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Chen, C., Wagg, D. and Girolami, M. (2026) Principles for applying AI to address the challenges of scaling digital twins. Digital Twins and Applications, 3 (1). e70025. ISSN: 2995-5629

https://doi.org/10.1049/dgt2.70025

Digital Twins and Applications

WILEY

The Institution of Engineering and Technology

REVIEW OPEN ACCESS

Principles for Applying AI to Address the Challenges of Scaling Digital Twins

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Received: 13 May 2025 | **Revised:** 17 December 2025 | **Accepted:** 12 January 2026

Keywords: artificial intelligence | deep reinforcement learning | digital twins | intelligent digital twins

ABSTRACT

Despite the increasing affordability of data processing and storage and the enhancement of artificial intelligence (AI) and digital technologies in recent years, scalability and adoption continue to be a challenge when it comes to digital twins (DTs). Common challenges that are often cited include the effort of designing and building DTs, high customisation, the cost to operate and maintain DTs, interoperability between DT components and DTs, and the extensive analysis and effort required to turn DT outputs into useful insights. AI has seen significant advancements and growth lately, driven by the release of popular AI products such as ChatGPT, Google Gemini and DeepSeek's R1. Many of the recent developments have the potential to address the challenges of scaling and adopting DTs. This paper examines the intersection of AI and DTs and explores how AI can be used to address some of the challenges of scaling and adopting DTs. It concludes with a set of principles that aim to apply to most DT applications, regardless of use case or industry, and proposes AI methods and techniques that can potentially be used for each principle. These principles are (1) reduce effort, cost and/or time; (2) optimise resource and system efficiency; (3) improve interaction and outcome and (4) improve interoperability, reusability and maintainability.

1 | Introduction

A digital twin (DT) is a virtual representation of a physical object, system or process. It is updated regularly with real-world data to mirror its physical counterpart and provides insights that can inform the real world. Unlike static digital models or shadows, DTs have a dynamic bi-directional relationship with their physical twins. The National Academies uses the following definition for a DT, modified from a definition published by the American Institute of Aeronautics and Astronautics [1]:

> A digital twin is a set of virtual information constructs that mimics the structure, context, and behaviour of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value. The bidirectional interaction between the virtual and the physical is central to the digital twin.
>
> [2]

Abbreviations: AGI, artificial general intelligence; AGV, automated guided vehicles; AI, artificial intelligence; AIAA, American Institute of Aeronautics and Astronautics; AR, augmented reality; BADA, Base of Aircraft Data; BESS, battery energy storage systems; BIM, building information model; BR, breathing rate; CDE, common data environment; CNC, computer numerical control; CPS, cyber-physical system; DL, deep learning; DRAO, dynamic resource allocation Optimisation; DRL, deep reinforcement learning; DT, digital twin; DTN, digital twin network; EPC, energy performance certificate; EV, electric vehicle; FRS, front running simulations; GAN, generative adversarial network; GenAI, generative AI; GGS-CNN, grasps-generation-and-selection convolutional neural network; GPT, generative pretrained transformer; HR, heart rate; IDT, intelligent digital twin; IoT, Internet of things; LLM, large language model; ML, machine learning; NASA, National Aeronautics and Space Administration; NLP, natural language processing; NMT, neural machine translation; PPC, production planning and control; RAG, retrieval-augmented generation; RL, reinforcement learning; SOC, state of charge; TCN, temporal convolution network; UAV, unmanned aerial vehicle; VAE, variational auto-encoder.

This research focuses on DTs that add value to the real world by either improving or informing the real world, and because of this focus, this research assumes increasing the adoption of DTs has the potential to deliver benefits to society and its users, and therefore, increasing adoption and the scalability of DTs is desirable. For the purposes of this work, we define a DT as follows:

> A digital representation of a physical object(s), system(s), behaviour(s) or process(s) that is capable of taking input from real world data, with the intention of being updated according to its physical twin when needed, of which its output has the potential to improve or inform the real world.

This definition highlights key points that have not been covered in previous literature:

1. It retains DTs' potential to process bi-directional data but does not index on the timeliness of the data. This is due to the recognition that real-life DTs often are not updated in real-time nor do they need to. For a DT to provide value and serve its intended purpose, it only needs to be updated as regularly as it needs to.
2. It highlights how the input data need not come from the physical twin, but can be any data directly obtained or derived from the real world. This is in recognition of the fact that in many use cases, the input data can be derived data, historical data or the physical twin may be fairly static, but its surrounding variables, such as environmental parameters, may be changing. The effect of those changes on the physical twin can be simulated to a good degree of accuracy on a simulated model without requiring sensory input from the physical twin; therefore, there is no reason to limit the data input of a DT to its physical twin.
3. It does not bind a DT to a 'model' form. For a DT to serve its purpose, it can be a collection of algorithms or equations. The shape or form of the DT is irrelevant to the user as long as the output has the potential to improve or inform the real world.
4. Importantly, this definition emphasises the usefulness of the DT in improving and informing not just its physical twin, but the real world, which the author believes better reflects the motivation behind why organisations adopt DTs. If DTs are to be adopted more widely, it must improve or inform the real world, and as a result, benefit the organisation or society that is using it.

Russell and Norvig defined AI as 'the study of [intelligent] agents that receive precepts from the environment and take action' [3]. AI has seen significant advancements in recent years with the launch of popular AI products, particularly relating to large language models (LLMs) and generative AI (GenAI). The virtual nature of DTs creates an ideal sandbox for AI to explore different scenarios, actions and strategies and learn from the outcomes without changing or impacting its physical twin. Akroyd et al. [4] refers to this as the 'base world' and the 'parallel world', where the 'base world' refers to the up-to-date DT that incorporates real-time data and is a true reflection of the physical twin, whereas the 'parallel worlds' support the intelligent exploration of alternative designs and configurations without affecting the base world. The connection between the DT and its physical twin forms a link between the digital and physical world, its output informing its physical twin and the real world in the shape of insights, recommendations and predictions. This relationship between the digital and physical worlds creates the perfect feedback loop for an AI to test, validate and improve. The result can then be applied to its physical twin to achieve the goal of the DT, whether that is to improve operational effectiveness, mitigate a design failure, optimise in-life support or the many other use cases DTs have been found useful. For the purposes of this work, we define the application of AI in DTs as 'intelligent digital twins' (IDTs). IDTs in this research refers to DTs that incorporate AI techniques and methods to achieve a DT's intended purpose in a faster, cheaper, more efficient or more effective manner. This research focuses on the practical aspects of adopting DTs and therefore, assumes the purpose of a DT is the problem it is solving, and if that can be done in a faster, cheaper or better way, the author theorises this will improve DT scalability and adoption.

2 | Selected Literature Review of AI for Digital Twinning

In 2024, Tao et al. identified the under-utilisation of AI as a key reason DTs have not matured as rapidly as other digital technologies. The concept of a DT was first introduced by Michael Grieves in October 2002 during a presentation on product lifecycle management (PLM) at the Society of Manufacturing Engineering Conference in Troy, Michigan. The concept was popularised by the National Aeronautics and Space Administration (NASA) by using it in spacecraft simulations. The term 'digital twins' was not introduced until a lot later by Shafto et al. in 2010. In comparison, the exact origin of the term 'intelligent digital twin (IDT)' is harder to pinpoint. The term likely emerged in 2017–2018 as the capabilities of DT with the advancements in AI, and the desire for more sophisticated and autonomous DTs naturally led to the addition of 'intelligent' to emphasise these advanced capabilities. One early use of the term was found in 2018 where Grieves defined the term intelligent digital twin (IDT) as a combination of AI and DTs, contrary to the conventional DT that is a passive repository of the physical product information that is available, the IDT is proactive, it presents appropriate information based on the contextual cues of the product status and has the potential to play a critical role in the product lifecycle.

