Advancing Security with Digital Twins: A Comprehensive Survey

Blessing Airehenbuwa, *Student Member IEEE*, Touseef Hasan, *Student Member IEEE*, Souvika Sarkar, *Member IEEE* and Ujjwal Guin, *Senior Member IEEE*

***Abstract*—The proliferation of electronic devices has greatly transformed every aspect of human life, such as communication, healthcare, transportation, and energy. Unfortunately, the global electronics supply chain is vulnerable to various attacks, including piracy of intellectual properties, tampering, counterfeiting, information leakage, side-channel, and fault injection attacks, due to the complex nature of electronic products and vulnerabilities present in them. Although numerous solutions have been proposed to address these threats, significant gaps remain, particularly in providing scalable and comprehensive protection against emerging attacks. Digital twin, a dynamic virtual replica of a physical system, has emerged as a promising solution to address these issues by providing backward traceability, end-to-end visibility, and continuous verification of component integrity and behavior. In this paper, we present a comprehensive survey of the application of digital twins based on their functional role and application domains. We comprehensively present the latest digital twin–based security implementations, including their role in cyber-physical systems, Internet of Things, cryptographic systems, detection of counterfeit electronics, intrusion detection, fault injection, and side-channel leakage. To the best of our knowledge, this is the first work to consider these critical security use cases within a single study to offer researchers and practitioners a unified reference for securing hardware with digital twins. Additionally, we discuss the integration of large language models into digital twins to enhance the security of systems by leveraging their advanced reasoning capabilities and highlight the challenges and limitations of applying digital twins to solve hardware security problems, with possible solutions. Further, we discuss current research trends and future directions in advancing hardware security through digital twins.**

***Index Terms*—Digital Twin, Heterogeneous Integration, IoT, Hardware Security, Large Language Models, Counterfeit ICs.**

I. Introduction

The modern electronics supply chain is a highly intricate and globalized ecosystem that spans across multiple countries and involves various independent entities responsible for different stages of the product lifecycle, including design, fabrication, packaging, assembly, and distribution [1], [2]. This complexity is compounded by the presence of both trusted and untrusted actors, increasing the risk of vulnerabilities being introduced at any point in the supply chain [3]. The cross-border nature of operations makes oversight and accountability particularly challenging, as different regions may follow varying standards of security, regulation, and quality assurance. Furthermore, the supply chain consists of multiple hierarchical layers, often including subcontractors and third-party vendors, which makes it difficult for original equipment manufacturers to maintain complete visibility into every component's origin and traceability information. A significant limitation is the lack of real-world implementation of a tracking system that provides the ability to trace components back to their source and verify their integrity [4]–[6]. This lack of transparency and visibility not only complicates risk management but also creates opportunities for adversaries to insert counterfeit parts, malicious circuitry, or compromise intellectual properties. As the demand for faster, cheaper, and more powerful electronics grows, addressing these challenges becomes critical to ensuring the security, reliability, and trustworthiness of electronic systems deployed across commercial, industrial, and national security applications.

Although solutions exist to address these security challenges – such as counterfeit ICs [2], [3], [7], information leakage [8]–[10], hardware Trojans [11]–[13], and side-channel attacks [14]–[16]. However, there still exist research gaps as these approaches often focus on a specific threat, while the attack surface continues to expand due to the constant development of new threats by malicious actors [17], [18]. Therefore, there is a need for comprehensive and scalable solutions that can adapt to emerging threats. A promising solution to address these security concerns can be the adoption of digital twin (DT) technology, which creates a virtual replica of the physical object and enables real-time monitoring, forecasting, simulation, and analysis of each step in the manufacturing and delivery process.

Leveraging these abilities, DTs are able to capture and analyze data throughout the lifecycle of electronics to detect anomalies indicative of counterfeit components. They support robust security analysis and real-time threat detection by continuously evaluating system behavior against expected virtual models. Additionally, they facilitate the simulation and emulation of physical systems within a virtual environment, allowing for the identification and mitigation of potential leakage points in designs early in the development phase to improve the security of the system. This paper, therefore, demonstrates the current status of digital twin-enabled hardware security by reviewing relevant research from recent years. There already exists a few work that surveys the use of digital twins for security [19], [20], but none is focused towards ensuring security in hardware (i.e., electronics). The main contribution of our work is to provide the history and fundamental concept of digital twins, a comprehensive review of DT applications

Blessing Airehenbuwa and Ujjwal Guin are with the Department of Electrical and Computer Engineering, Auburn University, AL, USA (e-mail: {b.airehenbuwa and ujjwal.guin}@auburn.edu).

Touseef Hasan and Souvika Sarkar are with the School of Computing, Wichita State University, KS, USA (e-mail: {txhasan4@shockers.wichita.edu and souvika.sarkar@wichita.edu}).

in hardware security, and future research directions. Our paper makes the following contributions:

- *Application of Digital Twins:* We present detailed applications of digital twin technology across multiple domains, including manufacturing, smart cities, healthcare, and energy, highlighting how DTs enable real-time monitoring, predictive maintenance, performance optimization, and enhanced decision-making. Although few surveys exist in the literature [19], [21], [22], this survey focuses primarily on the security aspects.
- *Digital Twin for Security Enhancement:* We present a comprehensive survey of the latest digital twin–based security implementations and applications spanning both counterfeit detection and information-leakage prevention in electronics. To the best of our knowledge, this is the first work to consider these critical security use cases within a single study to offer researchers and practitioners a unified reference for safeguarding hardware with digital twins. We also discuss the use of digital twins to enhance security in IoT and cyber-physical systems.
- *Large Language Models in Digital Twins:* The paper examines how the integration of large language models (LLMs) into digital twin frameworks strengthens hardware security via natural-language understanding and advanced reasoning capabilities. Such LLM-enhanced digital twins have the potential to enable conversational and interactive interfaces, generate detailed scene descriptions, and provide evidence-based decision-making. These features ensure secure and resilient operations across diverse applications, including hardware security.
- *Future Directions:* We outlined the current challenges and limitations associated with applying digital twins in hardware security, as identified in prior works [18], [23]–[25], along with proposed solutions to address them. Recent studies employing LLMs for security verification [26], [27] have demonstrated significant potential. Since digital twins and LLMs individually enhance security, we envision that their convergence will play a pivotal role in shaping the future of security solutions. Although the integration of DTs with LLMs is currently in the research phase within non-security domains, it is yet to be explored for security.

The remainder of this paper is organized as follows. In Section II, we present an overview of digital twins. We investigate the applications of digital twins in different domains in Section III. Section IV discusses digital twins for ensuring the security of electronic products. In Section V, we discuss the use of large language models in DT frameworks. We summarize the challenges and limitations of digital twins in Section VI. Section VII summarizes the research trend. Finally, we conclude the paper in Section VIII.

II. Digital Twin

Digital Twin has received different definitions by different authors over the years based on their perspectives of the concept [28] and applications. According to Glaessgen et al. in 2012, a digital twin is an integrated multiphysics, multiscale, probabilistic simulation of a system that uses the best available physical models, sensor updates, history, etc., to mirror the life of its corresponding twin [29]. Years later, in 2017, Grieves and Vickers defined it as a set of virtual information constructs that fully describe a potential or actual physical manufactured product from the micro-atomic level to the macro-geometrical level. Therefore, a digital twin is a dynamic or living virtual replica of a physical object, system, or process. An important thing to note is that the digital twin evolves continuously by integrating real-time data from sensors, IoT devices, and other data sources, to ensure the virtual twin stays in sync with its physical counterpart throughout its lifecycle. The real-time synchronization enables the virtual twin to reflect the current state of its physical counterpart at any given time, thereby providing remote access to the status and conditions of the physical system from anywhere around the globe [30]. In addition to the aforementioned benefit, it also provides intelligent feedback (e.g., forecasting, optimization of parameters, root cause analysis, real-time control) to the physical world through a combination of simulation, emulation, data analytics, and AI modeling [18].

Although DT was originally introduced for PLM [31]. However, we have in recent times seen its application in various fields such as in agriculture [32]–[34], healthcare [35], manufacturing [36], [37], etc. In healthcare, based on real-time health data (e.g., vital signs, medical history, and test results) available, healthcare professionals can use digital twins to simulate how a patient might respond to different treatments, medications, or surgical procedures and predict potential complications, provide personalized treatment plans, and improve diagnostic accuracy without putting the patient at risk due to unnecessary tests and procedures [38]. In a manufacturing setting, a digital twin provides predictive maintenance capabilities by detecting anomalies in machines from operational data early before they lead to failures, thereby reducing downtime and repair costs.

A. History of Digital Twins

In 2002, Michael Grieves introduced the concept of digital twin during a University of Michigan presentation to industry for the formation of a Product Lifecycle Management center in what was referred to as “Conceptual Ideal for PLM”. Although the idea of twinning things can be traced back to NASA’s Apollo programs in the 1960s, where identical space vehicles were built to mirror the conditions of the space vehicle during space missions [39], [40]. During flight missions, another physical vehicle (a twin) remained on Earth and was used to mirror the flight conditions as precisely as possible, based on available flight data. The physical twin on Earth was used to simulate ways to assist crew members onboard in critical situations. This groundbreaking initiative laid the foundation for what would later become a widely recognized framework, leveraging the advanced technological and scientific methodologies developed to ensure mission success and innovation in space exploration. However, building such physical twins has become increasingly expensive as the cost of physical materials (atoms) has continued to increase. Hence, the need to create and operate the twin in a virtual or digital space was proposed by Grieves.

Since its conceptual introduction in 2002, it has been referred to by different names over the years. In 2005, Grieves referred to it as the Mirrored Spaces Model, which he later referred to as the Information Mirroring Model in 2006 [31]. However, this concept was significantly expanded on in his 2011 work [30], where the term "Digital Twin" was used for the first time, a name coined by John Vickers, NASA. While the name has changed over the years, the concept and model have remained the same. DT has gained applications and recognition in various fields. In 2010, NASA included the technology in their technology roadmap [41] and explored its potential application in spacecraft [29]. Similarly, the U.S. Air Force leveraged the concept for jet fighters, as highlighted by Tuegel et al. [42]. This marked a pivotal moment in the evolution of digital twin technology, showcasing its growing importance in advanced applications.

B. *Concept of Digital Twins*

The basic idea of the digital twin is to represent a physical product, system, or process in the virtual domain to monitor, simulate, and optimize its performance through real-time data integration. By doing so, we can obtain the same information from the virtual twin as could have been obtained if we had access to the physical object. In addition, we can perform what-if analysis on the virtual twin without putting the physical counterpart at risk. In principle, a digital twin consists of three (3) components, namely, the physical twin in the real space, the virtual twin, and the communication links between them [43], [44].

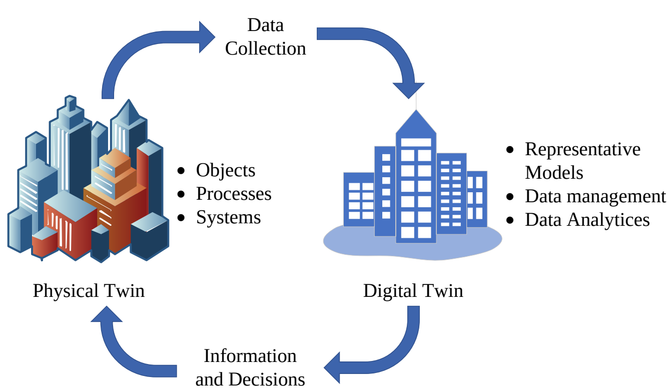

Figure 1: The conceptual diagram of a digital twin [45].

