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A Survey on GenAI-Driven Digital Twins: Toward Intelligent 6G Networks and Metaverse Systems

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ABSTRACT Sixth-Generation (6G) networks aim to deliver unprecedented network performance by facilitating intelligent, ultra-low-latency, and massively connected applications that seamlessly integrate the physical and digital domains through context-aware operation. These applications work across physical and digital environments. Within this broader shift, digital twins (DTs) have demonstrated notable improvements in overall network performance by creating high-fidelity digital counterparts of physical 6G systems. These DTs give researchers and operators a way to view network behavior as it evolves, to forecast likely performance patterns, and – crucially – to adjust key processes such as beamforming, resource allocation, and interference management. Even so, the value of DT-based optimization is limited by several practical factors. Their effectiveness depends a great deal on access to reliable and sufficiently rich data, and the inherent complexity of 6G environments often makes accurate modeling and efficient resource coordination challenging. This paper examines how a range of generative artificial intelligence (GenAI) models can be used alongside DTs to strengthen resource allocation and improve security in 6G networks. It also sets out a GenAI-enabled DT framework for various 6G-enabling applications, highlighting the potential roles of different GenAI models in supporting semantic communications, the metaverse, integrated sensing and communication (ISAC), AI-generated content (AIGC), and reconfigurable intelligent surfaces (RIS). This paper concludes by drawing attention to emerging conceptual frameworks for DT–GenAI integration. It notes several research challenges that have yet to be resolved, and outlines future directions for deploying GenAI-augmented DTs to achieve intelligent, adaptive, and resilient 6G networks.

INDEX TERMS Generative AI, digital twins, metaverse, 6G network design, resource management, network security.

I. INTRODUCTION

Sixth-Generation (6G) wireless networks mark a substantial shift in the way communication systems are envisioned. In fact, they are expected to deliver performance levels that far exceed current capabilities (including peak data rates reaching 1 Tbps and end-to-end latency of under 1 ms), and highly pervasive connectivity across a wide range of environments [1]. The 6G ecosystem is expected to enable applications, including the metaverse, augmented reality (AR), immersive extended reality (XR), virtual reality (VR), and 3D holography [2], [3]. These 6G applications require adaptable, zero-orchestration network architectures that seamlessly integrate ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC) use cases within a unified framework [4], [5], [6], [7].

To support the vision and stringent requirements of 6G networks, reconfigurable intelligent surfaces (RISs) can dynamically adjust the phase shifts and amplitudes of reflected signals to smartly control wireless propagation environments [8]. Semantic communication is a networking technology that focuses on transmitting the intended meaning of information rather than raw data. It supports context-aware and task-driven information exchange [9]. Artificial intelligence-generated content (AIGC) is an emerging technology that can generate content in real time, facilitating ultra-low-latency communication, adaptive security mechanisms, and efficient bandwidth utilization in 6G networks [10]. Integrated sensing and communication (ISAC) is a networking technology that enhances network intelligence by combining the sensing and communication capabilities through dual-functional radar-communication systems, thereby facilitating the development of a unified framework. Collectively, when integrated into 6G networks, these technologies can deliver ultra-reliable, intelligent, and context-aware communication infrastructures. To understand how these enabling technologies shape practical system design, it is also important to consider several outstanding technical challenges.

A. CHALLENGES

Although the technologies that enable 6G provide significant gains in overall network performance, they also introduce a number of related challenges [11]. A significant difficulty lies in creating intelligent frameworks that can keep a DTs aligned with the physical 6G network it represents, and to do so in real time [12]. A further challenge arises from the need for high-fidelity AI models that can both capture the behavior of a 6G network with precision and predict how its state is likely to change [11]. Another important issue is ensuring that trained AI models can generalize well across heterogeneous 6G networks [13], [14], [14], [15], [15]. A related challenge stems from 6G networks being expected to rely on a decentralized and zero-trust architecture. As a result, novel security threats will arise from integrating 6G technologies into a distributed network. This requires developing intelligent and resilient frameworks to protect data integrity in decentralized 6G environments [15], [16], [17]. Getting this right matters for two reasons: it supports more efficient use of network resources, and it underpins strong security in future 6G systems. These challenges motivate recent efforts to explore how generative artificial intelligence (GenAI) and digital twins (DTs) can jointly improve 6G systems.

B. MOTIVATION

A growing body of literature shows that both GenAI models [18], [19], [20], [21] and DTs [22], [23], [24] contribute noticeably to performance optimization in a range of 6G-enabling technologies [25], [26]. DTs, in particular, offer a high-fidelity, real-time view of the physical 6G network [22], [23]. These virtual counterparts make it possible to run predictive analyses and monitor network conditions continuously, both of which are essential for achieving the expected levels of performance. In addition, they support more flexible integration of network components; they allow 6G systems to adjust more effectively to demanding performance and reliability constraints. GenAI models play a complementary role by producing synthetic datasets and adversarial examples that mirror real 6G operating conditions. This helps reduce dependence on collecting large volumes of real-time data. For this reason, GenAI is regarded as a key element in building self-managing 6G networks that can adapt to unfamiliar scenarios while remaining robust and intelligent [27], [28], [29], [30], [31].

The integration of GenAI methods and DTs within the 6G environment has led to substantial gains in operational efficiency and in the quality of services delivered by 6G systems. The authors in [32] developed a GenAI and DT framework that generates high-fidelity network scenarios for smart cities. Their work enabled proactive network planning and improved resilience in dynamic 6G environments. In addition, a hybrid edge-cloud DT and GenAI framework has been proposed to support mobile AIGC services in the Internet of Everything (IoE). In this architecture, GenAI facilitates intelligent, zero-touch decision-making. Meanwhile, the DTs are leveraged to optimize the allocation of computing resources required for efficient and personalized AIGC service delivery [33].

Beyond IoE applications, the researchers in [34] developed a DT-assisted framework for Internet-of-Vehicles (IoV) networks to optimize task offloading across edge servers. This approach supports real-time decision-making, energy-efficient operations, and timely task completion by continuously mirroring the states of vehicular and roadside units. The authors developed a Gen-TWIN framework, in which a GenAI model generated realistic synthetic RF datasets to address limited measurements for AI-driven RAN optimization. The results indicated improvements in model training as well as prediction accuracy [35].

Across recent literature, there is clear evidence that GenAI and DTs are being used within 6G networks for purposes such as network optimisation and security [32], [33], [34], [35]. Even so, a more systematic study is still needed. It is necessary to develop a unified framework that brings DTs and GenAI together in a way that fully supports 6G-enabling applications. The main aim of this paper is to examine how DTs and different GenAI models can work jointly to optimize the performance and security of 6G-enabling applications. In doing so, the paper also reviews current progress in the field and outlines several challenges and future research directions for integrating GenAI models and DTs into 6G network design. Overall, this combined DT–GenAI approach allows for smoother data synchronization, more intelligent network optimization, and stronger predictive analytics—capabilities that are essential for addressing the emerging challenges associated with 6G deployment.

C. COMPARISONS AND KEY CONTRIBUTIONS

Recent surveys have examined the role of GenAI in next-generation wireless systems. For example, the authors of [18] explored the applications of various GenAI models to improve wireless communication systems and outlined their potential applications specifically for 6G networks. In [46], the researchers took a closer look at the role of large language models (LLMs) and provided a systematic review of how such models could be introduced into the telecommunications sector. The paper analyzed the applications of large GenAI models in 6G networks, summarized potential use cases, and provided details on the associated practical and theoretical challenges. It further highlighted how 6G can achieve promising results by connecting multiple on-device large GenAI models, thereby laying the groundwork for the collective intelligence paradigm. In addition, [29] explored various GenAI models and their applications in enhancing the physical-layer security of 6G networks.

Beyond GenAI-oriented work, existing studies also highlight the role of DTs in improving performance in 6G networks. The authors in [37] systematically reviewed the applications of DTs for 6G networks. They investigated the role of DTs in intelligent transportation systems, 6G networks, healthcare, aviation, manufacturing, and urban intelligence in smart cities. The paper [38] developed a DT-enabled framework for 6G networks. The study concluded that DTs will serve as a major enabler of 6G services, providing reliability and scalability. In another paper [39], the researchers explored the applications of DT technology in 6G communication networks, considering it a promising tool for research, design, implementation, and optimization of next-generation systems. The researchers also identified several open challenges for deploying DT technology in evolving 6G systems, including data provisioning, cross-application access management, network management, and security.

The researchers [41] systematically reviewed DT-based 6G applications and discussed the associated challenges and future directions related to infrastructure and connectivity, management of mobile users, data security, and privacy. In [42], the authors explored DT as an emerging technology to design, simulate, diagnose, and optimize 6G networks. They further discussed how DT networks (DTNs) can be deployed in Omniverse, a scalable and real-time reference platform for building and operating metaverse services, and also emphasized the potential of DT technology to transform industries and improve lives in 6G systems and beyond. These works highlight the significance of DTs as virtual representations of physical network components, enabling tasks such as simulation, analysis, and network optimization.

Taken together, these studies show that DT technology has significant potential for emulating, evaluating, and optimizing wireless systems. While the upcoming era of 6G communication promises substantial improvements in network performance, it also introduces new challenges for the development and implementation of wireless network DTs. The authors of [44] analyzed the requirements for DTs of 6G networks and investigated the applications of GenAI technology for addressing these requirements. They also examined the applications of generative models (GMs), including diffusion models (DMs) and transformers, for empowering 6G-enabled DTs from varied aspects, such as deployment, slicing capability, and physical-digital synchronization.

In [43], the researchers developed a metaverse framework for healthcare networks to enhance resource allocation. The integration of the metaverse allowed healthcare systems to leverage AI for efficient data access and analysis, improve patient care with prompt diagnoses, and address security concerns with innovative encryption methods. This integration facilitated better coordination and optimization of healthcare services and supported more effective management of data and resources within the network.

Paper [40] explored the application of VR and the metaverse for wireless network design, with a main focus on enhancing collaboration and communication in 3D virtual environments. By employing DTs to simulate real-world settings, the study aimed to improve training and operational practices in smart factories through interactive avatar models. An experimental framework for a VR-powered metaverse was proposed that featured key components such as object-oriented configurations and multi-user systems. Initial testing within a smart factory context aligned with Industry 4.0 standards demonstrates the framework's efficacy and potential for real-time global connectivity, yielding promising results for educational and commercial adoption.

In [13], the authors provided a thorough discussion on the role of 6G and AI in realizing immersive metaverse experiences. Particularly, they explored several fundamental technologies of 6G and AI, for instance, wireless communication technology, learning paradigms, and computer vision in the metaverse context. In addition, they examined the combined role of 6G and AI technologies in acquiring self-optimizing capabilities, tactile feedback, and ubiquitous intelligence for various metaverse applications ranging from remote surgeries to holographic telepresence. They also highlighted the sustainable facet of metaverse applications followed by the services, ongoing projects, and use cases and clarified several open challenges and future directions for researchers and developers of metaverse services. Another study [45] comprehensively reviewed the transformative impact of GenAI in the metaverse and explored how GMs like autoregressive models, transformers, generative adversarial networks (GANs) and variational autoencoders (VAEs) can generate contextually relevant and realistic content in domains like 3D objects, video, image, and text. The authors also identified the open challenges, such as interoperability, computational efficiency, ethics, content control, realism, and data quality, which need further attention.

TABLE 1. Survey comparison.