Kreuzer et al. conducted a systematic literature review in 2024 on AI in DTs and found an increasing amount of research in this space between 2018 and 2023 summarised below. The literature shows a clear and accelerating trend towards the integration of AI with DTs as evidenced by the dramatic increase in publications between 2018 and 2022. This literature review primarily draws upon the findings presented by Kreuzer et al. in their 2024 review. Additional works were identified by extending the search beyond Kreuzer et al.'s research and by exploring other pertinent publications.

Between 2018 and 2020, we find a number of research focused on discovery and experimenting with applying AI in DTs. Most of the research was high-level and based on trial and error, focusing on exploration without a clear end goal in mind. This included applying deep learning (DL) techniques with simulation models [5], combining AI and smart technologies for dynamic resource allocation [6], ideas for IDT high level architectures and potential methods of applying AI to DTs, such as the anchor-point method and agent-based method [7]. 2019–2020 saw the emergence of the terminology 'hybrid digital twins' [8, 9], combining physics-based modelling with data-driven modelling and proposed opportunities where AI can help improve data-driven DTs.

2020 saw continued interest in applying AI in DTs, moving away from discovery and experimentation, with increasing focus on using AI to improve DTs, examples such as continuous and automated calibration of a DT model [10], increasing battery lifetime [11], leveraging synthetic data using Generative Adversarial Network (GAN) [12], while others [13, 14] took an opposite approach and sought to use DTs to improve AI. It is worth noting that although most of the research during this period attempts to use AI to improve DTs, most of the improvements have been based on the assumption that the outcome will make DTs better. There has been little to no effort in taking a more systematic approach to identifying the areas that need improving, defining what 'a better DT' means and the reasons why addressing those issues are desirable.

As AI research and techniques matured, its potential applications in DTs became an increasingly recognised opportunity, with more sophisticated architectures for IDT [15] and more advanced applications, such as using probabilistic modelling to achieve predictive DTs [16]. Lv et al. [17] discussed the application status of DTs in aerospace, intelligent manufacturing, unmanned vehicles and smart city transportation and reviewed the current challenges and topics for future opportunities. The work discovered that combining DTs and AI results in improvements in aerospace flight detection simulation, failure warning, aircraft assembly and unmanned flight saving 80% of time and cost in the virtual simulation testing of autonomous vehicle driving and greatly improving testing accuracy.

As indicated in Table 1, the number of publications on AI in DTs grew significantly between 2021 and 2022, possibly due to the maturing and productisation of AI and encouraged by public interest in GenAI and LLMs sparked by the launch of Midjourney and ChatGPT in 2022. Broader applications of AI in various DT use cases emerged, including wellbeing and health [18], electric vehicles (EV) [19] and autonomous vehicles [20–23], pharmaceutical manufacturing [24], train delay predictions [25], structural health monitoring [26], building energy consumption [27], battery systems [28], food waste monitoring [29], network cybersecurity [30] and wind farm monitoring and power generation predictions [31]. This period not only sees continued interest in applying AI to DTs to drive efficiencies and improvements but also applications broadened to newer and wider industries. At this stage, the method of applying AI to DTs does not seem to vary by industry. The methods are industry-agnostic, and there has been no particular method or framework that stands out as particularly useful to one industry over another.

TABLE 1 | Number of publications on AI in digital twins according to ref. [32].

Year	2018	2019	2020	2021	2022
Number of publications	1	9	11	40	85

2022 sees more methodological research centred on the challenges on DTs. Rather than applying AI in DTs and observing the outcome, several researches start from the challenges of DTs and then explore the various ways of how AI can potentially address those challenges. Following on from his proposal of the term IDT, Grieves further elaborated on the definition of IDTs in 2022 and proposed that compared to traditional DTs, IDTs are active, online, goal seeking and anticipatory. Several literature examined the use of training robots through AI-infused DTs [33–36]. Huang et al. [37] highlights the limitations of the scalability and fidelity of DTs in manufacturing due to heterogeneous data and modelling uncertainties. It proposes a novel approach to overcoming these deficiencies by leveraging AI on aggregated data throughout the product development process. Bondoc et al. [38] investigated the impact of effective sensor placement for smart maintenance and points out how too many sensors can jeopardise the ability of the DT to perform effectively, resulting in resource wastage. It also describes how a surplus of sensors and large datasets can increase the computational costs, highlighting a challenge of operating DTs that is often overlooked in existing research. Almasan et al. [39] explored using AI in DT networks (DTN) and proposed a general architecture of the DTN and the main ML technologies that can enable the proposed DTN architecture.

Entering 2023, we observe a trend in deploying more sophisticated AI techniques to enhance DTs, such as neural networks, k-nearest neighbour and symbolic regression algorithms [40]. Several literature explored the concept of time-evolving and self-evolving DTs using DRL and hybrid DTs [41, 42], where through the bidirectional flow of time-varying physical and virtual data, the DT system can self-learn and update autonomously, significantly reducing the need for additional sensor systems, data analysis and manual processing. Emmert-Streib [43] highlighted the pivotal role of AI and ML for DT research and explored six AI techniques—(1) optimisation (model creation), (2) optimisation (model updating), (3) generative modelling, (4) data analytics, (5) predictive analytics and (6) decision making—and their potential to advance applications in health, climate science and sustainability. Zayed et al. [44] and Tuhais et al. [45] proposed development tools for integrating AI with DTs and pointed to several opportunities for future work.

2023 and 2024 continues to see more research in using AI to drive efficiencies and improvements in DTs [46, 47], with more focus shifting to the human, which is a positive change, including the human-machine interface [48] and context-aware DTs that take advantage of combining several technologies such as Internet of things (IoT), DT and blockchain [49]. This echoes Medina et al.'s extensive literature review in 2025 to identify and summarise research themes of product DTs. They concluded the top technical challenges of DT implementation are as follows:

development cost, data interpretability, usability and human interaction, cyber-physical fusion and connectivity, computational demand and scalability, data acquisition and data management and interoperability and data continuity. They identified a key shortcoming in DT literature: There is currently little evidence and understanding of DT value, highlighting the need to focus more on the human, its experience and the value it perceives it is deriving from the DT in order to improve adoption.

Kreuzer et al. [32] conducted an in-depth review of 149 papers related to AI applications in DTs. They found that there is very little research on applying AI to DTs that use real-time data and even fewer on bidirectional data. Most research focuses on the high-level architecture of DTs, or a simplified DT, and typically works with supervised learning or reinforcement learning. It recommends future DT research to focus on using real-time and bidirectional data to separate itself from simulation models.

Wagg et al. [50] pointed out that '...learning and reasoning are highly desirable functions that we often want to build into our digital twins applications, meaning that AI techniques are very important in this respect.' and proposed using AI to deal with complexity and uncertainty that are common features of DT applications. Moreover, finally, in the preprint by ref. [51], the authors highlighted the value of autonomous decision-making within DT. The research applied DRL to DTs to autonomously make optimal, sequential decisions in complex, dynamic and changing environments, resulting in self-improving systems that enhance the decision-making processes.