Figure 1 shows a conceptual diagram of a digital twin [45]. The physical twin is the real-world product, process, system, or asset being digitally represented. It serves as the foundation or source for the digital twin's data and functionality. This component of the digital twin resides in real space and interacts with its environment, performs its designated tasks, and undergoes wear and tear. All of these provide the essential data needed for the digital twin to simulate, analyze, and predict future behaviors and outcomes. On the other hand, there is the virtual or digital twin, which is a representation of the physical counterpart in the virtual space or environment, and is capable of emulating the behavior of its physical twin in great detail. The virtual twin can be modeled as a physics-based model from first principles. However, obtaining a physics-based model may be infeasible for some complex systems. In such situations where the physics-based models are not easily available, data-driven models are used. This approach is based on the assumption that data is a manifestation of both known and unknown physics [21]. To build this type of model, one is required to perform data collection, data pre-processing, and data analysis with Artificial Intelligence (AI). An example of this type of model is found in [36], [37]. Sometimes, a combination of physics-based and data-driven models is required to model the system. This type of digital twin model is referred to as the hybrid model [46], [47]. A graphical approach to modeling a system was discussed in [48]. In short, the virtual twin is the component of the digital twin that enables detailed simulations, optimization, diagnosis, and predictions to support decision-making. Lastly, the connection link is the component of digital twins that allows data to flow from the physical twin to the virtual twin in the form of sensor data and historical data. Depending on the system being modeled, information and decisions will flow from the virtual space to the real space.

To better understand digital twins, we present a comprehensive and visualized taxonomy of digital twins in Figure 2 based on their types and virtual twin modeling methods. We also present the applications of digital twins based on their role and domain of application in the outer layers.

Digital twins are classified into three types [43] – digital twin prototype, digital twin instance, and digital twin aggregate, shown in the second ring of Figure 2 and described in Section II-C. The third ring describes the virtual twin modeling methods, which are grouped into physics-based, data-driven, hybrid, and graphical methods. In the fourth and fifth rings, we present the applications of digital twins based on their role and domain applied, respectively. These applications are described in Section III.

C. *Types of Digital Twins*

Digital twins are categorized into three main types, each serving a distinct role throughout a product's lifecycle. From the initial design phase to real-time monitoring and large-scale analysis. According to [43], the three types of digital twins are as follows:

1) *Digital twin prototype (DTP)*: DTP represents a product in its pre-manufacturing stage. It includes all the necessary information to design, produce, and describe a physical counterpart, such as requirements, fully annotated 3D models, bill of materials (BoM), and bills of processes, services, and disposal.
2) *Digital twin instance (DTI)*: DTI represents the digital counterpart of an individual manufactured product. It is created when the physical product rolls off the production line and is linked to its corresponding physical twin throughout its lifecycle. This connection allows for real-time synchronization and updates, enabling effective monitoring and management of the product's performance, maintenance, and overall lifecycle.

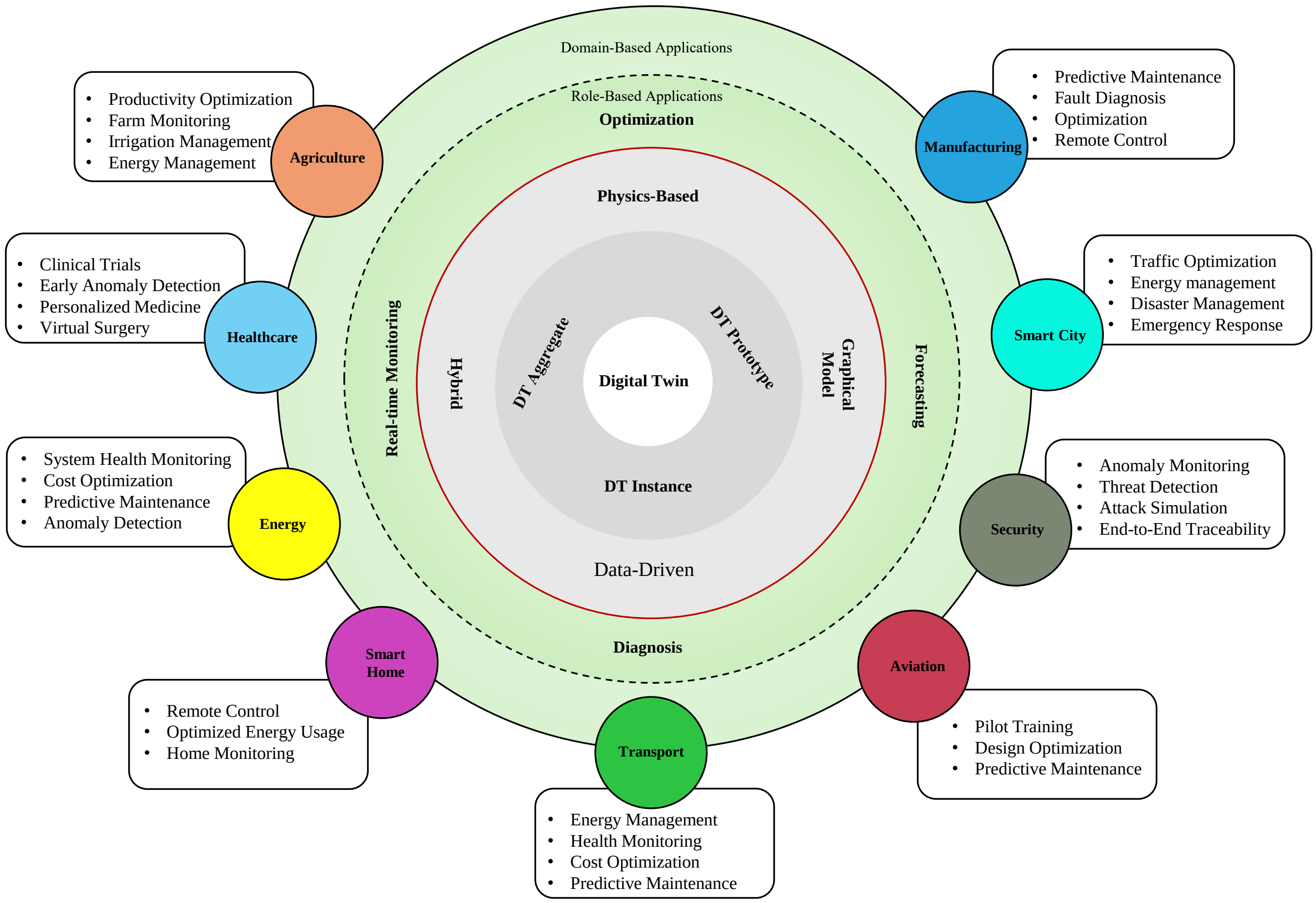

Figure 2: Digital Twin Taxonomy and Applications

3) *Digital twin aggregate (DTA)*: DTA aggregates multiple DTIs, providing a composite view of all instances of a product or system. This aggregation facilitates large-scale analysis, such as identifying trends, optimizing fleet performance, and improving operational efficiency across multiple units.

III. Application of Digital Twin

In this section, we categorize the applications of digital twins and briefly discuss them along two dimensions: first, based on the functional role of the digital twin, and second, based on the specific domain in which it is applied.

A. Role-Based Application of DT

Depending on the application, a DT performs any or a combination of these functions:

• *Real-time Monitoring:* This is the simplest function of a digital twin. Here, the digital twin simply reflects the state of the physical system at any point in time based on real-time data collected from the physical system. With this, no matter where the physical system is in the world, we can get information about its state and performance. For instance, we can monitor the health of industrial machines, bridges, vehicles, electronics, etc. A practical example is found in [49], where digital twin was used to monitor the Structural Health of bridges in Vietnam. The design incorporated sensors to collect operational data, and a fog layer for local pre-processing before transmitting the data to the cloud for further analysis and visualization. Similarly, Li et al. introduced a cloud-based Battery Management System (BMS) to build a digital twin of battery systems, ensuring accurate status monitoring [50]. Another application of digital twin for real-time monitoring can be found in [51], where Li et al. proposed a technique to monitor the health and performance of a boost converter in power electronics. In summary, as DT continues to evolve, its real-time monitoring applications will play an increasingly important role in optimizing performance and decision-making across various domains.

• *Optimization:* With digital twin, we have access to real-world data from the physical system, the virtual twin, and AI. The integration of these components for real-time simulations allows engineers to explore multiple design configurations and optimize critical parameters to improve the performance of the system. Let us consider a scenario such as the design of an aircraft. With the digital twin of the aircraft, we can simulate airflow, thermal stresses, and component interactions to refine the designs, leading to an optimal design that reduces drag and improves engine efficiency. Similarly, in manufacturing, digital twins have the potential to simulate material flow, machine-to-machine interactions, and energy consumption to optimize production layouts and waste. The application of digital twin for optimization can be found in [28], [52], where the Digital Twin Shop Floor (DTS) was proposed to optimizes manufacturing through an iterative process that integrates real-time data from the Physical Shop Floor (PS), Virtual Shop Floor (VS), and Shop Floor Service System (SSS). The digital twin detects potential resource allocation conflicts and provides optimization strategies to enhance efficiency before actual execution. During manufacturing, PS transmits the real-time state data to VS, which updates itself to reflect the physical changes, ensuring alignment with predefined plans. This continuous feedback loop minimizes disruptions, enhances precision, and maximizes overall operational efficiency, making DTS a powerful tool for intelligent and adaptive manufacturing optimization.

We can also find the optimization capability of digital twins as proposed by Bellalouna [53]. The author used real-time sensor data and advanced processing technologies to precisely determine material stress and load conditions to facilitate efficient product design as opposed to traditional mechanical structure analysis, which relied on estimated data and theoretical calculations, often leading to over-dimensioning and material waste due to high safety factors. In summary, design teams can use digital twins to identify and mitigate inefficiencies, minimize production costs, and accelerate time-to-market while ensuring the highest quality and performance.

• *Forecasting:* Digital twin serves as a predictive tool to forecast the future behavior and performance of the physical twin. The digital twin achieves this function by using its AI component to analyze the observed measurements coming from sensors attached to the physical twin. With this, we could predict when a system or its subsystem will fail. Thereby, eliminating the unexpected failure of the system. It is important to know that this function of digital twins is the reason for the widespread adoption of digital twins in manufacturing in recent years, to reduce operational downtime. For example, in a recent study, Aivaliotis et al. demonstrated the use of digital twins to predict the health condition of a six-axis robotic structure used for welding in order to reduce downtime [54]. Similarly, the authors used digital twins to predict the health status and maintenance cycles of machines [55]. Similarly, [50], [51], [56] employed digital twins to predict the remaining useful life of systems.

• *Diagnosis:* Digital twin technology is a transformative leap in predictive maintenance and fault detection, enabling engineers to detect faults [57] and also trace the origin of such faults from the observed historical data of a physical system [18]. By employing advanced analytics, machine learning (ML), and real-time data integration, the diagnosis function of digital twins empowers industries to transition from reactive to proactive maintenance strategies. Ultimately, this improves systems' reliability, sustainability, and performance.

B. Domain-Based Application of Digital Twins

Here, we provide a comprehensive summary of the literature on the application of digital twins across various domains such as agriculture, healthcare, smart homes, manufacturing, transportation, energy, and aviation.

• *Agriculture:* Digital twin enables real-time monitoring of farms and greenhouses [32], [58], [59], allowing farmers to track key parameters like soil moisture, temperature, crop health, and weather patterns [60], [61]. Digital twin in agriculture supports resource optimization (e.g., water, energy) and early detection of pests or diseases. Manocha et al. proposed a smart irrigation framework using digital twins and IoT that processes soil, crop, and weather data to optimize water usage [62]. Digital twins have also been applied to greenhouse control using IoT and actuators [63], [64], and Moghadam et al. introduced a digital twin orchard for predicting crop stress and disease based on environmental simulations [65]. Chaux et al. developed a digital twin architecture to improve crop productivity in controlled environment agriculture by optimizing climate control and crop treatment strategies [66].

• *Aviation:* Digital twins are revolutionizing the aviation sector by enabling predictive maintenance, real-time structural health monitoring, and early anomaly detection, which are critical for enhancing safety, reliability, and improving operational efficiency. Given the high reliability demands of aerospace applications, Kapteyn et al. demonstrated the use of structural digital twins for unmanned aerial vehicle fleets to optimize operations through real-time sensor-driven simulations and mission planning [48], while Tuegel et al. introduced a high-fidelity aircraft digital twin updated with flight data to predict damage and lifespan using Bayesian learning [42]. Wang et al. combined fatigue mechanics with advanced filtering to forecast crack growth accurately [67], and Zakrajsek and Mall developed a physics-based digital twin for aircraft tires, using high-fidelity data and probabilistic models to predict wear and failure under varying touchdown conditions [68]. These studies underscore digital twins' growing role in improving aerospace design, maintenance, and sustainability across the product lifecycle.

