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Opinion

What Is the Role of AI for Digital Twins?

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Abstract: The concept of a digital twin is intriguing as it presents an innovative approach to solving numerous real-world challenges. Initially emerging from the domains of manufacturing and engineering, digital twin research has transcended its origins and now finds applications across a wide range of disciplines. This multidisciplinary expansion has impressively demonstrated the potential of digital twin research. While the simulation aspect of a digital twin is often emphasized, the role of artificial intelligence (AI) and machine learning (ML) is severely understudied. For this reason, in this paper, we highlight the pivotal role of AI and ML for digital twin research. By recognizing that a digital twin is a component of a broader Digital Twin System (DTS), we can fully grasp the diverse applications of AI and ML. In this paper, we explore six AI techniques—(1) optimization (model creation), (2) optimization (model updating), (3) generative modeling, (4) data analytics, (5) predictive analytics and (6) decision making—and their potential to advance applications in health, climate science, and sustainability.

Keywords: digital twin; artificial intelligence; data science; machine learning; sustainability; climate science

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Citation: Emmert-Streib, F. What Is the Role of AI for Digital Twins? *AI* **2023**, *4*, 721–728. https://doi.org/10.3390/ai4030038

Academic Editor: Gianni D'Angelo

Received: 1 July 2023
Revised: 7 August 2023
Accepted: 25 August 2023
Published: 1 September 2023

1. Introduction

Recently, there has been a growing fascination with the concept of a digital twin, as evidenced by the exponential rise in publications dedicated to this topic [1]. The fundamental idea behind a digital twin can be succinctly described as follows: "The Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" [2]. While originally used for problems in industrial engineering and manufacturing, there is more and more interest in all fields of science including architecture, health, immunology, climate science, material science, sustainability and urban planning [3–6].

So far, most publications about digital twins and their application focus on the role of simulations and modeling [7–11]. This is understandable, as the simulation model serves as an essential component within every digital twin model, which is complemented by a mechanism that facilitates constant updates between the physical object being modeled. In contrast, in this paper, we want to highlight the role of artificial intelligence (AI) and machine learning (ML) for Digital Twins Systems.

When conducting a literature search, one finds that the importance of AI and ML for digital twin research has been noted [12–14]. For instance, in [15], the value of combining a digital twin with AI methods has been highlighted. This includes the use of AI within the digital twin model itself and the support of the entire analysis system. Furthermore, there are extensions one can find for specific application domains. An example is the studies by [16–18] where the crucial role of AI for the internet of things (IoT) and Cyber–Physical System (CPS) in Industry 4.0 is discussed. Yet a different aspect of AI methods is discussed in [19], where a digital twin has been utilized for creating sufficiently large training datasets to improve the training of machine learning models. This brief overview shows that despite the recognized importance of AI and machine learning for digital twin research, dedicated discussions of this topic are very limited. In [20], this has been succinctly described as "the published literature on using ML for Digital Twin is scanty".

In this paper, we fill this gap by providing a dedicated discussion of the role of AI for digital twin research. To achieve this, we begin by examining the framework of a Digital Twin System, of which a digital twin is a part. This approach enables us to uncover the diverse functions of AI as the connecting thread among the structural components that comprise a Digital Twin System. Consequently, AI becomes intricately amalgamated with the architecture of a Digital Twin System, forming an integral part of its operation. Hence, the study of a digital twin and AI is inherently intertwined in order to attain the optimal outcome.

This paper is organized as follows. Next, we discuss main contributions AI can make to study digital twins. Then, we highlight specific opportunities of AI approaches to contribute to digital twin research. Finally, we present a discussion and a summary of the main points.

2. Contributions of AI for Digital Twins

In order to clarify the role of AI for digital twins in general, we want to emphasize that a digital twin is a component of a Digital Twin System (DTS) [21]; see Figure 1. In this figure, we use the term virtual entity in analogy to physical entity which is realized via a digital twin. Hence, both virtual entity and digital twin are used synonymously [22,23]. It is important to discuss applications of AI for a DTS, as its architecture provides a direct platform to showcase the diverse contributions that AI can offer.

From the structural architecture of the Digital Twin System, one can identify 6 different AI techniques. We call these techniques AI-DTS (AI for Digital Twin Systems):

1. AI: optimization (model creation);
2. AI: optimization (model updating);
3. AI: generative modeling;
4. AI: data analytics;
5. AI: predictive analytics;
6. AI: decision making.