Between 2018 and 2024, we see a growing interest in applying AI to DTs to drive efficiencies, the increasing use of sophisticated AI techniques, with a gradual shift towards focusing on the human experience and user value in the last couple of years. This work aims to build on previous literature and examine the potential applications of AI for the purpose of addressing the challenges of scaling and adopting DTs.

Looking across the selected literature, there is a general consensus on the necessity and benefit of infusing DTs with AI, leading to the concept of IDTs. The field has evolved from initial high-level trial-and-error experimentation between 2018 and 2020, to more sophisticated problem-focused applications. Although early research focused on discovery and experimentation (e.g., [5]), this shifted around 2020 to 2022 to using AI to specifically improve DTs and vice versa. The applications of AI in DTs have also broadened across industries, with the underlying methods and frameworks pointing to potentially industry-agnostic techniques. There is also an increasing deployment of advanced AI techniques, including deep learning (DL), generative adversarial networks (GAN) [12], probabilistic modelling [16] and deep reinforcement learning (DRL) for time-evolving self-improving systems [43, 53].

Although the interest in AI-infused DTs has been increasing, there remains several critical gaps that must be addressed for the field to achieve maturity and widespread adoption.

1. Lack of validation through real-time bi-directional data: A fundamental gap, highlighted by ref. [32], is the limited research on applying AI to DTs using real-time and bi-directional data flow. Most research still relies on high-level architecture, simplified DTs and basic supervised or reinforcement learning on nonreal-time data. This prevents current IDTs from differentiating themselves from traditional simulation models and fulfilling the promise of a truly 'online' and 'active' system, which requires closing the feedback loop with the physical entity.
2. Ill-defined value proposition and optimisation goals: There is a notable gap in systematically defining what constitutes a 'better DT' and the demonstrable value derived from it. Existing literature is based on the assumption that the research outcome will improve DTs without attempting to measure the quantifiable or qualifiable value of the improvement. A significant shortcoming is the lack of evidence and understanding of the DT value it provides to the user [52].
3. Human-centric focus: Despite a recent shift since 2023 towards topics, such as human–machine interface and context-aware DTs [48, 49], the field still lacks sufficient focus on the human experience. Medina et al. [52] identified usability, human interaction and data interpretability as paramount technical challenges, suggesting that current IDT research has overlooked the human element essential for successful implementation and widespread adoption.
4. Lack of industry diversity: Most of the examples from existing research focus on the manufacturing and infrastructure industries, with a distinct lack of examples from other industries such as healthcare, transport and energy. This reflects a potential bias and skewed research outcomes towards certain industries and may be an area for future research.

3 | Principles for Applying AI in Digital Twins

Existing research has cited various barriers to DT adoption. Tao et al. lists the reasons why overall maturity of DTs remains relatively low in their research, despite advancements in industrial applications in recent years [53]. These are as follows:

- Insufficient recognition;
- Overly simplistic or overly complex models;
- Incomplete data or inappropriate data;
- Inadequate human interaction;
- Underused AI;
- Security of digital assets;
- Lack of common industrial software and platforms;
- Fragmentary standards in industry;
- Ethical and privacy concerns.

On the other hand, Medina et al.'s research in 2025 concluded the top technical challenges of DT implementation are as follows:

- Development cost;
- Data interpretability;
- Usability and human interaction;
- Cyber-physical fusion and connectivity
- Computational demand and scalability;
- Data acquisition and data management
- Interoperability and data continuity;
- Lack of understanding of DT value.

This research builds on Tao et al.'s theory that underused AI is one of the pitfalls of DT applications and examines how AI can be used to address some of the challenges identified by Tao et al. and Medina et al. This author believes in the value DTs bring to the world and so the main goal of this research is to improve DT adoption and scalability. This research proposes a set of principles for what AI can achieve when it's applied in DTs, with the intent of addressing the common scaling and adoption challenges of DTs. This work does not attempt to test or validate the principles. It is the author's intent to validate the principles using real-life DTs in future research.

3.1 | Principle 1 Reduce Effort, Cost and/or Time

One of the common reasons why DTs are expensive to build is due to the effort and cost required to collect data and simulate various hypothetical scenarios. Some examples of how AI can reduce effort, cost and/or time to design and build a DT are:

1. **Generating synthetic data:** A key cost driver for DTs is generating accurate data and running what-if analyses. DTs can collect data from various sources, some examples include the sensors installed on the physical twin, manually inputted data, derived data or a combination of multiple sources. Physical and virtual sensors are costly to deploy and maintain, whereas manual input is labour-intensive and hard to scale. When the physical twin changes, the DT needs to be updated, often requiring site visits for measurements, parameter adjustments, partial reconstructions and updates to documentation and interfaces. GANs are AI frameworks where two neural networks compete to generate data resembling its training dataset. In DTs, GANs can create synthetic data with similar statistical profiles, resulting in enhanced model granularity at a lower cost. Gayon-Lombardo et al. [12] demonstrated this by using a DC-GAN to produce realistic n-phase microstructural data, reducing computational costs for electrochemical simulations. This approach is valuable when synthetic data are representative of real data, especially for consistent data profiles or well-known patterns such as shopping trends, website traffic and infrastructure wear and tear. DTs can also be built entirely from synthetic data during early-stage research and have been found to outperform physics based models [54], although the reliability and repeatability of such models will require further validation.
2. **Determining the right level of accuracy:** Overly complex models and reliance on big data can unnecessarily drive up computational costs. Although many assume it is desirable to have highly accurate DTs, real-world constraints often make this impractical. Achieving the perfect accuracy requires vast data, real-time updates and high computational power, resulting in diminishing returns of the DT. For critical applications, such as medical DTs, high accuracy may be useful, but in most use cases, it is sufficient to match the fidelity of the DTs to the required accuracy of the application. Finding the right balance of accuracy and data is a common challenge. Leveraging AI-generated synthetic data can help determine whether higher accuracy justifies the added cost of sensors and computational demands.
3. **Expedite the design and development process:** AI can accelerate the design and development of DTs. Kastelein et al. [55] showed that in fluid dynamics, AI can calibrate models, analyse early test data and predict unperformed tests, eliminating the need for manual tuning of complex systems, such as natural gas flow metres, resulting in a 25% reduction in development time.
4. **Hybrid modelling:** AI can expedite DT development by adopting a data-driven approach alongside traditional physics-based modelling. Physics-based models rely on natural laws, sensor data and manual input to create replicas, a process that is time-consuming, costly and labour-intensive. In contrast, data-driven models use system data to identify relationships between inputs and outputs, reducing the need for manual scanning and measurement. A hybrid approach combines both methods, using AI to fill gaps where physical modelling is impractical or costly. By training the data-driven part of the DT with a combination of synthetic data, derived data and sensory data, the cost of simulation, optimisation and uncertainty analysis can be expected to be reduced, lowering the overall cost of developing and operating DTs [41].

3.2 | Principle 2 Optimise Resource and System Efficiency

Current DT deployments often overlook computing costs during the procurement and development stage. Studies by refs. [22, 23], Zhou et al. [56] and Ferriol-Galmes et al. [57] demonstrate how AI-driven DTs can optimise its computing resource management. As DTs become more granular, their data processing demands grow, driving up computing costs, where operating costs rise with complexity and data volume.