• *Energy:* Significant advancements have been made using digital twins to enhance the monitoring, optimization, and maintenance of power systems. Digital twins have been applied to renewable energy management, such as in wind and solar farms, to optimize energy output and reduce operational costs. GE [69], a pioneer in this field, showcased the use of digital twins in their digital wind farm to monitor turbine performance in real time and predict maintenance needs using sensor data. Li et al. proposed a data-driven digital twin approach for power electronic converters, using machine learning models (MLP, CNN, RNN) to monitor degradation in critical components like capacitors and MOSFETs, thereby improving reliability and efficiency through predictive maintenance [51]. Similarly, Wunderlich et al. developed real-time, embeddable digital twin models of power converters using NARX-ANNs, capable of performing fault detection, prognostics, health management, and risk assessment directly on embedded controllers [70]. In addition to performance optimization, digital twins have also shown potential for improving power system security, as demonstrated by Saad et al., who used IoT-based digital twins to detect and mitigate cyberattacks such as false data injection and denial of service, thereby enhancing the resilience of interconnected microgrids [71]. Further applications of digital twins in power systems can be found in [57], [72]–[75].

• *Healthcare:* In healthcare, digital twins enable personalized and proactive treatment by digitally replicating patient physiology [38], [76]. Numerous smart healthcare applications have emerged, such as CloudDTH, which monitors, diagnoses, and predicts elderly health using wearable IoT devices [35], and a smart home healthcare that detects atrial fibrillation and falls using ECG and WiFi signals [77]. Thiong'o et al. proposed a DT to predict neurological complications in pediatric cancer patients by interfacing AI with patient-specific cancer profiles [78]. Another application is found in virtual medical training [79]. Ultimately, it enhances patient outcomes and overall quality of life.

• *Manufacturing:* Digital twin is a key enabler of Industry 4.0, supporting real-time monitoring, prognostics, fault diagnosis, process optimization, and enhancing security. By leveraging digital twins, manufacturers gain agility, reduce waste, and enhance product quality. A prominent example is the Digital Twin Shopfloor (DTS) proposed by Tao et al., which integrates physical systems (PS), virtual systems (VS), service systems (SSS), and shop floor data (SDTD) to enable dynamic interaction for adaptive control and production planning. Real-time updates from the PS continuously refine the VS, enabling iterative optimization and correction [28], [52]. Similarly, Xu et al. introduced a Digital-Twin-Assisted Fault Diagnosis (DFDD) framework using deep transfer learning to overcome data scarcity in early production phases using synthetic data from virtual models to pretrain the system [36]. The pretrained model is then fine-tuned using real-world data to improve early fault detection, demonstrated in a case study on car body-side production. Additionally, Booyse et al. developed Deep Digital Twins (DDTs) trained solely on healthy operational data to detect asset degradation by identifying deviations and addressing the limitations of physics-based models in complex systems [37]. To secure Smart Factories, Salim et al. proposed a Blockchain-enabled Digital Twin framework that uses deep learning and smart contracts to detect botnets early by inspecting only packet headers without decrypting encrypted traffic, ensuring data integrity, privacy, and preventing bot spread [80]. Also, Becue et al. proposed a digital twin with cyber-range to assess attack impacts on avionics quality monitoring, enhance cobotic system resilience, and support iterative design of safety and security functions [81]. Collectively, these studies highlight digital twins' capabilities in enabling accurate diagnostics, health monitoring, data privacy, and real-time decision-making.

• *Smart Home:* The integration of digital twin technology in smart homes represents a transformative advancement in home automation, integrating advanced technologies, such as IoT sensors, machine learning, actuators, and other interconnected devices, to create an intelligent ecosystem that enhances comfort, security, energy efficiency, and convenience for residents. For example, Liu et al. proposed a DT framework to improve the indoor safety of intelligent buildings. The system processes data collected by IoT sensors to automatically obtain the types and levels of danger in the building [82]. In [83], S.H. Khajavi et al. demonstrated the use of digital twins for safety and fire detection. Gopinath et al. introduced the re-design of smart homes using DT, integrating sensors with fans, front door locks, and lighting systems to enable remote control and real-time power usage monitoring. The integration of DT further allows engineers to test solutions virtually before physical maintenance, therefore minimizing unplanned downtime and improving system reliability [84]. Additionally, the implementation of DT in smart homes contributes to efficient usage of energy at home [84], [85].

• *Transportation:* Kumar et al. introduced an AI-driven traffic congestion management system that integrates real-time data analytics, machine learning, blockchain, and digital twins. Central to this system is the Virtual Vehicle (VV) model, a digital replica of the driver and vehicle, which uses LSTM-based neural networks and edge/fog computing to predict driver behavior, analyze traffic patterns, and recommend optimized routes [86]. To ensure security, Arya et al. proposed a DT framework with machine learning to secure Vehicular ad-hoc networks by detecting malicious nodes and preventing DDoS attacks [87]. DTs are also advancing EV energy management and component health monitoring. Tesla, for instance, has adopted large-scale DTs by assigning each vehicle a unique virtual counterpart [88], enabling real-time sensor data processing for predictive maintenance, improved driving experiences, and over-the-air updates. Ye et al. proposed a DT-enhanced Q-learning energy management system that simulates driving forces and degradation dynamics to optimize energy use and extend battery life [89]. Venkatesan et al. proposed an intelligent digital twin (i-DT) framework for monitoring and predicting the health of electric motors in EVs using MATLAB/Simulink [90]. The system employs ANN and fuzzy logic to map operational data, such as travel distance, temperature, and magnetic flux, to critical outputs like lubricant schedules and remaining useful life. Their dual-layer approach combines in-vehicle monitoring with a cloud-based Remote Health Monitoring and Prognosis Center for real-time performance tracking, enhancing motor reliability and efficiency. In broader traffic applications, Kuši'c et al. developed the Geneva Motorway digital twin (DT-GM), which synchronizes real-time traffic data with SUMO-based microscopic simulations, updating every minute to dynamically model highway conditions [91].

IV. Digital Twin for Security

The DT framework presents itself as the ideal tool to enhance security in electronic devices due to its inherent abilities in detecting anomalies (e.g., vulnerabilities/flaws in design) from data, and the formulation of robust security strategies through playing what-if scenarios. The potential of DT in this domain has been widely acknowledged by security researchers, hence the need for this study [18], [92]–[97]. In this section, we present recent studies on the exploration of DT for securing electronic systems. Figure 3 shows how DTs have been employed to address security concerns, including cyber-physical systems, counterfeit hardware, IoT devices, and information leakage, and is described in the following.

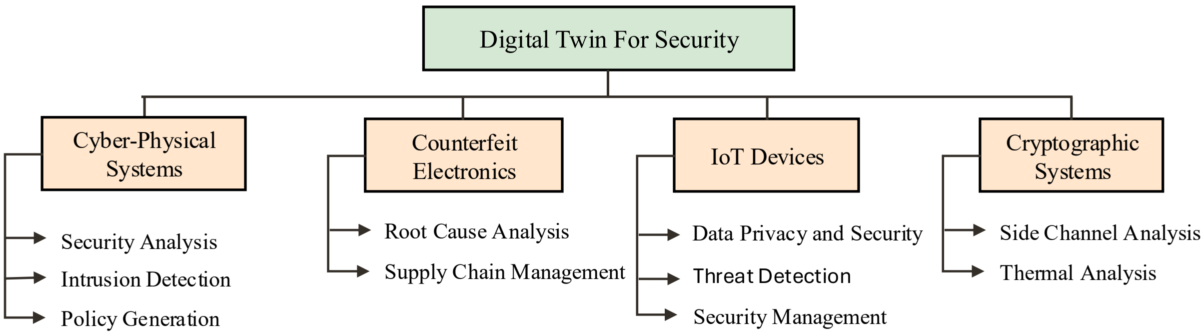

Figure 3: A taxonomy of applications of digital twins for enabling security.

A. Cyber-Physical Systems

DTs are employed as a cutting-edge tool to address security challenges due to their predictive and diagnostic strengths. DTs provide security experts with valuable benefits, providing the ability to detect, predict, simulate, and test cyber-attacks without interacting with the physical system [92], [98]. Several approaches have recently been proposed in this domain, utilizing DTs to detect and prevent threats and attacks. The goal is for cyber threats to be predicted and mitigated before they occur, ensuring that the physical system remains secure and updated on potential risks. In this work, we categorize the application of DT in cyber-physical systems into three key areas: security analysis, intrusion detection, and policy generation, each of which is discussed below.

1) Security Analysis: Digital twins have emerged as a powerful tool for conducting security analysis in cyber-physical systems, particularly where direct testing on live systems is impractical or risky. Security testing in CPS is critical due to their exposure to real-world cyber threats; however, performing such analysis on live systems can compromise their operation and safety. DTs overcome this problem by offering a virtual replica of the physical system, allowing researchers to simulate attacks, analyze vulnerabilities, and develop mitigation strategies in a safe and cost-effective environment. This approach was employed by Shitole et al. where a low-cost, real-time DT of interconnected residential energy storage systems was introduced to enable accurate security analysis and intrusion detection without modifying or risking the physical system [99]. In another work, Dietz et al. developed a process-based security framework to incorporate digital twin security simulations in the Security Operations Center (SOC). The authors demonstrated a man-in-the-middle attack and analyzed the effect using the virtual counterpart without risking the physical system [100]. Eckhart and Ekelhart demonstrated a proof of concept, using a digital twin to detect a man-in-the-middle attack inside the virtual environment, to test the detection of violated security and safety rules [92].

2) Intrusion Detection: DTs are increasingly being used to enhance the security of CPS by tapping into their anomaly detection ability to detect intrusions in systems. Here, we review studies that utilize DTs to address intrusion detection and cyberattacks in CPS. Akbarian et al. proposed a digital twin-based intrusion detection system that leverages advanced techniques such as Kalman filter and support vector machine for attack detection and classification [101]. Balta et al. proposed a DT framework designed to detect cyberattacks in cyber-physical manufacturing systems by monitoring both controlled transient behaviors and anticipated process anomalies using run-time data [102]. El-Hajj used DT with an intrusion detection system to secure physical devices in CPS [103]. The framework effectively detected Hping3 attacks while also showing how different cyberattacks affect specific parts of a system. By understanding these effects, designers are able to create security defenses that are better suited to the system's architecture and workload. Gehrmann and Gunnarsson introduced a DT-based security architecture to protect industrial automation and control systems (IACS) when opening up IACS low-level control functions and data exchange [104].

3) Policy Generation: Traditionally, security policies are defined manually by domain experts to provide protection for an organization's communication and computing infrastructures. As infrastructure update cycles accelerate and cyberattacks grow in complexity, manually defined policies struggle to keep pace with emerging threats. To address this challenge, Hammar and Stadler proposed digital twins as a solution for automating the development of effective security policies by simulating security scenarios in a controlled, virtual environment. Utilizing the data collected from simulations, reinforcement learning models are trained to automatically derive robust and adaptive security policies [97]. This approach not only enhances policy accuracy but also reduces human error and response time in rapidly evolving threat landscapes.

The integration of digital twins into CPS offers a proactive and scalable solution to evolving security challenges due to their predictive, diagnostic, and simulation capabilities, allowing for effective security analysis, real-time intrusion detection, and policy generation without endangering the physical infrastructure. The reviewed studies demonstrate the versatility of DTs in detecting emerging threats and guiding adaptive defense strategies, making them increasingly essential in securing future CPS environments.