Year	Ref.	Contributions	GenAI	DT	Metaverse	Interplay
2021	[36]	Discussed the applications of DT technology in networking and elaborated on its potential relationship with 6G	×	✓	×	×
	[37]	Provided a thorough survey of DTN to analyze the potential of DTs in B5G/6G	×	✓	×	×
2022	[38]	Presented the major design requirements needed to achieve DT-enabled 6G systems and discussed the potential applications of DT-enabled 6G	×	✓	×	×
	[39]	Conducted a comprehensive survey of DT technology to understand its significance in the upcoming 6G communication systems and identified open challenges	×	✓	×	×
	[40]	Proposed a framework that integrates VR and the metaverse for wireless network design, focusing on enhancing collaboration and communication in 3D virtual environments.	×	×	✓	×
	[41]	Provided a systematic review of the existing DT-powered 6G applications and identified potential future directions	×	✓	×	×
2023	[42]	Provided an overview of DTNs for 6G and demonstrated the creation and operation of such networks in Omniverse through a real-world example	×	✓	✓	×
	[43]	Presented a metaverse-based architecture to enhance the resource allocation and security of healthcare networks	×	×	✓	×
	[27]	Discussed the efficacy of GenAI for cyber threat-hunting in 6G-assisted IoT networks, revolutionizing how cyberattacks are detected and prevented	✓	×	×	×
	[44]	Explored the applications of GenAI to empower 6G DTs from multiple perspectives and identified the potential future directions for GenAI-assisted 6G wireless network DTs	✓	✓	×	×
	[45]	Comprehensively explored the areas where GenAI technologies might be applied for enhancing and enriching experiences in virtual worlds	✓	×	✓	×
2024	[18]	Discussed the role of GenAI in shaping the future of wireless communication systems and its implications for 6G networks	✓	✓	×	×
	[13]	Reviewed how AI and 6G can create immersive experiences in the metaverse and explored how advancements in these technologies can enable features like ubiquitous intelligence, realistic touch sensations, and self-optimizing systems	✓	✓	✓	×
	[46]	Discussed the applications of large GenAI models in next-generation wireless networks and their capabilities to realize self-evolving networks	✓	×	×	×
	[29]	Presented a thorough review of the applications of GenAI in 6G physical-layer security and demonstrated its crucial role in protecting networks against emerging threats	✓	×	×	×
	Ours	Conducted an in-depth investigation into the synergistic interplay between GenAI and DTs for 6G-enabling applications and technologies for the design and security of 6G networks	✓	✓	✓	✓

While existing research has explored various aspects of 6G, including GenAI, DT, and metaverse technologies, as summarized in Table 1, there remains, to the best of our knowledge, a gap in the literature concerning the interplay between different GenAI models and DTs for 6G-enabling applications. This paper addresses this gap by providing a comprehensive analysis of the synergies and potential applications of these emerging paradigms in the context of the challenges posed by 6G network design. The contributions of our survey are as follows.

- This paper conducts a comprehensive investigation into the collaborative interplay between various GenAI models and DTs to support the integration of enabling technologies and the metaverse into 6G networks, with a focus on optimizing performance and security. Through a systematic analysis of existing literature and emerging trends, this study identifies the potential applications, opportunities, and challenges associated with this technological integration.
- It develops a synergistic framework for a diverse range of 6G use cases that demonstrate the practical applications of integrating GenAI and DTs as potential enablers in 6G network design. The enabling technologies and applications explored span multiple domains, including semantic communications, the metaverse, ISAC, AIGC, and RIS, showcasing the transformative impact of this synergy on the security and optimization of next-generation wireless networks.
- Lastly, the paper identifies key research directions and open issues that need further investigation in GenAI- and DT-assisted 6G network design, particularly in how these technologies support enabling applications. This involves addressing fundamental challenges such as data interoperability, computational scalability, privacy, and ethical concerns, as

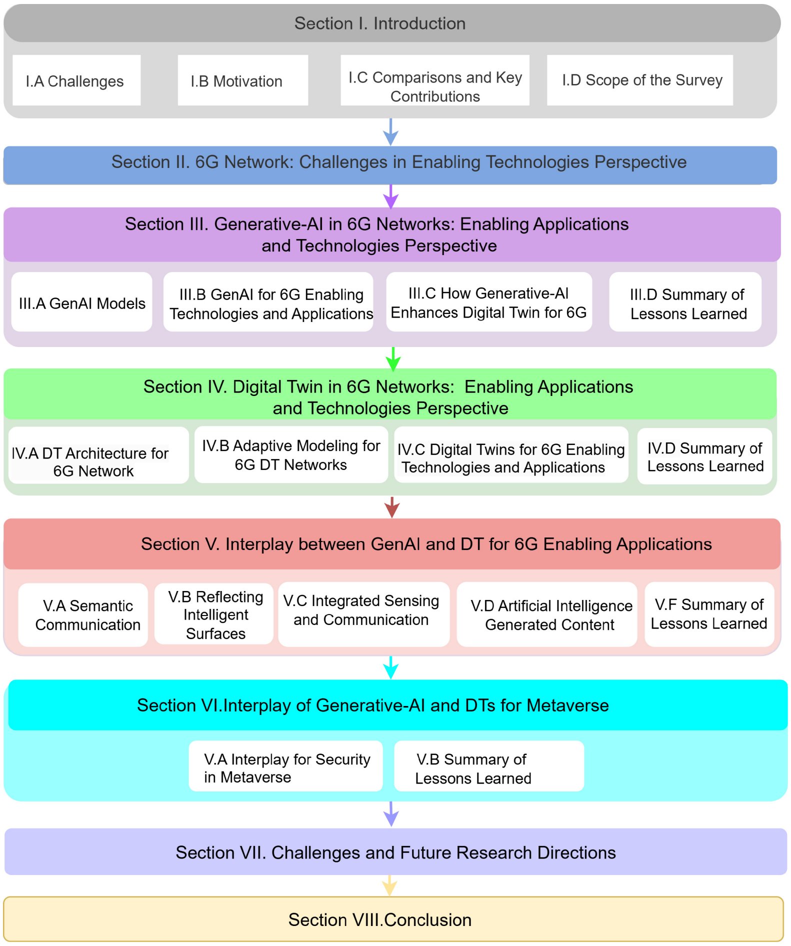

FIGURE 1. The organization of this paper.

well as developing standardized frameworks and methodologies.

D. SCOPE OF THIS SURVEY

This survey paper is structured to investigate the integration of GenAI and DT for 6G and the metaverse. The organizational structure of this paper is given in Fig. 1. Sections I and II provide the background knowledge, open challenges, and the main motivation behind the study of the GenAI-DT interplay in 6G and the metaverse. Section III focuses on the role of GenAI in 6G networks and discusses its uses for optimizing the physical layer, resource allocation, traffic synthesis, and security. It also evaluates applications of various GenAI models. Section IV assesses the design and architecture of DTs within 6G-enabling technologies and applications. Section V comprehensively develops a framework for the interplay between GenAI and DTs for the optimization and security of key 6G applications, including semantic communications, ISAC, THz, AIGC, and RIS. Section VI explores the value of using GenAI and DT together in metaverse applications. Section VII identifies future research directions and challenges that could be enabled by this synergy for 6G network design. Finally, the conclusion of the survey is presented in Section VIII.

II. CHALLENGES IN ENABLING TECHNOLOGIES FOR 6G NETWORKS

The advancement of 6G networks, driven by the need to support sophisticated applications such as autonomous systems, XR, DTs, the metaverse, and massive IoT, necessitates the successful integration of key enabling technologies [18], [47]. These technologies, including RIS, ISAC, THz communication, and AIGC, are crucial for maximizing network performance, reliability, and security. However, their convergence introduces significant technical problems [11]. First, establishing efficient data synchronization across diverse, heterogeneous systems is essential. Second, constructing high-fidelity models that can accurately reflect dynamic network conditions is critical for reliable operation. Third, optimizing DT synchronization is necessary to ensure cost-effective data transfer. Furthermore, two additional factors complicate deployment: the development of robust security mechanisms to counter emerging threats and the generalization of AI models across varied applications. Finally, in order to realize the full potential of 6G technology,

TABLE 2. Challenges for 6G-enabling applications and technologies.

Challenge	Description
Data Synchronization	Efficient synchronization of data across heterogeneous systems in 6G networks is essential for real-time operation, where any misalignment can lead to inaccurate decision-making and resource misallocation [25].
High-Fidelity Modeling	Accurate, real-time digital models of the network environment are required for optimizing decision-making processes. These models must adjust dynamically to varying conditions to ensure high efficiency [26].
Generalization	The solutions developed must be applicable across diverse network environments, from urban to rural areas, ensuring consistent performance without compromise [25].
Security	With the increasing interconnectivity of devices and systems, ensuring robust security mechanisms is vital. Vulnerabilities can arise in AI-driven models and communication systems, necessitating proactive defense mechanisms against adversarial threats [26].

it is essential to overcome these challenges. Table 2 provides a summary of the specific technical challenges that are associated with the integration of these enabling applications.

1) *Data Synchronization:* A key technical challenge in integrating new technologies into 6G networks is achieving precise data synchronization across disparate systems [11], [48]. Efficient 6G functionality relies on the exact coordination of components, such as communication, sensing, and AI solutions. For example, real-time synchronization between sensing and communication modules is critical to accurately align acquired data with network protocols. Failure in this process, which becomes more severe as the network expands, directly causes resource misalignment, inaccurate decision-making, and inefficient network operation. This underscores the requirement for robust, real-time synchronization mechanisms in 6G.
2) *High-Fidelity Modeling:* The development of high-fidelity models for complex network environments is a significant challenge when integrating technologies into 6G [54], [55]. These models are required to accurately represent the network's real-time physical and digital states by incorporating dynamic elements like traffic, environmental conditions, and user behavior. This accuracy is critical for real-time decision-making and optimization in demanding applications, such as autonomous driving. Although essential for simulating and predicting network performance, these models must simultaneously be adaptive and computationally efficient to effectively manage large, dynamic systems. Their absence severely limits the network's ability to dynamically adjust, predict failures, and optimize resources.
3) *Generalization Across Diverse 6G Environments:* A further challenge concerns the generalization of AI frameworks when integrating enabling technologies and applications into 6G networks, particularly given the diverse range of environments in which 6G systems will operate [18], [49]. These networks will span urban, rural, indoor, and outdoor environments, each with its unique challenges. A solution that works well in one environment may not perform as effectively in another, particularly when considering complex factors such as signal propagation, environmental noise, and user behavior. For instance, the communication models used in dense urban areas with numerous connected devices may not work well in rural areas, where fewer devices are involved and network conditions are less predictable. To ensure consistent network performance and reliability across all applications, the employed models, algorithms, and solutions must be generalizable across diverse environments. Moreover, AI technologies should be adaptable to diverse applications, such as communication, sensing, and other 6G services, which is crucial for their broader applicability.
4) *Security:* The integration of enabling technologies and applications into 6G networks presents a significant security challenge because of the increased exposure to diverse threats [16]. The convergence of communication, sensing, and AI in 6G networks increases the network's susceptibility to malicious attacks. For example, the increased interconnectivity of devices and sensors in smart cities, the metaverse, or industrial systems may expose the network to vulnerabilities such as data breaches, unauthorized access, and manipulation of critical systems. Additionally, the use of advanced technologies like AIGC can be exploited to generate misleading data or launch cyberattacks, further complicating security measures [10]. Ensuring robust security while maintaining the high performance and scalability of 6G networks is essential. This challenge involves securing sensitive data, preventing adversarial threats to network models, and ensuring the integrity and trustworthiness of communication and sensing functions. Given the interconnected and dynamic nature of 6G networks, developing secure protocols and defense mechanisms that can handle diverse threats while maintaining optimal performance will be essential for enabling safe and reliable network operations.

III. GenAI IN 6G NETWORKS: ENABLING APPLICATIONS AND TECHNOLOGIES

Generative artificial intelligence (GenAI) is a subset of AI that focuses on generating content, such as text, images, or videos, by learning from extensive datasets [50]. In the context of 6G, GenAI can be leveraged to create realistic network traffic models, simulate complex user interactions, and generate predictive scenarios that aid in network planning and management [18]. These capabilities are crucial for optimizing network operations and service provisioning in real-time, thereby enhancing the adaptability and efficiency of 6G networks. For instance, reference [26] discusses how GenAI models can optimize resource allocation and improve overall network performance in complex and dynamic 6G environments. Additionally, reference [18] provides a comprehensive survey on GenAI applications in 6G wireless intelligence, emphasizing its role in physical-layer design, network optimization, and security enhancements. They demonstrate how GenAI can model complex channel conditions and design adaptive communication strategies, resulting in improved spectral efficiency and reduced latency. Furthermore, reference [14] explores the concept of wireless network DTs for 6G, identifying GenAI as a key enabler for real-time monitoring, optimization, and predictive maintenance, thereby enhancing network reliability and performance. These studies collectively underscore the transformative potential of GenAI in addressing the challenges of 6G networks, offering innovative solutions for performance enhancement across various use cases.

The following section provides a brief overview of key GenAI algorithms relevant to 6G. Subsequently, we explore how these models can enhance 6G-enabling technologies and applications, including network optimization, security frameworks, and physical-layer design.