1. **Dynamic resource allocation:** Over 30% of cloud expenditure is wasted due to inefficient resource allocations [58]. DTs require frequent updates, driving up operational costs. Traditional DT architectures use fixed

resource allocation. AI can optimise this by identifying inefficiencies and dynamically allocating resources as needed, automatically increasing computing resource allocation during peak traffic, reducing usage during off-peak hours and auto-scaling based on predicted demand. Zhang et al. [6] proposed a dynamic resource allocation optimisation (DRAO) model, which showed promising results. AI can also detect anomalies, spot bottlenecks and recommend optimal system configurations, ensuring efficient, cost-effective and adaptable DT operations.

2. **Predict computing demands based on business need:** AI can be used to predict query volumes, forecast usage trends and recommend flexible cloud subscription plans instead of traditional fixed plans. AI can also forecast changing business needs and adjust DTs' own resources accordingly. For instance, higher accuracy may be required near the end-of-life for ships or production lines, during peak traffic hours or for vehicles in unpredictable driving conditions. AI can fine-tune DT parameters in real-time, dynamically switching between sensors or computer monitoring in areas or times of the day where it is less relevant, focusing resources where needed and reducing unnecessary processing, thereby cutting costs and extending hardware lifespan.

3. **AI as a data orchestrator:** AI has the potential to optimise data storage, organisation and retrieval based on access frequency and retention needs. It can autonomously package filtered data for different services, provision and manage IoT devices and orchestrate DTNs. Unlike traditional preprogramed orchestrator layers, AI can act as a 'learning orchestrator dynamically deciding which endpoints receive specific outputs, learning from the outcome, and adapting as needs change. This shift from human-driven orchestration to AI-driven logic boosts efficiency and resource optimisation. Although current AI computing costs may limit adoption, falling prices—driven by AI-dedicated chips and cheaper models such as OpenAI's GPT-4 Turbo or DeepSeek's R1—make this approach increasingly viable.

3.3 | Principle 3 Improve Interactions and Outcomes

AI can enhance the user experience with DTs by making interactions more intuitive and personalised, similar to AI-powered search engines, photo editors and chat agents. These applications can improve how users engage with DTs and optimise their outcomes.

1. **Improve user experience:** As GenAI applications, such as Google's Gemini and OpenAI's ChatGPT, gain popularity, it is possible that users may interact solely with digital interfaces, such as assistants or smart devices, without ever being aware of the DTs' existence. What matters to users is the output of the DT, which improves or informs its physical counterpart, not the DT itself. AI can enhance user interaction by abstracting complex knowledge and presenting recommendations in natural language or in a visual format. It can also visualise the outcome of various simulated scenarios, enhancing the visual impact of the DT's insights and recommendations.

2. **Visualisation and summarisation:** AI can help visualise the insights and predictions from DTs, presenting them in an intuitive format, such as executive summaries, presentations or motion videos. For example, a before-and-after image could highlight the impact of an outdated production line on earnings and stock price, aiding financial planning and decision-making. As a result, AI enhances the DTs' role as a powerful tool for informed decision-making.

3. **Reduce training and skills requirements:** DTs often require domain expertise, which limits their use to trained and skilled experts. AI can act as the 'interpreter' between input and output data, enabling a DT to understand input in the form of natural language and present the output in an intuitive way, removing the need for users to understand the technical details of the DT or acquire domain knowledge to be able to interpret and make use of the DTs output. This enhances the user experience, reduces training overhead and broadens impact.

4. **Decision input and decision-making:** DTs today often rely on humans to analyse outputs, make decisions and take actions, which is especially challenging in DTNs that involve multiple DTs. This human intervention slows down the process. In the future, AI is expected to play a bigger role in data analysis, decision-making, logic and reasoning and executing actions. Research is already exploring AI-driven recommendations for physicians [59], and there are AI agents that are capable of setting goals, making decisions and taking actions.

3.4 | Principle 4 Improve Interoperability, Reusability and Maintainability

1. **Ontology alignment and translation:** Interoperability between DTs, particularly in DTNs, is a major challenge due to differing definitions, data models and taxonomies across units from various vendors and industries. This presents a challenge both between DTs but also within the DT itself where the output from one component may not be the right input. This complexity is further compounded by language differences. AI can help bridge these gaps by interpreting discrepancies, aligning data models and creating a common data environment (CDE), making DTs more adaptable across various use cases. Additionally, AI can dynamically update terminologies and libraries across the network, improving reusability, maintainability and reducing the cost and time needed for development and deployment [60].

2. **Reuse, review and generate code and components:** Although still relatively immature, in the future, AI can potentially be used to conduct code and component similarity analysis between DT systems to identify similar code

or modules, suggest reusable components and reduce development effort. AI can also improve the maintainability of DTs via software techniques that are common today, such as automated code review and code refactoring, bug detection, quickly identifying and even predicting downtime and recommending solutions based on what it has learnt in the past.

3. **Self-evolving and self-improving DTs:** DTs′ usefulness requires it to stay up to date to the changes in the real world. Tracking and reflecting the changes in the DT manually is labour-intensive, but AI can predict and update DTs over time, reflecting physical changes with minimal effort. By integrating reinforcement learning (RL) and DRL, DTs can autonomously evolve based on environmental changes and human feedback. This allows for more accurate predictions, such as wear and tear of machinery, or weather impacts on structures. Future applications may include self-evolving DTs for disease prediction and healthcare optimisation.

4 | Discussion

Various AI methods and techniques exist today, and more are being discovered as the race to artificial general intelligence (AGI) continues. Table 2 below provides a summary of the four principles, their potential use cases and AI methods and techniques that are available today that could be used to validate each principle. Table 2 is then further illustrated in Figure 1. Most techniques focused on optimisation and predictive analytics have demonstrable existence in current research, whereas those focused on natural language interaction and autonomous code and ontology generation are still in earlier more speculative stages.

The integration of AI into DTs presents a range of significant limitations and risks that necessitate comprehensive mitigation strategies. The primary concerns revolve around data privacy and security. Since DTs frequently aggregate highly sensitive, real-time operational and personal data, particularly in sectors, such as critical infrastructure or healthcare, unauthorised access or data breaches could lead to devastating outcomes. The second major challenge is the inherent risk associated with reliance on data-driven models: model biases and algorithmic opacity. If the training datasets used to develop the AI component are unrepresentative or flawed, the system will perpetuate and potentially exacerbate existing biases, resulting in inequitable or suboptimal decision-making in the real world, such as flawed resource allocation or inaccurate predictive maintenance schedules. Lastly, the development of IDTs, which exhibit autonomous goal-seeking behaviour [51, 63], introduces complex ethical and legal questions. Specifically, issues of accountability and control arise when a self-evolving system makes a sequential decision that leads to an unforeseen negative physical consequence, making it exceptionally difficult to ascertain responsibility and effectively manage these sophisticated human–machine interactions. Furthermore, managing the complexity and ensuring the trustworthiness of these autonomous, self-evolving systems represents a major ongoing research and development hurdle.

5 | Conclusion

This work has outlined four fundamental principles for applying AI in DTs with the express purpose of addressing the persistent challenges of scalability and adoption. Despite significant advancements in AI, including the emergence of GenAI and LLMs, DTs continue to struggle with high development cost, computational demand, limited interoperability and inadequate human–machine interaction. The core argument presented here is that strategic application of AI, guided by the four principles detailed in this work, is the key to unlocking the full potential and value of the IDTs.