B. Counterfeit Electronics

The increase in counterfeit electronic parts poses significant reliability and security threats to critical applications in defense, aircraft, vehicles, and medical devices due to their substandard quality, leading to major concerns for both government and industry [3], [105]. As most electronic devices are produced with limited oversight and pass through insecure supply chains, they are vulnerable to malicious compromise. For example, an adversary can tamper with the device and create a backdoor, which can be exploited for malicious purposes. When deployed in systems, the compromised devices can jeopardize the entire infrastructure. Note that counterfeit electronics are non-authentic electronics originating from the recycling of used components from discarded electronics, defective/out-of-spec parts, overproduced, cloned, forged documentation, tampered, and remarking of low-grade components to their higher grade counterpart (e.g., commercial grade components as military grade components).

1) Root Cause Analysis: One of the key advantages of DTs is their diagnostic capability, which allows for root cause analysis based on data collected throughout the system's lifecycle. This idea can be extended to the electronics supply chain to investigate the cause of electronics failures. In [18], Shaikh et al. mentioned that data collected during traditional design, verification, validation, and testing phases can be used to trace the root cause of faults, such as accelerated failure of new chips. The authors proposed a DT framework that is capable of detecting defective chips based on the data gathered throughout the electronics' lifecycle, as the DT is capable of looking at data associated with defective/out-of-spec chips and related data such as master results and wafer results records in the standard test data format database to determine if there is an observed anomaly. This framework uses causality analysis to provide traceability, thereby enabling comprehensive, end-to-end security management across the lifecycle.

2) Supply Chain Management: Hornik and Rachamim explored the application of DT and blockchain in what they referred to as Counterfeit Digital Twins (CoDT) to detect and prevent counterfeit electronics in/from the supply chain [93]. The authors mentioned the limitations of traditional counterfeit detection methods, which often operate in isolation and lack real-time data sharing. As a solution, they proposed CoDT, as a primary data fusion technology to aggregate multiple counterfeit detection measures and technologies to more effectively detect counterfeits in real-time and provide recommendations to stakeholders, with the CoDT providing a secure and transparent means of tracking and monitoring the entire history of the electronics and verifying their authenticity using technologies such as CoDT-enabled blockchain, RFID and machine learning. The authors mentioned that the framework can verify the authenticity of electronics by comparing recorded data with actual product attributes to detect discrepancies.

With the rise of counterfeit electronics posing serious reliability and security risks to critical systems, DTs can offer a promising solution to enhance traceability and transparency across the supply chain. Leveraging data collected throughout the electronics lifecycle, DTs can provide insight into the root cause of component failures and support the detection of anomalies and unauthorized modifications. These capabilities can position DTs as a powerful tool for safeguarding electronic systems and ensuring the authenticity and integrity of devices from production to deployment.

C. IoT Devices

IoT devices are generally not equipped to run strong encryption mechanisms to secure the data they transmit [20] and also suffer from weak authentication mechanisms due to their limited computing resources, which make them susceptible to unauthorized access. Below is a review of some digital twins-inspired solutions under three headings, namely: data privacy and security, threat detection, and security management.

1) Data Privacy and Security: Low-powered devices often suffer from limited computational resources, memory, and power capacity, making them vulnerable to security breaches and privacy violations. To improve the privacy and security of the data being collected, Kumar et al. proposes a blockchain and deep learning-based framework to enhance security and data privacy in DT-empowered Industrial IoT networks by ensuring secure data transmission through smart contracts. The framework also detects attacks using a hybrid long short-term memory - sparse autoencoder and multi-head self-attention (MHSA)-based bidirectional gated recurrent unit intrusion detection model [106]. Similarly, in [107], the authors proposed the use of multiple digital twins for a single physical device to enhance data security in IoT devices. This use of multiple twins enables the separation of data among different virtual objects based on assigned tags and hence limits access to different data points to authorized users or applications, thereby preventing unauthorized data access.

2) Threat Detection: An approach to enhance the performance of intrusion detection systems in IoT networks was proposed by Alharbi et al. leveraging AI, DTs, and Blockchain technologies. In this framework, AI is utilized for real-time anomaly detection, DT replicates device behavior to predict potential threats, and Blockchain ensures secure and decentralized data transmission, collectively strengthening the overall security of the IoT networks [108]. Pirbhulal et al. proposed a conceptual DT framework to enhance cybersecurity in IoT-based healthcare systems by creating a virtual replica of the targeted systems, enabling the identification of security vulnerabilities and potential breaches [109]. To combat the threats facing Edge of Things (EoT) networks, Yigit introduced a digital twin-empowered smart attack detection system for 6G EoT networks, which integrates DT technology and edge computing to enable real-time monitoring and proactive threat detection, bolstering the security of IoT environments [110]. The system uses an online learning module to ensure continuous improvement by updating feature selection and classification methods, making it adaptable to dynamic attack landscapes.

3) Security Management: DTs are a promising solution for improving security management in IoT environments. Empl et al. proposed the SOAR4IoT framework, which integrates DTs with security orchestration, automation, and response (SOAR) to improve IoT security management through real-time monitoring, automated playbook-based responses, and enhanced coordination of security tools, effectively addressing the scale and complexity of IoT environments while reducing manual effort and human error [111]. In another work, Empl et al. proposed the creation of a digital twin of the IoT network to enable proactive security management. This approach allows security analysts to continuously monitor the virtual representation of the network, detect potential threats early, and assess the impact of new configurations and updates to the network without putting the physical network at risk [111]. Pittaras and Polyzos introduced a framework that uses DTs as a secure intermediary layer, enabling sensing and actuation through distributed ledger technologies [112]. The authors mentioned that the consumers can interact with the physical devices solely through their digital representations, which were implemented with a smart contract, thereby minimizing direct exposure of physical devices and reducing attack surfaces.

The application of DTs in securing IoT devices presents transformative opportunities in addressing critical challenges of low-powered devices, such as data privacy, intrusion detection, and security management. Therefore, leveraging DTs to safeguard IoT environments deserves greater attention and further exploration by the research community.

D. Cryptographic Systems

Besides the mathematical security of cryptographic algorithms, the security of cryptographic systems is also affected by their implementations. A poorly implemented cryptographic system introduces side-channel leakage vulnerabilities, allowing sensitive assets to be leaked during encryption or decryption processes. Digital twins represent a promising solution to mitigate these risks through the simulation, monitoring, and analysis of side-channel behavior of the system in a virtual environment without interfering with the physical system. In the following, we describe two DT-based approaches that address information leakage in cryptographic systems based on recent studies.

1) Side Channel Analysis : Side-channel attacks exploit the implementation flaws in cryptographic algorithms to expose secret keys by observing power consumption, electromagnetic emissions, and execution time during cryptographic operations. To address this issue, Yi et al. proposed a DT framework for side-channel resistant cryptographic devices by simulating the side channel information generated during the encryption process of cryptographic devices. By testing and analyzing the simulation model, the relevant side channel information and potential leakage points can be accurately captured and addressed. The authors tested different encrypted plaintexts, using a proposed measurement algorithm to accurately determine whether there is any side channel leakage [113].

2) Thermal Analysis: Thermal attacks are another subtle form of side-channel attack in which attackers may infer cryptographic keys or other sensitive information by analyzing the heating and cooling patterns of the system. To counter this, a thermal digital twin (TDT) solution was proposed to defend against thermal attacks with a focus on 3D System-in-Package (3D-SiP) [94]. The authors utilized a high-fidelity simulation model that combines real thermal data with finite element modeling to analyze and monitor the thermal behavior of 3D-SiP systems in real time to enable proactive thermal risk management and improve system reliability and security. The application of DTs to develop side-channel resistant cryptographic systems is a promising approach to mitigating information leakage and thus deserves further investigation.

V. Large Language Models in Digital Twin Frameworks

The preceding sections have explored how DTs revolutionize physical system modeling by creating dynamic virtual replicas that mirror real-world environments. Building upon this foundation, this section examines the integration of large language models (LLMs) with DT technology. As DTs evolve from static simulations to intelligent, predictive entities, LLMs emerge as powerful enablers that enhance their cognitive capabilities. This convergence creates systems that not only replicate physical counterparts but also understand, communicate, and reason about them in human-like ways. The following discussion explores the evolution of LLMs, their broad applications across domains, and their specific implementations within DT frameworks.

A. An Introduction to Large Language Models

LLMs represent a groundbreaking advancement in AI, functioning as sophisticated deep learning systems capable of processing and generating human-like text. The evolution of these models began with the introduction of the ‘transformer’ architecture in 2017 by Google Brain, which marked a significant shift from traditional recurrent neural networks [114]. This revolutionary architecture processes text in parallel rather than sequentially, dramatically improving training efficiency and comprehension of lengthy text sequences. The core technological foundation of modern LLMs consists of transformer neural networks containing encoders and decoders with self-attention capabilities that extract meaning from text sequences and understand relationships between words and phrases. Unlike earlier models, transformers process entire sequences in parallel, allowing for GPU-accelerated training and reduced processing time.

Significant milestones in LLM development include Google’s bidirectional encoder representations from transformers (BERT) in 2018, which demonstrated unprecedented versatility through extensive training on natural language data [115]. OpenAI’s GPT series marked another crucial evolution phase, with GPT-3’s 2020 release representing a quantum leap in capabilities through massive scaling to 175 billion parameters. Their recent advances in GPT-4 and beyond have further enhanced LLMs through instruction tuning and conversational interfaces, making these technologies increasingly accessible through various platforms [116]. These models have demonstrated remarkable abilities in few-shot and zero-shot learning scenarios, setting new benchmarks in tasks ranging from text generation to semantic understanding.

LLMs have transformed numerous industries through their natural language processing capabilities. The versatility of LLMs is noticed in their ability to perform multiple language tasks - answering questions, summarizing documents, translating languages, and completing text sequences. This flexibility enables them to enhance traditional workflows across domains. Their remarkable ability to make predictions based on relatively small input prompts has enabled generative AI applications that produce human-like content in response to natural language instructions [117].

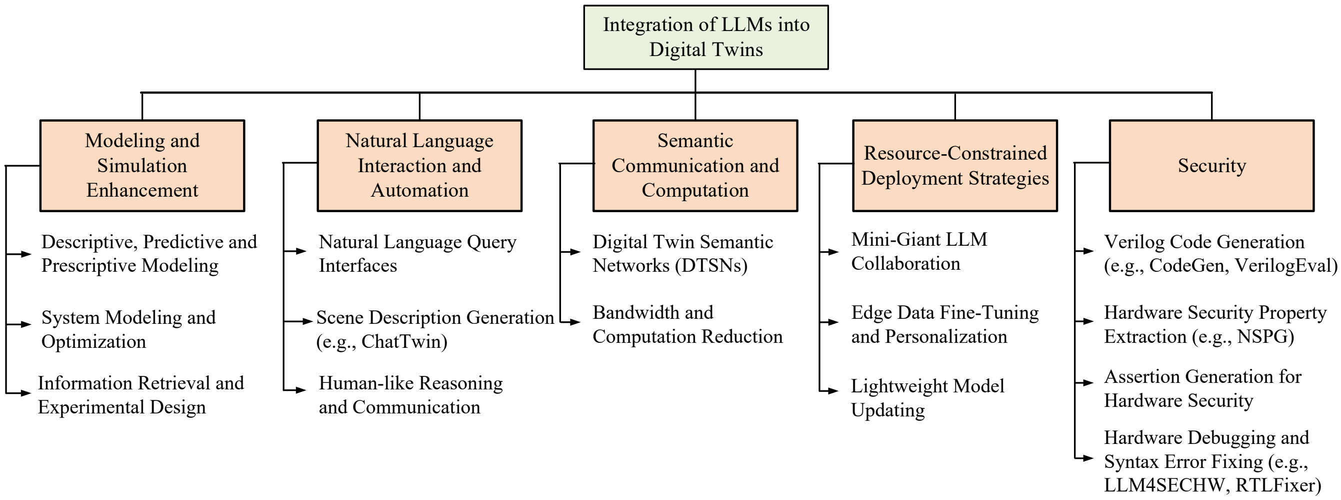

Figure 4: Taxonomy of the integration of LLMs in DT frameworks.

