

Paper Type: Review Article

A Comprehensive Exploration of Internet of Digital Twins (IoDT) – Architecture, Applications, State-of-Art AI-based Solutions

Alaa Elmor^{1,*} ¹ Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt; alaaelmor@zu.edu.eg.**Received:** 20 Oct 2023**Revised:** 13 Dec 2023**Accepted:** 12 Jan 2024**Published:** 15 Jan 2024

Abstract

Digital twins (DTs) have emerged as a powerful technology with wide-ranging applications across various fields including industry, healthcare, agriculture, smart city applications, etc. The convergence of Artificial Intelligence and the IoT with DTs can fulfill the system's requirements in modeling and communication infrastructure. This convergence also enhances their potential by boosting predictive capabilities and facilitating data-driven decision-making. However, as DTs and AI are increasingly adopted, cybersecurity requirements have grown exponentially. In this study, the architecture and applications of the Internet of Digital Twins (IoDT) and review the state-of-the-art defense approaches. Lastly, we discuss research challenges and open research directions related to IoDT.

Keywords: Digital Twins; Internet of Digital Twin; IoDT; Cybersecurity; Blockchain; Artificial Intelligence; Internet of Things; Industry 4.0.

1 | Introduction

An important factor changing the industrial landscape is Industry 4.0. Fundamentally, automation is the aim of Industry 4.0, which aims to transform conventional industrial processes. As production and distribution procedures are modernized and optimized, this transition is having an increasingly positive effect on the value chain [2]. The core objectives of Industry 4.0 are in perfect harmony with the quick and continuous digital revolution that is occurring in our current age. Industry 4.0 seeks to convert a large amount of physical equipment from the real world into the virtual one. The idea of DTs serves as the foundation for this operation [3]. An object, process, human, or human-related aspect can all be represented by a DT. It allows for the monitoring, control, and optimization of its functions by closely mimicking the life cycle of the actual entity or process it represents. Moreover, a DT reliably predicts future circumstances, such as faults, damage, and malfunctions, enabling preventive maintenance. The continuous interaction, exchange of information, and synchronization—known as closed-loop optimization—between the DT, its physical counterpart, and the external world around it enable this proactive approach [4]. DTs are used in many different systems and industries, including manufacturing [5], healthcare [6], aerospace [7], transportation [8], and smart cities [9]. These domains can enable a wide range of intelligent services, including car accident avoidance [10], COVID-19 pandemic mitigation [11], and ramp merging [12], among others, by utilizing DTs.

Artificial intelligence (AI) and the Internet of Things (IoT) are two modern technologies that are being actively implemented in response to the growing complexity of traditional services. The use of DTs as powerful

**Corresponding Author:** alaaelmor@zu.edu.eg

Licensee **International Journal of Computers and Informatics**. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0>).

representational tools for a range of real-world entities is noteworthy. In this particular context, DTs serve as dynamic and adaptable representations, informed by the architectural model proposed by Grieves and Vickers [13], which divides the DT into three primary components, explained below:

- Physical space: represents the real-world system, object, or environment that is the subject of the modeling and monitoring process. It includes the hardware, sensors, and data sources in the process of gathering data from the outside environment.
- Digital space: it utilizes digital counterparts to represent physical entities, and these counterparts can also act as controllers for the physical entities.
- Communication space: serving as an essential link between the digital and physical domains, the communication space allows real-time information exchange across both domains. It makes sure that information moves smoothly from physical space to digital space and vice versa.

The DT can record, observe, and forecast the behaviors of physical systems and objects due to the bidirectional real-time connectivity between the virtual and physical worlds. It also provides effective resource allocation.

DTs are currently able to represent an enormous number of things due to the rapid deployment of Internet of Things (IoT) infrastructures. Each of these dynamically-featured DTs generates enormous volumes of data that when aggregated, can yield comprehensive insights across different physical things, like vehicles, charging stations, and whole cities. As a result of this convergence, shared virtual environments—where people and physical objects communicate, participate, and operate together with their digital counterparts—are created, thus, the concept of the "Internet of Digital Twin" IoDT was born[14].

Despite its great potential, IoDT has significant privacy and security issues. One of the main concerns is the complex route that mission-critical, delay-sensitive DT data takes across several networks, necessitating extensive security and trust procedures. Furthermore, there is a greater chance of privacy violations due to the detailed nature of the personal data that ubiquitous IoT devices acquire. Due to its diverse functionalities, IoDT presents new security vulnerabilities in addition to inheriting old ones, necessitating innovative security solutions. Conventional approaches are insufficient due to IoDT's unique characteristics and the varying quality-of-service requirements across applications. Moreover, IoDT's connectivity between cyber and physical spaces exposes critical systems to cyberattacks, requiring robust Cybersecurity defenses.

We aim to answer the following research questions in this survey:

RQ1: What is IoDT?

RQ2: Is IoDT truly necessary?

RQ3: What are the various applications of IoDT?

RQ4: What challenges exist in IoDT implementation, and what state-of-the-art solutions?

1.1 | Existing Surveys

Many surveys about DTs in general or particular areas have been published. Nevertheless, none of them offer a comprehensive exploration of IoDT and its applications, as well as research challenges and state-of-the-art techniques such as federated learning (FL), transfer learning (TL), explainable artificial intelligence (XAI), and blockchain—all of these form significant and future IoDT research directions. Alcaraz, C. and J. Lopez, [2] examine how the DT paradigm is currently being used and categorize any possible hazards associated with it while taking into account its operational requirements and functionality layer. Additionally, they offer an initial set of security guidelines and tactics that can support ensuring the proper and reliable deployment of a DT. DT technology, challenges, and opportunities are covered by Mihai et al. [3]. Also gives readers a thorough understanding of the technology, outlines design objectives and goals, draws attention to industry-specific design issues and constraints, and offers use cases and applications for DTs. Barricelli et al.

[4] examine the most recent definitions of DT, the key attributes that a DT ought to have, and the domains where DT applications are presently being created. Wang et al. [14] explore the internet of DTs architecture and classification techniques for defense against security and privacy threats. DT Networks (DTN) are defined and emphasized in detail by Wu et al. [15]. The main technologies and challenges associated with DTN are also covered. A comprehensive review of DT concepts across industries is given by Minerva et al. [16]. They also consolidate a common definition and analyze the technical and business value of DTs using architectural models and application scenarios. Tao al. [17] reviews the applications of DT across industries, highlighting their significance for Industry 4.0 and smart manufacturing. They also address some issues and suggest prospective directions for DT research and development in the industry. The obstacles, applications and enabling technologies for DT, IoT, and AI are presented by Fuller et al. [18] they have been classified by study areas: industrial, medical, and smart cities. Khan et al. [19] present an overview of the primary concepts (i.e., design aspects, high-level architecture, and frameworks) of the DT of wireless systems. Furthermore, a comprehensive taxonomy is created for the two distinct aspects, wireless and wireless Twins.

1.2 | Contributions

Our main goal in this survey is to examine the complicated IoDT system. Our work provides readers with a sophisticated understanding of this complex field by representing an in-depth investigation of significant aspects within it. An outline of its architecture, modes of communication, AI prospects, and state-of-the-art safety procedures. The utmost contributions of this review article are summarized as follows:

- We start an in-depth examination of the IoDT's architecture, as well as intricate communication modes essential to the IoDT's operation, and explore security threats.
- Within the IoDT, we investigate how Artificial Intelligence (AI) is transforming various tasks and domains.
- We review state-of-the-art solutions that address major security, efficiency, and scarcity challenges.
- As part of our dedication to improving the IoDT and expanding the perspectives of researchers and the IoDT communities, we focus on exciting opportunities and potential future directions.

The following is an overview of this survey. In Section 2, we will provide an in-depth overview of IoDT, including its Architecture of IoDT systems and Communication Modes. Section 3 provides a comprehensive review of existing work related to AI-empowered IoDT. Section 4 State-of-the-Art Solutions for IoDT Security, Integrity, Scarcity, and Efficiency. Finally, Section 5 presents key lessons learned in this survey, Section 6 identifies research challenges and future directions. Table 1 lists the acronyms utilized in this paper. Table 2 summarizes the existing surveys on DT.

Table 1. Acronyms utilized in this paper.

Acronym	Definition
AI	Artificial Intelligence
IoT	Internet of Things
IoDT	Internet of Digital Twin
ITS	Intelligent Transport Systems
PEs	Physical Entities
Des	Digital Entities
DSRC	Dedicated Short Range Communication
V2V	Vehicle to Vehicle
V2P	Vehicle to Pedestrian
V2S	Vehicle to Sensor
V2I	Vehicle to Infrastructure

DSRC	Dedicated Short Range Communication
MEC	Multi-access Edge Computing
NFT	Non-Fungible Token
DRL	Deep Reinforcement Learning
RHM	Remote Health Monitoring
VR	Virtual Reality
IoRT	Internet of Robotic Things
REI	Robot-Environment Interaction
IoRT	Internet of Robotic Things
AR	Augmented Reality
GUI	Graphical User Interface
CCAs	Coordinated Cyber Attacks
V2G-CPSs	Vehicle-to-Grid-enabled Cyber-Physical Systems
LSTM	Long Short-Term Memory
DRL	Deep Reinforcement Learning
TAs	Traffic Accidents
TSD	Time Series Data
PF	Particle Filter
EMT	Electromagnetic Transients
RMES	Regional Multiple Energy Systems
DCs	Data Centers
EVs	Electric vehicles
SOH	State of Health
SOC	State of Charge
BDA	Big Data Analytics
ML	Machine Learning
BDA	Big Data Analytics
EIoT	Energy Internet of Things
FL	Federated Learning
TL	Transfer Learning
XAI	Explainable Artificial Intelligence
DTN	Digital Twin Networks
IIoT	Industrial Internet of Things
DITEN	Digital Twin Edge Networks
IoVs	Internet of Vehicles
XAI	Explainable Artificial Intelligence

Table 2. Our novel contributions in IoDT compared to previous surveys.