The principles provide a strategic framework for future research and implementation, moving the field beyond unsystematic experimentation towards targeted improvements. For instance, Principle 1 leverages techniques, such as GANs and VAEs, to create synthetic data, directly mitigating the costly and labour-intensive process of data collection and sensor deployment. Principle 2 focuses on economic viability, utilising optimisation techniques, such as time series analysis and clustering, to ensure that increased complexity and data processing do not result in prohibitive computing costs and resource wastage.

Crucially, the framework addresses the critical gaps identified in the current literature, particularly the lack of a human–centric focus and an ill-defined value proposition. Principle 3 directly tackles this by proposing the use of NLP, LLMs, and RAG to abstract complex technical knowledge, making the DT's insights and recommendations intuitive and accessible to general users. This is essential for improving usability and deriving demonstrable value. Principle 4 prepares DTs for complex, large-scale deployment by using DRL and AI-driven similarity analysis to achieve self-evolving and reusable components, overcoming challenges such as heterogeneous data models and fragmented standards in the industry.

Although the opportunities are significant, the discussion also underscored the non-trivial risks inherent in this integration, including challenges related to data privacy, model biases and the ethical accountability of autonomous goal-seeking IDTs. Future research must not only focus on the validation of these four principles through real-world case studies and prototypes but also on establishing a rigorous validation framework that measures key metrics, such as time savings, user satisfaction and cost reduction, thereby proving the tangible value of AI infusion. Ultimately, the pathway to achieving widespread DT maturity lies in the balanced and strategic application of intelligent technologies, guided by a clear understanding of what 'a better DT' means from the perspective of adoption and societal benefit.

TABLE 2 | Summary of the principles of applying AI in DYTs with the intention of increasing adoption and scalability.

Principle	Potential use cases	Potential AI methods and techniques	Nascent applications
Reduce effort, cost and/or time	1. Generating synthetic data	*Synthetic data generation:* Techniques, such as *GenAI* (e.g., GPT, *GANs* or *variational auto-encoders (VAEs)*), can produce synthetic data, reducing the reliance of DTs on sensor data. This, in turn, lowers the time, effort and cost of DT development. When applied to hybrid DTs, this approach helps balance the use of both sensor and synthetic data.	The validity of predictive analytics in DTs has been previously established. However, the potential for GenAI, VAEs, DRL and synthetic data to enhance DTs remains largely unexplored and is currently speculative.
	2. Determining the right level of accuracy	*Agent-based modelling:* This method allows for the study of how microlevel behaviours and interactions lead to emergent, macrolevel patterns in systems. This can be valuable for determining the appropriate level of accuracy for DTNs and reduce design and development time.	
	3. Expedite the design and development process	*Accelerated what-if analysis:* By combining *predictive analytics* and *Monte Carlo simulations* with AI-generated synthetic data, we can quickly forecast outcomes in various scenarios, leading to faster and more cost-effective real-time results. Although predictive analytics does not strictly require AI, AI enhances its capability to deliver real-time or near real-time predictions.	
	4. Hybrid modelling	*Rules engines:* These enable DTs to process incoming data based on predefined logic, triggering actions or updating the DT's state in real-time. This results in immediate evaluation, dynamic state updates and automated actions. When combined with *DRL*, rules engines can potentially result in DTs that can self-evolve based on predefined logic or desired outcomes, thereby reducing design and development time.	
Optimise resource and system efficiency	1. Dynamic resource allocation 2. Predict computing demands based on business need 3. AI as a data orchestrator	AI can significantly enhance cloud resource optimisation and system efficiency by applying techniques such as time series analysis, classification, regression, clustering and DL. Specifically: • ***Time series analysis*** can forecast resource demand and detect anomalies, a valuable application for DTs. • ***Classification*** (predicting discrete labels) and ***regression*** (predicting continuous quantities) are both effective for anticipating resource needs and optimising their allocation. • ***Clustering*** helps group similar workloads and uncover usage patterns in computing resources. By leveraging these combined techniques, AI facilitates cost reduction and performance improvement in cloud environments. Commercial AI solutions, such as Google's optimisation AI, already demonstrate these benefits in cloud resource optimisation. We anticipate similar positive outcomes when these solutions are applied to DT cloud infrastructures.	DL-enabled DTs and AI's ability in acting as a 'learning orchestrator' that dynamically decides which endpoints receive specific outputs and adapts its logic remains largely unproven.
Improve interaction and outcome	1. Improve user experience	Improving the DT user experience can be achieved through several advanced AI techniques. ***Natural language processing (NLP) and LLMs*** are particularly effective as evidenced by current research on developing conversational agents for DT interfaces [61]. These agents enable users to interact with DTs using natural language, removing the need	Multimodal outputs, adaptive and customisable interfaces and LLMs' and RAG's ability to provide reliable

(Continues)

Principle	Potential use cases	Potential AI methods and techniques	Nascent applications
		for specialised domain expertise or technical understanding of the twin's functionality.	and consistent results are still to be proven.
	2. Visualisation and summarisation	Further enhancing the performance of LLMs, *retrieval-augmented generation (RAG)* can refine outputs by referencing authoritative knowledge bases. This approach leverages resources, such as domain-specific dictionaries, legal frameworks or internal company databases, to provide accurate and contextually relevant information. When combined with AI agents, RAG facilitates quick and efficient self-service, answering queries, offering support and even independently completing tasks.	
		3. Reduce training and skills requirements	
4. Decision input and decision-making		Other valuable techniques include ***recommendation systems*** *and adaptive interfaces*, which personalise the DT experience by adapting to individual user requirements. These systems can also suggest improvements by comparing the DTs' use case with publicly available data. *GenAI* can generate various outputs, such as video and audio summaries or executive briefs, and customise recommendations to suit different audiences. Additionally, *image recognition* can analyse visual data to provide relevant information or assistance, though its application in building and updating DTs is still in its early stages [62].	
Improve interoperability, reusability and maintainability	1. Ontology alignment and translation	AI offers promising solutions for DT interoperability through its capabilities in *similarity analysis*, automated code and data translation via techniques such as *neural machine translation (NMT)*. This approach minimises the need for manual coding efforts and facilitates smooth information flow between different systems. Additionally, AI can analyse DTs to identify and resolve inconsistencies in interfaces, aligning them with established standards and best practices, potentially automating this process. Leveraging *NLP* techniques, AI can also unify diverse taxonomies into a cohesive common ontology library.	Using AI to conduct similarity analysis and suggest reusable components, automated code and data translation are yet to be proven. DTs ability to leverage DRL to self-evolve also remains an emerging and speculative space.
	2. Reuse, review and generate code and components	Current tools, such as Microsoft's CoPilot, already demonstrate AI's ability to perform code reviews, prediction and generation. Future advancements are expected to bring more sophisticated tools and techniques for performing similarity analysis across various DT use cases and their corresponding codebases.	
	3. Self-evolving and self-improving DTs	*DRL* can significantly reduce the effort required to maintain alignment between digital and physical twins by enabling self-learning and self-evolving DTs. This involves using AI to forecast the physical twin's evolution over time and mirroring these changes in its digital counterpart. DRL integrates function approximation with target optimisation, mapping states and actions to their resulting rewards, which empowers models and software to learn goal achievement. When applied to DTs, DRL leads to models that can evolve and learn autonomously. As described in the first principle, the combination of *rule engines* and DRL has the potential to create DTs that self-evolve based on predefined logic or desired outcomes, thereby cutting down design and development time.	