B. *Integration of LLMs in DT Frameworks*

Digital twins used across industries, from manufacturing to healthcare and urban planning, generate vast amounts of data that can be difficult to interpret and utilize effectively. LLMs address this challenge by bringing unprecedented levels of intelligence to these virtual environments. The integration of LLMs into these frameworks represents a significant advancement in the field, enhancing the capabilities of digital twins through natural language processing, reasoning, and data generation. This enables more intuitive interaction with DTs, automates the generation of scene description documents, and aids explainable decision-making across multiple domains. This substantially enhances the value proposition of DTs by converting data abundance into meaningful intelligence [118]. Figure 4 showcases the exploration of LLMs in DT systems so far, with the potential to go even beyond the following scopes:

1) Modeling and Simulation Enhancement: LLMs facilitate sophisticated descriptive, predictive, and prescriptive modeling by interpreting vast and complex datasets, thus holistically improving accuracy and reliability of predictions. TWIN-GPT, for example, is fine-tuned on a pre-trained LLM (ChatGPT) on clinical trial datasets to generate personalized digital twins for different patients [119]. This approach accounts for individual patient variations and disease complexities, producing data that closely aligns with diverse real-world scenarios, while also ensuring patient privacy. Additionally, they assist in system modeling and optimization through intelligent analysis of parameter interactions and system dynamics, and LLMs support efficient information retrieval and experimental design by automatically synthesizing insights from extensive simulations, streamlining hypothesis testing and data-driven decision-making in complex simulation scenarios. For instance, a recent study proposes using LLM agents within a shopping mall twin to simulate human behaviors and thermal preferences [120]. These LLM agents interact with the digital twin environment to provide realistic data for optimizing HVAC systems.

2) Natural Language Interaction and Automation: LLMs bring natural language understanding to DT systems, greatly improving human-system interaction and automation. Natural language query interfaces enable intuitive interactions, allowing users to communicate with digital twins without requiring deep technical expertise. LLMs can automate the generation of scene description documents for DTs, reducing the need for manual processes and domain expertise. ChatTwin, a system that utilizes GPT-4 to automate the generation of scene description documents for data center DTs, employs a segment-and-generate workflow to address the challenges of long-text generation, achieving a higher success rate and completeness compared to baseline prompting methods [121]. This directly demonstrates the use of LLMs in automatically creating digital twin specifications. LLMs can also provide an explainability platform, generating natural language explanations of the system's decision-making by leveraging domain-specific knowledge bases [58]. Retrieval-augmented generation allows LLMs to utilize technical documents, scientific papers, and computer code to explain the decisions being taken by the system in real-time. LLMs further facilitate effective communication and automate complex analytical processes, bridging the gap between technical complexity and end-user accessibility.

3) Semantic Communication and Computation: Semantic communication within digital twin frameworks is greatly improved by integrating LLMs, notably through the concept of digital twin semantic networks, which enable more efficient communication and computation within DT environments [122]. This approach reshapes both intra-twin and inter-twin communication architectures through semantic-level frameworks that unify efficient communication and computation. By enabling DTs to communicate and compute at the semantic level rather than through raw data exchange, this framework significantly reduces bandwidth requirements and computational overhead.

4) Resource-Constrained Deployment Strategies: Resource-constrained environments pose unique challenges for deployment, which can be effectively addressed through integration with LLMs. This is addressed via a mini-giant

LLM collaboration scheme designed for resource-constrained environments. This approach involves edge data fine-tuning and instruction prompts, where larger models provide rich knowledge information while smaller models handle personalized expertise updating. This collaboration enhances the capabilities of DTs for multimodal data processing, scalability, and adaptability without overwhelming computational resources. Moreover, lightweight model updating techniques facilitated by LLMs enable continuous and efficient model refinement, ensuring up-to-date system intelligence without extensive computational resources.

5) Security: Security is critically enhanced by incorporating large language models into digital twin environments. LLM-powered tools facilitate automatic generation of secure hardware description code, improving accuracy and security at the hardware design level. Advanced property extraction mechanisms, such as neural security property generation, utilize the semantic understanding capabilities of LLMs to reliably identify and extract hardware security properties. Furthermore, LLM-based assertion generation tools support proactive hardware vulnerability detection, while debugging and syntax error correction solutions enable faster resolution of security-critical errors, strengthening the resilience of digital twin systems. Recent research has extensively investigated employing LLMs to enhance hardware security assurance. Thakur et al. demonstrated how LLMs, such as CodeGen, can automate synthesizable Verilog code generation [123]. Their comparative study, involving fine-tuning models against a large-scale Verilog corpus, revealed competitive performance against established models like ChatGPT, showcasing the feasibility of automating hardware digital twin creation at the register transfer level. Kande et al. investigated OpenAI's code-davinci-002 model for automatic generation of hardware security assertions [124]. Their research explored how varying prompt detail levels impacted the quality of generated SystemVerilog assertions, essential components in hardware verification, which directly influence digital twin security assurance. Advancing the role of LLMs in hardware debugging, Tsai et al. introduced RTLFixer, a framework employing LLMs to automatically identify and rectify syntax errors in RTL code [125]. Such automated correction tools substantially streamline the hardware design and validation processes for digital twins, significantly reducing manual debugging overhead and enhancing overall system security.

C. Future Prospects of LLMs and DTs in Security

Despite promising advancements, integrating large language models with digital twins introduces several critical challenges that warrant ongoing attention. Among these are security concerns arising from semantic-level operations, potentially opening new vulnerabilities and attack vectors unique to LLM-driven digital twin frameworks. Moreover, computational efficiency remains a pivotal issue, particularly in resource-constrained deployment scenarios where computing resources and energy budgets are limited. Ensuring the accuracy, reliability, and robustness of insights and security assurances derived from LLM-generated outputs requires robust validation frameworks and rigorous testing methodologies, especially within safety-critical domains such as healthcare, manufacturing, and infrastructure management.

The integration of LLMs with DTs represents a promising frontier for advancing security measures across various cyber-physical systems. Utilizing the logical reasoning and generative capabilities of LLMs, future digital twin frameworks can potentially offer unprecedented levels of security analysis, anomaly detection, and automated response to threats. Specialized models trained explicitly for security-related applications could significantly enhance the accuracy and efficiency of threat identification, vulnerability assessment, and proactive defense mechanisms. Emerging research directions include developing multimodal LLMs capable of interpreting and analyzing combined textual, numerical, and visual data to provide comprehensive, real-time security evaluations of digital twin environments. Furthermore, the adoption of federated learning methods holds promise for enabling decentralized and privacy-preserving intelligence across networks of interconnected twins, thereby improving resilience against centralized points of failure and coordinated cyberattacks. We anticipate increased convergence between physical systems and their digital representations, augmented by sophisticated security-aware language models. This evolution will not only enhance situational awareness and rapid incident response but also facilitate proactive risk mitigation strategies, thus significantly strengthening the security posture of critical infrastructure and cyber-physical systems.

VI. Challenges and Limitations

Despite recent studies showcasing the potential of DTs across various domains, as discussed in Section III, due to their ability to create virtual representations of physical systems to carryout optimization, fault detection, enhanced security, and all forms of analysis without interfering with the physical systems, this promising technology is not without its challenges and limitations. In this section, we examine some of these challenges and limitations of this technology and present some of the solutions proposed in the literature.

A. Implementation Cost

The implementation of DTs demands significant technical expertise, resources, and investment. For the accurate representation of a physical system in the digital space, the DT must incorporate detailed modeling of the system's structure, behavior, and interactions, which are often at multiple levels of abstraction. This includes the integration of high-fidelity physics-based models, real-time data from sensors, and AI-driven simulations that reflect real-time changes in the physical environment. Achieving this level of precision often requires specialized tools, high-performance computing infrastructure, and extensive domain knowledge, which can be difficult to assemble and maintain, making the DT more costly than the physical asset at times.

B. Data Acquisition

DTs rely heavily on high-quality, real-time data streams to accurately mirror the behavior and condition of their physical counterparts. However, missing data points, sensor noise, or inconsistencies in measurements can significantly degrade the accuracy and reliability of the twins' predictions and decision-making capabilities. As a result, substantial effort must be invested into data cleaning, validation, and preprocessing to ensure the digital twin operates as intended.

In the semiconductor industry, this challenge is further compounded by data accessibility issues, as key stakeholders such as foundries, testing facilities, and equipment vendors may be reluctant to share proprietary or sensitive operational data due to intellectual property concerns, data privacy, or competitive reasons. This reluctance can hinder the construction of comprehensive digital twins by creating blind spots in critical process stages or component behavior. Without full visibility into the system, the digital twin may be forced to rely on approximations or incomplete models, reducing its value in optimization and root-cause analysis.

C. Security and Privacy

The continuous flow of data between the physical twin and its virtual counterpart introduces significant security and privacy risks. This data exchange creates entry points for cyberattacks, including denial of service, false data injection, and unauthorized access [71]. Attackers may exploit these vulnerabilities to manipulate data, falsify system states, or mislead predictive algorithms, and ultimately compromise the integrity and functionality of the digital twin.

The increased use of IoT devices further amplifies the security issues due to their limited built-in security features. IoT devices are resource-constrained devices, making them susceptible to firmware vulnerabilities, weak encryption, and weak authentication mechanisms. Once compromised, these devices can serve as gateways for attackers to infiltrate the broader digital twin infrastructure.

From a privacy perspective, the data collected and transmitted in healthcare, smart cities, or industrial operations can contain sensitive or proprietary information. Without the use of strong encryption and access control mechanisms, this information may be exposed to unauthorized entities, leading to undesired privacy breaches. Possible ways to address these challenges are the integration of blockchain as discussed in [23]–[25]. However, this may add an extra layer of complexity and latency to the system.

D. Token Size and Hallucination Problem

Large language models are inherently constrained by a fixed token window, which limits the amount of input data they can process in a single inference. This limitation poses a significant challenge when analyzing digital twins of complex hardware systems, as large-scale system logs, event traces, or multi-modal telemetry data often exceed this limit. When truncated inputs omit critical contextual information, the model's reasoning becomes less robust, increasing the risk of generating incomplete or misleading outputs. This is particularly problematic in security-sensitive applications, where overlooking a subtle dependency or omitting a causal signal can result in false negatives or misdiagnosed vulnerabilities.

In addition to context loss, LLMs are susceptible to hallucination, generating information that is syntactically plausible but semantically incorrect. For example, when tasked with identifying side-channel vulnerabilities in a hardware digital twin, an LLM may fabricate data dependencies or invent leakage channels that do not exist in the actual system. Such hallucinations not only reduce analytical trustworthiness but may also lead to wasted debugging cycles, misallocated resources, or worse, neglect of real threats.

In order to mitigate these limitations, techniques such as Retrieval-Augmented Generation (RAG) [126] and extended context models like Longformer [127] can be used to integrate longer or dynamically indexed context windows. Additionally, domain-specific fine-tuning [128] ensures that the LLM internalizes accurate patterns from hardware-centric corpora. Human-in-the-loop strategies [129] provide a final layer of validation, enabling real-time correction of hallucinated outputs and alignment with operational ground truth. Together, these interventions help improve the semantic fidelity, robustness, and reliability of LLMs deployed within workflows.

VII. Research Trends

In the last two decades, digital twin-related publications in conference proceedings, journals, or magazines have increased tremendously. The rapid growth in the number of publications in this field is due to the promising future of DTs and the advantages they offer in any given application. More recently, their use in enhancing the security of systems has emerged as a topic of growing interest within the research community, as discussed in Section IV, and this is expected to continue in the years to come.