Ref	Year	Main Contribution	Taxonomy/ Classification	Trends Identified	Theoretical vs Practical aspects	Applications	Security	Intelligence	Challenges Highlighted	Future Directions
[2]	2022	Analyzing operational	Functionality	cyber-physic	Theoretical		✓		The need to guarantee secure	- Establish simple countermeasures to

		requirements, possible threats to the digital twin model, and related security measures	layers and corresponding technologies.	al systems/ IIoT/ edge computing / AI/ Big Data					deployment and protection of DT.	safeguard the DT and its implementation. - Examine the ways in which DTs might be leveraged to augment the safeguarding of other crucial infrastructures, and consequently put forth specific online cyber security strategies predicated on DTs.
[3]	2022	A survey on technologies, case studies, applications, and the future of the digital twin	Applications/ Technologies	ML/ cloud / fog and edge computing / IoT/IoT, Cyber Physical Systems/ VR/ AR	Practical	✓		✓	- Development expenses and ROI that is hard to measure. - The absence of standardized methods for modeling digital twins presents new difficulties for addressing their interoperability to optimize interconnectivity. - Data ownership and governance	-Enhancing interdisciplinary collaboration -Developing standardized protocols and APIs -Improving model validation and verification
[4]	2019	Exploration of fundamental principles, attributes, applications, and lifecycle of digital twins	Applications	AI/ IoT	Theoretical	✓			Ethical issues, security and privacy concerns, high development costs, the need for globally distributed knowledge and technology, government regulations, and challenges with end-user development.	-Collaborative and sociotechnical design methods -Dissemination visual information and simple interaction between the end-user and the DT data. -Defining the degree of human virtualization
[14]	2023	Investigating decentralized Internet of digital twins architecture and classification schemes to protect against privacy and security risks	Security and privacy threats	AI/ block chain / cloud and edge computing	Theoretical		✓		- Network environment dynamics, privacy, and security -Regulatory and Interoperable -High fidelity	-Multilayered and multidimensional resource allocation. -Dynamic network/security resource cooperation. - Explainable AI, with a trade-off between accuracy and interpretation

[15]	2021	A thorough examination of the challenges, applications, and technologies of digital twin networks	Applications/ Technologies	Federated learning/ Blockchain / Edge intelligence	Theoretical	✓			-Balance the data utilization and protection -Cost and resources -Service delay	- Enhance security and privacy -Cost-Effective Solutions -Real time communication
[16]	2020	A thorough overview of digital twin applications in the context of IoT	Application domains / Properties	Virtual Augmented Reality/ Multi agent Systems/ Virtualization	Theoretical	✓			- The ability to entanglement and aggregate. - The gathering and analyzing of data. - Knowledge on people's usage patterns will unavoidably result from the servitization of commonly used items and products.	- Consider more intricate combinations of objects and components - Apply DT concept in the design, control, and management of Smart cities - Represent a significant portion of the real world with the use of softwarized objects to construct applications, or be employed in specialized systems
[17]		Review of the advancements and issues in using digital twin technology in the industry	Development/ Applications	Cloud Computing /Big Data/ IoT	Theoretical	✓			- Limited scope and difficult integration between historical data and real time data in prognostics and health management. - There's been no agreement on how to construct a general DT model - Security threats	- Extend the use of DTs beyond expensive machinery - Create a standard framework for DT modeling - Enhance security
[18]		Study on use cases, issues, and current methodologies in the deployment of digital twins	Applications/ Challenges/ Enabling technologies	AI/ Cloud Computing / IoT	Theoretical	✓	✓		- IT infrastructure limitations - Data privacy and security concerns - Trust issues - Real-time data streams	- Improving real-time data integration - More AI-based case studies - Standardisation

[19]		An in-depth taxonomy for fusing wireless systems and digital twin technology	Design/ Deploy ment	Feder ated Learn ing/ block chain / AI/ 6G/ IoT/ exten ded reality (XR)	Theor etical	✓	✓		- Security and privacy concerns - The need for accurate prototyping and designing	- Developing incentive mechanisms for twinning - Develop AI models for dynamic and real-time systems
Our survey		A comprehensive survey on IoDT. Particularly, (1) Architecture of IoDT and communication modes. (2) State-of-the-art AI-empowered IoDT, challenges, solutions. (3) In our effort to assist fellow researchers in broadening their perspectives on this subject, we discuss challenges and open research issues while identifying emerging trends and suggesting potential future directions.	Applicat ions/ AI Techniq ues	Feder ated Learn ing/ Trans fer Learn ing/ XAI/ Cloud Comp uting / IoT/ Block chain	Theor etical	✓	✓	✓	- Synchronization - Data Security - Scaling Outside Proof of Concept	- 6G Network Development - Enhanced Data Security - Scaling Solutions

2 | Internet of Digital Twins: Overview

The general architecture and communication modes of the IoDT are presented in this section.

2.1 | The Internet of Digital Twins' Architecture

As shown in Figure 1, the construction of a digital twin for an intelligent transportation system involves the physical space, the DTs along with their virtual assets in cyberspace, and emerging technologies (e.g., IoT, AI, and blockchain) that play as the engine for our system.

Physical Space: Intelligent Transport Systems (ITS) are intelligent systems that leverage cutting-edge technologies in traffic pattern management and transportation system modeling. They provide end users with more variety of information, enhanced safety, and better quality of road user interactions than traditional transportation systems [20]. PEs in physical space (ITS) are divided into four primary categories: sensing entities, control entities, infrastructure entities, and communication entities. Particularly, Sensing Entities: 1- traffic sensors: these might be LiDAR sensors mounted on traffic lights, radar sensors, or inductive loop sensors placed in the road. Data about vehicle presence, speed, and volume of traffic are gathered by them. 2-surveillance cameras: which are placed at strategic points along roads, record and capture images in real-time. This data can be used for security, incident detection and prediction, and traffic monitoring. Control Entities: 1- traffic management centers, which use data gathered from cameras and sensors to schedule traffic signals, manage lanes, and predict and respond to incidents. 2-variable message signs (VMS): Messages about accidents, detours, and road conditions can be updated and shown on VMS remotely by control centers. 3-traffic signal controllers: are designed to optimize traffic flow by regulating the timing and sequencing of traffic signals at intersections. Infrastructure Entities such as traffic lights, roadside cabinets, road signs, and lanes. Communication Entities: 1- Wireless communication networks: facilitate data transmission, such as Wi-Fi, cellular networks, and dedicated short range communication (DSRC). 2- Fiber optic cables: form fiber optic networks that connect sensors, cameras, and control centers. 3- Vehicle-to-Everything (V2X) Communication Units: facilitate communication between vehicles, pedestrians, and road infrastructure.

Digital Twin: Autonomous vehicles, despite their advanced onboard sensing and processing capabilities, face critical challenges that hinder their full potential. These challenges include limited sensing range, with sensors like LiDAR and millimeter-wave radar only covering short distances, as well as their susceptibility to adverse weather conditions. Additionally, the processing capacity within autonomous vehicles is often insufficient for handling complex traffic scenarios, resulting in high costs. Moreover, communication barriers in existing networks make it challenging for autonomous vehicles to efficiently cooperate with each other. The development and growth of the DT provided insight into how to address the aforementioned challenges with autonomous vehicles. The goal of a DT is to accurately representing a real object's lifecycle and status as a virtual representation on cloud or MEC servers. The definition of the vehicular DT is the cloud-based DT of the physical vehicle that wirelessly synchronizes real-time sensor data from the vehicle [21].

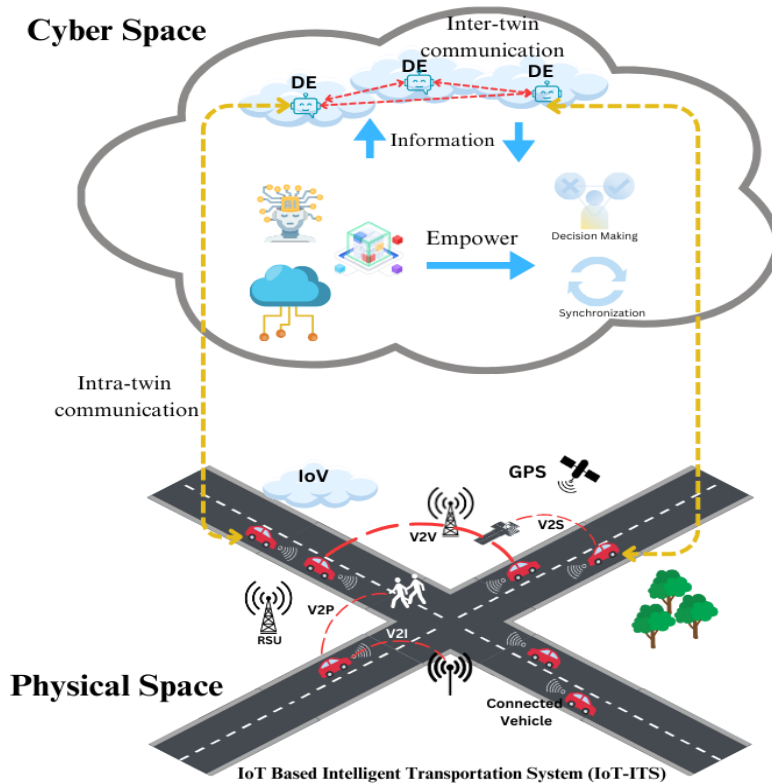


Figure 1. The general architecture of the digital twins empowered intelligent transportation system.

Technologies: data exchange is necessary for the bidirectional communication between physical entities and their digital counterparts in the modeling, creation, maintenance, and continual improvement, and representations of digital entities. According to [14], this intricate process is backed by several cutting-edge technologies, including blockchain, IoT, AI, and extended reality. These topics will be covered in more detail below:

- IoT utilizes a fusion of technologies, general-purpose computing, a variety of sensors, artificial intelligence, and increasingly robust embedded systems. It serves as the foundational technology that provides the essential sensing, networking, and computing infrastructures and capabilities for physical assets. The widespread IoT sensors conduct real-time data collection from various sources and direct this data. In the context of transportation, the twin of a vehicle can be easily constructed and maintained by fusing data from various sensors, such as radars, cameras, and LiDAR.
- AI: by learning from both historical and real-time data, AI algorithms enable accurate simulations to build and develop DTs with high fidelity and reliability in replicating the physical assets, processes, and systems. For example, deep learning models can assist with accident tracking, route planning, and predictive maintenance.
- Blockchain technology is an important component of our system. It provides consensus-based distributed protocols, trustworthy smart contracts, and distributed ledgers, all working together to autonomously establish the origins and ownership of assets, as well as increase trust in data and value exchanges among virtual twins. Through the use of chained blocks and advanced cryptographic techniques, data stored in historical blocks becomes immutable and irreplaceable, guaranteeing the utmost reliability of records. Non-fungible tokens (NFTs), integrated with blockchain ledgers, serve as a mechanism for validating authentic rights, such as virtual asset identification and ownership history. This contribution extends to shaping the economic framework of IoDT. Furthermore, distributed consensus protocols aid in IoDT governance and regulation, fostering democratic and efficient decision-making. Additionally, digital contracts enable the automatic and trustworthy flow of information, knowledge, resources, and assets between virtual twins.