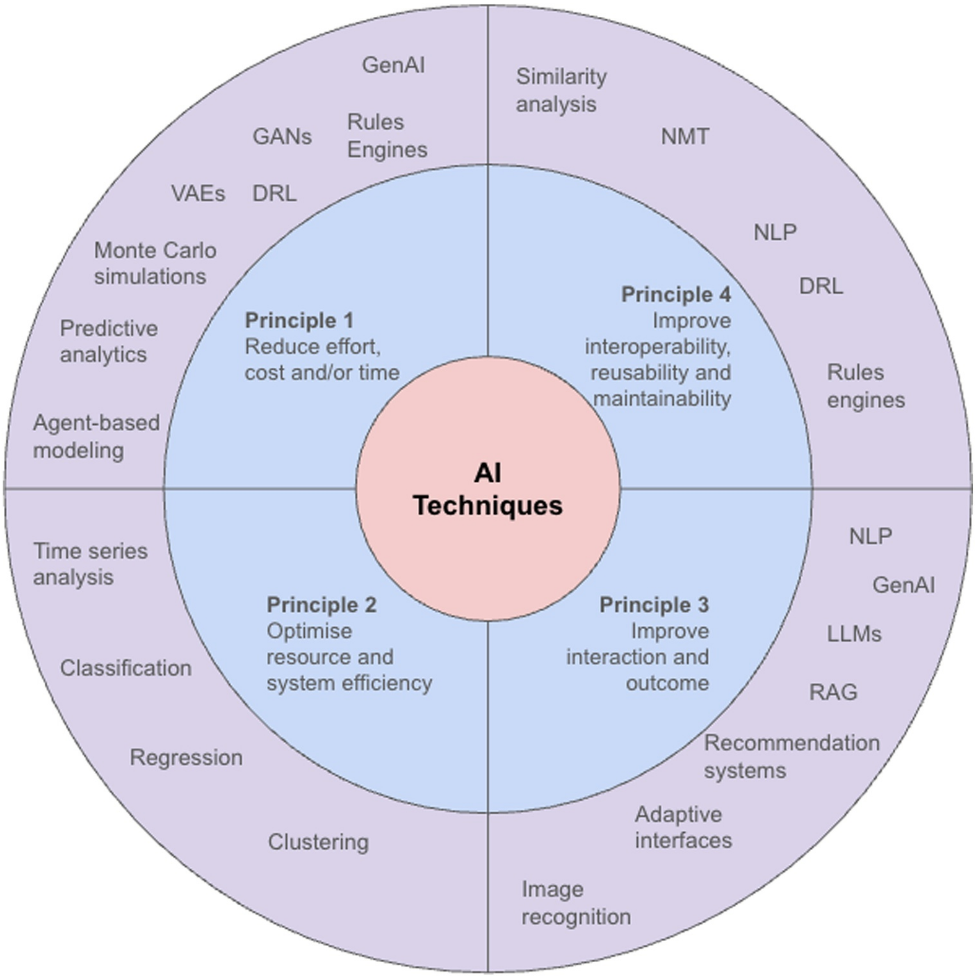

FIGURE 1 | Mapping AI techniques to the four principles.

Author Contributions

Christine Chen: conceptualisation, methodology, data curation, data visualisation, writing – original draft, writing – review and editing. **David Wagg:** writing – review and editing. **Mark Girolami:** writing – review and editing. All authors approved the final submitted draft.

Acknowledgements

We are grateful for the guidance and mentoring of M. Enzer.

Funding

The authors have nothing to report.

Ethics Statement

The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

Conflicts of Interest

The lead author is currently employed full time at Google and serves pro-bono on the Women in Digital Pivot strategy steering board at the City of London Corporation. The author declares no conflict of interest as the research is fully self-funded and does not represent or relate to the author's work at both organisations. The remaining authors declare no conflicts of interest.

Data Availability Statement

No data and code were produced as part of this research.

Impact Statement

This work proposes four principles for applying AI in digital twins for the purpose of improving digital twin scalability and adoption. AI can enhance digital twins in many ways, but when it is used to address scaling and adoption challenges, it should achieve at least one of the four principles. This work describes the four principles, provide examples and potential applications as well as some AI methods and techniques that can be used for each principle.

References

1. *Digital Twin: Definition & Value – an AIAA and AIA Position Paper* (Aerospace Industries Association, 2020), https://www.aia-aerospace.org/publications/digital-twin-definition-value-an-aiaa-and-aia-position-paper/.

2. National Academies of Sciences, Engineering, and Medicine, *Foundational Research Gaps and Future Directions for Digital Twins* (National Academies Press, 2024), https://doi.org/10.17226/26894.

3. S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach* (Pearson Education, Limited, 2010), http://ebookcentral.proquest.com/lib/cam/detail.action?docID=5495854.

4. J. Akroyd, S. Mosbach, A. Bhave, and M. Kraft, "Universal Digital Twin—A Dynamic Knowledge Graph," *Data-Centric Engineering* 2 (2021): e14, https://doi.org/10.1017/dce.2021.10.

5. M. Uzun, M. Umut Demirezen, E. Koyuncu, and G. Inalhan, “Design of a Hybrid Digital Twin Flight Performance Model Through Machine Learning,” *2019 IEEE Aerospace Conference* (2018): 1–14, https://doi.org/10.1109/AERO.2019.8741729.

6. H. Zhang, G. Zhang, and Q. Yan, “Dynamic Resource Allocation Optimization for Digital Twin-Driven Smart Shopfloor,” in *2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)*, (IEEE, 2018), 1–5, https://doi.org/10.1109/ICNSC.2018.8361283.

7. B. A. Talkhestani, T. Jung, B. Lindenmann, et al., “An Architecture of an Intelligent Digital Twin in a Cyber-Physical Production System,” *Automatisierungstechnik* 67, no. 9 (2019): 762–782, https://doi.org/10.1515/auto-2019-0039.

8. F. Chinesta, E. Cueto, E. Abisset-Chavanne, J. L. Duval, and F. El Khaldi, “Virtual, Digital and Hybrid Twins: A New Paradigm in Data-Based Engineering and Engineered Data,” *Archives of Computational Methods in Engineering* 27, no. 1 (2018): 105–134, https://doi.org/10.1007/s11831-018-9301-4.

9. A. Rasheed, O. San, and T. Kvamsdal, “Digital Twin: Values, Challenges and Enablers From a Modeling Perspective,” *IEEE Access* 8 (2020): 1–22012, https://doi.org/10.1109/ACCESS.2020.2970143.

10. R. Ward, R. Choudhary, A. Gregory, et al., “Continuous Calibration of a Digital Twin: Comparison of Particle Filter and Bayesian Calibration Approaches,” *Data-Centric Engineering* (2020), https://doi.org/10.48550/arXiv.2011.09810.

11. B. Wu, W. D. Widanage, S. Yang, and X. Liu, “Battery Digital Twins: Perspectives on the Fusion of Models, Data and Artificial Intelligence for Smart Battery Management Systems,” *Energy and AI* 1 (2020): 100016, https://doi.org/10.1016/j.egyai.2020.100016.

12. A. Gayon-Lombardo, L. Mosser, N. P. Brandon, and S. J. Cooper, “Pores for Thought: Generative Adversarial Networks for Stochastic Reconstruction of 3D Multi-Phase Electrode Microstructures With Periodic Boundaries,” *Npj Computational Materials* 6, no. 1 (2020): 1–11, https://doi.org/10.1038/s41524-020-0340-7.