A. GENAI MODELS

The focus of GenAI models is to understand and learn the original input data distribution using iterative training. This acquired knowledge helps generate data closely resembling the original distribution, thereby ensuring a high degree of accuracy. GenAI models have shown promising results in applications, including robotics, natural language processing (NLP), speech recognition and generation, and visual recognition tasks [51], [52]. This section discusses five fundamental GenAI models: GANs, VAEs, energy-based models (EBMs), diffusion-based GMs (DGMs), and flow-based GMs (FGMs).

1) *GANs:* GANs consist of two primary components: a generative model G and a discriminative model D [53]. The generative network learns to generate synthetic data that closely resembles the original data distribution, while the discriminative network distinguishes between real and generated data [54]. This process is formulated as a minimax game, with the objective function $V(D, G)$ defined as:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)}\big[\log D(x)\big] + \mathbb{E}_{z \sim p_z(z)}\big[\log(1 - D(G(z)))\big] \quad (1)$$

Here, $p_{\text{data}}(x)$ denotes the distribution of real data samples, and $p_z(z)$ denotes the distribution of random noise vectors. The objective function comprises two terms: the first term learns to optimize the likelihood that the discriminator accurately classifies real data samples as real, while the second term learns to maximize the likelihood that the discriminator accurately classifies the generated data samples as fake.

2) *VAEs:* A VAE is a type of GenAI composed of two primary components: an encoder and a decoder network [55]. The encoder network, denoted as $q_\phi(z|x)$, maps the input data x to a probability distribution over latent variables z with parameters ϕ. This distribution is typically Gaussian, parameterized by a mean vector μ and a covariance matrix Σ. The decoder network, denoted as $p_\theta(x|z)$, takes samples from the latent space z and generates reconstructed data points $\tilde{x}$. The objective function for training VAEs involves maximizing the evidence lower bound (ELBO), which is defined as:

$$\mathcal{L}(\theta, \phi; x) = \mathbb{E}_{q_\phi(z|x)}\big[\log p_\theta(x|z)\big] - D_{KL}\big[q_\phi(z|x)||p(z)\big] \quad (2)$$

where $\mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)]$ represents the reconstruction loss, and $D_{KL}[q_\phi(z|x)||p(z)]$ is the KL divergence between the approximate posterior $q_\phi(z|x)$ and the prior distribution $p(z)$. This objective function motivates the encoder to learn a latent-variable distribution that closely matches the prior distribution and ensures that the generated samples are faithful to the input data [56].

3) *Energy-Based Models:* EBMs are a class of GenAI models that assign an energy value $E(x)$ to each input data sample x, representing how likely the sample is under the model. The training objective of an EBM is to minimize the energy for real data samples while assigning higher energy to generated or unlikely samples, shaping the energy landscape of the data space. Unlike traditional generative models that explicitly compute probability distributions, EBMs focus on learning this implicit energy function [57]. In the context of EMs [58], the energy function is realized through the discriminator D, and the corresponding objective functions for the discriminator and generator are defined as:

$$L_D(x, z) = E(x) + \big[m - E(G(z))\big]_+, \qquad L_G(z) = E(G(z)), \quad (3)$$

where x is a real data sample, z is a noise vector, $G(z)$ is the generated sample, $E(\cdot)$ is the energy assigned by the discriminator, m is a positive margin, and $[\cdot]_+ = \max(0, \cdot)$ yields non-zero gradients only when $E(G(z)) < m$. Minimizing L_D encourages the discriminator to assign low energy to real samples and high energy to generated ones, while minimizing L_G trains the generator to produce samples with low energy.

4) *DGMs:* A DGM is defined as a Markov process that gradually perturbs a data sample x_0 into noise over T timesteps through a forward noising process. This

process is not a simple Gaussian perturbation with increasing variance, but is formally expressed as [59]:

$$q(x_t \mid x_0) = \mathcal{N}\big(x_t; \sqrt{\alpha_t}\, x_0,\ (1-\alpha_t)I\big), \tag{4}$$

where $\alpha_t = \prod_{s=1}^{t}(1-\beta_s)$ is the cumulative product of the noise schedule β_s, and I denotes the identity matrix. This recursive formulation ensures that the forward process is a Markov chain.
To enable sample generation, a reverse process is learned via a neural network $\epsilon_\theta(x_t, t)$ that predicts the noise added at each timestep. The training objective is typically formulated as the *epsilon-prediction loss*:

$$L_\epsilon = \mathbb{E}_{x_0,\epsilon\sim\mathcal{N}(0,I),t}\big[\|\epsilon - \epsilon_\theta(x_t, t)\ \|^2\big], \tag{5}$$

which directly minimizes the error in noise estimation. Alternatively, the *v-prediction loss* has been proposed to stabilize training and improve performance [60]:

$$L_v = \mathbb{E}_{x_0,\epsilon,t}\big[\|v - v_\theta(x_t, t)\ \|^2\big], \tag{6}$$

where v denotes a reparameterized target that combines both x_0 and ϵ. These training objectives allow DMs to learn the reverse generative process that maps Gaussian noise to realistic data samples.

5) *Flow-Based Models:* FGMs are a class of GenAI that employ probabilistic flow formulations to support data generation. Unlike other GMs, such as GANs and VAEs, which directly model the data distribution, FGMs convert a simple distribution, typically a Gaussian distribution, into the target distribution through a series of invertible transformations. The transformation process is differentiable, allowing for the computation of gradients during both training and generation using back-propagation algorithms. This property enhances the efficiency of training and learning in flow-based models [61].
Mathematically, the transformation process in flow-based models is represented as a sequence of invertible functions. Let $z \sim p(z)$ be a random variable sampled from a simple distribution, such as a Gaussian distribution with mean μ and covariance matrix Σ. The flow-based model maps z through a series of invertible transformations f_i to generate the output sample x. This transformation process can be expressed as:

$$x = f_K \circ f_{K-1} \circ \cdots \circ f_1(z) \tag{7}$$

where K represents the number of transformations in the flow, and $\circ$ denotes the composition of functions. Each invertible transformation f_i is parameterized by a set of learnable parameters θ_i, which are optimized during the training process to reduce a suitable loss function.

6) *LLMs:* LLMs are trained on vast, heterogeneous datasets, enabling them to capture semantic structures and knowledge representations, which makes them powerful tools for network management in 6G networks [62]. These models demonstrate exceptional proficiency across a spectrum of downstream tasks. They exhibit the capacity to comprehend input prompts and generate text responses that closely resemble human-produced content. Their impact on technology interaction is profound, contributing significantly to advancements in artificial general intelligence (AGI). Mathematically, their behavior can be described using a parameterized function f_θ, where θ denotes the model parameters. Given an input prompt x, an LLM generates text output $\hat{y}$ by optimizing the parameters θ to maximize the likelihood of producing $\hat{y}$ conditioned on x. This process can be formulated as:

$$\hat{y} = \arg\max_y P(y|x;\theta) \tag{8}$$

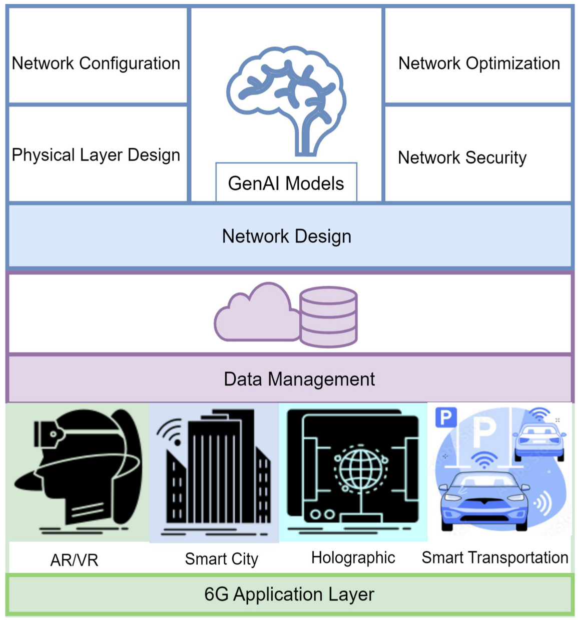

FIGURE 2. The role of GMs in 6G networks: design and applications.

B. GENAI FOR 6G-ENABLING TECHNOLOGIES AND APPLICATIONS

The integration of GenAI into 6G network architecture has a crucial part in enhancing performance, security, and resource management across 6G core applications. Fig. 2 illustrates the role of GMs in 6G applications. These applications, including AIGC, THz communication, the metaverse, ISAC, and RIS, generate distinct traffic demands that necessitate compliance with strict requirements for ultra-low latency, high reliability, and massive connectivity. For instance, ISAC demands the seamless merging of communication and sensing data for dynamic resource allocation [63], while RIS needs real-time signal reflection optimization [22]. Moreover, THz communication relies on optimal frequency deployment [18]. In the same manner, metaverse experiences and AIGC require adaptive, high-quality, and low-latency

TABLE 3. Summary of the potential role of GenAI models in wireless networks.

Category	Potential Role of GenAI Models	Reference
Physical Layer Design	GMs improve channel estimation and equalization	[19], [65], [66]
	Modulation scheme recognition	[67]
	Spectrum sensing and recovery in wireless networks	[68]
	Detection and decoding in wireless networks	[69]
Network Optimization, Organization, and Management	GenAI enhances network adaptability	[70]–[72]
	Predicts user requirements	[73]
	Deals with imbalanced data	[74]
	Enables dynamic network slicing	[75], [76]
	Transformative potential for next-generation networks	[46], [77]
Network Traffic Analytics	GMs generate synthetic network traffic	[78], [79]
	Address class imbalance	[80], [81]
	Enable dynamic traffic camouflaging	[82]
	Improve temporal link prediction in dynamic networks	[83], [84]
Network Security	GenAI enhances physical-layer security in 6G networks through intrusion detection	[85]–[88]
	Detects anomalies and attacks	[89]–[92]
	Identifies spoofing/jamming	[93]–[95]

delivery services [10], [64]. GenAI facilitates these necessities by employing MEC servers at the network's periphery. GenAI utilizes this platform to process varied traffic data, performing necessary pre-processing, feature extraction, and intelligent storage and thus guarantees optimal resource allocation and maximizes system-wide efficiency.

In addition to data management, the GenAI architecture provides a robust framework for predictive and adaptive optimization across the enabling technologies. Central to this architecture is the integration of GenAI models that exploit both real-time and historical network data to dynamically adjust network parameters and optimize system performance. For example, traffic characteristics and propagation models are synthesized by GenAI models for refining signal reflection patterns during RIS deployment. This results in enhanced coverage and beamforming [96]. For ISAC, these models enable the fusion of sensing and communication information to allow quick adjustments for resource allocation, interference control, and QoS maintenance [97].

Moreover, in THz communication, GenAI plays an important role in modeling high-frequency wave propagation to optimize frequency resource allocation and reduce environmental signal degradation [19], while in AIGC, it adapts content encoding and transmission strategies based on real-time network conditions [21]. Besides that, in metaverse applications, GenAI generates highly detailed, dynamic, and immersive virtual environments, which enhance the user experience [98]. This integrated GenAI framework can be a transformative enabler for continuous, autonomous optimization, ensuring that the unique requirements of each enabling technology are met while simultaneously bolstering network security through proactive threat detection and anomaly simulation. Thus, the inclusion of GenAI models improves the performance and functionality of applications across 6G networks. Table 3 lists the applications of GenAI in 6G network design and explains how it optimizes the technologies that enable various use cases.

1) PHYSICAL LAYER DESIGN

GenAI is crucial for enhancing the physical-layer design of 6G networks and overcoming the inherent primary obstacles in 6G systems [18]. GenAI utilizes its capacity for identifying intricate data patterns to boost the efficiency of wireless communication across various domains:

1) *Channel Estimation and Equalization:* In RIS-assisted and THz communication environments, dynamic and highly reflective propagation conditions introduce severe channel impairments. GenAI can learn and adapt to these complex characteristics, and make more accurate channel estimation and equalization, which are crucial for maintaining reliable, low-latency communication [19], [65], [66].
2) *Modulation Scheme Recognition and Classification:* The dynamic and heterogeneous nature of THz and ISAC-based communication networks also require effective modulation schemes. GenAI can automatically identify and categorize modulation schemes from received signals, facilitate adaptive waveform design, and enhance spectral efficiency across various 6G applications [67].
3) *Advanced Detection and Decoding:* Signals in the THz, RIS, and millimeter-wave bands suffer significant signal degradation due to pronounced high path losses and molecular absorption. Systems can learn the intrinsic structures of signals, effectively compensate for channel noise and distortions, and significantly enhance existing error-correction mechanisms by utilizing advanced GenAI-powered detection and decoding techniques. This approach achieves robust, consistent data transmission by directly solving

the core challenge of maintaining high reliability in the highly complex 6G environments [18], [99].