In the following, we provide a brief discussion for each AI-DTS. From the visualization in Figure 1, one can see that the physical entity to be modeled can come from a wide range of applications including engineering, manufacturing, health, urban development, sustainability or climate science (top of the figure). Based on this, a digital twin is created corresponding to a dynamical system which is implemented via a computer simulation capturing essential features of the physical entity. Usually, this involves additional data from which, e.g., parameters of the digital twin are estimated. This is an optimization process we call 1.AI: optimization (model creation). Importantly, there is another optimization step involving AI which is different from the first one. The second optimization step ensures the synchronization of the digital twin and its physical counterpart during its operation. This leads to the optimization of the updating mechanism of the digital twin (called 2.AI: optimization (model updating); see Figure 1). To avoid confusion between the optimization processes of model creation and model updating, we provide information about their usage in brackets. This reveals also a problem discussed in detail later: namely, that particular AI techniques are not unique for AI-DTS. In this case, optimization techniques have multiple purposes for a DTS.

The third AI involvement is given by generative modeling. An example thereof is generative adversarial networks (GANs) [24]. In general, a GAN can be used to generate data with charateristics learned from large-scale data. In certain cases, a GAN may be used to replace or complement a traditional simulation model, e.g., based on differential equations, agent-based models or boolean networks [25,26]. That means AI does not only help optimize a simulation model, but it can constitute the simulation model itself. In Figure 1, this is called 3.AI: generative modeling. For reasons of clarity, we would like to add that a simulation model is not equipped with an updating mechanism whereas a digital twin is a mathematical model with an updating mechanism.

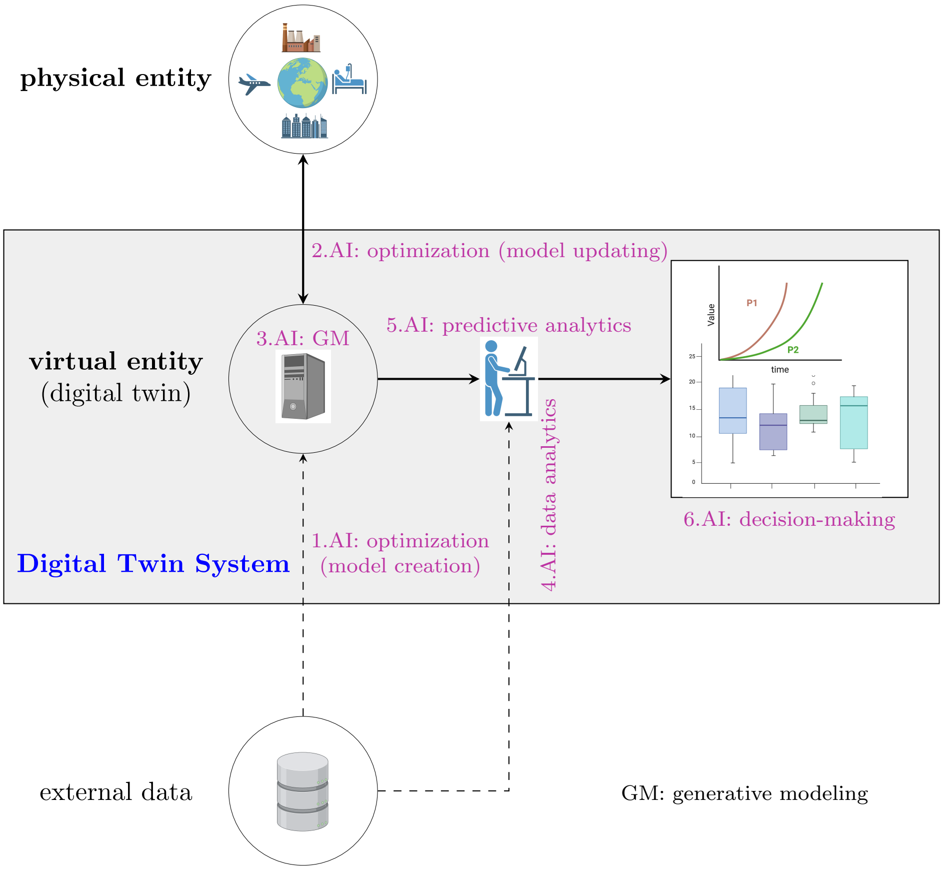

Figure 1. Digital Twin System (shown as a gray rectangle) with an interface to a physical entity and external data [21]. Its structural architecture allows highlighting the various contributions that AI can offer for optimizing the outcomes of a Digital Twin System. These contributions are highlighted from 1.AI to 6.AI.

