on an algorithm level highly desirable properties. To achieve model-level explainability, more detailed, in-depth modeling approaches can be used to describe the proposed digital twins. As deep learning models are inherently not explainable, using post-hoc explainability methods in combination with them can provide algorithmic explanations while also maintaining predictive performance. Alternatively, white-box algorithms, such as decision trees, can be integrated with a DT to achieve the same goal. However, the explanations from post-hoc methods differ from white-box explanations, often adding uncertainty [57].

Variety of tasks and machine learning algorithms used in digital twins

In the analyzed studies, deep learning, reinforcement learning, and traditional machine learning algorithms see consistent usage. This highlights that the problems tackled by digital twins are diverse and require the use of different ML algorithms. From our analysis, it becomes clear that most digital twins are proposed for a unique type of problem, while only a few problems are common across multiple studies. The diversity of problems that digital twins are designed for is aligned with the fact that the AI component in digital twins pursues different tasks, such as optimization, classification, or regression. Overall, AI in digital twins typically works with supervised learning or reinforcement learning, and only rarely with unsupervised learning. A possible reason for this is that digital twins mainly work with labeled data while being less like to perform exploratory tasks on unlabeled data. Additionally, most publications in the field test their algorithms' performance, providing concrete evidence of their predictive power.

RQ1: How can an artificial intelligence component improve the processing functionality of a digital twin regarding its tasks?

In this review, we found that AI components can fulfill a variety of tasks within a digital twin. On the algorithmic level, tasks such as optimization, classification, and regression are commonly seen. Digital twins with an AI component can tackle a broader range of problems, which require predictive functionality, with most proposed twins focusing on a unique problem. An example of a problem that can be tackled by integrating AI with the DT is the forecast of temperatures in a building, allowing adaptive control of heating and ventilation. Depending on the task of the DT, the AI component fulfills its role as a predictive algorithm, relying on the data of the DT to make predictions. Further, without an AI component, certain tasks, such as forecasting of temporal data streams, could not be tackled by a DT on its own, showing that the integration of AI with DT opens the possibility to approach new problem types. It became clear that in the literature, a number of different ML approaches are used for the AI component. This demonstrates that different ML approaches are suited for different tasks, and due to the given variety of tasks, a similar variety in algorithms can be observed.

RQ2: Which modeling approaches are used for digital twins employing artificial intelligence in the literature?

AI-DT systems are commonly modeled with high-level schematic models. Most research work in the field focuses on the implementation and evaluation of the AI component, with little focus being given to the modeling part of the DT. Conceptual models are not present in the literature analyzed in this review, which proves that the field is in need of more detailed, in-depth models for digital twins integrating an AI component. Overall, about 20% of the studies provide a system architecture for the proposed digital twin, which is modeling the DT at a lower level, giving more attention to detail and more clearly specifying the functionality of the system.

RQ3: Are digital twins with artificial intelligence components demonstrating a bidirectional connection between physical and virtual representations?

The bidirectional connection between physical and virtual representation consists of two parts: Firstly, the physical-to-virtual connection, which is the data stream that supplies the digital twin; Secondly, the virtual-to-physical connection, which is the feedback loop from the DT to the physical system. Most publications in the field work with historical data stemming from a real system, while only a small fraction works with live data, providing an automated data flow between physical and virtual systems. This illustrates that, although most proposed DTs are based on real data, the physical-to-virtual connection still follows a manual procedure. The virtual-to-physical connection is demonstrated by a small number of papers, where a feedback loop to the real system is shown. Although articles commonly show a visionary feedback loop in schematic models, for most articles, this feedback loop is not implemented in practice, and a manual information flow between digital twin and real-world system is necessary. In summary, the majority of digital twins presented in the analyzed papers either lacked an implementation of the physical-to-virtual connection or did not demonstrate a virtual-to-physical connection.

6. Conclusion

The convergence of Artificial Intelligence and Digital Twin technologies represents a transformative shift in how physical systems are designed, monitored, and optimized across various domains. This review has explored the foundational principles, AI methodologies, and diverse application areas of AI-powered digital twins, emphasizing their potential to drive efficiency, resilience, and autonomy in complex systems. While significant progress has been made, key challenges remain—particularly in ensuring data integrity, managing computational complexity, achieving interoperability, and maintaining security and privacy. Addressing these challenges will require continued interdisciplinary collaboration and innovation in AI algorithms, system architectures, and data governance strategies. Looking ahead, the evolution of AI-powered digital twins will play a critical role in shaping the future of smart industries, personalized healthcare, sustainable cities, and beyond. As research in this field matures, AI-driven digital twins are poised to become central enablers of intelligent, adaptive, and context-aware systems in the digital era.

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