2) NETWORK OPTIMIZATION

Integrating 6G technologies requires advanced network optimization to achieve low latency, ultra-reliability, spectrum efficiency, and adaptive resource allocation [100], [101]. Traditional fixed optimization methods are unable to handle the complex, dynamic, and high-dimensional nature of these systems. GenAI offers a data-driven solution that enhances intelligence, real-time adaptation, and decision-making by generating optimal network configurations based on learning from network history.

The influence of GenAI in optimizing 6G-enabling technologies is discussed below:

1) *Adaptability towards Non-Stationary Environments:* 6G networks typically function within non-stationary environments. The performance under such environments is challenged by factors such as varying user movements, constantly fluctuating channel conditions, and changes in available spectrum. This is particularly evident in RIS-assisted networks, ISAC, AIGC, and THz communication systems, where real-time adaptability is essential for beamforming, interference mitigation, and link reliability. GenAI continuously learns from past network states to enhance adaptability and also predict optimal configurations in response to environmental changes [10], [70], [71], [102].
2) *Resource Allocation:* The efficient management and distribution of resources is considered to be critical for RIS, AIGC, the metaverse, and ISAC in heterogeneous 6G networks. This resource distribution can be effectively optimized through GenAI, which can predict user demands for key network resources, including bandwidth, transmission power, and specialized network slices. GenAI facilitates the proactive optimization of resource allocation by predicting these requirements in real time. This predictive capability of GenAI is highly critical for dynamically adjusting RIS configurations and implementing adaptive spectrum management in 6G. The automated prediction of demand and the consequent adjustment of network resources are essential for overall system optimization and sustained user satisfaction, irrespective of the highly variable operational conditions inherent to 6G environments [73].
3) *Data Augmentation:* Data scarcity and generalization issues are key challenges within the context of 6G-enabling applications and technologies. In order to mitigate these issues, GenAI produces synthetic data to augment limited real-world datasets. This approach is critical for network optimization and ensuring high-fidelity performance and robust network configurations, even in non-stationary environments, thereby enhancing 6G network reliability [18], [26], [74].

3) GENAI FOR NETWORK SECURITY

The convergence of 6G technologies and applications introduces novel vulnerabilities and attack vectors that need advanced security solutions [18], [103]. GenAI can play a crucial role in strengthening the robustness of 6G systems. It can assess extensive network data by identifying complex anomalies and continuously learning from real-time network behaviors. This enables GenAI to detect emerging threats, mitigate risks, and adapt to evolving attack patterns, thereby ensuring the resilience of 6G networks against advanced cyberattacks.

1) *Anomalies and Attack Detection:* Due to high data rates, ultra-low latency, and massive connectivity, 6G networks significantly increase the attack surface and create diverse security challenges [104]. GenAI addresses these threats by continuously evaluating network traffic and learning from real-time data to detect and mitigate threats [18], [103]. Moreover, security is further enhanced when cutting-edge technologies like blockchain are integrated with GenAI, as this can help analyze large datasets for anomaly detection and offer early threat warnings. The use of blockchain and quantum computing provides immutable and transparent data storage for secure, verifiable transactions. This combined approach is vital for environments with rapidly fluctuating network conditions, allowing GenAI to predict and prevent threats by detecting subtle anomalies across diverse settings [89], [90], [91], [92], [103].
2) *Spoofing/Jamming Detection and Protection:* Sophisticated 6G communication techniques, such as beamforming and resource allocation, are vulnerable to spoofing and jamming attacks that disrupt the signal flow [94]. GenAI is essential for identifying and mitigating these attacks [18]. GenAI can analyze traffic in real-time to detect unusual signal manipulations and differentiate between legitimate and malicious signals by learning expected network and signal behaviors. This capability guarantees the robustness of 6G networks and prevents service disruptions, especially in applications that need precise coordination, such as ISAC-based systems [93], [95].

C. HOW GENAI ENHANCES DTs FOR 6G

DTs provide virtual representations of physical 6G networks for simulation, monitoring, and intelligent control. However, DTs face several inherent limitations when deployed independently. These include data scarcity that limits model fidelity, adaptability issues that hinder generalization to unseen scenarios, and semantic gaps that prevent interpretation of high-level context. These issues restrict the capability of DTs to fully capture the dynamic 6G and metaverse environments.

TABLE 4. DT limitations and GenAI solutions in 6G networks.

DT Limitations	GenAI Solutions
Data scarcity: Insufficient real-world data limits accurate DT modeling of dynamic network states.	**Synthetic data generation:** GANs and DMs generate realistic network states, traffic patterns, and user behaviors to augment training data [105]–[107].
Rare or extreme events: DTs cannot capture unusual network conditions or failures due to limited observations.	**Transfer learning and simulation:** GenAI leverages virtual environments and metaverse simulations to synthesize rare or extreme network scenarios for DT training [18], [44], [108]–[110].
Dynamic and high-dimensional network states: Complex, time-varying interactions in 6G networks are difficult for conventional DTs to model.	**Generative model-based learning:** GenAI models capture high-dimensional distributions and temporal patterns, enabling DTs to predict network state fluctuations and optimize resource allocation [18], [44], [109], [110].
Context-aware / semantic modeling: DTs struggle to capture semantic relationships in signaling, user behavior, and network interactions.	**Semantic-aware generative training:** Transformers and other generative models encode contextual and semantic relationships, supporting predictive, context-driven decisions for resource allocation, semantic communications, and holographic services [18], [44], [109], [110].

As summarized in Table 4, GenAI is utilized in the following sections to effectively address these constraints, thus enhancing DT performance and adaptability.

1) GENERATIVE DATA AUGMENTATION FOR DTs

DTs in 6G networks are limited by data scarcity, which impairs their ability to accurately model complex network dynamics and develop reliable resource allocation policies. This significantly reduces the robustness and reliability of DT simulations [44]. This issue is addressed by GANs, which generate high-quality synthetic data that has unobserved network states and diverse traffic patterns to supplement insufficient real-world measurements. This augmentation enhances model fidelity and generalization and supports accurate performance evaluation and optimization in dynamic 6G environments [105], [106].

2) GENERATIVE TRANSMISSION FOR DTs

DTs often struggle to accurately model transmission processes in 6G wireless networks, particularly when unpredictable interference, dynamic channel conditions, and varying traffic loads are present [111]. This constraint limits a DT's ability to capture semantic relationships between signals and network behaviors, which ultimately reduces 6G network performance. In addition, DMs address this concern by generating realistic synthetic transmission scenarios that reflect diverse channel conditions. The integration of DMs enables DTs to optimize transmission strategies, improve semantic communication accuracy, and enhance overall network performance [111], [112].

3) GENAI AS DTs

The utility of 6G DTs is limited by data constraints. However, GenAI can function as a virtual DT to generate high-fidelity synthetic representations for accurate simulation and evaluation [108]. GenAI models like Transformers learn the semantic and temporal relationships between network states and actions by interpreting network control messages (e.g., resource allocation, handover, etc.) as structured sequential data. This enables the generation of realistic policies that replicate network functions. This approach establishes message-level DTs that support semantic communication and adaptive resource management in 6G, even without fully deployed physical DTs.

When functioning as a DT, GenAI significantly enhances 6G network performance [44]. These GenAI models simulate real-time network states and application characteristics, offering predictive insights into channel conditions, traffic demands, and resource utilization [109], [113], [114]. 6G networks can achieve higher efficiency, scalability, and adaptability by leveraging GenAI-based DTs, which would unlock new possibilities for wireless communication systems in the era of advanced connectivity [13].

4) GENAI-ENHANCED DT TRAINING FOR 6G APPLICATIONS

DTs in 6G networks are constrained by insufficient real-world data, rare network events, the time-varying nature of network states, and dynamic traffic conditions, which limit their ability to accurately model network states and optimize resource allocation. GenAI models, such as GANs and DMs, provide a solution by generating high-fidelity synthetic network data, including traffic patterns, user behaviors, and previously unobserved network scenarios. By training DTs on both real and generative data, the twins learn to predict fluctuations in spectrum demand, latency, and throughput, enabling proactive and context-aware resource allocation for applications such as holographic communications, semantic-driven services, and URLLC. Additionally, a GenAI model functioning as DT training supports semantic-aware adaptation, allowing DTs to capture not only quantitative metrics but also the contextual meaning of network interactions. This approach ensures that DTs maintain optimal performance and predictive capability even in conditions where conventional training data is sparse or incomplete, effectively bridging the gap between theoretical DT modeling and practical 6G deployment [110], [115].

D. SUMMARY OF LESSONS LEARNED

GenAI has emerged as a main enabler for optimizing 6G performance and security. It notably augments the physical layer by enhancing signal processing that leads to higher data rates, reliability, and spectral efficiency. In network optimization, GenAI greatly facilitates dynamic resource allocation and adaptive management to reduce latency. Most importantly, GenAI ensures high-level security by providing advanced-level threat detection and anomaly mitigation in real time. Additionally, GenAI also generates synthetic datasets and predictive models to facilitate improvements in key 6G applications, such as MEC, AIGC, semantic communications, ISAC, and AR/VR. All the above-mentioned core capabilities set GenAI up as a cornerstone for enhancing the efficiency, adaptability, and security of 6G networks [13], [109], [114].

IV. DTs IN 6G NETWORKS: ENABLING APPLICATIONS AND TECHNOLOGIES

The DT paradigm creates virtual replicas of physical network elements for comprehensive modeling, simulation, and analysis [116]. By bridging physical and digital realms, DTs provide deep predictive insights that might be crucial for informed decision-making. In 6G networks, where high data rates, low latency, and reliability are essential, DTs are central to network optimization [41], [117]. DTs permit testing configurations, resource allocation, and performance under varying conditions, enabling proactive management that reduces costs and enhances efficiency [23]. Real-time data updates ensure DTs support adaptive decision-making and increase 6G network resilience.

DTs are pivotal in enhancing 6G security [118]. They provide a platform to develop robust defense strategies by simulating diverse attack scenarios, such as DDoS and unauthorized access [10]. Furthermore, an important feature of DT technology is the integration of real-time network data to develop proactive, adaptive security schemes for emerging threats. Moreover, DTs model behaviors like interference and mobility to reduce system vulnerabilities, improve resource allocation, and optimize network configuration [22], [24]. The DTs' predictive capacity thus strengthens security and sustains performance in dynamic 6G environments [23], [115].

A. DT ARCHITECTURE FOR A 6G NETWORK

A DTN is a digital replica of the entire lifespan of a physical network, which utilizes models and data

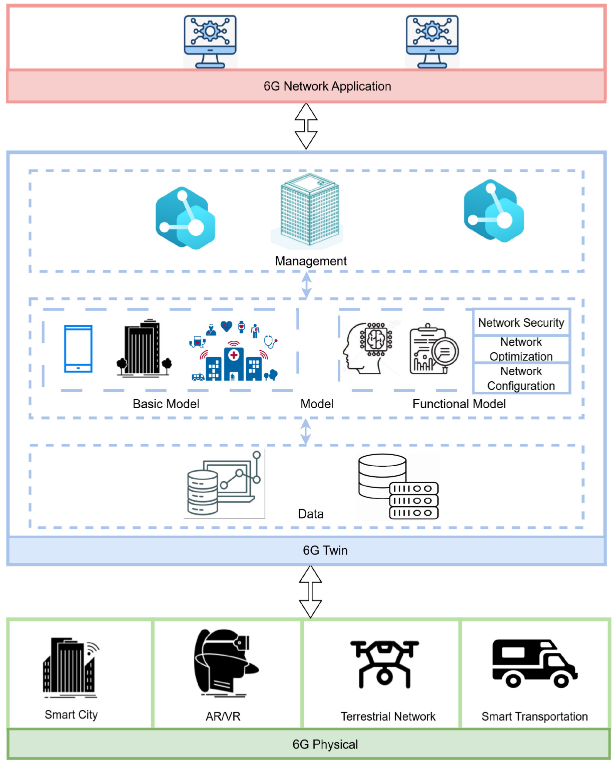

FIGURE 3. DTNs for 6G network optimization, management, and security [42].

to create a physically precise platform for network simulations, to offer up-to-date network state and predict future status [38]. According to the ITU-T recommendation [119], there will be three layers in a reference 6G DTN architecture: (1) 6G physical network layer, (2) 6G twin layer, and (3) 6G network application layer. Figure 3 highlights the integration of DT technology into 6G networks, demonstrating its potential to fundamentally revolutionize network design and optimization.