At first glance, the fourth and fifth AI applications may seem similar to each other, since both techniques are utilized for a data analysis. However, the sources of the data for such an analysis are entirely different. Specifically, one can distinguish two data sources, one from external data and one from the digital twin. For this reason, one can also distinguish two types of data analysis where we call the first *data analytics* and the second *predictive analytics* (called 4.AI: data analytics and 5.AI: predictive analytics; see Figure 1). It should be clear that the source of data has a crucial influence on the interpretation of an analysis; hence, 4.AI: data analytics and 5.AI: predictive analytics provide complementary means, and the technique we discuss next aims at their integration.

Specifically, the sixth AI application, called 6.AI: decision making, is used for the summarizing of all individual results achieved up to this point and for decision making. This step integrates everything together and produces a quantitative or qualitative summary that can be seen as the ultimate output of a DTS. Examples for a quantitative summarization are visualizations in the form of plots or charts. Depending on the presentation of such visualizations, these figures could be even interactive, allowing the exploration of results. Considering the fact that the results of a DTS can be complex, such an interactive exploration is very beneficial, especially for the usage of non-AI experts, e.g., managers, clinicians or administrators. A particular realization for such an interactive visualization could be a dashboard.

For the quantitative integration, different approaches can be utilized, including multi-task learning, multi-label learning or transfer learning [27–29]. These learning paradigms provide flexibility in addressing different tasks, such as classification or regression, where deep learning could be used for learning the underlying models [30]. In addition, for decision making under uncertainty, it has been shown that graphical models [31] provide promising approaches. Considering that the decision-making capability of a DTS is crucial and practically the most important aspect of the entire system, it is foreseeable that this problem will receive significant attention in the coming years.

3. Highlighting AI Opportunities

In the following, we discuss specific AI techniques that offer immense potential for advancing the fields of health, climate science, and sustainability. The purpose for selecting these three application domains is to showcase a few examples rather than providing an exhaustive list of topics. In the following, we will not only highlight promising opportunities that exist in these domains but also delve into the challenges that must be addressed for their successful implementation.

3.1. Challenges for Health

For the health sciences, generative adversarial networks (GANs) offer a promising solution to address the challenges of limited data in the context of health-related issues often encountered in medical and clinical studies.

In general, generative adversarial networks (GANs) are a type of AI model that consists of two main components: a generator and a discriminator. The purpose of a GAN is to generate new data that resemble a given training dataset. The generator is responsible for creating new samples, such as images that mimic the patterns and characteristics of the training data. It starts by generating random noise and then gradually refines it to produce more realistic samples. The goal of the generator is to generate samples that are indistinguishable for the discriminator from real samples.

Currently, generative adversarial networks (GANs) have been utilized for the image generation from various medical imaging modalities, including X-rays, fMRI, and CT scans [32–34]. These imaging technologies hold significant clinical relevance and are widely employed in hospitals and therapeutic institutions for purposes such as diagnoses, treatment planning, and prognoses. Hence, the advancement of generative adversarial networks (GANs) and their integration with a Digital Twin System holds tremendous potential for the progress of personalized medicine and precision medicine [35,36].

Another important area that holds significance for AI is the virtual testing of medical hypotheses [37]. Conventionally, a medical drug needs to be tested in clinical trials to demonstrate its safety and efficacy while also ruling out potential side effects. These trials are crucial in providing evidence-based data that regulatory authorities rely on to evaluate the drug's suitability for widespread use. Instead, digital twin models of patients could be used to perform a virtual testing enabling to study "What-If" questions with respect to the administration of medical drugs. This is also another example where AI can help in decision making.

3.2. Challenges for Climate Science

Digital twins for climate science is another emerging field of application, where advanced computational models are coupled with sensory data to simulate and predict complex climate phenomena [38]. The European Destination Earth (DestinE) initiative targets as priority areas climate change adaptation and disaster risk management for weather extremes [39]. However, further domains where a digital twin holds potential is in the realm of El Niño/Southern Oscillation (ENSO) predictions and global surface temperature forecasts [40–43].

One of the challenges of these problems lies in the evaluation of model predictions. For instance, evaluating predictions related to the global surface temperature of the Earth [44], which encompasses averaged sea surface and land surface temperature, poses significant challenges due to the absence of controlled laboratory conditions. This means that already obtaining summarized measurements requires approaches outside an ordinary laboratory setting [45].

Additional examples were statistical and AI methods, which are needed to enhance our knowledge are due to limited spatial coverage, and missing data and temporal discontinuities. Limited Spatial Coverage: Estimating the global surface temperature requires measurements from various locations across the Earth's surface. However, the spatial coverage of temperature measurement stations can be uneven, leading to challenges in obtaining representative and comprehensive data. Missing Data and Temporal Discontinuities: Gaps in temperature data, either due to equipment malfunctions, data collection errors, or missing observations, pose challenges for estimating the global surface temperature. Additionally, temporal discontinuities caused by changes in measurement practices or station relocations can introduce complexities in creating continuous and reliable temperature records.