The integration of virtual reality (XR) into the Internet of Digital Twin architecture improves the capacity to manipulate and visualize DTs, hence facilitating the seamless transition between digital and physical spaces [22]. XR offers a range of visualization modalities along the Reality-Virtuality continuum. It comprises VR for visualizing a fully synthetic environment composed of digitally reconstructed objects, AR for superimposing digital content onto the real world, and MR for matching digital and physical entities [23-25]. Along with enhancing visualization, this integration makes it easier to implement immersive feedback and 3D interaction techniques.

2.2 | Digital Twins Communication Modes

The architecture of the digital twin network is investigated from the perspectives of both intra- and inter-twin communication [21, 26]:

Intra-twin Communications: The link between PE and DE consists of two fundamental components: raw data transmission and processed information exchange. Raw data refers to information collected by various sensors, flowing from the PE to the DE. Processed information, on the other hand, encompasses analytical outcomes generated by the DE and transmitted back to the PE. Together, these three components—PE, DE, and intra-twin communication—form a full inner loop of the system. This inner loop serves as a foundation for effective simulation, prediction, and feedback mechanisms within the digital twin. In the context of transportation, intra-twin communication refers to the channel that exists between a vehicle and its cloud-based digital twin. The vehicle uses wireless connection technologies like Wi-Fi or 5G cellular networks to send real-time sensor data to its dedicated digital twin through intra-twin communication. Concurrently, the digital twin in the cloud transmits the data it gathers to the vehicle. Therefore, this

communication has several essential features: Firstly, consistent communication. The digital twin and the autonomous vehicle must stay in constant contact to guarantee information consistency. Thus, throughout the ride, digital twins can be updated continuously with sensed data and condition information from the vehicle. Another necessary feature is real-time synchronization to ensure not only the accuracy of data transfer but also its security and compliance with relevant regulations, and it plays a pivotal role in providing users with a smooth and reliable experience. Moreover, a private and engaged connection is central to intra-twin communication. As digital collaborators, the primary objective of digital twins is to assist physical autonomous vehicles in accessing virtual cloud resources effectively. In order to enable safe and private twin synchronization, the digital twin and its matching autonomous car are purposefully connected in a private manner. As a result, the digital twin stays private to its corresponding vehicle.

Inter-twin communication: It describes the interaction between digital twins hosted in the cloud. Through inter-twin communication, cloud-based digital twins can exchange valuable information, leverage AI insights, and provide feedback to ground-based vehicles. Due to the relay of inter-twin communication, the autonomous vehicle can indirectly connect with other vehicles outside of their communication range. This enables autonomous vehicles to access global traffic information effectively. Assume that PE2 will learn about the route along its driving path from PE3, as shown in Figure 2. Due to the out of purview, direct vehicle-to-vehicle connections between PE2 and PE3 might not be possible. To be able to perform this, DE2 can engage in inter-twin communication with DE3 to obtain PE 3's sensory data. DE2 can then transmit this information to PE2 using its intra-twin communication capabilities. Therefore, this communication has several essential features: Firstly, it is characterized by a distributed peer-to-peer connection, where each digital twin functions as an independent entity within a larger network of digital twins. In this network, each digital twin assumes a dual role as both a resource provider and acquirer, sharing various resources or services. Additionally, inter-twin communication involves the management of private data assets. Each digital twin, closely associated with its respective autonomous vehicle, securely houses an enormous quantity of data collected from the vehicle. These data hold significant value and sensitive user information, which is a part of the private data assets of the digital twin. Furthermore, inter-twin communication can be viewed as a form of multi-agent communication. Because the digital twin is an independent, intelligent virtual entity, it might be considered an agent. As a result, the properties of multi-agent communication apply to communication between digital twins.

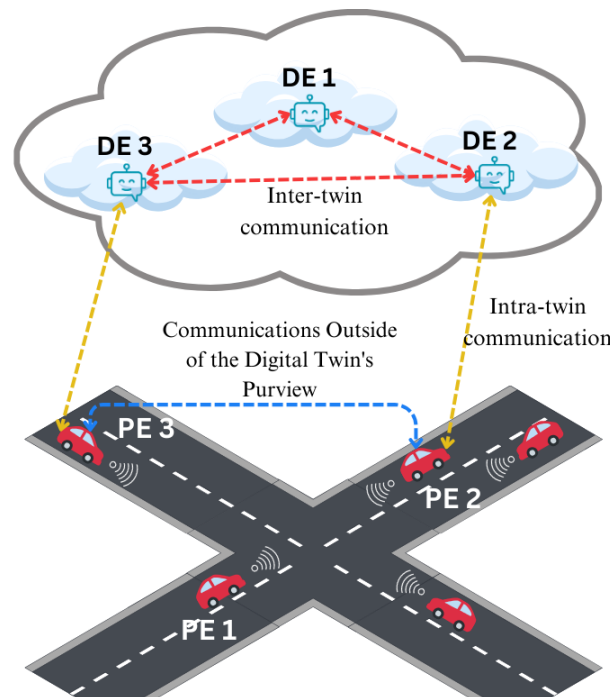


Figure 2. Digital twin communication model.

3 | IoDT Applications Across Various Domains

There is no end to the applications of IoT. The global count of IoT devices is expected to nearly double, rising from 15.1 billion in 2020 to surpass 29 billion by 2030 [1] as shown in Figure 3. This substantial growth encourages leveraging the benefits of DT and IoDT throughout a range of industries, including transportation, healthcare, industrial manufacturing, agriculture, and more. In this section, we discuss existing real-world applications across various domains, encompassing areas like robotics, transportation, and energy, summarized in Table 3.

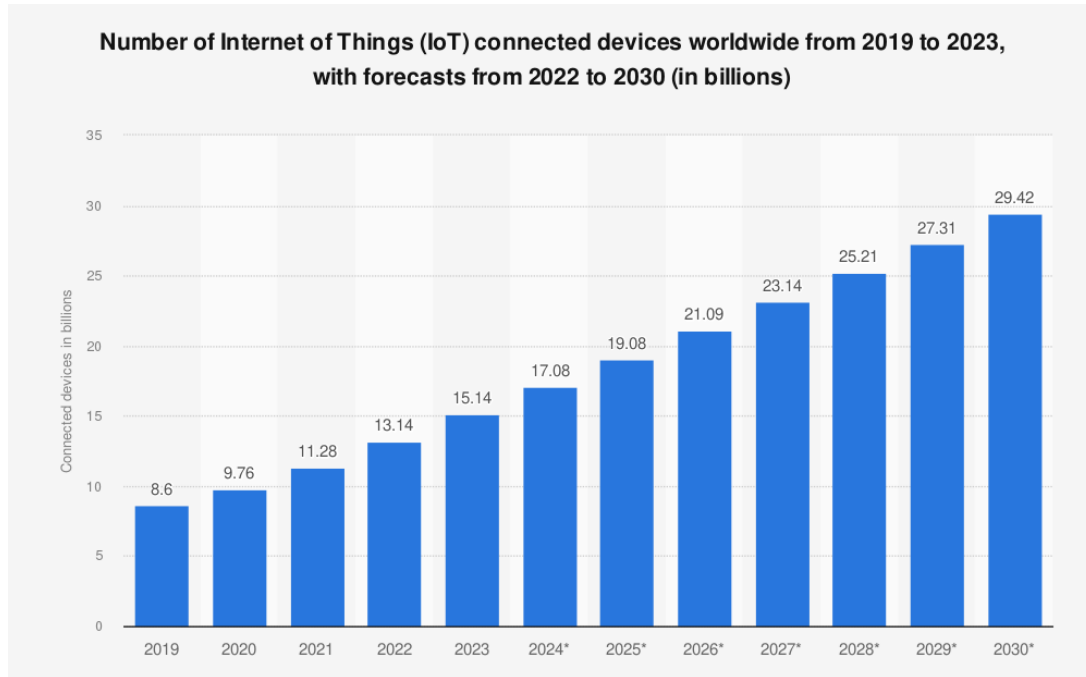


Figure 3. IoT device count worldwide [1].

Table 3. IoDT applications across various domains.

Taxonomy	Ref.	Year	Problem	Key Technologies / Approach	Main contributions
Robotics	[27]	2020	Cloud-based Digital Twin implementations struggle with high computational demands, causing latency and reliability issues, while Edge and Fog Computing offer a solution by bringing computation closer to physical entities. However, this shift introduces new networking needs, including requirements for low latency, high reliability, and real-time data transmission	ROS, 5G, DT, DL	Proposes an Edge-based Digital Twin solution for robotics within Industry 4.0, leveraging ROS middleware to provide a common interface for different robotic systems, thereby avoiding vendor lock-in situations. It offloads computational and analytics stacks to intelligent edge and fog infrastructure, introducing modules for control, motion planning, task learning, predictive maintenance, and fault detection.
	[28]	2021	Current monitoring of Robot-Environment Interaction (REI) lacks accuracy and granularity. Challenges include accurately capturing and understanding the dynamics of real-world interactions.	DT, VR, DL	Introduces a semantic-enhanced DT system, utilizing sensory modalities for monitoring states and inferring semantics in REI. And develops a 3-D model that mirrors authentic interactive scenes, extracting entity appearance, and physical properties.