13. K. Alexopoulos, N. Nikolakis, and G. Chryssolouris, “Digital Twin-Driven Supervised Machine Learning for the Development of Artificial Intelligence Applications in Manufacturing,” *International Journal of Computer Integrated Manufacturing* 33, no. 5 (2020): 429–439, https://doi.org/10.1080/0951192X.2020.1747642.

14. D. Allison, P. Smith, and K. McLaughlin, “Digital Twin-Enhanced Methodology for Training Edge-Based Models for Cyber Security Applications,” *2022 IEEE 20th International Conference on Industrial Informatics (INDIN)* (2022): 226–232, https://doi.org/10.1109/INDIN51773.2022.9976095.

15. N. Jazdi, B. Ashtari Talkhestani, B. Maschler, and M. Weyrich, “Realization of AI-Enhanced Industrial Automation Systems Using Intelligent Digital Twins,” *Procedia CIRP* 97 (2021): 396–400, https://doi.org/10.1016/j.procir.2020.05.257.

16. M. G. Kapteyn, J. V. R. Pretorius, and K. E. Willcox, “A Probabilistic Graphical Model Foundation for Enabling Predictive Digital Twins at Scale,” *Nature Computational Science* 1, no. 5 (2021): 337–347, https://doi.org/10.1038/s43588-021-00069-0.

17. Z. Lv and S. Xie. 2021. Artificial Intelligence in the Digital Twins: State of the Art, Challenges, and Future Research Topics, https://digitaltwin1.org/articles/1-12.

18. I. Al-Zyoud, F. Laamarti, X. Ma, D. Tobón, and A. El Saddik, “Towards a Machine Learning-Based Digital Twin for Non-Invasive Human Bio-Signal Fusion,” *Sensors* 22, no. 24 (2022): 9747, https://doi.org/10.3390/s22249747.

19. K. S. S. Alamin, Y. Chen, E. Macii, et al., “A Machine Learning-Based Digital Twin for Electric Vehicle Battery Modeling,” in *2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS)*, (IEEE, 2022), 1–6, https://doi.org/10.1109/COINS54846.2022.9854960.

20. D. Chen and Z. Lv, “Artificial Intelligence Enabled Digital Twins for Training Autonomous Cars,” *Internet of Things and Cyber-Physical Systems* 2 (2022): 31–41, https://doi.org/10.1016/j.iotcps.2022.05.001.

21. Y. Gao, C.-H. Chen, D. Chang, S. Chen, and X. T. Song, “Machine Learning and Digital Twin-Based Path Planning for AGVs at Automated Container Terminals,” *Advances in Transdisciplinary Engineering* (2022), https://doi.org/10.3233/ATDE220672.

22. B. Li, Y. Liu, L. Tan, H. Pan, and Y. Zhang, “Digital Twin Assisted Task Offloading for Aerial Edge Computing and Networks,” *IEEE Transactions on Vehicular Technology* 71, no. 10 (2022): 10863–10877, https://doi.org/10.1109/TVT.2022.3182647.

23. J. Li, D. Pang, Yu Zheng, X. Guan, and X. Le, “A Flexible Manufacturing Assembly System With Deep Reinforcement Learning,” *Control Engineering Practice* 118 (2022): 104957, https://doi.org/10.1016/j.conengprac.2021.104957.

24. R. Barriga, M. Romero, D. Nettleton, and H. Hassan, “Advanced Data Modeling for Industrial Drying Machine Energy Optimization,” *Journal of Supercomputing* 78, no. 15 (2022): 16820–16840, https://doi.org/10.1007/s11227-022-04498-0.

25. S. Chen, X. Chen, M. Zhou, et al., “Digital Twin Based Train Delay Prediction System: Design and Realization,” in *2022 41st Chinese Control Conference (CCC)*, (IEEE, 2022), 305–310, https://doi.org/10.23919/CCC55666.2022.9901773.

26. H. V. Dang, M. Tatipamula, and H. X. Nguyen, “Cloud-Based Digital Twinning for Structural Health Monitoring Using Deep Learning,” *IEEE Transactions on Industrial Informatics* 18, no. 6 (2022): 3820–3830, https://doi.org/10.1109/TII.2021.3115119.

27. L. Kannari, K. Piira, H. Bistrom, and T. Vainio, “Energy-Data-Related Digital Twin for Office Building and Data Centre Complex,” *2022 37th Conference on Design of Circuits and Integrated Circuits (DCIS)* (2022): 01–05, https://doi.org/10.1109/DCIS55711.2022.9970040.

28. N. Kharlamova, C. TrÃ¦holt, and S. Hashemi, “A Digital Twin of Battery Energy Storage Systems Providing Frequency Regulation,” in *2022 IEEE International Systems Conference (SysCon). 2022 IEEE International Systems Conference (SysCon)*, (IEEE, 2022), 1–7, https://doi.org/10.1109/SysCon53536.2022.9773919.

29. T. Y. Melesse, M. Bollo, V. Di Pasquale, F. Centro, and S. Riemma, “Machine Learning-Based Digital Twin for Monitoring Fruit Quality Evolution,” *Procedia Computer Science* 200 (2022): 13–20, https://www.sciencedirect.com/science/article/pii/S1877050922002095?via%3Dihub.

30. A. Mozo, A. Karamchandani, S. Gómez-Canaval, M. Sanz, J. I. Moreno, and A. Pastor, “B5GEMINI: Ai-Driven Network Digital Twin,” *Sensors* 22, no. 11 (2022): 4106, https://doi.org/10.3390/s22114106.

31. M. Fahim, V. Sharma, T.-Vu Cao, B. Canberk, and T. Q. Duong, “Machine Learning-Based Digital Twin for Predictive Modeling in Wind Turbines,” *IEEE Access* 10 (2022): 14184–14194, https://doi.org/10.1109/ACCESS.2022.3147602.

32. T. Kreuzer, P. Papapetrou, and J. Zdravkovic, “Artificial Intelligence in Digital Twins—A Systematic Literature Review,” *Data & Knowledge Engineering* 151 (2024): 102304, https://doi.org/10.1016/j.datak.2024.102304.

33. W. Hu, C. Wang, F. Liu, X. Peng, P. Sun, and J. Tan, “A Grasps-Generation-and-Selection Convolutional Neural Network for a Digital Twin of Intelligent Robotic Grasping,” *Robotics and Computer-Integrated Manufacturing* 77 (2022): 102371, https://doi.org/10.1016/j.rcim.2022.102371.

34. S. Liu, Y. Lu, P. Zheng, H. Shen, and J. Bao, “Adaptive Reconstruction of Digital Twins for Machining Systems: A Transfer Learning Approach,” *Robotics and Computer-Integrated Manufacturing* 78 (2022): 102390, https://doi.org/10.1016/j.rcim.2022.102390.

35. Y. Liu, He Xu, D. Liu, and L. Wang, “A Digital Twin-Based Sim-to-Real Transfer for Deep Reinforcement Learning-Enabled Industrial

Robot Grasping," *Robotics and Computer-Integrated Manufacturing* 78 (2022): 102365, https://doi.org/10.1016/j.rcim.2022.102365.

36. Z. Liu, C. Yuan, Z. Sun, and C. Cao, "Digital Twins-Based Impact Response Prediction of Prestressed Steel Structure," *Sensors* 22, no. 4 (2022): 1647, https://doi.org/10.3390/s22041647.