1) 6G PHYSICAL NETWORK

The 6G physical network layer encompasses all tangible network components–including the core, transport, and radio access networks–which serve as the direct interface for exchanging data and control messages with the DT layer [42]. This layer is optimized for ultra-low latency and high capacity, supporting complex industrial applications. It thereby outperforms previous generations [5]. It covers all logical and physical assets (e.g., network elements, services, and base stations). These are digitally twinned to create a holistic virtual replica that enables optimized resource orchestration, performance enhancement, and cost-efficient network management by operators [120]. Enabling applications (e.g., smart transportation, AR/VR, THz, and AIGC) facilitate the transmission of network states and characteristics from the physical layer to the 6G twin layer, as shown in Fig. 3. These resulting DT states function as real-time virtual representations, capturing crucial operational parameters, such as channel conditions, mobility patterns, and QoS requirements, derived from deployed network sensors and devices.

2) 6G TWIN

The core of a 6G DTN is the 6G twin layer, which is structured into three critical domains: the data domain, the model domain, and the management domain, as in Fig. 3. The data domain collects real-time data from the physical network to create a detailed repository that informs the model domain. The model domain integrates both functional and basic models to represent the network's topology and constituent elements. These models are essential for numerous key functions, including network planning, fault detection, traffic analysis, and performance optimization. Functional models utilize machine learning algorithms to improve network configuration, security, and optimization. Furthermore, the integration of enabling technologies (e.g., RIS, ISAC, THz frequencies, and AIGC) enhances network performance by optimizing physical-layer characteristics, ensuring seamless communication, and increasing network flexibility. The modular architecture of 6G DTNs facilitates hybrid simulations and real-time, data-driven decision-making, which are essential for effective network design. The management domain integrates vital security mechanisms (e.g., encryption, authentication, and integrity protection) and employs continuous model updates to sustain optimal performance. By merging AI-driven decision-making with virtualized environments, the 6G twin layer enables dynamic, secure, and efficient network management, thus forming a robust foundation for future 6G networks.

3) 6G NETWORK APPLICATION

Various applications in the 6G network application layer interface with the twin layer to effectively convey the service demands. This interaction allows the intelligent provisioning and control of the underlying physical network [42]. Traffic demands and user requirements from 6G-enabling technologies, such as dynamic spectrum allocation, adaptive beamforming, intelligent traffic routing, and predictive maintenance based on real-time network conditions, are continuously forwarded to the twin layer, wherein these inputs are processed to optimize network performance. The application layer uses twin-layer insights to guarantee seamless service delivery and efficient resource utilization, thereby fulfilling the strict QoS and energy efficiency demands of next-generation networks.

B. ADAPTIVE MODELING METHODS FOR 6G DTNs

In 6G DTNs, it is crucial to maintain accurate and adaptive models due to the highly dynamic nature of network environments [121]. Classic modeling techniques mostly depend on fixed reward functions in reinforcement learning (RL), which might limit the model's ability to respond to varying network conditions [122]. To address these limitations, an intelligence-based reinforcement learning (IRL) framework has been proposed that introduces a high-level metric, termed *intelligence*, for quantifying cognitive improvement. This method helps the DTs in autonomously adapting to network dynamics and thus eliminates the need for explicit reward functions, which in turn leads to better flexibility and robustness. In their framework, network requirements and network states are modeled as multi-dimensional random variables by allowing the DT to handle uncertainties and optimize multiple objectives simultaneously [123], [124].

Adaptive modeling also incorporates multi-granularity techniques in which the DT adjusts the level of detail in its representation according to real-time network conditions. It is particularly valuable for 6G applications, in scenarios like URLLC, eMBB, and mMTC, wherein the network conditions can fluctuate in a rapid and unpredictable manner. DTs can accurately reflect the state of physical network elements, support predictive maintenance, and optimize resource allocation by dynamically updating models on the basis of real-time telemetry and network feedback [125]. This adaptability is particularly crucial for 6G because each application area poses distinct challenges, for instance, URLLC use-case requires precise real-time synchronization to avert service interruptions, eMBB demands high-throughput optimization under variable traffic loads, and mMTC must efficiently scale to support massive device connectivity. Adaptive DTs may tailor their models to these heterogeneous requirements through the integration of reinforcement learning and AI-driven feedback loops, and by doing so, ensure accurate network representation while maintaining computational efficiency [126]. Ultimately, adaptive modeling enhances the robustness, reliability, and scalability of 6G applications, which in turn, facilitates intelligent resource management together with robust end-to-end service delivery across various use cases [127].

C. DTs FOR 6G-ENABLING TECHNOLOGIES AND APPLICATIONS

DT technology is essential for optimizing the security, intelligence, and efficiency of 6G-enabling technologies [41], [128]. DT models enable rapid prototyping, facilitating the creation of virtual models and network simulations, and helping with the optimal placement of network resources (e.g., nodes and access points) to enhance AR and VR performance and coverage. This approach supports iterative design and testing in a virtual environment, substantially minimizing the cost and time associated with physical prototyping and ultimately contributing to the development of resilient and adaptive network architectures [129], [130].

Besides immersive AR/VR services, short video streaming is a major source of traffic in 6G networks. DTs improve short video streaming applications by modeling user behavior, content demand, and network conditions in real time, thereby enabling predictive caching, adaptive resource allocation, and edge computing optimization [131]. This proactive management approach reduces latency, minimizes buffering, and ensures a high quality of experience (QoE), underscoring the significant role of DTs in optimizing high-volume, latency-sensitive 6G services.

DTs play an essential role in the development of 6G-enabling technologies. Particularly, within AIGC networks, their function is to construct high-fidelity virtual models that meticulously replicate the end-to-end network parameters and services governing the generation, transmission, and final delivery of AIGC [10]. This capability also supports proactive threat detection, anomaly identification, and the development of robust security measures [10]. In the case of ISAC networks, DTs jointly optimize communication and sensing parameters by simulating key factors, i.e., CSI, interference levels, and mobility patterns [24]. This act ensures seamless coordination between the sensing and communication functions, which is essential for emerging 6G applications such as autonomous transportation and smart city infrastructures.

Additionally, in RIS and THz communication networks, DTs provide a virtual simulation platform for iterative testing and optimization of signal processing techniques, phase-shift configurations, and beamforming strategies [22], [42], [132]. This helps ensure greater reliability and security in dynamic environments [22], [42], [132]. Furthermore, DTs notably contribute to semantic communication, which focuses on transmitting meaningful information instead of raw data. By digitally emulating the semantic feature structures of transmitted signals, DTs allow for the optimization of signal encoding and interpretation processes. This function effectively reduces bandwidth consumption and improves communication efficiency. This is particularly useful in AI-driven 6G applications, where accurately capturing the semantic intent of transmitted information is essential to maintain data integrity to ensure context-aware network operation.

DTs play a vital part in large-timescale resource allocation by integrating predictive modeling with optimization-based decision-making. DTs construct accurate virtual models of spatio-temporal network dynamics by continuously aggregating historical user mobility patterns, network telemetry, and service demand statistics [37], [133]. These models enable proactive reservation of computing, spectrum, and storage resources, thereby ensuring reliable service delivery for 6G networks.

Such capabilities are especially important for 6G applications. For instance, in eMBB, DT-assisted forecasting enables the pre-allocation of capacity for high-throughput services such as immersive XR. In URLLC, long-horizon resource reservation guarantees mission-critical service reliability under dynamic conditions, whereas in mMTC, periodic IoT traffic can be anticipated to enable scalable and efficient allocation strategies [134].

DTs employ predictive intelligence, simulation, and long-term optimization to achieve robust, reliable, and efficient management across large timescales, surpassing instantaneous control for all 6G applications. The incorporation of DTs within the core of 6G network design and operation allows researchers and engineers to realize unprecedented efficiency, adaptability, and security. This convergence is anticipated to establish a robust and intelligent next-generation communication ecosystem. Following this, we will examine the specific enhancements DTs provide to 6G networks, with a focus on their contributions to optimizing network design, improving physical-layer security, and bolstering overall network security.

1) DT FOR PHYSICAL LAYER DESIGN

DTs are crucial for improving 6G physical-layer design. They simulate the real-time behavior of enabling technologies, making it possible to address security vulnerabilities and optimize RF communication [135]. These capabilities are essential for ensuring the robustness of RIS-assisted communication, metaverse, THz links, ISAC, and AIGC in 6G networks [128]. DTs improve physical-layer security in the following key areas:

a) *Dynamic Threat Landscape:* DTs enable real-time monitoring and anomaly detection for RIS-based wireless environments to prevent unauthorized beam manipulation or adversarial attacks on reconfigurable metasurfaces [118]. For THz communication, DTs predict path loss, signal degradation, and jamming attacks, which allow dynamic reconfiguration of transmission strategies to maintain secure and efficient links [136]. Furthermore, DTs improve metaverse security through comprehensive monitoring and predictive analytics, which facilitate early threat detection and proactive mitigation. Continuous analysis of network behavior helps DTs identify vulnerabilities and reinforce the resilience of the infrastructure supporting AR applications within the metaverse [137].

b) *Vulnerability to Physical Attacks:* DTs can replicate possible physical attack scenarios on ISAC systems. Their primary utility is to pinpoint weaknesses within the system where malicious entities could compromise or exploit the integrated sensing and communication capabilities [138]. DTs ensure secure operation of joint communication and radar sensing by preemptively addressing limitations in waveform design and spectrum sharing. In the same manner, DTs improve RIS deployment by mitigating eavesdropping risks through optimized phase-shift configurations.

c) *Securing RF Communication:* DTs enhance security for high-frequency THz and mmWave transmissions by optimizing RF signal management and encryption techniques [136], [139]. This capability is critical for AIGC-powered immersive applications, which necessitate robust encryption and interference mitigation to prevent unauthorized access and content manipulation. Moreover, this function simultaneously guarantees the ultra-reliable wireless connectivity required for real-time services, such as holographic communication.

2) DT FOR NETWORK OPTIMIZATION

DTs have turned out to be a transformative enabler for 6G networks that offer real-time simulations, predictive analytics, and intelligent decision-making to enhance the performance and security of 6G technologies and applications [140], [141]. DTs enable proactive resource allocation, adaptive security mechanisms, and energy-efficient network management by continuously integrating real-time data acquired directly from network components. These functionalities are necessary for optimizing several 6G-enabling technologies, such as RIS, THz communication, ISAC, the metaverse, and AIGC.

The optimization capabilities of DTs improve 6G network performance and security in these key areas:

a) *Dynamic Resource Allocation:* 6G networks require dynamic and intelligent resource allocation to efficiently handle varying traffic loads and service demands. DTs facilitate real-time traffic modeling, predictive analytics, and the development of optimization strategies. The preliminary goal is to enhance spectrum utilization, reduce latency, and ultimately improve overall network performance [142]. By simulating network behaviors under different conditions, DTs help fine-tune configurations for RIS-assisted communication, metaverse, ISAC frameworks, and THz-based ultra-high-speed networks [2], [143].

b) *Energy Efficiency:* Given the growing complexity of 6G infrastructures, it is critical to achieve energy efficiency [144]. DTs simulate power consumption patterns, which facilitate the implementation of dynamic energy-saving strategies across varied network elements, such as RIS-assisted smart environments, THz transceivers, and AI-driven network functions. The critical insights drawn from these simulations contribute directly to green 6G deployments [145]. Specifically, they not only optimize power management within wireless access points, edge computing nodes, and intelligent base stations but also simultaneously ensure the maintenance of high system reliability.