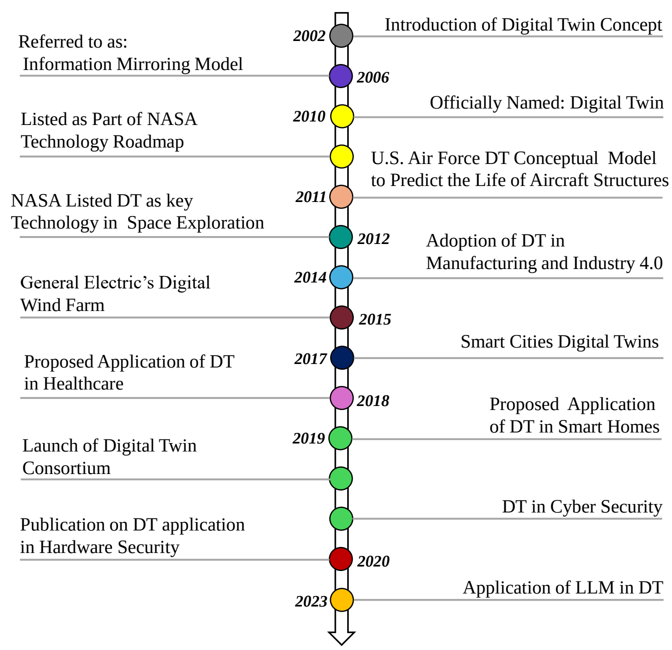

Figure 5: Major milestones in the development and adoption of digital twin technology.

Figure 5 shows the major milestones in the development and adoption of digital twin technology. Although DT was introduced by Dr. Michael Grieves in 2002 as a framework for product lifecycle management, there were only a few research works on the topic until 2014, when it was adopted in the manufacturing industry. This was a turning point that marked the beginning of digital twins' practical relevance. Its widespread adoption in manufacturing and Industry 4.0 was catalyzed by the IoT and IIoT technologies that provided the necessary real-time data streams and sensor infrastructure to operationalize digital twin systems. This adoption in Industry 4.0 and the rise in IoT caused increased attention from researchers in this field. In 2015, 'Digital Wind Farm' was announced by General Electric, which was one of the earliest commercial implementations of digital twin systems. Since then, several studies have been done by academia in industry to reduce downtime, optimize production lines, and perform predictive maintenance [28], [37], [54]. In the last decade, research in the development and implementation of digital twins of cities, smart homes, and healthcare has received huge attention from the research community, leveraging the power of IoT and wearable devices. These developments highlight the versatility of digital twins in modeling dynamic, human-centric, and infrastructure-rich environments. Since 2019, we have experienced an increased number of publications on the use of DT to solve some cybersecurity problems, such as intrusion detection. This number is expected to keep rising in the coming years. Since 2020, researchers in hardware security have begun exploring the use of digital twin frameworks to address critical challenges such as information leakage, fault injection, and hardware counterfeiting [18], [93], [100], [113], [130]. While this emerging line of research holds significant promise, it remains in its early stages as most of the existing studies are conceptual in nature, with practical implementations being limited.

These milestones are not merely historical footnotes; they reflect the maturation of digital twins from an abstract concept into a multidimensional technology with real-world impact. Each turning point — whether the entry into manufacturing, healthcare, or security — has incrementally extended the capabilities and scope of DT systems. As the fusion of digital twins with LLMs becomes more prominent, we are likely to witness the emergence of intelligent, adaptive DTs capable of semantic reasoning, self-optimization, and autonomous decision-making [119], [121]. The convergence of these technologies represents a pivotal shift, potentially transforming DTs from passive monitoring systems into active, explainable, and secure agents across critical domains.

VIII. Conclusion

Digital twins are rapidly gaining attention, and their applications in security demonstrate enormous potential. Therefore, the integration of DTs into security frameworks is critical and demands focused attention. In this paper, we reviewed how DTs improve performance, reliability, and security across key domains, such as energy, smart homes, transportation, healthcare, and manufacturing. We presented, for the first time, a unified study that surveys recent digital twin–based security applications across cyber-physical systems, the Internet of Things, and cryptographic systems, focusing on security use cases of digital twins for counterfeit electronics detection, intrusion detection, and information leakage prevention. We also summarized the integration of LLM with DT for security workflows, the challenges and limitations of DT applications in hardware security, and highlighted the ongoing research trends, concluding with a future roadmap for advancing DT-based hardware security solutions.

Acknowledgment

This work was supported by the National Science Foundation under Grant Number CNS-2312139.

References

[1] U. Guin, D. Forte, and M. Tehranipoor, "Anti-counterfeit techniques: From design to resign," in *International workshop on Microprocessor Test and Verification (MTV)*, pp. 89–94, 2013.

[2] M. Tehranipoor, U. Guin, and D. Forte, *Counterfeit Integrated Circuits: Detection and Avoidance*. Springer International Publishing, 2015.

[3] U. Guin, K. Huang, D. DiMase, J. M. Carulli, M. Tehranipoor, and Y. Makris, "Counterfeit Integrated Circuits: A Rising Threat in the Global Semiconductor Supply Chain," *Proceedings of the IEEE*, vol. 102, no. 8, pp. 1207–1228, 2014.

[4] S. T. Valapu, A. Saha, B. Krishnamachari, V. Menon, and U. Guin, "Reward-based Blockchain Infrastructure for 3D IC Supply Chain Provenance," in *to appear IEEE International Symposium on Hardware Oriented Security and Trust (HOST)*, pp. 1–11, 2025.

[5] Y. Zhong, A. Ebrahim, U. Guin, and V. Menon, "A modular blockchain framework for enabling supply chain provenance," in *IEEE Physical Assurance and Inspection of Electronics (PAINE)*, pp. 1–7, 2023.

[6] P. Cui, J. Dixon, U. Guin, and D. DiMase, "A blockchain-based framework for supply chain provenance," *IEEE Access*, vol. 7, pp. 157113–157125, 2019.

[7] U. Guin, D. DiMase, and M. Tehranipoor, "Counterfeit Integrated Circuits: Detection, Avoidance, and the Challenges Ahead," *Journal of Electronic Testing*, vol. 30, no. 1, pp. 9–23, 2014.

[8] W. Hu, A. Ardeshiricham, and R. Kastner, "Hardware information flow tracking," *ACM Computing Surveys (CSUR)*, vol. 54, no. 4, pp. 1–39, 2021.

[9] J. Rajendran, A. M. Dhandayuthapany, V. Vedula, and R. Karri, "Formal security verification of third party intellectual property cores for information leakage," in *29th International conference on VLSI design and 2016 15th international conference on embedded systems*, pp. 547–552, 2016.

[10] J. Hovanes, Y. Zhong, and U. Guin, "Beware of Discarding Used SRAMs: Information is Stored Permanently," in *IEEE Physical Assurance and Inspection of Electronics (PAINE)*, pp. 1–7, 2022.

[11] R. Karri, J. Rajendran, K. Rosenfeld, and M. Tehranipoor, "Trustworthy hardware: Identifying and classifying hardware trojans," *Computer*, vol. 43, no. 10, pp. 39–46, 2010.

[12] A. Jain, Z. Zhou, and U. Guin, "Survey of Recent Developments for Hardware Trojan Detection," in *IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1–5, 2021.

[13] M. Tehranipoor, H. Salmani, and X. Zhang, "Integrated circuit authentication," *Switzerland: Springer, Cham. doi*, vol. 10, pp. 978–3, 2014.

[14] P. Kocher, J. Jaffe, and B. Jun, "Differential power analysis," in *Advances in Cryptology—CRYPTO'99: 19th Annual International Cryptology Conference Santa Barbara, California, USA, August 15–19, 1999 Proceedings 19*, pp. 388–397, Springer, 1999.

[15] F.-X. Standaert, "Introduction to side-channel attacks," *Secure integrated circuits and systems*, pp. 27–42, 2010.

[16] T. Schneider and A. Moradi, "Leakage assessment methodology: A clear roadmap for side-channel evaluations," in *Cryptographic Hardware and Embedded Systems–CHES 2015: 17th International Workshop, Saint-Malo, France, September 13-16, 2015, Proceedings 17*, pp. 495–513, Springer, 2015.

[17] Y. Jin, "Introduction to hardware security," *Electronics*, vol. 4, no. 4, pp. 763–784, 2015.

[18] H. A. Shaikh, M. B. Monjil, S. Chen, N. Asadizanjani, F. Farahmandi, M. Tehranipoor, and F. Rahman, "Digital twin for secure semiconductor lifecycle management: prospects and applications," *arXiv preprint arXiv:2205.10962*, 2022.

[19] A. Pokhrel, V. Katta, and R. Colomo-Palacios, "Digital twin for cybersecurity incident prediction: A multivocal literature review," in *Proceedings of the IEEE/ACM 42nd international conference on software engineering workshops*, pp. 671–678, 2020.

[20] M. El-Hajj, T. Itäpelto, and T. Gebremariam, "Systematic literature review: Digital twins' role in enhancing security for industry 4.0 applications," *Security and Privacy*, vol. 7, no. 5, p. e396, 2024.

[21] A. Rasheed, O. San, and T. Kvamsdal, "Digital twin: Values, challenges and enablers from a modeling perspective," *IEEE access*, vol. 8, pp. 21980–22012, 2020.

[22] M. M. Rathore, S. A. Shah, D. Shukla, E. Bentafat, and S. Bakiras, "The role of ai, machine learning, and big data in digital twinning: A systematic literature review, challenges, and opportunities," *IEEE Access*, vol. 9, pp. 32030–32052, 2021.

[23] S. Huang, G. Wang, Y. Yan, and X. Fang, "Blockchain-based data management for digital twin of product," *Journal of Manufacturing Systems*, vol. 54, pp. 361–371, 2020.

[24] B. Putz, M. Dietz, P. Empl, and G. Pernul, "Ethertwin: Blockchain-based secure digital twin information management," *Information processing & management*, vol. 58, no. 1, p. 102425, 2021.

[25] S. Son, D. Kwon, J. Lee, S. Yu, N.-S. Jho, and Y. Park, "On the design of a privacy-preserving communication scheme for cloud-based digital twin environments using blockchain," *IEEE Access*, vol. 10, pp. 75365–75375, 2022.

[26] X. Meng, A. Srivastava, A. Arunachalam, A. Ray, P. H. Silva, R. Psiakis, Y. Makris, and K. Basu, "Unlocking hardware security assurance: The potential of llms," *arXiv preprint arXiv:2308.11042*, 2023.

[27] W. Fu, K. Yang, R. G. Dutta, X. Guo, and G. Qu, "Llm4sechw: Leveraging domain-specific large language model for hardware debugging," in *Asian Hardware Oriented Security and Trust Symposium*, pp. 1–6, 2023.

[28] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *The International Journal of Advanced Manufacturing Technology*, vol. 94, pp. 3563–3576, 2018.

[29] E. Glaessgen and D. Stargel, "The digital twin paradigm for future nasa and us air force vehicles," in *53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference*, p. 1818, 2012.

[30] M. Grieves, *Virtually perfect: driving innovative and lean products through product lifecycle management*, vol. 11. Space Coast Press Cocoa Beach, 2011.

[31] M. Grieves, "Product lifecycle management: driving the next generation of lean thinking," *(No Title)*, 2006.

[32] M. K. A. Madjid, S. Noureddine, B. Amina, B. Khelifa, A. Sofiane, and C. Ahmed, "Design a digital twin sensors system using cgan-lstm for greenhouse climate control," in *4th International Conference on Embedded & Distributed Systems (EDiS)*, pp. 132–136, 2024.

[33] C. Pylianidis, S. Osinga, and I. N. Athanasiadis, "Introducing digital twins to agriculture," *Computers and Electronics in Agriculture*, vol. 184, p. 105942, 2021.

[34] P. Angin, M. H. Anisi, F. Göksel, C. Gürsoy, and A. Büyükgülcü, "Agrilora: a digital twin framework for smart agriculture.," *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl.*, vol. 11, no. 4, pp. 77–96, 2020.

[35] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, and M. J. Deen, "A novel cloud-based framework for the elderly healthcare services using digital twin," *IEEE access*, vol. 7, pp. 49088–49101, 2019.

[36] Y. Xu, Y. Sun, X. Liu, and Y. Zheng, "A digital-twin-assisted fault diagnosis using deep transfer learning," *Ieee Access*, vol. 7, pp. 19990–19999, 2019.

[37] W. Booyse, D. N. Wilke, and S. Heyns, "Deep digital twins for detection, diagnostics and prognostics," *Mechanical Systems and Signal Processing*, vol. 140, p. 106612, 2020.