37. B. Huang, D. Wang, H. Li, et al., "Network Selection and QoS Management Algorithm for 5G Converged Shipbuilding Network Based on Digital Twin," in *2022 10th International Conference on Information and Education Technology (ICIET)*, (IEEE, 2022), 403–408, https://doi.org/10.1109/ICIET55102.2022.9779044.

38. A. E. Bondoc, M. Tayefeh, and A. Barari, "Employing LIVE Digital Twin in Prognostic and Health Management: Identifying Location of the Sensors," *IFAC-Papers On Line* 55, no. 2 (2022): 138–143, https://doi.org/10.1016/j.ifacol.2022.04.183.

39. P. Almasan, M. Ferriol-Galmes, J. Paillisse, et al., "Digital Twin Network: Opportunities and Challenges," *arXiv* (2022), https://doi.org/10.48550/arXiv.2201.01144.

40. A. Chiurco, M. Elbasheer, F. Longo, L. Nicoletti, and V. Solina, "Data Modeling and ML Practice for Enabling Intelligent Digital Twins in Adaptive Production Planning and Control," *Procedia Computer Science* 217 (2023): 1908–1917, https://doi.org/10.1016/j.procs.2022.12.391.

41. L. Edington, N. Dervilis, A. Ben Abdessalem, and D. Wagg, "A Time-Evolving Digital Twin Tool for Engineering Dynamics Applications," *Mechanical Systems and Signal Processing* 188 (2023): 109971, https://doi.org/10.1016/j.ymssp.2022.109971.

42. C. Hao, Z. Wang, Yi Zou, and Z. Zhao, "Self-Learning Time-Varying Digital Twin System for Intelligent Monitoring of Automatic Production Line," *Journal of Physics: Conference Series* 2456, no. 1 (2023): 012021, https://doi.org/10.1088/1742-6596/2456/1/012021.

43. F. Emmert-Streib, "What Is the Role of AI for Digital Twins?," *AI* 4, no. 3 (2023): 721–728, https://doi.org/10.3390/ai4030038.

44. S. Zayed, G. M. Attiya, A. El-Sayed, and E. El-D. Hemdan, "A Review Study on Digital Twins With Artificial Intelligence and Internet of Things: Concepts, Opportunities, Challenges, Tools and Future Scope," *Multimedia Tools and Applications* 82, no. 30 (2023): 47081–47107, https://doi.org/10.1007/s11042-023-15611-7.

45. V. V. Tuhaise, J. H. M. Tah, and F. H. Abanda, "Technologies for Digital Twin Applications in Construction," *Automation in Construction* 152 (2023): 104931, https://doi.org/10.1016/j.autcon.2023.104931.

46. H. Yu, D. Yu, C. Wang, Yi Hu, and Y. Li, "Edge Intelligence-Driven Digital Twin of CNC System: Architecture and Deployment," *Robotics and Computer-Integrated Manufacturing* 79 (2023): 102418, https://doi.org/10.1016/j.rcim.2022.102418.

47. V. Michalakopoulos, S. Pelekis, G. Kormpakis, et al., "Data-Driven Building Energy Efficiency Prediction Using Physics-Informed Neural Networks," *arXiv* (2024), https://doi.org/10.48550/arXiv.2311.08035.

48. C. Li, P. Zheng, Y. Yin, Y. M. Pang, and S. Huo, "An AR-Assisted Deep Reinforcement Learning-Based Approach Towards Mutual-Cognitive Safe Human-Robot Interaction," *Robotics and Computer-Integrated Manufacturing* 80 (2023): 102471, https://doi.org/10.1016/j.rcim.2022.102471.

49. A. Manocha, Y. Afaq, and M. Bhatia, "Digital Twin-Assisted Blockchain-Inspired Irregular Event Analysis for Eldercare," *Knowledge-Based Systems* 260 (2023): 110138, https://doi.org/10.1016/j.knosys.2022.110138.

50. D. Wagg, C. Burr, J. Shepherd, et al., *The Philosophical Foundations of Digital Twinning* (Engineering Archive, 2024), https://doi.org/10.31224/3500.

51. Z. Ghauch, L. Bull, and Z. Xuereb Conti, On self-improving Digital Twins as Deep Reinforcement Learners, (n.d.).

52. F. G. Medina and V. M. Hernandez, "Product Digital Twins: An Umbrella Review and Research Agenda for Understanding Their Value," *Computers in Industry* 164 (2025): 104181, https://doi.org/10.1016/j.compind.2024.104181.

53. F. Tao, H. Zhang, and C. Zhang, "Advancements and Challenges of Digital Twins in Industry," *Nature Computational Science* 4, no. 3 (2024): 169–177, https://doi.org/10.1038/s43588-024-00603-w.

54. G. Tsialiamanis, D. J. Wagg, N. Dervilis, and K. Worden, "On Generative Models as the Basis for Digital Twins," *Data-Centric Engineering* 2 (2021): e11, https://doi.org/10.1017/dce.2021.13.

55. B. Kastelein and R. Ahfield, Smarter Energy Measurements, Faster, Using AI, Control Engineering, (n.d.), Accessed, July 28, 2024, https://www.controleng.com/motors-drives/energy-efficiency/.

56. Z. Zhou, Z. Jia, H. Liao, et al., "Secure and Latency-Aware Digital Twin Assisted Resource Scheduling for 5G Edge Computing-Empowered Distribution Grids," *IEEE Transactions on Industrial Informatics* 18, no. 7 (2021): 4933–4943, https://doi.org/10.1109/TII.2021.3137349.

57. M. Ferriol-Galmes, J. Suárez-Varela, J. Paillissé, et al., "Building a Digital Twin for Network Optimization Using Graph Neural Networks," *Computer Networks* 217 (2022): 109329, https://doi.org/10.1016/j.comnet.2022.109329.

58. E. Kuss 2024. Enhancing Cloud Resource Allocation Using ML, https://hystax.com/enhancing-cloud-resource-allocation-using-machine-learning/.

59. M. Nagendran, P. Festor, M. Komorowski, A. C. Gordon, and A. A. Faisal, "Quantifying the Impact of AI Recommendations With Explanations on Prescription Decision Making," *npj Digital Medicine* 6, no. 1 (2023): 1–7, https://doi.org/10.1038/s41746-023-00955-z.

60. Shen, X., P. Devaraja, D. Wagg, and M. S. Bonney "A Structured Knowledge Graph for a Geometric and Behavioral Digital Twin in the Context of Modal Testing," in *Model Validation and Uncertainty Quantification* ed. R. Platz 3, (Springer Nature Switzerland, 2024): 5–14, https://doi.org/10.1007/978-3-031-68893-5_2.

61. P. Luo, E. Parn, and I. Brilakis, "ChatTwin: Enabling Natural Language Interactions With Infrastructure Digital Twins," in *EC3 Conference 2024, European Council on Computing in Construction (Computing in Construction)*, (IEEE, 2024), https://doi.org/10.35490/EC3.2024.259.

62. H.-H. Benzon, X. Chen, L. Belcher, O. Castro, K. Branner, and J. Smit, "An Operational Image-Based Digital Twin for Large-Scale Structures," *Applied Sciences* 12, no. 7 (2022): 3216, https://doi.org/10.3390/app12073216.

63. M. Grieves 2022. Intelligent Digital Twins and the Development and Management of Complex Systems, https://digitaltwin1.org/articles/2-8.