		Ensuring consistency between the DT and the real system response.		
[29]	2021	Inaccurate simulation and control could result from current cloud-based digital models that don't correctly represent the actual state of physical robotic manufacturing systems.	DT, Cloud Computing, Ontology Models	Proposes a framework for industrial robotic control called DTICR, which combines high-fidelity digital models with sensory data to enable fine-grained control of actual manufacturing processes.
[30]	2022	The process of training robots to perform a grasping process in the actual world is time-intensive, expensive, and fraught with safety issues. It is a challenge to transfer robot learning policies from simulation to reality.	DRL, TL, DT	Proposes a method for effectively transferring Deep reinforcement learning (DRL) algorithms to a real robotic, which is facilitated by the combination between DT and TL.
[31]	2022	Teleportation and coordination of multiple industrial robots in collaborative manufacturing systems lack user-friendly approaches, resulting in redundant learning costs and limited intuitive control capabilities.	AR, DT, RL	Proposes a novel multi-robot collaborative manufacturing system with human-in-the-loop control, leveraging AR and DT techniques, while integrating reinforcement learning for enhanced motion planning and conducting experimental studies to validate efficiency and applicability.
[32]	2023	Potential infection risks for medical staff during direct interactions with patients, especially during the COVID-19 pandemic. Remote health monitoring (RHM) limitations with passive IoT sensors in DTs. Need to extend monitoring beyond specific locations.	DT, VR, IoT	Proposes a real-time RHM system for COVID-19 patients utilizing DTs-based Internet of Robotic Things (IoRT) and a VR interface.
[33]	2023	For rehabilitation, people with upper limb dysfunction (ULD) frequently need long-term support from therapists; however, access to physical therapists is restricted because of scheduling, budgetary, and geographic limitations. The requirement to travel to many places for therapy also impedes continuity of care, making it difficult to provide customized therapy programs with feedback and real-time monitoring.	IoT, AR-based Graphical User Interface (GUI), DT	Proposed a framework for telerehabilitation for rehabilitation robots that enables users to control rehab robots remotely for upper limb exercises using an AR-based GUI. This efficiently addresses issues with accessibility and continuity of care that arise in conventional rehabilitation settings. Experiments using commercially available and custom-built rehabilitation robots validated the telerehabilitation framework and successfully demonstrated the transmission of upper limb rehab activities in 2D and 3D planes via AR, enabling stable and successful remote rehabilitation sessions.
[34]	2018	The current infrastructure is being challenged by the rapid growth in road traffic, therefore smarter cities must allocate and use resources optimally. For dynamic city environments, current automated traffic management methods are reactive and inefficient;	AI, DT, IoT, 5G, Blockchain	Provides a real-time traffic congestion avoidance approach using fog analytics, DT, and Machine Learning (ML) which integrates data gathering, driver behavior analysis, and historical data storage.

			requiring real-time, adaptive, and predictive alternatives.		
Transportation	[35]	2021	For transportation infrastructure systems to be safe and functional, bridge groups must be managed effectively. Traditional approaches are incapable of sophisticated management and real-time monitoring, which makes it difficult to maintain ideal bridge conditions and guarantee safety.	DT, AI	Proposed a virtual system for monitoring bridge groups in real time using measured traffic loads. It uses an information fusion of weigh-in-motion (WIM) and machine vision for full-bridge traffic load monitoring, Bridge functioning conditions, and safety alerts evaluated and predicted by creating mechanical analysis models in a digital environment. A set of bridges near Shanghai, China proved the system's feasibility which is a present opportunity for intelligent transportation infrastructure.
	[36]	2021	Poor safety performance for the Maritime Transportation Systems	DT, IoT, DL	Propose an IoDT model for maritime transportation safety by acquiring and preprocessing historical transportation data of the Maritime Silk Road. Presents a smart DT-enabled security framework for the detection and mitigation of Cyber-Physical Attacks, integrating the LSTM-DRL algorithm to ensure stability in Vehicle-to-Grid Cyber-Physical Systems.
	[37]	2022	Traffic Accidents	DT, PF, DL	Propose a traffic accident prediction model utilizing DTs and AI and show how well in comparison to existing models. Particle Filter (PF) increases the effectiveness of controlling traffic incidents by improving particle dilution and target tracking precision.
	[38]	2023	Vulnerability of vehicle-to-grid-enabled cyber-physical systems (V2G-CPSs) to coordinated cyber-attacks (CCAs).	DT, DL, IoT	Proposes a robust and secure framework for CCA detection and mitigation in V2G-CPSs, utilizing DT. Using LSTM-DRL, the framework presents a more intelligent DT orchestrator that can estimate system states, detect CCAs, and take appropriate actions to reduce their effects.
Energy	[39]	2020	Given the complexity of multiple-energy, multiple-time scale, and multi-functional collaborative distribution networks, modeling and simulating large-scale regional multiple energy systems (RMES) using conventional approaches is time-consuming and inefficient financially.	CloudPSS, DT	Introduces a general approach to creating a multi-timescale digital twin model using CloudPSS for RMES. This approach combines electromagnetic transient (EMT) and power flow models to meet the needs of multi-timescale analysis. The RMES digital twin model can handle many stages such as planning, operation optimization, maintenance, and prototype modeling and verification by utilizing power flow calculations, real-time EMT simulations, and multi-scenario simulations.

[40]	2022	Higher consumption of energy in data centers (DCs) as a result of the DCs' rapid expansion and the quick expansion of cloud computing, mobile internet, and the Internet of Things (IoT). This increase in energy consumption is unfavorable to energy conservation, emission reduction, and sustainable development.	DT, AI	Propose energy-saving method, lowers DC energy usage while maintaining safe and effective operation by combining AI and DT technologies. The method produces a 41.07% reduction in energy usage ratio for the cooling system by optimizing air distribution and redundancy in the cooling system.
[41]	2022	Electric vehicles (EVs) are not as widely adopted as they could be due to their dependency on batteries, which age and perform worse than liquid fuels and have poorer energy and power densities. To ensure the efficient and secure functioning of EV batteries, it is essential to monitor their state over time, especially their State of Charge (SOC) and State of Health (SOH).	DT, ML, EKF	Proposes a battery digital twin-based solution for EVs with the goal of improving situational awareness of battery management systems and optimizing battery storage unit performance. The proposed solution allows correct prediction of SOC and SOH, increases battery useable life, and makes it easier to manage batteries effectively throughout their lifecycle by utilizing DT and AI.
[42]	2022	Alternative Situation Awareness (SA) approaches are required in place of traditional model-based SA due to the growing complexity of energy systems, which includes distributed generation, interconnected utilities, coupling of physical disciplines, and the development of energy infrastructure for smart cities.	DT, ML, BDA	Proposes the new data-driven SA paradigm known as DT-SA is a viable substitute for the traditional model-based SA in the context of the Energy Internet of Things (EIoT). DT-SA tackles the issues of coupling effects, variety, and uncertainty in modern energy systems by utilizing the capabilities of DT, Big Data Analytics (BDA), and ML techniques.

3.1 | Robotics

The architecture of the digital twin network is investigated from the perspectives of both intra- and inter-twin communication [21, 26]:

Internet of Robotic Things (IoRT) is a cutting-edge domain that converges IoT with robotic systems and introduces distinctive features from traditional robotics services like cloud robotics and networked robotics such as widespread network accessibility, composability, spatial distribution, virtualized diversification, and extensibility. IoRT finds applications in various domains such as military, agriculture, industry, and healthcare [43, 44]. The characteristics of IoRT systems are emphasized by the following points [45]:

- **Sensing:** Sensing is a standard feature of the Internet of Things and robotic systems. It allows them to communicate intelligently with other machines and with humans as well as with other IoT devices. Several systems have already included sensing-as-a-service under this functionality.
- **Actuating:** Actuating is defined as taking appropriate action in considering all kinds of virtual and physical actions that are now unavailable in the IoT environment. Actuating must search for a reliable, secure, and safe environment for the creation, implementation, and management of open, multi-vendor IoT application services. "Actuating-as-Service" is a revolutionary concept that has been developed in recent research advancements to provide user adaptability and interactivity for IoT devices.

- **Control:** Control loops or series of loops are two ways that IoT might give IoRT sophisticated control mechanisms. To provide IoRT with greater autonomous control, control loops can be readily mapped to virtually anything, including virtual and real devices, clouds, and other networks.
- **Planning:** This will grant IoRT systems a unique capability called Orchestration-Organizer logic, which effectively works with inner platform components to fulfill service requests and observe quality standards all the way through the service life cycle. Planning uses an automated workflow engine to set up the necessary features for each service request.
- **Perception:** The power of robotics' perception can be greatly increased with IoT. Robotics regards perception as the integration of sensor data and knowledge modeling to facilitate machine-human interaction through a variety of applications including artificial intelligence, cloud computing, software engineering, machine learning, big data, and sensor communications. IoT enables IoRT robots to do sophisticated tasks and sense their surroundings in real-time with more intelligence.
- **Cognition:** IoRT-based systems using IoT are able to perceive data from sensors from various devices. Stated differently, IoRT is capable of analyzing data from various environmental occurrences and determining the appropriate course of action. IoRT devices can benefit from both distributed and local intelligence in this way.

Using edge computing and 5G connection, Girletti et al. [27] offer a convincing approach for an Intelligent Edge-based Digital Twin for Robotics. By efficiently shifting computing responsibilities from robots to the network, the suggested approach enhances flexibility and performance. The effectiveness of the solution is shown via a sequence of experiments carried out in a real-world setting. Experiment 1 demonstrates the significance of 5G connectivity in achieving superior synchronization between physical and digital entities. Findings show that 5G makes it possible to transfer processing to the edge, guaranteeing the robotic manipulator reliably. However, 4G has limitations because of latency problems, which highlights the importance of new communication technologies. Experiment 2 demonstrates how resilient the system is to changing loads and how 5G outperforms 4G in terms of bandwidth. It is mentioned that there is a possibility of improvement with 5G SA's sophisticated Quality of Service (QoS) policies, which would guarantee Digital Twin's continuous operation even with high network traffic. Experiment 3 demonstrates an adaptive control loop configuration mechanism to decrease the impact of network latency on the Quality of Experience (QoE). By dynamically adjusting control parameters based on real-time network conditions, the system maintains synchronization between physical and digital entities.