[38] V. Ankitha, "Digital twin in healthcare: What it is, what it does," Sept. 12 2024. [Online]. Available: https://toobler.com/blog/digital-twin-in-healthcare.

[39] S. Ferguson, "Apollo 13: The first digital twin," April 2020. [Online]. Available: https://blogs.sw.siemens.com/simcenter/apollo-13-the-first-digital-twin.

[40] B. D. Allen, "Digital twins and living models at nasa," in *Digital Twin Summit*, 2021.

[41] R. Piascik, J. Vickers, D. Lowry, S. Scotti, J. Stewart, and A. Calomino, "Technology area 12: Materials, structures, mechanical systems, and manufacturing road map," *NASA Office of Chief Technologist*, pp. 15–88, 2010.

[42] E. J. Tuegel, A. R. Ingraffea, T. G. Eason, and S. M. Spottswood, "Reengineering aircraft structural life prediction using a digital twin," *International Journal of Aerospace Engineering*, vol. 2011, no. 1, p. 154798, 2011.

[43] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," *Transdisciplinary perspectives on complex systems: New findings and approaches*, pp. 85–113, 2017.

[44] M. W. Grieves, "Digital twins: past, present, and future," in *The digital twin*, pp. 97–121, Springer, 2023.

[45] B. Bothwell, "Science & Tech Spotlight: Digital Twins—Virtual Models of People and Objects," Tech. Rep. GAO-23-106453, U.S. Government Accountability Office, feb 2023. Published and Publicly Released: Feb 14, 2023.

[46] M. Segovia and J. Garcia-Alfaro, "Design, modeling and implementation of digital twins," *Sensors*, vol. 22, no. 14, p. 5396, 2022.

[47] J. Willard, X. Jia, S. Xu, M. Steinbach, and V. Kumar, "Integrating scientific knowledge with machine learning for engineering and environmental systems," *ACM Computing Surveys*, vol. 55, no. 4, pp. 1–37, 2022.

[48] M. G. Kapteyn, J. V. Pretorius, and K. E. Willcox, "A probabilistic graphical model foundation for enabling predictive digital twins at scale," *Nature Computational Science*, vol. 1, no. 5, pp. 337–347, 2021.

[49] S. Mihai, M. Yaqoob, D. V. Hung, W. Davis, P. Towakel, M. Raza, M. Karamanoglu, B. Barn, D. Shetve, R. V. Prasad, *et al.*, "Digital twins: A survey on enabling technologies, challenges, trends and future prospects," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 4, pp. 2255–2291, 2022.

[50] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, "Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation," *Journal of energy storage*, vol. 30, p. 101557, 2020.

[51] Y. Li, B. Bohara, H. S. Krishnamoorthy, and J. Seshadrinath, "Data-driven digital twins for monitoring the health and performance of converters," in *IEEE International Communications Energy Conference (INTELEC)*, pp. 1–6, 2024.

[52] F. Tao, M. Zhang, J. Cheng, and Q. Qi, "Digital twin workshop: a new paradigm for future workshop," *Computer Integrated Manufacturing Systems*, vol. 23, no. 1, pp. 1–9, 2017.

[53] F. Bellalouna, "Case study for design optimization using the digital twin approach," *Procedia CIRP*, vol. 100, pp. 595–600, 2021.

[54] P. Aivaliotis, K. Georgoulias, and G. Chryssolouris, "The use of digital twin for predictive maintenance in manufacturing," *International Journal of Computer Integrated Manufacturing*, vol. 32, pp. 1067–1080, 2019.

[55] S. Centomo, N. Dall'Ora, and F. Fummi, "The design of a digital-twin for predictive maintenance," in *25th IEEE International Conference on Emerging Technologies and Factory Automation*, vol. 1, pp. 1781–1788, 2020.

[56] M. Xiong, H. Wang, Q. Fu, and Y. Xu, "Digital twin–driven aero-engine intelligent predictive maintenance," *The International Journal of Advanced Manufacturing Technology*, vol. 114, pp. 3751–3761, 2021.

[57] P. Jain, J. Poon, J. P. Singh, C. Spanos, S. R. Sanders, and S. K. Panda, "A digital twin approach for fault diagnosis in distributed photovoltaic systems," *IEEE Transactions on Power Electronics*, vol. 35, no. 1, pp. 940–956, 2019.

[58] N. Zhang, C. Vergara-Marcillo, G. Diamantopoulos, J. Shen, N. Tziritas, R. Bahsoon, and G. Theodoropoulos, "Large language models for explainable decisions in dynamic digital twins," *arXiv preprint arXiv:2405.14411*, 2024.

[59] M. J. Smith, "Getting value from artificial intelligence in agriculture," *Animal Production Science*, vol. 60, no. 1, pp. 46–54, 2018.

[60] I. A. Lakhiar, G. Jianmin, T. N. Syed, F. A. Chandio, N. A. Buttar, and W. A. Qureshi, "Monitoring and control systems in agriculture using intelligent sensor techniques: A review of the aeroponic system," *Journal of sensors*, vol. 2018, no. 1, p. 8672769, 2018.

[61] F. Vicente-Guijalba, T. Martinez-Marin, and J. M. Lopez-Sanchez, "Dynamical approach for real-time monitoring of agricultural crops," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 6, pp. 3278–3293, 2014.

[62] A. Manocha, S. K. Sood, and M. Bhatia, "Iot-digital twin-inspired smart irrigation approach for optimal water utilization," *Sustainable computing: Informatics and systems*, vol. 41, p. 100947, 2024.

[63] Y. Qu, *A Digital Twin Framework for Commercial Greenhouse Climate Control System*. PhD thesis, University of Southern Denmark, 2023.

[64] W. J. Knibbe, L. Afman, S. Boersma, M.-J. Bogaardt, J. Evers, F. Van Evert, J. Van der Heide, I. Hoving, S. Van Mourik, D. De Ridder,

et al., "Digital twins in the green life sciences," *NJAS: Impact in Agricultural and Life Sciences*, vol. 94, no. 1, pp. 249–279, 2022.

[65] P. Moghadam, T. Lowe, and E. J. Edwards, "Digital twin for the future of orchard production systems," in *Proceedings*, vol. 36, p. 92, MDPI, 2020.

[66] J. D. Chaux, D. Sanchez-Londono, and G. Barbieri, "A digital twin architecture to optimize productivity within controlled environment agriculture," *Applied Sciences*, vol. 11, no. 19, p. 8875, 2021.

[67] H.-K. Wang, R. Haynes, H.-Z. Huang, L. Dong, and S. N. Atluri, "The use of high-performance fatigue mechanics and the extended kalman/particle filters, for diagnostics and prognostics of aircraft structures," *CMES: Computer Modeling in Engineering & Sciences*, vol. 105, no. 1, pp. 1–24, 2015.

[68] A. J. Zakrajsek and S. Mall, "The development and use of a digital twin model for tire touchdown health monitoring," in *58th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, p. 0863, 2017.

[69] A. M. Lund, K. Mochel, J.-W. Lin, R. Onetto, J. Srinivasan, P. Gregg, J. E. Bergman, K. D. Hartling, A. Ahmed, S. Chotai, *et al.*, "Digital system and method for managing a wind farm having plurality of wind turbines coupled to power grid," Nov. 20 2018. US Patent 10,132,295.

[70] A. Wunderlich and E. Santi, "Digital twin models of power electronic converters using dynamic neural networks," in *IEEE Applied Power Electronics Conference and Exposition (APEC)*, pp. 2369–2376, 2021.

[71] A. Saad, S. Faddel, T. Youssef, and O. A. Mohammed, "On the implementation of iot-based digital twin for networked microgrids resiliency against cyber attacks," *IEEE transactions on smart grid*, vol. 11, no. 6, pp. 5138–5150, 2020.

[72] A. Saad, S. Faddel, and O. Mohammed, "Iot-based digital twin for energy cyber-physical systems: design and implementation," *Energies*, vol. 13, no. 18, p. 4762, 2020.

[73] H. Pan, Z. Dou, Y. Cai, W. Li, X. Lei, and D. Han, "Digital twin and its application in power system," in *5th International Conference on Power and Renewable Energy (ICPRE)*, pp. 21–26, 2020.

[74] X. Song, T. Jiang, S. Schlegel, and D. Westermann, "Parameter tuning for dynamic digital twins in inverter-dominated distribution grid," *IET Renewable Power Generation*, vol. 14, no. 5, pp. 811–821, 2020.

[75] A. Saad, T. Youssef, A. T. Elsayed, A. Amin, O. H. Abdalla, and O. Mohammed, "Data-centric hierarchical distributed model predictive control for smart grid energy management," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4086–4098, 2018.

[76] T. Erol, A. F. Mendi, and D. Doğan, "The digital twin revolution in healthcare," in *4th international symposium on multidisciplinary studies and innovative technologies*, pp. 1–7, 2020.

[77] J. Chen, W. Wang, B. Fang, Y. Liu, K. Yu, V. C. Leung, and X. Hu, "Digital twin empowered wireless healthcare monitoring for smart home," *IEEE Journal on Selected Areas in Communications*, vol. 41, no. 11, pp. 3662–3676, 2023.

[78] G. M. Thiong'o and J. T. Rutka, "Digital twin technology: The future of predicting neurological complications of pediatric cancers and their treatment," *Frontiers in Oncology*, vol. 11, p. 781499, 2022.

[79] A. Haleem, M. Javaid, R. P. Singh, and R. Suman, "Exploring the revolution in healthcare systems through the applications of digital twin technology," *Biomedical Technology*, vol. 4, pp. 28–38, 2023.

[80] M. M. Salim, A. K. Comivi, T. Nurbek, H. Park, and J. H. Park, "A blockchain-enabled secure digital twin framework for early botnet detection in iiot environment," *Sensors*, vol. 22, no. 16, p. 6133, 2022.

[81] A. Becue, Y. Fourastier, I. Praça, A. Savarit, C. Baron, B. Gradussofs, E. Pouille, and C. Thomas, "Cyberfactory# 1—securing the industry 4.0 with cyber-ranges and digital twins," in *14th IEEE international workshop on factory communication systems (WFCS)*, pp. 1–4, 2018.

[82] Z. Liu, A. Zhang, and W. Wang, "A framework for an indoor safety management system based on digital twin," *Sensors*, vol. 20, no. 20, p. 5771, 2020.

[83] S. H. Khajavi, M. Tetik, Z. Liu, P. Korhonen, and J. Holmström, "Digital twin for safety and security: Perspectives on building lifecycle," *IEEE Access*, vol. 11, pp. 52339–52356, 2023.

[84] V. Gopinath, A. Srija, and C. N. Sravanthi, "Re-design of smart homes with digital twins," in *Journal of Physics: Conference Series*, vol. 1228, p. 012031, IOP Publishing, 2019.

[85] T. Y. Fujii, V. T. Hayashi, R. Arakaki, W. V. Ruggiero, R. Bulla Jr, F. H. Hayashi, and K. A. Khalil, "A digital twin architecture model applied with mlops techniques to improve short-term energy consumption prediction," *Machines*, vol. 10, no. 1, p. 23, 2021.

[86] S. A. Kumar, R. Madhumathi, P. R. Chelliah, L. Tao, and S. Wang, "A novel digital twin-centric approach for driver intention prediction and traffic congestion avoidance," *Journal of Reliable Intelligent Environments*, vol. 4, no. 4, pp. 199–209, 2018.

[87] V. Arya, A. Gaurav, B. B. Gupta, C.-H. Hsu, and H. Baghban, "Detection of malicious node in vanets using digital twin," in *International Conference on Big Data Intelligence and Computing*, pp. 204–212, Springer, 2022.

[88] M. Kalil, "Tesla's digital twins," March 2024. [Online]. Available: https://mikekalil.com/blog/tesla-digital-twins/.

[89] Y. Ye, B. Xu, J. Zhang, B. Lawler, and B. Ayalew, "Reinforcement learning-based energy management system enhancement using digital twin for electric vehicles," in *IEEE Vehicle Power and Propulsion Conference (VPPC)*, pp. 1–6, 2022.