3) DT FOR NETWORK SECURITY

DTs offer a substantial enhancement to 6G network security by creating a virtual simulation platform that accurately mirrors the entire physical 6G network environment. This capability enables proactive threat detection, continuous security monitoring, and the implementation of dynamic responses to security incidents [146]. This approach addresses the unique security and privacy challenges inherent in 6G applications and technologies such as RIS, THz communication, ISAC, metaverse, and MEC, by offering predictive insights and improving resilience against emerging threats.

a) *Proactive Threat Detection:* The growing dynamic nature and complexity of 6G networks lead to a proportional increase in the sophistication of cyber threats that target 6G-enabling applications [147]. Traditional, reactive security methods fail to fulfill the demands of 6G networks due to the large scale and extensive complexity introduced by complicated 6G environments. In order to address this challenge, DTs provide real-time simulations that create virtual replicas of network activities within the physical environment. These virtual network replicas help with the constant monitoring of the network for the timely identification of anomalies [135], [137], [148]. Moreover, in order to enhance proactive security measures, DTs also simulate attack scenarios and assess the response in real time. This leads to robust security designs for 6G technologies.

b) *AI-Based DTs for Enhanced Security:* Due to the increased complexity and massive volumes of data generated in 6G networks, it is necessary to devise advanced analytics to efficiently detect and respond to cyber threats [16]. The AI-driven algorithms combined with DTs serve as a very powerful tool for increasing the security of 6G networks [140]. DTs can leverage ML models to analyze vast amounts of data from 6G-enabling applications to detect patterns that may indicate potential security risks. For instance, AI models can be trained on the synthetic datasets created by DTs to predict attack vectors, identify unusual activity, and generate automated real-time threat responses [149]. AI-driven DTs significantly improve the accuracy and efficiency of security within 6G infrastructure by continuously adapting to evolving cyber threats. This enhanced resilience assists AI-driven DTs in safeguarding sensitive information and maintaining reliable communication across diverse 6G technologies, including THz systems, ISAC, and distributed cloud platforms.

D. SUMMARY OF LESSONS LEARNED

DTs are instrumental in optimizing 6G networks by furnishing real-time virtual representations that are highly critical for network design, resource allocation, security management, and overall network optimization. DTs facilitate precise simulations and predictive modeling capabilities, which eventually serve to enhance the performance of complex 6G systems, particularly in applications such as THz communication, semantic communications, and AIGC. By facilitating dynamic resource allocation, DTs optimize spectrum usage, minimize latency, and maximize data rates, thereby ensuring efficient communication in environments requiring high throughput and low latency. Furthermore, DTs improve security by continuously monitoring network activity, detecting anomalies, and mitigating cyber threats in real time, ensuring resilience and reliability. Through these capabilities, DTs support intelligent network management, bolster security measures, and enable seamless operation of 6G applications, driving innovation and accelerating digital transformation across industries and societies.

V. INTERPLAY BETWEEN GENAI AND DT FOR 6G-ENABLING APPLICATIONS

The 6G network is designed to achieve ubiquitous connectivity, integrate native intelligence, and ensure global coverage. This objective necessitates novel network design approaches to effectively manage both the highly dynamic nature of wireless environments and the demands of diverse service requirements [14], [150]. These challenges need the development of an intelligent framework that can precisely synchronize data across various network infrastructures to ensure seamless connectivity [151]. Achieving high-fidelity modeling is another critical network design factor for accurately representing the physical and virtual elements of the network and facilitating effective optimization and simulation [23]. Successful generalization of AI models to cover unseen and diverse wireless environments is a critical step while developing robust frameworks for enhanced performance across varying wireless conditions.

To address these challenges, a framework is proposed (as illustrated in Fig. 4) that seamlessly integrates DTs and GenAI to offer a transformative solution for optimizing 6G network design. This framework establishes a synergistic interaction by combining the real-time modeling precision of DTs with GenAI's predictive and generative capabilities that result in a scalable and adaptable solution that enhances both network performance and security. The framework is organized into multiple connecting layers to ensure efficient resource allocation, real-time adaptability, and high-fidelity modeling. The layers of the proposed framework are comprehensively discussed as follows:

1) *Real-Time Emulation Layer:* The real-time emulation layer incorporates the DT that serves as the foundation of the architecture by offering a real-time, digital representation of the physical 6G network. It continuously updates data from the physical 6G network to ensure that the network remains synchronized with its current operational state, providing an accurate and up-to-date model for performance optimization. Based on this foundation, different GenAI models, such as LLM, transformers, GANs, and DMs, are used to emulate real-time semantic-level user preferences and network conditions based on 6G applications in order to improve DTs' capabilities. The requirement of constant data updates for DT is significantly reduced by these GenAI models. As a result, real-time data collection constraints are minimized, and model accuracy is maintained at the same time. The integration of GenAI models and DT technologies ensures the adaptability of the system. This enables 6G applications to quickly adjust to changes in environments, traffic demands, and users' mobility, and to maintain smooth operations even in rapidly changing scenarios.
2) *Feature Abstraction Layer:* The main function of this layer is to abstract and reduce the high-dimensional data generated by the real-time emulation layer. GenAI techniques, such as VAEs, reduce redundancy and retain important features to compress and encode high-dimensional data into a low-dimensional representation. Moreover, transformers further extract important network characteristics, such as traffic attributes and sophisticated propagation, which are crucial for managing resources and optimizing communication. This feature extraction process ensures that only relevant information is processed, which will result in reduced system overhead and efficient decision-making.
3) *Decision-Making Layer:* The features extracted in the feature abstraction layer are used in the decision-making layer for intelligent decision-making. This layer uses predictive models, such as LLMs, VAEs, and RL, to decode the traffic and then optimize resource allocation methods. LLMs interpret network and application context to extract semantic insights, while

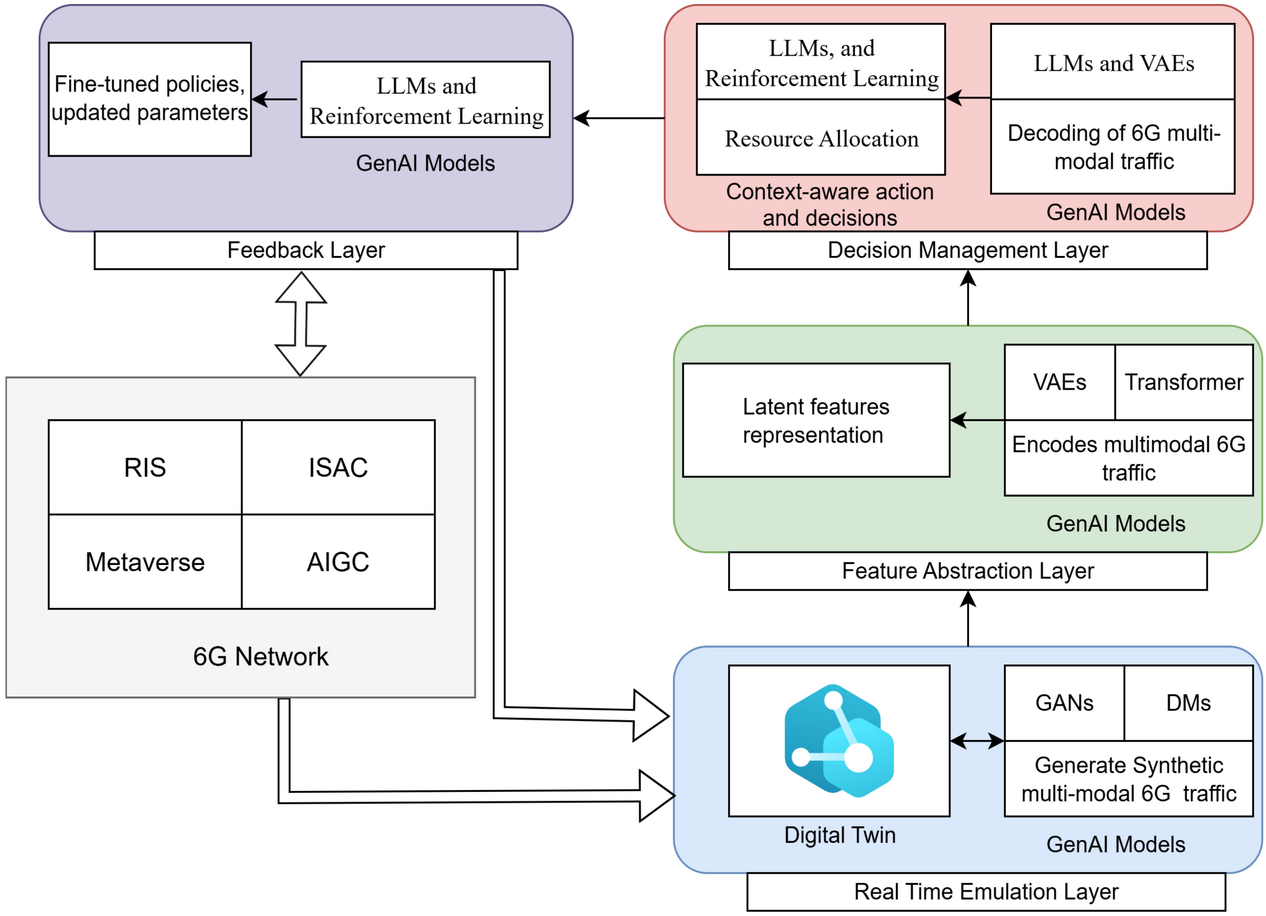

FIGURE 4. **The proposed GenAI-DT architecture for 6G network optimization and security.**

RL agents iteratively explore and evaluate actions. Together, they learn optimal 6G resource allocation policies by updating decision strategies on the basis of the observed network states and performance feedback.

4) *Feedback Validation Layer:* The feedback validation layer provides a feedback loop to DTs, ensuring that the decisions made in the decision-making layer are aligned with 6G-enabling applications. This layer performs validation by comparing simulated outcomes within the DT against actual network performance. It uses LLMs and RL to regularly fine-tune decision parameters based on real-world feedback and enhance 6G network accuracy and reliability. This ensures network adaptation to unforeseen environments and maintains optimal performance, which is vital for mission-critical 6G applications.

Next, we will discuss how this integrated framework, combining the strengths of DTs and GenAI, can be applied to various 6G-enabling technologies, demonstrating its potential to optimize network security, enhance resource allocation, and support a wide range of advanced use cases.

A. SEMANTIC COMMUNICATION

Semantic communication is an enabling technology for 6G networks that shifts communication from traditional bit-based transmission to a context-aware framework focused on the meaning of transmitted data [160]. Unlike traditional wireless networks that prioritize bit-level transmission, semantic communication aims to convey only the useful meaning of the transmitted data. By doing so, it enhances communication efficiency and improves the overall performance of 6G applications.

Semantic communication architecture consists of a semantic encoder that extracts useful information from raw data, a semantic wireless channel that transmits the encoded information, and a semantic decoder that is used to reconstruct the intended meaning at the receiver [160]. Consequently, the development of semantic communication presents significant challenges for6G networks. Some of the key challenges are to handle diverse multimodal data while preserving context [161] and to fulfill the stringent URLLC requirements for 6G applications like immersive experiences. Besides this, real-time collaboration, intelligent automation [160], and accurate data synchronization across distributed communication networks [162] are other notable challenges. Additionally, developing robust and reliable AI models with generalization capability is particularly challenging for 6G network design.

In the following subsection, we delve into the applications of GenAI and DTs and their synergistic interplay

TABLE 5. GenAI models and their applications in semantic communications.

GenAI model	Key function in semantic communications	References
Variational Autoencoder (VAE)	Semantic coding, joint source-channel coding (JSCC), semantic reconstruction	[152], [153]
Generative Adversarial Network (GAN)	Semantic coding/JSCC, signal distortion suppression	[154], [155]
DMs	Semantic coding/JSCC, channel modeling, channel equalization	[156], [157]
Large Language Model (LLM) / Transformer	Multimodal semantic alignment, knowledge sharing, physical-layer semantic coding	[158], [159]

in optimizing the performance and security of semantic communications. The discussion highlights how the interplay of these technologies influences the adaptability, efficiency, and resilience of next-generation networks.

GenAI: GenAI has emerged as a key technology for enabling semantic communications within 6G networks to optimize data extraction, encoding, and transmission. It also accurately reconstructs the intended semantic information across multiple modalities. In the past few years, different GenAI architectures have been used for specific semantic communication tasks. VAEs, with probabilistic encoder-decoder architectures, efficiently map high-dimensional data into a structured latent space and enable joint source-channel coding (JSCC), semantic compression, and robust reconstruction across image, text, and audio modalities [152], [153]. GANs are employed to enhance JSCC and semantic coding as well as to mitigate signal distortions, and thus improve reconstruction fidelity for image and text transmissions [154], [155]. DMs leverage forward diffusion and reverse denoising processes to provide channel modeling, semantic coding, and channel equalization, which makes them particularly suitable for audio, image, and multimodal transmissions over noisy wireless channels [156], [157]. LLMs and transformer-based architectures serve as both semantic encoders and decoders, as well as auxiliary knowledge bases, which enable precise multimodal semantic alignment, context-aware reasoning, and dynamic multi-user knowledge sharing. These capabilities enable physical-layer semantic coding by capturing complex correlations across data modalities and interpreting high-level semantic information, thus making them very suitable for multi-user and adaptive 6G wireless communication scenarios [158], [159].