3.3. Challenges for Sustainability

Sustainability spans across multiple domains and sectors with the objective of advancing environmental conservation, social equality, and economic viability. Energy sustainability is an important part of it involving the transitioning to cleaner and renewable energy sources, improving energy efficiency, and reducing pollution [46]. This includes also the development and adoption of sustainable energy systems, such as solar and wind power [47]. A problem with renewable energies is that they can be intermittent and dependent on weather conditions. For example, solar energy is not available during the night, and wind energy can be highly fluctuating within minutes [48,49]. This variability in energy generation can pose challenges for ensuring a consistent and reliable power supply. Additionally, the deployment and integration of renewable energy technologies necessitate significant infrastructure redesign and grid upgrades to effectively accommodate their variable output. This is where AI can contribute, e.g., by advanced predictive analytics for non-stationary time-series prediction [50,51].

Furthermore, AI can play a crucial role in optimizing the update process of a digital twin for wind energy generation. These digital twin models, which encompass wind farms or individual wind turbines, rely on real-time data collected from sensors installed on the physical turbines or obtained from weather forecasting systems [52]. By utilizing these data, the digital twin provides a dynamic and interactive representation of the wind energy system, allowing operators to monitor and analyze its performance in real time. However, keeping the digital twin up to date with the latest data presents a significant challenge. This is where AI techniques can come into play. AI algorithms can be employed to automate the collection, integration, and processing of data from various sources. These algorithms can efficiently handle large volumes of real-time data, ensuring that the digital twin remains accurate and reflects the current state of the wind energy system.

4. Discussion

When discussing a digital twin, commonly, their applications are showcased or challenges regarding their technological implementation are thematized. Instead, in this paper, we present a methodological perspective of digital twin research, emphasizing the pivotal role of AI. It is important to clarify that in this paper, the term AI is used in a broad sense, encompassing methods from data science, machine learning, and statistics. These fields collectively represent the domain of "learning from data". Additionally, we would like to emphasize that a digital twin is an integral component of a Digital Twin System, which serves as the central entity that allows underscoring the significance of AI.

One problem with discussing specific methods from AI is that their usage is usually not unique. That means that in general, one methodology can be used for more than one of the 6 AI-DTS techniques given by:

1. AI: optimization (model creation);
2. AI: optimization (model updating);
3. AI: generative modeling;
4. AI: data analytics;
5. AI: predictive analytics;
6. AI: decision making.

For example, deep learning models can be used as models of digital twins for generative adversarial networks (GANs), data analytics, predictive analytics and decision making. Other examples are parameter estimations that can be used for the optimization of model creation and model updating, and classification methods that find application in data analytics and predictive analytics tasks.

These examples clearly illustrate that the six AI-DTS techniques are superior in categorizing the contributions of AI, surpassing the methodological categories of AI. Consequently, any discussion on this matter should be closely tied to the functional relations of a Digital Twin System. Merely examining a digital twin in isolation, without taking into account the Digital Twin System, falls short in providing the comprehensive perspective needed for a thorough evaluation of the role AI can assume in the entire system. This emphasizes the crucial role of the Digital Twin System in laying the groundwork for various AI techniques in digital twin research.

Finally, we would like to note that traditionally, each of the 6 AI-DTS techniques is studied independently. This means that the outcome of each technique can be seen as a result of an analysis, and there are thousands of publications focused on these respective fields [53–56]. However, taken together, this gives a glimpse of the intricate complexity of a Digital Twin System that functions only properly if all of its parts are synchronized in an optimal manner. Hence, the difficulty level to establish a working Digital Twin System is even higher than that of its constituting AI components.

5. Conclusions

The digital twin concept is fascinating because it aims at elevating ordinary simulation models to the next level. However, this comes at a cost that involves approaches beyond simulation models. In this paper, we emphasize *six* AI-DTS techniques that are crucial for optimizing a Digital Twin System. These techniques include (1) optimization (model creation), (2) optimization (model updating), (3) generative modeling, (4) data analytics, (5) predictive analytics and (6) decision making. Hence, without the incorporation of AI and related fields such as data science, machine learning and statistics, the full potential of the digital twin concept cannot be realized.

Overall, our discussion required an abstract, theory-driven view on the digital twin concept, which stands in contrast to the conventional application- or technology-driven approaches. In general, we think that such a theoretical view is more fruitful in identifying conceptual directions because it offers a holistic perspective. In our case, this approach has enabled us to recognize the Digital Twin System as the fundamental and central functional unit.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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