Li et al. [32] integrate DTs, IoRT, and VR technologies to present a real-time solution for RHM of COVID-19 patients. Robotic things (RTs) use IoRT to navigate in the environment and gather real-time data from sensors attached to patients to produce a DE that reflects the status of the PE. The DE reduces the danger of infection by allowing medical personnel to remotely check patients' health without direct interaction with them. The system improves medical staff members' situational awareness by using VR as a user interface for real-time interaction and DT visualization. Rather than relying on conventional camera-based methods, the navigation system, which was created with the Unity-3D game engine, uses DE and VR technology to guide the PE in real space. Navigational precision and safety are further improved by real-time obstacle recognition and visualization systems. NRF24L01+ communication modules enable data transmission between DTs, while Bluetooth modules (HC-05) link the PT to medical sensors (DS-18B20 and MAX30100) to gather health data.

3.2 | Transportation

ITS have transformed transportation by incorporating AI and smart sensors to optimize routes and coordinate traffic in real time. This not only reduces costs but also enhances safety and efficiency while alleviating accidents and congestion. By leveraging DT, automated vehicles and ITS can be virtually modeled and analyzed, allowing instrument failure forecast, autonomous guide, traffic management, process

improvement and the evaluation of predicted behavior. This virtualization reduces testing expenses and uncertainties, saves energy, boosts drivers' health, and increases performance [34, 46-49].

Using an intelligent DT-enabled approach, Ali et al. [38] propose a robust and secure framework for detecting and decreasing CCAs in V2G-CPSs. Using LSTM-DRL approaches, the proposed architecture improves V2G-CPS security and resilience against various cyberthreats. The framework employs an intelligent DT orchestrator that continuously monitors system security constraints and activates the LSTM block to estimate system states when security threats are detected. The DRL network then makes use of the states obtained from LSTMs to detect and efficiently mitigate CCAs, particularly attacks targeting malicious V2G nodes and control commands. Case studies on a modified IEEE 30-bus system-based V2G-CPS show how the proposed framework may be used to detect and mitigate different types of CCAs, especially switching attacks (SA) and False Data Injection Attack (FDIA). Results indicate the capability of the framework to prevent potential blackouts by rerouting power from Wind Turbines (WTs) and V2G nodes while maintaining network constraints.

Lv et al. [37] proposes a system for preventing Traffic Accidents (TAs) and ensuring the safety of both drivers and pedestrians. The system incorporates prediction models, target tracking algorithms, and video analysis techniques to enhance TA prevention and processing capabilities, leveraging DTs and AI. Firstly, decomposed TA Time Series Data (TSD) into sub-layers using a double-scale decomposition equation. Then the system uses an LSTM network for prediction. Next, a PF is used for target tracking, and resampling methods are used to handle possible occlusion problems. In the end, the proposed target tracking algorithm and DTs are integrated and utilized for TA processing, enabling real-time analysis and response. The results of the experiments show how well and reliably the proposed study predicts TSD. The proposed model shows superior performance than other models. Additionally, the optimized Particle Swarm Optimization (PSO) model enhances target identification and improves system performance. The design of the system consists of multiple parts, such as twin data analysis methods, identification analysis systems, and 3D Geometric Modeling (GM) schemes for Highway Transportation. By combining these elements, an efficient intelligent TA prevention system is reached, capable of providing accurate predictions and timely responses to potential accidents.

3.3 | Energy

With the emergence of new energy technologies such as distributed energy and renewable energy, along with new Information and communication technology (ICT) such as big data, IoT, and cloud computing, the global energy revolution is gradually moving toward intelligence and interconnection. Developing an energy internet is one of the goals of China's energy revolution, as it is crucial for the networking and informationization of diverse sources of energy [50-52]. Three characteristics highlight the fusion of ICTs and energy networks: deep integration, intelligence, and digitalization[53]. Digitalization and intelligence are now common goals in energy internet management. The integration of energy technologies and ICTs is necessary for the implementation of the Energy Internet. To achieve the extremely intelligent and integrating of energy sources, Energy Internet sets new requirements of ubiquity, reliability, and intelligence for different energy sources. To accomplish these goals, a complex system with interface architecture, virtual models, simulations, and data storage is needed. One of the most important tools for addressing the digitization and intelligence demands of the Energy Internet's development is IoDT, which combines big data, IoT, and high-performance computing technologies[54].

Zhang et al.[40] propose a Smart DC that utilizes DT and AI technologies to decrease DCs energy usage. The solution takes into consideration DCs' growing energy needs, it focuses on maximizing air distribution efficiency while minimizing cooling duplication within DCs to save energy. It integrates physical space, AI engine, and digital space components. The physical space is divided into device layers for data collection and control layers for implementing energy-saving measures. AI prediction models, such as predicting power consumption, heat balance, and rack temperature, are trained using an AI engine utilizing datasets that are gathered from both the physical and digital domains. Building information modeling (BIM) and

Computational fluid dynamics (CFD) are used in digital space to model and examine DC airflow and temperature field. It facilitates the investigation of rising temperature limits and configuration optimization for energy efficiency and safe operation. The results of the simulation show how well the Smart DC solution works for reducing energy consumption. By implementing AI and AI-CFD optimized strategies, the solution achieves significant reductions in Power Usage Effectiveness (PUE) and refrigeration energy savings rates (RESR), showing superior energy-saving performance compared to AI-only approaches.

A systematic approach to critical engineering and scientific issues is provided by He et al. [42] proposed DT-SA framework. These issues include virtual-real interaction mechanisms, unified standardized modeling of diverse spatial and temporal data, configuration and evolution of digital twins, and characterization of domain-specific DT-SA. A complete roadmap based on random matrix theory (RMT) and an overall DT-SA framework is established by integrating cloud-edge-terminal configurations, big data analytics, DT, and SA indicator systems. Three essential characteristics of the Fourth Paradigm—data-driven mode, seamless digital-physical space interaction, and iterative, closed-loop feedback—support the framework. These characteristics allow DT-SA to effectively handle the complexity and uncertainty inherent with modern energy systems while also allowing it to adapt to the changing scientific environment. Three case studies that demonstrate the use of DT in the EIoT are presented in this paper: In order to achieve flexible energy and data flow, Case#1 EIoT-DT of Lingang, China demonstrates the integration of cutting-edge ICT with urban energy infrastructure. This supports the development of digital cities and optimizes urban management. Case#2 Dassault, France: Demonstrates the use of DT in the aerospace sector, emphasizing the creation of a 3-D experience platform for precise modeling, simulation, and visualization as well as the digitization of product lifecycles. Case#3 51WORLD, China: Demonstrates the use of DT platforms to support digital transformation and smart city development through AI-driven decision-making, intelligent vehicle virtual simulation, and urban and industrial simulation.

3.4 | Summary of Discussion

Several important conclusions are drawn from our examination of IoDT applications. Automation is a fundamental component that is stressed in a variety of disciplines while developing intelligent IoDT systems. But there's a significant lack of predictive power in IoDT applications, thus more data gathering and study are needed to improve the predictive power of digital twins. The energy domain is still mostly unexplored in IoDT applications, despite the growing research effort in domains like robotics and transportation. This emphasizes the necessity of developing intelligent energy-related solutions to fill this gap. For robotics, real-time sensor feedback is critical for decision-making, particularly in quick movement. In transportation, via real-time system, pedestrian, and traffic data, IoDT systems can save time and money, improve driver mental health, and boost performance.

4 | State-of-art AI solutions

This section explores state-of-the-art AI techniques that address issues with interpretability, efficiency, and data scarcity during model training, including federated learning, transfer learning, and explainable AI.

4.1 | Federated Learning

DTs are data-driven, and in order to support decision-making in IoT systems, an enormous amount of data must typically be distributed across various training devices. Additionally, "data islands" exist in the majority of data sources due to privacy, security, and competitive concerns [55]. Integrating data that is dispersed across multiple devices is practically impossible. The opportunity to create new technologies that aggregate and model data under stringent requirements is presented by the existing challenges of big data and privacy protection. In the context of IoT, FL proves to be an effective method for enabling distributed advanced analysis [56, 57].

FL is a machine learning paradigm; its objective is to develop a superior centralized model while keeping training data distributed among numerous clients. Every time a round occurs, every client separately updates the current model using its local data. It then sends this updated version to a central server, where all of the client-side updates are aggregated to produce a new global model[58]. FL is actively being developed, and in order to implement its underlying technology in real-world scenarios, it employs a range of methods and strategies. The categorization of its methods according to network topology, data partition[59], and synchronization method:

Network Topology

FL can be classified as fully decentralized or centralized based on the network topology.

Centralized Federated Learning

Although FL is basically based on a decentralized data strategy, it depends on a centralized server to manage the work of collecting trained models from clients taking part in the FL environment, generating a global model, and sharing it back with all clients. Establishing a third-party system is mostly favored in order to increase client trust. Following the hub-and-spoke topology/single server and many clients topology [60] guarantees a centralized authority to manage and monitor the continuous process of learning. In the FL environment, the centralized server only works on a shared model through synchronous or asynchronous updates from clients, in contrast to the traditional centralized server which hosts data and trains a particular model on shared data. Digital twins and sixth-generation mobile networks (6G) are integrated by Lu et al. [61]. By establishing strong instantaneous wireless connectivity, this integration solves the problems caused by unreliable communication channels, limited resources, and privacy concerns over data. The proposed framework uses digital twins to move computing and real-time data processing to the edge plane, improving security and dependability while maintaining data privacy. Further addressing privacy concerns, the system makes distributed data processing and learning possible on wireless networks by integrating federated learning. To further improve the system's dependability and security, a blockchain-enabled federated learning framework is presented, offering a clear and verifiable method for data exchanges. The formulation of an edge association issue takes into account the digital twin association, batch size of training data, and bandwidth allocation in order to maximize the learning accuracy and time cost. To solve this problem optimally, a multi-agent reinforcement learning algorithm is developed.

Fully Decentralized Federated Learning

The fully decentralized method does not rely on model aggregation via a central server. Algorithms take the role of centralized authority in establishing reliability and trust. There is no such thing as a global model, as [62] shows, and each participant enhances their model by exchanging data with neighbors. During training rounds, the network adheres to a protocol established once by the central authority, while maintaining a peer-to-peer topology.

Data Partition

FL can be classified as Horizontal, Vertical, or Transfer learning based on how data is shared amongst the devices in the FL system.