[90] S. Venkatesan, K. Manickavasagam, N. Tengenkai, and N. Vijayalakshmi, "Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin," *IET Electric Power Applications*, vol. 13, no. 9, pp. 1328–1335, 2019.

[91] K. Kušić, R. Schumann, and E. Ivanjko, "A digital twin in transportation: Real-time synergy of traffic data streams and simulation for virtualizing motorway dynamics," *Advanced Engineering Informatics*, vol. 55, p. 101858, 2023.

[92] M. Eckhart and A. Ekelhart, "Towards security-aware virtual environments for digital twins," in *Proceedings of the 4th ACM workshop on cyber-physical system security*, pp. 61–72, 2018.

[93] J. Hornik and M. Rachamim, "Leveraging ai-enabled digital twins to combat counterfeit brands," *Journal of Forensic Sciences & Criminal Investigation*, pp. 1–8, 2024.

[94] A. Z. Benelhaouare, A. Oukaira, M. Oumlaz, and A. Lakhssassi, "Enhancing thermal security of 3d-sip systems through thermal digital twin (tdt)," in *IEEE Canadian Conference on Electrical and Computer Engineering*, pp. 20–24, 2024.

[95] F. Böhm, M. Dietz, T. Preindl, and G. Pernul, "Augmented reality and the digital twin: State-of-the-art and perspectives for cybersecurity," *Journal of Cybersecurity and Privacy*, vol. 1, no. 3, pp. 519–538, 2021.

[96] I. H. Sarker, H. Janicke, A. Mohsin, A. Gill, and L. Maglaras, "Explainable ai for cybersecurity automation, intelligence and trustworthiness in digital twin: Methods, taxonomy, challenges and prospects," *ICT Express*, 2024.

[97] K. Hammar and R. Stadler, "Digital twins for security automation," in *IEEE/IFIP Network Operations and Management Symposium*, pp. 1–6, 2023.

[98] M. Dietz and G. Pernul, "Unleashing the digital twin's potential for ics security," *IEEE Security & Privacy*, vol. 18, no. 4, pp. 20–27, 2020.

[99] A. B. Shitole, N. K. Kandasamy, L. S. Liew, L. Sim, and A. K. Bui, "Real-time digital twin of residential energy storage system for cyber-security study," in *IEEE 2nd International Conference on Smart Technologies for Power, Energy and Control*, pp. 1–6, 2021.

[100] M. Dietz, M. Vielberth, and G. Pernul, "Integrating digital twin security simulations in the security operations center," in *Proceedings of the 15th International Conference on Availability, Reliability and Security*, pp. 1–9, 2020.

[101] F. Akbarian, E. Fitzgerald, and M. Kihl, "Intrusion detection in digital twins for industrial control systems," in *International Conference on Software, Telecommunications and Computer Networks*, pp. 1–6, 2020.

[102] E. C. Balta, M. Pease, J. Moyne, K. Barton, and D. M. Tilbury, "Digital twin-based cyber-attack detection framework for cyber-physical manufacturing systems," *IEEE Transactions on Automation Science and Engineering*, vol. 21, no. 2, pp. 1695–1712, 2023.

[103] M. El-Hajj, "Leveraging digital twins and intrusion detection systems for enhanced security in iot-based smart city infrastructures," *Electronics (Switzerland)*, vol. 13, no. 19, p. 3941, 2024.

[104] C. Gehrmann and M. Gunnarsson, "A digital twin based industrial automation and control system security architecture," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 1, pp. 669–680, 2019.

[105] M. M. Tehranipoor, U. Guin, and D. Forte, *Counterfeit Integrated Circuits: Detection and Avoidance*. Springer International Publishing, 2015.

[106] P. Kumar, R. Kumar, A. Kumar, A. A. Franklin, S. Garg, and S. Singh, "Blockchain and deep learning for secure communication in digital twin empowered industrial iot network," *IEEE Transactions on Network Science and Engineering*, vol. 10, no. 5, pp. 2802–2813, 2022.

[107] G. Cathey, J. Benson, M. Gupta, and R. Sandhu, "Edge centric secure data sharing with digital twins in smart ecosystems," in *Third IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications*, pp. 70–79, 2021.

[108] O. Alharbi, R. A. Shaikh, and R. Asif, "Data-aided intrusion detection systems: Leveraging ai, blockchain and digital twin technology," in

IEEE International Conference on Big Data (BigData)*, pp. 8214–8215, 2024.
[109] S. Pirbhulal, H. Abie, and A. Shukla, "Towards a novel framework for reinforcing cybersecurity using digital twins in iot-based healthcare applications," in *IEEE 95th Vehicular Technology Conference:(VTC2022-Spring)*, pp. 1–5, 2022.
[110] Y. Yigit, C. Chrysoulas, G. Yurdakul, L. Maglaras, and B. Canberk, "Digital twin-empowered smart attack detection system for 6g edge of things networks," in *IEEE Globecom Workshops (GC Wkshps)*, pp. 178–183, 2023.
[111] P. Empl, D. Schlette, D. Zupfer, and G. Pernul, "Soar4iot: securing iot assets with digital twins," in *Proceedings of the 17th International Conference on Availability, Reliability and Security*, pp. 1–10, 2022.
[112] I. Pittaras and G. C. Polyzos, "Secure and efficient web of things digital twins using permissioned blockchains," in *7th International Conference on Smart and Sustainable Technologies (SpliTech)*, pp. 1–5, 2022.
[113] H. Yi, R. Lin, H. Song, C. Li, and X. Lin, "Experimental study of cryptographic algorithm based on digital twin technology side channel leakage intelligent measurement and assessment," *Rev. Adhesion Adhesive*, vol. 11, no. 25, pp. 856–880, 2023.
[114] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
[115] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, pp. 4171–4186, 2019.
[116] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, *et al.*, "Gpt-4 technical report," *arXiv preprint arXiv:2303.08774*, 2023.
[117] H. Naveed, A. U. Khan, S. Qiu, M. Saqib, S. Anwar, M. Usman, N. Akhtar, N. Barnes, and A. Mian, "A comprehensive overview of large language models," *arXiv preprint arXiv:2307.06435*, 2023.
[118] L. Yang, S. Luo, X. Cheng, and L. Yu, "Leveraging large language models for enhanced digital twin modeling: Trends, methods, and challenges," *arXiv preprint arXiv:2503.02167*, 2025.
[119] Y. Wang, T. Fu, Y. Xu, Z. Ma, H. Xu, B. Du, Y. Lu, H. Gao, J. Wu, and J. Chen, "Twin-gpt: digital twins for clinical trials via large language model," *ACM Transactions on Multimedia Computing, Communications and Applications*, 2024.
[120] H. Yang, M. Siew, and C. Joe-Wong, "An llm-based digital twin for optimizing human-in-the loop systems," in *IEEE International Workshop on Foundation Models for Cyber-Physical Systems & Internet of Things*, pp. 26–31, 2024.
[121] M. Li, R. Wang, X. Zhou, Z. Zhu, Y. Wen, and R. Tan, "Chattwin: toward automated digital twin generation for data center via large language models," in *Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, pp. 208–211, 2023.
[122] Y. Hong, J. Wu, and R. Morello, "Llm-twin: mini-giant model-driven beyond 5g digital twin networking framework with semantic secure communication and computation," *Scientific Reports*, vol. 14, no. 1, p. 19065, 2024.
[123] S. Thakur, B. Ahmad, H. Pearce, B. Tan, B. Dolan-Gavitt, R. Karri, and S. Garg, "Verigen: A large language model for verilog code generation," *ACM Transactions on Design Automation of Electronic Systems*, vol. 29, no. 3, pp. 1–31, 2024.
[124] R. Kande, H. Pearce, B. Tan, B. Dolan-Gavitt, S. Thakur, R. Karri, and J. Rajendran, "Llm-assisted generation of hardware assertions," *arXiv e-prints*, pp. arXiv–2306, 2023.
[125] Y. Tsai, M. Liu, and H. Ren, "Rtlfixer: Automatically fixing rtl syntax errors with large language model," in *Proceedings of the 61st ACM/IEEE Design Automation Conference*, pp. 1–6, 2024.
[126] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.-t. Yih, T. Rocktäschel, *et al.*, "Retrieval-augmented generation for knowledge-intensive nlp tasks," *Advances in neural information processing systems*, vol. 33, pp. 9459–9474, 2020.
[127] I. Beltagy, M. E. Peters, and A. Cohan, "Longformer: The long-document transformer," *arXiv preprint arXiv:2004.05150*, 2020.
[128] J. Zheng, H. Hong, F. Liu, X. Wang, J. Su, Y. Liang, and S. Wu, "Fine-tuning large language models for domain-specific machine translation," *arXiv preprint arXiv:2402.15061*, 2024.
[129] W. Takerngsaksiri, J. Pasuksmit, P. Thongtanunam, C. Tantithamthavorn, R. Zhang, F. Jiang, J. Li, E. Cook, K. Chen, and M. Wu, "Human-in-the-loop software development agents," *arXiv preprint arXiv:2411.12924*, 2024.
[130] P. Empl, H. Hager, and G. Pernul, "Digital twins for iot security management," in *IFIP Annual Conference on Data and Applications Security and Privacy*, pp. 141–149, Springer, 2023.

Blessing Airehenbuwa (S'22) received his M.S. in Electrical and Computer Engineering from Tuskegee University, Tuskegee, AL, USA, in 2024. He is currently pursuing his Ph.D. in Electrical Engineering from the Department of Electrical and Computer Engineering, Auburn University, AL, USA. He earned his B. Eng. in Electrical/Electronics Engineering from the University of Benin, Benin City, Nigeria, in 2016. His research interests include hardware security, VLSI design & test, cybersecurity, and digital twins. He is a student member of the IEEE.

Touseef Hasan (S'25) is currently pursuing his Ph.D. from the Department of Electrical and Computer Engineering in the School of Computing at Wichita State University, Wichita, KS, USA. He received his B.Sc. in Naval Architecture and Marine Engineering from Bangladesh University of Engineering and Technology, Dhaka, Bangladesh in 2024. His research interests include exploring the practicality and accessibility of LLMs. He is a student member of the IEEE.

Souvika Sarkar (M'25) received her Ph.D. in Computer Science and Software Engineering from Auburn University in 2020. She is currently an Assistant Professor in the School of Computing at Wichita State University, Wichita, KS, USA. Prior to that, she completed her B.Tech in Computer Science and Engineering from West Bengal University of Technology, India, in 2012, and earned her M.E. in Software Engineering from Jadavpur University in 2018.

Dr. Sarkar's research interests include natural language processing (NLP), generative AI, LLMs, and building scalable and adaptive AI systems. Her research centers on developing efficient NLP systems, with a strong focus on interpretability, adaptability, and real-world impact. She has published widely in top-tier venues in AI and NLP. She actively serves the research community as a reviewer for leading conferences, including ACL, EMNLP, NAACL, and AACL.

Ujjwal Guin (S'10–M'16–SM'22) received his Ph.D. in Electrical and Computer Engineering from the University of Connecticut in 2016. He is currently the Godbold Associate Professor in the Department of Electrical and Computer Engineering at Auburn University, Auburn, AL, USA. He earned his B.E. in Electronics and Telecommunication Engineering from Bengal Engineering and Science University, India, in 2004, and his M.S. in Electrical and Computer Engineering from Temple University, Philadelphia, PA, USA, in 2010.

Dr. Guin's research interests lie in the areas of hardware security and trust, supply chain security, cybersecurity, and VLSI design and test. He has developed a range of on-chip structures and techniques aimed at enhancing the security, trustworthiness, and reliability of integrated circuits. He has authored thirty-plus journal articles and over fifty conference papers, with several earning best paper nominations and awards. His research has been supported by the National Science Foundation (NSF) and several DoD institutions. He actively contributes to the academic community by serving on organizing and technical program committees of leading conferences, including HOST, ITC, VTS, PAINE, and several other well-regarded venues.