Overall, as summarized in Table 5, transformer-based LLMs are the preferred GenAI architecture for semantic communications under the semantic fidelity constraint. This preference arises from their advanced abilities in high-dimensional semantic feature extraction, context-aware reconstruction, and multimodal alignment, which are the key to guaranteeing strong semantic fidelity and low latency in rapidly changing 6G environments.

DTs: DTs significantly enhance semantic communications by serving as real-time virtual models of physical semantic communication networks [23]. These DTs constantly update critical parameters such as user mobility, SNR, and wireless channel conditions to synchronize with the physical network. DTs enable adaptive adjustments to the encoder-decoder architecture by maintaining real-time alignment, which ensures efficient data processing and robust transmission, even in fluctuating wireless environments [115]. In addition to real-time synchronization, DTs model a variety of wireless environments incorporating network digital twin, simulating unobserved network system conditions that improve prediction accuracy and enhance the system's adaptability [163]. These simulations allow the encoder-decoder architecture to process semantically rich information under variable network conditions, ensuring consistent performance across a wide range of 6G applications. Furthermore, to achieve efficient channel characterization and high fidelity, a digital twin channel (DTC) framework is developed to accurately mirror the physical channel characteristics in the digital domain to enable proactive decision-making for communication nodes [164]. The DTC enhances the semantic communication framework by the transmission of useful information by ensuring a synchronized alignment between the digital and physical channel representations. This interplay of DTC with semantic communications is crucial for optimizing context-aware data delivery and envisioning the development of efficient and intelligent 6G.

Interplay: The interplay between GenAI and DTs develops an adaptive and intelligent framework that addresses critical challenges, including high-fidelity modeling, data synchronization, and resource allocation to enhance semantic communication in 6G [165]. The framework (as illustrated in Fig. 5) consists of four main layers, i.e., the status emulation layer, feature abstraction layer, decision-making layer, and feedback validation layer. These layers are summarized in Table 5 and also further discussed in the following section.

1) *Real-Time Emulation Layer:* The real-time emulation layer integrates DTs to provide a virtualized representation of the physical semantic network by effectively capturing key parameters such as user behavior, traffic patterns, and channel conditions. This layer utilizes GenAI models (i.e., GANs and DMs) to emulate semantic network characteristics and thus establish a high-fidelity virtual representation of the physical infrastructure. GANs synthesize realistic network states by capturing correlations across key metrics, including semantic information, latency,

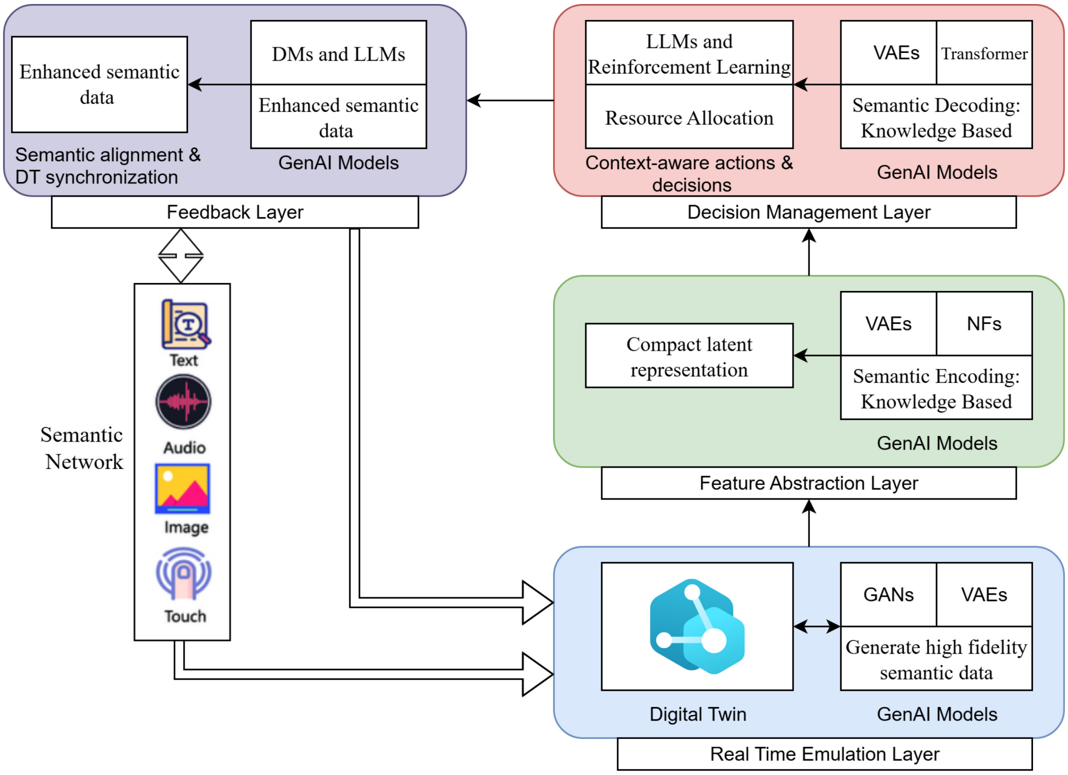

FIGURE 5. A layered framework of GenAI–DT for semantic-aware network optimization and security.

TABLE 6. Summary of GenAI–DT framework layers for semantic network optimization.

Layer	Function	GenAI models
Real-Time Emulation	Emulate semantic network characteristics and reduce DT synchronization overhead	GANs and DMs
Feature Abstraction	Encode high-dimensional semantic features, denoise and extract meaningful representations	VAEs
Decision-Making	Decode the data and generate context-aware actions, optimize content delivery and resource allocation	Transformers, LLMs and RL
Feedback	Evaluate and fine-tune outputs	DMs, LLMs

and throughput, whereas DMs refine these generated samples by modeling them and learning to map initial random noise into structured, realistic network scenarios. By integrating GenAI models with DTs, this layer minimizes the frequency of DT updates while maintaining accurate and representative network models.

2) *Feature Abstraction Layer:* This layer encodes and abstracts high-dimensional emulated data to derive actionable, meaningful insights, as the data received from the real-time emulation layer is time-series and highly dimensional, and cannot be used for network management policies. This layer utilizes VAEs to encode the emulated features into a latent space by effectively retaining critical semantic information and reducing dimensionality. VAEs enable efficient compression and robust representation of network states by learning the distributions of the semantic data. Additionally, GenAI models such as diffusion-based encoders can be integrated to compress the latent representations further and capture complicated high-dimensional dependencies under noisy network conditions. The resulting feature embeddings are used as inputs for the decision-management layer. This ensures that adaptive resource allocation and semantic-aware network control rely on high-fidelity, semantically meaningful data originating from the emulated network environment.

3) *Decision-Making Layer:* The decision-making layer receives the latent abstracted semantic features from the feature abstraction layer to derive intelligent, data-driven decisions. The encoded data from the feature abstraction layer is first processed by GenAI models, such as VAEs and transformers, that utilize a shared knowledge base. VAE decoders reconstruct and translate low-dimensional, context-enriched representations

into interpretable formats to retain critical information for network optimization. The shared knowledge base is crucial in this process, providing a common framework that improves the efficiency and accuracy of semantic decoding. By leveraging this shared information repository, variational autoencoders can interpret and reconstruct the intended meanings of the transmitted data in an effective manner. Subsequently, LLMs and reinforcement learning frameworks use these decoded insights to enable multi-user semantic coordination and context-aware decision-making. These frameworks further help in the formulation of policies that optimize the extraction, alignment, and reconstruction of semantic information across heterogeneous network scenarios [166].

4) *Feedback Validation Layer:* This layer simulates the decisions that are made at the decision-making layer in the DT environment and validates them against actual network performance. By feeding back predictions from the decision-making layer, this layer incorporates LLMs and RL agents to fine-tune the model parameters. This eventually enhances the semantic encoding-decoding pipeline for future iterations. This iterative process enhances the DTs' predictive semantic decoding capabilities and keeps the system responsive to dynamic network conditions. The constant improvement in model predictions ensures that the semantic encoder-decoder architecture is quite effective even in unseen network conditions.

Security: The security of semantic communication is enhanced by the interplay of GenAI and DTs, as this synergy allows for vulnerabilities to be addressed at both the semantic and operational levels [25]. DTs create virtual replicas of the network, having critical components such as a semantic encoder and decoder. This helps in doing controlled, simulation-based security testing across diverse operational environments [30]. These simulations enable the detection and analysis of threats, such as irregular traffic patterns, unauthorized access, and adversarial attacks [31]. The DTs provide a dynamic environment for detecting and countering threats in real-time through the replication of diverse network conditions, including potential attack scenarios, varying traffic loads, and interference. This capability considerably boosts defense mechanisms and facilitates the development of robust security techniques. The integration of DTNs further enhances security by permitting efficient processing of large datasets and real-time optimization [167].

GenAI further complements the capabilities of DTs and DTNs by addressing semantic vulnerabilities through its predictive capabilities [168]. For example, LLM-twin frameworks, in which the mini-giant model collaborations and novel intra-twin and inter-twin communication mechanisms are combined, enhance resource efficiency while mitigating potential security threats [167]. This approach simultaneously enhances resource efficiency and mitigates potential security threats. GenAI models, such as GANs and VAEs, can simulate adversarial attacks designed to exploit LLM-based components and proactively test countermeasures. Additionally, GenAI can safeguard sensitive data during the testing and training phases by generating semantically accurate yet anonymized datasets. Furthermore, the integration of LLMs into DTNs provides much better security against potential threats than federated learning-based DTNs. This synergy across GenAI, DTs, and DTNs establishes a robust and adaptive security framework that ensures the integrity, confidentiality, and resilience of semantic communication systems in 6G networks.

B. RECONFIGURABLE INTELLIGENT SURFACES

RIS are smart radio environments that can intelligently control the incoming incident waves by dynamically adjusting the amplitude and phase shifts of RIS elements to enhance signal coverage and energy efficiency and mitigateinterference in wireless networks [174]. RIS architectures developed for 6G network optimization and security pose significant challenges such as network generalization, high-fidelity network modeling, and real-time data synchronization [175]. To address these challenges, intelligent and adaptive frameworks are required to optimize RIS's performance and security in 6G networks. In the next section, we will explore the applications of GenAI and DTs and how their interplay can address these challenges in RIS for 6G network design.

GenAI: Integrating GenAI models with RIS in 6G networks introduces transformative capabilities for addressing challenges in wireless network optimization. By leveraging the data-driven emulation capabilities of GenAI, RIS can dynamically reconfigure electromagnetic wave properties to adapt to rapidly changing wireless propagation environments [96]. GenAI algorithms can generate realistic synthetic datasets that mimic diverse real-world applications and thus enable RIS to intelligently adapt phase shifts and beamforming strategies to varying wireless conditions [172]. Notably, GAN-based convolutional blind denoising and convolutional blind denoising networks enhance RIS's ability to mitigate interference, improve SNR, and maximize network coverage, particularly in multipath fading and mobile environments. For instance, studies [169] and [170] highlight the effectiveness of GANs in CSI estimation, wherein a convolutional blind denoising GAN for noise removal and enhanced CSI accuracy is introduced in [169]. Wei et al. [170] addressed instability challenges in GAN-based CSI estimation. Conditional GANs, as in [171], further demonstrate the ability to generate realistic channel responses through adversarial training by effectively learning data distributions and reducing reliance on exhaustive real-world data.

Beyond channel estimation, GANs also enable deployment design and phase shift optimization, as shown in [172], where a DRL framework combined with GANs optimizes IRS placement and beamforming matrices, improving scalability and resource allocation in 6G networks. In [173], the

TABLE 7. GenAI models and their applications in RIS networks.

GenAI Model	Key Benefits	Reference
GAN	Generates synthetic semantic traffic to enhance CSI accuracy, improves SNR, mitigates interference in multipath fading and mobile environments	[169], [170]
Convolutional Blind Denoising GAN	Improves channel estimation accuracy under noisy conditions	[169]
Conditional GAN	Reduces reliance on exhaustive real-world data and models realistic channels for RIS optimization	[171]
GAN + DRL	Optimizes RIS placement, beamforming, and resource allocation in 6G networks	[172]
LLMs	Semantic and cross-modal reasoning, few-shot learning, reduces training overhead, adapts RIS parameters dynamically	[173]

TABLE 8. Summary of GenAI–DT framework layers for optimizing RIS networks.