Horizontal Federated Learning

When datasets share the same features and different in samples. Clients in this FL category share features such as domain, derived statistical information utilization style, or any other FL outcome. Jiang et al. [63] present a framework for digital twin edge networks that makes use of blockchain technology. Cooperative federated learning, which uses access points (APs) to help resource-constrained smart devices create digital

twins at the network edges owned by various mobile network operators, is a key component of this approach. The authors suggest a directed acyclic graph blockchain-based model update chain to protect local and global model updates, guaranteeing the security and integrity of the process of building a digital twin. Furthermore, APs are encouraged to participate in local model training and verification through an iterative double auction-based joint cooperative federated learning and local model update verification system.

Vertical Federated Learning

A FL method called "vertical federated learning" uses shared data from unrelated domains to train the global model. In order to guarantee that only shared data stats are common, participants in this technique choose to have an intermediary third-party organization or resource provide encryption logic. Nevertheless, research work in [64] shows that vertical federated learning can be implemented without a third party involved for encryption, proving that the presence of an intermediary is not necessary.

Federated Transfer Learning

Federated Transfer Learning is an implementation of the well-known classical ML transfer learning method that allows one to train a new requirement on a model that has already been trained on a comparable dataset in order to solve an entirely different problem. Yang et al. [65] discuss the application of FL in TL mode. With a few modifications, vertical federated learning might resemble a real-time example. Participants can gain from larger datasets and well-trained ML model statistics to meet their specific needs, as opposed to confining conditions to share just matching data information. A novel networking architecture designed specifically for Human Digital Twin (HDT) systems is proposed by Okegbile et al. [66]. This scheme is essential for the evolution and dependable updating of virtual twins. Three fundamental methods lie at the core of this scheme: blockchain, federated multi-task learning (FML), and differential privacy. In order to provide improved accuracy, the framework captures the impact of heterogeneous environments by implementing federated multi-task learning, which enables personalized learning. Furthermore, accurate and approved model evolution in the virtual environment is ensured by a validation procedure during FML that is dependent on the quality of the trained model. This framework is essential to HDT networks since it speeds up learning without sacrificing accuracy, privacy, or communication costs. The study presents a blockchain-enabled validation method combined with a secure differentially private federated multi-task learning (DPFML) framework, guaranteeing security, privacy, and accuracy in HDT connectivity. The system model includes both virtual and physical environments that are connected by a blockchain and FML-enabled connectivity. It also includes procedures for Model Evolution, Validators, Local Aggregators (LAs), and Global Aggregators (GAs). To capture statistical heterogeneity, federated multitask learning is used, in which each LA learns a domain classifier to capture transferable feature representations across tasks, thus reinforcing each task while taking inter-task relevance and differences into account. Tan et al. [67] use FL and DT to present a novel framework for data exchange across vehicles on the Internet of Vehicles (IoVs). Using DTs—cloud-based digital representations of vehicles that are updated with real-time data—the proposed platform enables efficient data exchange between vehicles without physical limitations. FL, combined with TL, ensures privacy-preserving data sharing by exchanging computational models instead of raw data, with personalized model training for data requesters. Blockchain technology is used to securely store distributed data sharing transactions, controlled by smart contracts, in order to maintain fairness and transparency.

Synchronization Method

FL can be classified as Asynchronous or Synchronous based on synchronization method in the FL system.

Asynchronous Federated Learning

The devices update their models independently and asynchronously. Lu et al. [68] present Digital Twin Edge Networks (DITEN), a method that combines edge computing and digital twin technology to improve the quality of services in Industrial Internet of Things (IIoT) systems. DITEN builds digital twin models of IoT devices using operational data by utilizing federated learning. An asynchronous model update strategy for federated learning in DITEN is presented in this study with the goal of lowering energy expenses and communication overhead. By reducing the amount of data transmitted and allocating communication resources optimally, this technique increases communication efficiency.

Synchronous Federated Learning

Every connected device synchronizes their updates at the same time. FedHiSyn [69] is a representation of synchronous Federated Learning; it synchronizes model updates across different types of devices, reduces heterogeneity in data and straggler effects, and improves training accuracy and efficiency all within a decentralized data privacy framework.

4.2 | Transfer Learning

The constraints associated with ML, such as the need for large volumes of training data, costly and time-consuming labeling procedures for data samples, and lengthy training times for models, have led to a surge in interest in TL in recent years. Since TL focuses on applying information from previously completed tasks to new tasks, it can be helpful in solving these issues. Intelligent systems, such as digital twins, must employ TL to expand their knowledge base gradually and apply their prior experience to tackle new problems in a more autonomous manner [70].

TL problems are classified in a variety of ways in the literature. Traditionally, TL problems are divided into three categories: inductive, transductive, and unsupervised TL. These categories are based on the similarity across domains and the availability of labeled and unlabeled data [71]. Transductive TL refers to labeled data that is only available in the source domain; inductive TL refers to labeled data that is available in both the source and target domains. Unsupervised TL is used when neither the source domain nor the target domain contain any labeled data. Nonetheless, a flexible taxonomy [72] known as homogeneous and heterogeneous TL has surfaced in recent years. It is based on domain similarity and is independent of the availability of labeled and unlabeled data. The source and target domains in heterogeneous TL have distinct feature spaces, however the source and target domains in homogeneous TL share the same feature space.

Xu et al. [73] proposed Digital-twin-assisted Fault Diagnosis technique using Deep transfer learning (DFDD) transforms fault diagnosis in smart manufacturing. The two-phase method of DFDD allows for the seamless integration of physical entities with ultra-high-fidelity virtual models, enabling real-time monitoring and early fault detection. Virtual models are built and optimized during the development process, allowing for proactive fault detection and diagnostic model improvement. Deep TL is then used in the implementation phase to transfer knowledge from virtual to physical space, which guarantees precise diagnosis and effective adaptation to dynamic manufacturing conditions. By combining deep TL with DTs, Wang et al. [74] presented a novel method for improving MRI medical images. By utilizing metamaterial composite technology, the technique creates a deep neural network structure with super resolution for improving MRI images. Adaptive decomposition-based multi-mode medical image fusion algorithm takes into account the variations in medical imaging techniques. The proposed technique outperforms others in preserving spatial features and color information orientation across various imaging modalities, as seen by the experimental results, which show considerable increases in MRI truthfulness and sharpness. The digital twin-enabled domain adversarial graph network (DTDAGN) was introduced by Feng et al. [75] to address the challenges related to rolling bearing fault diagnosis. They proposed a complete digital twin model for rolling bearings, which generates vibration responses through dynamic simulation based on structural parameters and fault severity. Moreover, they proposed a TL framework based on graph convolutional networks to transfer knowledge from simulated datasets to measured ones, allowing efficient fault detection even with limited data. Zheng et al. [76] used

TL to present a unique method for data synchronization between vehicles and DTs in the IoVs. TL was used to improve learning effectiveness and reduce data synchronization delay by efficiently transferring knowledge from expert cars to trainee vehicles.

4.3 | Explainable Artificial Intelligence

IoDT is made to take into account a wide range of parameters, from human interactions to surrounding elements and more. Real-time data can be gathered and fed into the digital model with the use of sensors, cameras, and other data sources. Nevertheless, ML or MI algorithms are frequently utilized to train models used in IoDT, that work like black boxes, reducing the transparency and interpretability necessary for well-informed decision-making inside IoDT systems. This leads us to understand the significance of integrating Explainable Artificial Intelligence (XAI) into IoDT in order to improve the ability to manage diverse IoDT features.

XAI aims to help individuals oversee, comprehend, and have confidence in the next wave of artificially intelligent collaborators, by building more transparent models with robust learning capabilities. There are many methods that fall into two categories: interpretability and explainability. Interpretability focuses on understanding the cause-and-effect relationships within an AI model, while explainability extends this by offering a human-readable explanation of the process and reasoning behind the model's predictions.

In order to obtain dependable and trustworthy IoE service execution decisions, Munir et al. [77] presented an innovative neuro-symbolic XAI twin framework for zero-touch network and service management (ZSM) in wireless networks. The framework combined a virtual space that used a directed acyclic graph (DAG)-based Bayesian network for symbolic reasoning with a physical space that operated a neural network-driven multivariate regression, allowing transparent and understandable decision-making processes. Using XAI, Krzysiak, R., D. An, and Y. Chen. [78] presented an explainable digital-twin architecture for cardiovascular health monitoring. Through the use of ML algorithms and feature extraction from ECG data with SHAP (Shapley Additive Explanations), the framework guarantees interpretability and reliability. An, D. and Y. Chen. [79] addressed the issue of opaque decision-making in conventional models by presenting a XAI-powered Digital Twin framework for managing soil carbon emissions. By utilizing the SHAP and AI-enabled proximal sensing, it guaranteed transparent and trustworthy prediction findings, efficiently directing agricultural activities.

5 | Lesson Learned in this Survey

Section 2: IoDT Overview

- IoTD use AI algorithms for many purposes. An enormous amount of data is analyzed by these algorithms to maximize system performance and facilitate autonomous decision-making.
- 6G network research is necessary because synchronization between digital twins and IoT systems requires high-throughput, near-instantaneous communication networks.

Section 3: IoDT applications across various domains

- Multiple studies on automation have shown that automation is the essential feature of the IoDT.
- The number of studies on energy is limited, necessitating further studies and investigation.
- By using optimization algorithms, system performance can be improved. There is a need for more research on the integration of optimization techniques.

Section 4: State-of-art AI solutions

- Federated learning presents a viable solution to address issues related to limited computational and communication capabilities, as well as worries about data security and privacy in digital twin modeling.

- Leveraging transfer learning can yield substantial benefits for IoDT, including improved performance even with no prior information and accelerated model training.
- In conventional IoDT, the tradeoff between interoperability and accuracy highlights the crucial role of XAI in explaining the reasoning behind decisions as well as the effects they have, leading to increased precision, enhanced data efficiency, transparency, and reliability.
- Still, given their limited studies and criticality to the advancement of IoDT, these fields demand more exploration and research efforts.

6 | Research Challenges and Future Directions

The study explores the landscape of Arabic Optical Character Recognition (OCR), emphasizing its significance for Arab and Muslim communities.

6.1 | Synchronization

Bidirectional data exchange between PEs and their DEs must be carried out in a timely and reliable way in order to enable virtual interaction between physical twins over DTs. This requires 6G to handle simultaneous high throughput over enormous data lines[80]. Additionally, with the widespread coverage and high degree of time synchronization accuracy anticipated from 6G, a single DT can concurrently communicate with numerous people in arbitrarily various locations without causing conflicts or collisions between the operations. Telepresence can thus be used to achieve a distant collaboration that functions as seamlessly as on-site, significantly lowering the expenses and effort related to physical distance and access constraints[81].

6.2 | Data Security

Large amounts of data are produced by IoDT, and these data are usually sent to edge or cloud servers for immediate processing. However, a number of threats and attacks on this continuing communication are brought about by the instability of public communication channels and a lack of confidence among participating parties. There is a significant danger of important data loss with every data exchange between the servers hosting the DT and the physical system. This means that maintaining data integrity must receive more attention. Therefore, when developing IoDT, data security concepts like traceability, privacy, authentication, and integrity must be carefully taken into account. One of the new approaches to tackling these issues is to use blockchain technology to protect data privacy in IoDT communication networks. Distributed consensus protocols and cryptographic hashing techniques are used by blockchain to provide safe and secure data transfer. Blockchain's distributed ledgers can assist DTs with design data auditability, accessibility, and traceability. A central authority cannot alter or manipulate the encrypted data of DTs that is kept in the ledger. This functionality improves the efficiency and cost-effectiveness of the DTs audit process in addition to providing previously unheard-of levels of confidence and data integrity.[82-84]. Moreover, various security threats can affect AI models and corresponding training data, which will significantly reduce performance. Current security threats classified according to two aspects: the training phase and the testing/infering phase[85]. Threats during the Training Phase: For AI to produce an appropriate regression or classification model for a target dataset, training is essential. In order to create a high-performance AI model, the training data that are fed into the training phase are crucial. As a result, a large number of attackers target the training data, which significantly lowers the AI model's overall performance. An example of a common security threat against the training phase is a poisoning attack, type of causative attack, which injecting adversarial samples into the training data set in order to compromise the integrity and availability of AI models [86, 87]. Threats during the Testing/Infering Phase: Using the trained model to categorize or cluster new data is the primary process known as the testing or infering phase. Through the use of training model vulnerabilities, adversaries can create a set of complex samples to avoid detection, assume the identity of victims to gain unauthorized access, or even compromise the privacy of training data to obtain victim-

specific sensitive data. The most common types of threat against the testing/inferring phase are inversion attacks and spoofing (ex: evasion and impersonate attacks)[88, 89].

6.3 | Scaling Outside Proof of Concept

Organizations must overcome several obstacles when scaling digital twin technology beyond the proof-of-concept phase to guarantee successful deployment and broad adoption. A notable obstacle is the possibility that digital twin initiatives will stay in the lab, where they are conceived and prototyped but never go further. This standstill is frequently brought on by imprecise cost estimation and a lack of detail in the data collection required to create a strong business case. Furthermore, integrating data from multiple devices presents a significant challenge. Because they might employ different methods for data collecting, processing, and formatting, engineers have trouble integrating data from diverse sensors and pieces of equipment. Inconsistencies in the recording, storing, and processing of this data can hinder attempts to extract valuable insights, even in cases when it is integrated.

To meet the increased demand for modeling settings with multiple scales and scenarios, this study [90] presents a novel approach for building complicated digital twin models. Through the use of 4C architecture-based standardized model division and assembly processing, it facilitates rapid development, modularization, and an efficient focus on key components. The method facilitates behavior interaction and precise computation results in digital twin models by combining information fusion, multi-scale association, and scenario iterations.

7 | Conclusions

In conclusion, this paper has offered a thorough analysis of the fundamental concepts and advanced architecture of IoDT. By providing a comprehensive examination of the IoDT and an investigation of its applications in various domains, we have emphasized its importance in many tasks such as automation and prediction in the context of IoT. Moreover, the investigation into state-of-the-art AI solutions, including transfer learning, federated learning, and explainable AI, has shown promise for integrating IoDT frameworks in a complementary way. Moreover, we have shed light on how blockchain-based security solutions can strengthen the security and integrity of IoDT. This perspective not only enhances our comprehension of IoDT but also drives innovative research agendas aimed at advancing the integration of IoT, AI, blockchain, and 6G for revolutionary effects in the digital domain.

Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Funding

This research has no funding source.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

- [1] Vailshery, L.S. Number of Internet of Things (IoT) connected devices worldwide from 2019 to 2023, with forecasts from 2022 to 2030 2023; Available from: <https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/>.
- [2] Alcaraz, C. and J. Lopez, Digital twin: A comprehensive survey of security threats. *IEEE Communications Surveys & Tutorials*, 2022. 24(3): p. 1475-1503.
- [3] Mihai, S., et al., Digital twins: A survey on enabling technologies, challenges, trends and future prospects. *IEEE Communications Surveys & Tutorials*, 2022.
- [4] Barricelli, B.R., E. Casiraghi, and D. Fogli, A survey on digital twin: Definitions, characteristics, applications, and design implications. *IEEE access*, 2019. 7: p. 167653-167671.
- [5] Soori, M., B. Arezoo, and R. Dastres, Digital Twin for Smart Manufacturing, A Review. *Sustainable Manufacturing and Service Economics*, 2023: p. 100017.
- [6] Venkatesh, K.P., M.M. Raza, and J.C. Kvedar, Health digital twins as tools for precision medicine: Considerations for computation, implementation, and regulation. *NPJ digital medicine*, 2022. 5(1): p. 150.
- [7] Wang, L., Application and development prospect of digital twin technology in aerospace. *IFAC-PapersOnLine*, 2020. 53(5): p. 732-737.
- [8] Gao, Y., et al. Digital twin and its application in transportation infrastructure. in *2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI)*. 2021. IEEE.
- [9] Deren, L., Y. Wenbo, and S. Zhenfeng, Smart city based on digital twins. *Computational Urban Science*, 2021. 1: p. 1-11.
- [10] Almeaibed, S., et al., Digital twin analysis to promote safety and security in autonomous vehicles. *IEEE Communications Standards Magazine*, 2021. 5(1): p. 40-46.
- [11] Lv, Z., et al., Digital twins on the resilience of supply chain under COVID-19 pandemic. *IEEE Transactions on Engineering Management*, 2022.
- [12] Liao, X., et al., Cooperative ramp merging design and field implementation: A digital twin approach based on vehicle-to-cloud communication. *IEEE Transactions on Intelligent Transportation Systems*, 2021. 23(5): p. 4490-4500.
- [13] Grieves, M. and J. Vickers, Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. *Transdisciplinary perspectives on complex systems: New findings and approaches*, 2017: p. 85-113.
- [14] Wang, Y., et al., A survey on digital twins: architecture, enabling technologies, security and privacy, and future prospects. *IEEE Internet of Things Journal*, 2023.
- [15] Wu, Y., K. Zhang, and Y. Zhang, Digital twin networks: A survey. *IEEE Internet of Things Journal*, 2021. 8(18): p. 13789-13804.
- [16] Minerva, R., G.M. Lee, and N. Crespi, Digital twin in the IoT context: A survey on technical features, scenarios, and architectural models. *Proceedings of the IEEE*, 2020. 108(10): p. 1785-1824.
- [17] Tao, F., et al., Digital twin in industry: State-of-the-art. *IEEE Transactions on industrial informatics*, 2018. 15(4): p. 2405-2415.
- [18] Fuller, A., et al., Digital twin: Enabling technologies, challenges and open research. *IEEE access*, 2020. 8: p. 108952-108971.
- [19] Khan, L.U., et al., Digital twin of wireless systems: Overview, taxonomy, challenges, and opportunities. *IEEE Communications Surveys & Tutorials*, 2022. 24(4): p. 2230-2254.
- [20] Rudskoy, A., I. Ilin, and A. Prokhorov, Digital twins in the intelligent transport systems. *Transportation Research Procedia*, 2021. 54: p. 927-935.
- [21] He, C., et al., Security and privacy in vehicular digital twin networks: Challenges and solutions. *IEEE Wireless Communications*, 2022.
- [22] Stacchio, L., A. Angeli, and G. Marfia, Empowering digital twins with eXtended reality collaborations. *Virtual Reality & Intelligent Hardware*, 2022. 4(6): p. 487-505.
- [23] Milgram, P. and F. Kishino, A taxonomy of mixed reality visual displays. *IEICE TRANSACTIONS on Information and Systems*, 1994. 77(12): p. 1321-1329.
- [24] Azuma, R.T., A survey of augmented reality. *Presence: teleoperators & virtual environments*, 1997. 6(4): p. 355-385.
- [25] Speicher, M., B.D. Hall, and M. Nebeling. What is mixed reality? in *Proceedings of the 2019 CHI conference on human factors in computing systems*. 2019.
- [26] Luan, T.H., et al., The paradigm of digital twin communications. *arXiv preprint arXiv:2105.07182*, 2021.
- [27] Girletti, L., et al. An intelligent edge-based digital twin for robotics. in *2020 IEEE Globecom Workshops (GC Wkshps)*. 2020. IEEE.
- [28] Li, X., et al., Semantic-enhanced digital twin system for robot–environment interaction monitoring. *IEEE Transactions on Instrumentation and Measurement*, 2021. 70: p. 1-13.

- [29] Xu, W., et al., Digital twin-based industrial cloud robotics: Framework, control approach and implementation. *Journal of Manufacturing Systems*, 2021. 58: p. 196-209.
- [30] Liu, Y., et al., A digital twin-based sim-to-real transfer for deep reinforcement learning-enabled industrial robot grasping. *Robotics and Computer-Integrated Manufacturing*, 2022. 78: p. 102365.
- [31] Li, C., et al., AR-assisted digital twin-enabled robot collaborative manufacturing system with human-in-the-loop. *Robotics and Computer-Integrated Manufacturing*, 2022. 76: p. 102321.
- [32] Khan, S., et al., Digital Twins-Based Internet of Robotic Things for Remote Health Monitoring of COVID-19 Patients. *IEEE Internet of Things Journal*, 2023.
- [33] Khan, M.M.R., et al., Development of a robot-assisted telerehabilitation system with integrated iiot and digital twin. *IEEE Access*, 2023.
- [34] Kumar, S.A., et al., A novel digital twin-centric approach for driver intention prediction and traffic congestion avoidance. *Journal of Reliable Intelligent Environments*, 2018. 4(4): p. 199-209.
- [35] Dan, D., Y. Ying, and L. Ge, Digital twin system of bridges group based on machine vision fusion monitoring of bridge traffic load. *IEEE Transactions on Intelligent Transportation Systems*, 2021. 23(11): p. 22190-22205.
- [36] Liu, J., et al., Security in IoT-enabled digital twins of maritime transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, 2021. 24(2): p. 2359-2367.
- [37] Lv, Z., et al., Digital twins based VR simulation for accident prevention of intelligent vehicle. *IEEE Transactions on Vehicular Technology*, 2022. 71(4): p. 3414-3428.
- [38] Ali, M., et al., A smart digital twin enabled security framework for vehicle-to-grid cyber-physical systems. *IEEE Transactions on Information Forensics and Security*, 2023.
- [39] Tang, X., et al. Creating multi-timescale digital twin models for regional multiple energy systems on CloudPSS. in 2020 IEEE Sustainable Power and Energy Conference (ISPEC). 2020. IEEE.
- [40] Zhang, Z., et al. Smart DC: an AI and digital twin-based energy-saving solution for data centers. in NOMS 2022-2022 IEEE/IFIP Network Operations and Management Symposium. 2022. IEEE.
- [41] Jafari, S. and Y.-C. Byun, Prediction of the battery state using the digital twin framework based on the battery management system. *IEEE Access*, 2022. 10: p. 124685-124696.
- [42] He, X., et al., Situation awareness of energy internet of thing in smart city based on digital twin: From digitization to informatization. *IEEE Internet of Things Journal*, 2022.
- [43] Ray, P.P., Internet of robotic things: Concept, technologies, and challenges. *IEEE access*, 2016. 4: p. 9489-9500.
- [44] Bath, R.S., A. Nayyar, and A. Nagpal. Internet of robotic things: driving intelligent robotics of future-concept, architecture, applications and technologies. in 2018 4th international conference on computing sciences (ICCS). 2018. IEEE.
- [45] Vermesan, O., et al., Internet of robotic things—converging sensing/actuating, hyperconnectivity, artificial intelligence and IoT platforms, in *Cognitive Hyperconnected Digital Transformation*. 2022, River Publishers. p. 97-155.
- [46] Martínez-Gutiérrez, A., et al., Digital twin for automatic transportation in industry 4.0. *Sensors*, 2021. 21(10): p. 3344.
- [47] Ibrahim, M., et al., Overview on digital twin for autonomous electrical vehicles propulsion drive system. *Sustainability*, 2022. 14(2): p. 601.
- [48] M., et al., Digital twins based day-ahead integrated energy system scheduling under load and renewable energy uncertainties. *Applied Energy*, 2022. 305: p. 117899.
- [49] Jafari, M., et al., A review on digital twin technology in smart grid, transportation system and smart city: Challenges and future. *IEEE Access*, 2023. 11: p. 17471-17484.
- [50] Sun, H., Q. Guo, and Z. Pan, Energy internet: concept, architecture and frontier outlook. *Automation of Electric Power Systems*, 2015. 39(19): p. 1-8.
- [51] Deng, J., F. Jiang, and C. Tu, Study of NIST's interoperable smart grid technology architecture. *Power System Protection and Control*, 2020. 48(3): p. 9-21.
- [52] Tu, C., et al., A novel multi-function solid-state fault current limiter and its analysis of current-limiting filter selection. *Power System Technology*, 2014. 38(6): p. 1634-1638.
- [53] Cao, J., et al., Survey of big data analysis technology for energy internet. *Southern Power System Technology*, 2015. 9(11): p. 1-12.
- [54] Zhang, X., et al. Digital twin in energy internet and its potential applications. in 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2). 2020. IEEE.
- [55] Yang, Q., et al., Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 2019. 10(2): p. 1-19.
- [56] Chen, Z., et al., Zero knowledge clustering based adversarial mitigation in heterogeneous federated learning. *IEEE Transactions on Network Science and Engineering*, 2020. 8(2): p. 1070-1083.
- [57] Sun, W., et al., Adaptive federated learning and digital twin for industrial internet of things. *IEEE Transactions on Industrial Informatics*, 2020. 17(8): p. 5605-5614.
- [58] Konečný, J., et al., Federated learning: Strategies for improving communication efficiency. *arXiv preprint arXiv:1610.05492*, 2016.
- [59] Mothukuri, V., et al., A survey on security and privacy of federated learning. *Future Generation Computer Systems*, 2021. 115: p. 619-640.

- [60] Kairouz, P., et al., Advances and open problems in federated learning. *Foundations and trends® in machine learning*, 2021. 14(1–2): p. 1-210.
- [61] Lu, Y., et al., Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks. *IEEE Transactions on Industrial Informatics*, 2020. 17(7): p. 5098-5107.
- [62] Vanhaesebrouck, P., A. Bellet, and M. Tommasi, Decentralized collaborative learning of personalized models over networks. *arXiv preprint arXiv:1610.05202*, 2016.
- [63] Jiang, L., et al., Cooperative federated learning and model update verification in blockchain-empowered digital twin edge networks. *IEEE Internet of Things Journal*, 2021. 9(13): p. 11154-11167.
- [64] Yang, S., et al., Parallel distributed logistic regression for vertical federated learning without third-party coordinator. *arXiv preprint arXiv:1911.09824*, 2019.
- [65] Yang, H., et al., Fedsteg: A federated transfer learning framework for secure image steganalysis. *IEEE Transactions on Network Science and Engineering*, 2020. 8(2): p. 1084-1094.
- [66] Okegbile, S.D., et al., Differentially Private federated multi-task learning framework for enhancing human-to-virtual connectivity in human digital twin. *IEEE Journal on Selected Areas in Communications*, 2023.
- [67] Tan, C., et al., Digital twin enabled remote data sharing for internet of vehicles: System and incentive design. *IEEE Transactions on Vehicular Technology*, 2023.
- [68] Lu, Y., et al., Communication-efficient federated learning for digital twin edge networks in industrial IoT. *IEEE Transactions on Industrial Informatics*, 2020. 17(8): p. 5709-5718.
- [69] Li, G., et al., FedHiSyn: A hierarchical synchronous federated learning framework for resource and data heterogeneity. in *Proceedings of the 51st International Conference on Parallel Processing*. 2022.
- [70] Nivarthi, C.P., Transfer Learning as an Essential Tool for Digital Twins in Renewable Energy Systems. *arXiv preprint arXiv:2203.05026*, 2022.
- [71] Pan, S.J. and Q. Yang, A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 2009. 22(10): p. 1345-1359.
- [72] Weiss, K., T.M. Khoshgoftaar, and D. Wang, A survey of transfer learning. *Journal of Big data*, 2016. 3: p. 1-40.
- [73] Xu, Y., et al., A digital-twin-assisted fault diagnosis using deep transfer learning. *Ieee Access*, 2019. 7: p. 19990-19999.
- [74] Wang, J., et al., Deep transfer learning-based multi-modal digital twins for enhancement and diagnostic analysis of brain mri image. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 2022.
- [75] Feng, K., et al., Digital twin enabled domain adversarial graph networks for bearing fault diagnosis. *IEEE Transactions on Industrial Cyber-Physical Systems*, 2023.
- [76] Zheng, J., et al., Digital twin empowered heterogeneous network selection in vehicular networks with knowledge transfer. *IEEE Transactions on Vehicular Technology*, 2022. 71(11): p. 12154-12168.
- [77] Munir, M.S., et al., Neuro-symbolic explainable artificial intelligence twin for zero-touch ioc in wireless network. *IEEE Internet of Things Journal*, 2023.
- [78] Krzysiak, R., D. An, and Y. Chen. XCardio-Twin: An explainable framework to aid in monitoring and analysis of cardiovascular status. in *2023 IEEE 3rd International Conference on Digital Twins and Parallel Intelligence (DTPI)*. 2023. IEEE.
- [79] An, D. and Y. Chen. Explainable Artificial Intelligence (XAI) Empowered Digital Twin on Soil Carbon Emission Management Using Proximal Sensing. in *2023 IEEE 3rd International Conference on Digital Twins and Parallel Intelligence (DTPI)*. 2023. IEEE.
- [80] Jiang, W., et al., The road towards 6G: A comprehensive survey. *IEEE Open Journal of the Communications Society*, 2021. 2: p. 334-366.
- [81] Han, B., et al., Digital twins for industry 4.0 in the 6G era. *IEEE Open Journal of Vehicular Technology*, 2023.
- [82] Kumar, P., et al., PPSF: A privacy-preserving and secure framework using blockchain-based machine-learning for IoT-driven smart cities. *IEEE Transactions on Network Science and Engineering*, 2021. 8(3): p. 2326-2341.
- [83] Kumar, P., et al., Blockchain and deep learning for secure communication in digital twin empowered industrial IoT network. *IEEE Transactions on Network Science and Engineering*, 2022.
- [84] Yaqoob, I., et al., Blockchain for digital twins: Recent advances and future research challenges. *Ieee Network*, 2020. 34(5): p. 290-298.
- [85] Liu, Q., et al., A survey on security threats and defensive techniques of machine learning: A data driven view. *IEEE access*, 2018. 6: p. 12103-12117.
- [86] Li, B., et al., Data poisoning attacks on factorization-based collaborative filtering. *Advances in neural information processing systems*, 2016. 29.
- [87] Alfeld, S., X. Zhu, and P. Barford. Data poisoning attacks against autoregressive models. in *Proceedings of the AAAI Conference on Artificial Intelligence*. 2016.
- [88] Tramèr, F., et al., The space of transferable adversarial examples. *arXiv*, 2017. *arXiv preprint arXiv:1704.03453*, 2017.
- [89] Papernot, N., P. McDaniel, and I. Goodfellow, Transferability in machine learning: From phenomena to black-box attacks using adversarial samples. *arXiv* 2016. *arXiv preprint arXiv:1605.07277*, 2016.
- [90] Jia, W., W. Wang, and Z. Zhang, From simple digital twin to complex digital twin Part I: A novel modeling method for multi-scale and multi-scenario digital twin. *Advanced Engineering Informatics*, 2022. 53: p. 101706.