Layer	Function	GenAI Model
Real-Time Emulation	Generates a virtual replica of the physical RIS, performs data emulation, and simulates channel characteristics.	GANs, DMs
Feature Abstraction	Extracts semantic, multi-modal, and high-level features from emulated data to reduce dimensionality and prepare inputs for decision-making.	VAE
Decision Management	Optimizes RIS configurations and control policies, leveraging extracted features to make adaptive, context-aware decisions.	LLMs, RL, Transformers
Feedback	Aligns virtual and physical RIS states, updates models based on real-world performance, and refines decision policies for continual improvement.	LLMs, RL

authors developed an LLM-based framework that leverages pre-trained LLMs to optimize reconfigurable intelligent metasurface antenna configurations. By utilizing the semantic and cross-modal reasoning capabilities of LLMs, along with few-shot learning, the framework can dynamically adjust RIS parameters to achieve high-performance wireless communication with reduced training overhead.

As highlighted in Table 7, under the common constraint of dynamic propagation environments, GAN integrated with DRL and transformer-based LLMs are the preferred GenAI models for RIS networks, due to their ability to perform optimized real-time adaptive beamforming, dynamic resource allocation, and context-aware semantic parameter tuning in rapidly varying 6G channel environments.

DTs: DTs play a key role in optimizing RIS performance by offering real-time simulations and accurate RIS environment modeling [22], [132]. DTs constantly monitor and assess various factors, including terrain, interference, signal strength, and mobility patterns, to ensure effective resource allocation. Furthermore, DTs simulate RIS performance across varied scenarios in order to identify resource allocation optimization demands for power, beamforming, channel estimation, and user scheduling [176]. These simulations provide useful insights regarding the impact of RIS configurations on network performance, which enable dynamic adjustments for an improved data throughput, reduced interference, and improved signal coverage [177]. This real-time feedback mechanism ensures the adaptive response of RIS to changing network conditions, thereby ensuring smooth integration with complex network topologies. DTs are instrumental in optimizing RIS deployment strategies. DTs can create a detailed environmental model that helps the system make data-driven decisions regarding resource assignment and thus maximize spectral efficiency [177].

Interplay: Integrating GenAI and DTs with RISs offers a groundbreaking approach for 6G network optimization by addressing challenges, such as non-line-of-sight (NLOS) propagation and user mobility, in an effective manner. This collaboration ensures high-fidelity modeling and better data synchronization by leveraging the ability of GenAI to generate diverse synthetic datasets and the ability of DTs to create real-time virtual replicas [166]. The proposed framework is composed of several layers, as summarized in Table 8, which collectively demonstrate its effectiveness in RIS network optimization.

1) *Real-Time Emulation Layer:* The real-time emulation layer receives a virtual replica of the physical RIS-based networks that consists of RIS configuration states, channel characteristics, and user mobility patterns. GANs are integrated to emulate interference dynamics, generate realistic CSI samples, perform blind denoising, and enhance the accuracy of CSI, particularly in multipath fading scenarios. Furthermore, DMs are incorporated to learn stochastic temporal variations, iteratively refine noisy CSI samples through denoising iterations, and support adaptive equalization in highly dynamic wireless environments. The DMs and GANs together provide a data-driven emulation framework that learns RIS–channel interactions, reduces the overhead of frequency DT updates, and provides high-fidelity inputs to the feature abstraction layer.
2) *Feature Abstraction Layer:* In this layer, high-dimensional data from the RIS network is converted

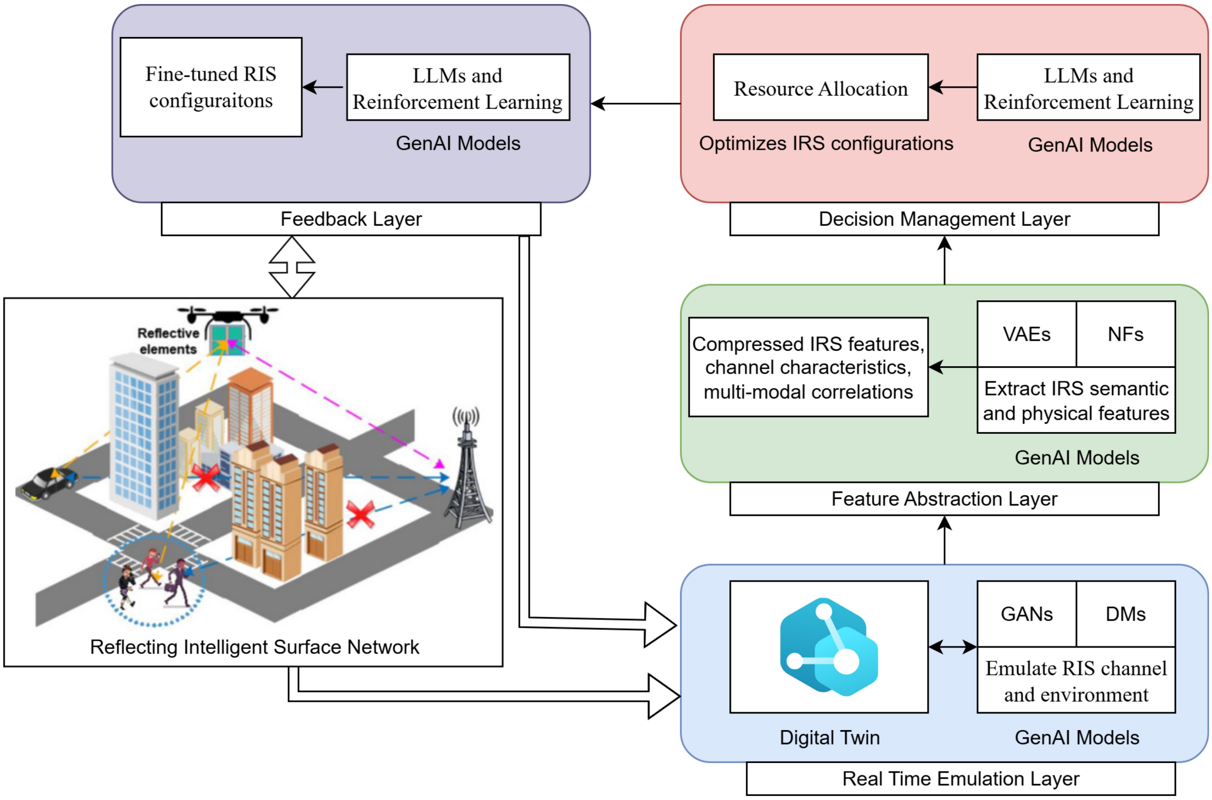

FIGURE 6. A synergistic GenAI and DT framework for optimizing performance and security in RIS networks.

into compact representations required for effective data transmission. GenAI algorithms, such as VAEs, are used to reduce complex RIS data into a concise latent space, preserving the most pertinent features needed to optimize RIS reflection parameters. Moreover, transformers are also incorporated to learn the spatiotemporal correlations within RIS networks, including user demand, traffic flow, and interference patterns, thereby accurately predicting RIS performance across dynamic network states. This abstraction reduces communication overhead while preserving essential features needed for RIS control and semantic-aware decision-making.

3) *Decision-Making Layer:* The latent features that are extracted from the feature abstraction layer are leveraged in this layer to improve security and resource allocation decisions within RIS networks. LLMs provide context-aware reasoning capabilities used to interpret network and RIS states. This interpretation, in turn, helps in making effective decisions regarding the optimal configurations of phase shifts, beamforming vectors, and physical deployment parameters. RL agents obtain operational policies through environmental interaction and then utilize network performance metrics such as energy efficiency, latency, and throughput as reward signals to adaptively refine RIS configurations. Together, LLMs and RL enable semantic-aware, real-time, and high-performance RIS control in 6G networks.

4) *Feedback Validation Layer:* This layer incorporates LLMs and RL to analyze feedback and validate RIS configurations through iterative learning and dynamic adaptation. The DT environment is used to systematically compare the outcomes of RIS-based networks against real-world performance metrics to ensure operational alignment. In addition, adaptive feedback loops combine LLMs and RL to dynamically fine-tune RIS parameters, such as phase shifts and beamforming directions, in response to changes in network conditions. This constant refinement process ensures optimal SNR, enhanced coverage, and seamless performance, even in dynamic 6G environments, which are characterized by high mobility and changing environmental conditions.

Security: The interplay between GenAI models [178], [179], [180] and DTs [148], [181] can substantially enhance the security of RIS networks. The GenAI and DT interplay provides an adaptive and proactive framework that can effectively counter the constantly evolving cyber threats. However, the capability of RIS systems to dynamically manipulate electromagnetic waves may introduce security threats, for instance, signal jamming, malicious beamforming, and eavesdropping attacks [182]. GenAI can leverage historical and synthetic data to create predictive models that identify attack patterns and simulate

TABLE 9. GenAI models and their applications in ISAC.

GenAI Type	ISAC Applications	Reference
GANs	Channel estimation, beamforming, data generation	[97], [185]
VAEs	Data compression, distributed training, denoising	[97], [188]
DMs	High-fidelity data generation, denoising, channel reconstruction	[187], [188]
Transformers	Sequence modeling, predictive beamforming, semantic feature extraction	[189]
LLMs	Semantic communication, context-aware decisions, multimodal ISAC interpretation	[186]–[188]

possible weaknesses within RIS configurations. For example, GenAI models can predict the location and intensity of a jammer in case of a signal jamming attack, which would enable the RIS system to adjust its reflection coefficients dynamically. Moreover, by integrating these predictions with DT simulations, RIS networks can maintain their secure and reliable settings in various environments.

This security framework is further improved by DTs, which create high-fidelity virtual environments that precisely replicate RIS operations and potential attack scenarios [181]. These simulations help DTs in testing the efficacy of countermeasures that are predicted by GenAI against diverse attack strategies. For example, DTs can model the impact of eavesdropping attempts on RIS communication channels. It will help to ensure that the RIS configurations generated by GenAI models reduce signal leakage while preserving privacy. DTs enable real-time monitoring of RIS behaviors by continuously updating the virtual twin with real-world data, and provide immediate alerts for irregularities, such as adjustments of unauthorized beamforming or unusual interference patterns. This dynamic interplay between GenAI and DTs ensures that RIS networks remain resilient against emerging security challenges while optimizing their operational performance in 6G environments.

C. INTEGRATED SENSING AND COMMUNICATION

ISAC is a networking paradigm that jointly designs the communication and sensing modules by leveraging the dual-functional radar communication systems to develop a unified system [26], [183]. The ISAC network enables the network infrastructure to function as a distributing sensing network, with elements like BSs, user devices, and RIS serving as data acquisition nodes [184]. Through the propagation, scattering, and propagation of radio waves, ISAC systems extract wireless environmental data, such as signal propagation characteristics, mobility patterns, and user locations. This real-time sensing capability of ISAC optimizes the dynamic resource allocation and improves user experiences [26]. ISAC optimizes spectrum efficiency and redefines how networks interact with their environment adaptively, making it a transformative enabling application for 6G network design. Next, we discuss the applications of GenAI and DT and how their interplay can enhance the performance and security of ISAC-enabled 6G networks.

GenAI: GenAI offers transformative capabilities to optimize ISAC for 6G by addressing critical challenges, such as data scarcity and resource allocation [18], [97]. GANs are widely applied in ISAC for enhancing signal processing and generating realistic synthetic data. The GANs optimize beamforming, channel estimation, CSI compression, and resource allocation with incentive and scheduling mechanisms [185]. They are also effective for synthetic ISAC data generation, feature compression, signal reconstruction, noise suppression, and modeling of complex high-dimensional joint sensing communication distributions [97]. At the physical layer, GenAI models such as VAE and transformers optimize high-dimensional data, where efficient reconstruction, compression, and channel representation are critical. They optimize scenarios such as denoising noisy signals, feature extraction, and robust modeling of continuous data distributions [97]. For example, GenAI generates optimized signal beams that improve target detection accuracy while mitigating interference, which is crucial for ISAC systems. GenAI models, such as normalizing flows, are used in ISAC for probabilistic modeling and posterior estimation, which enable accurate latent variable inference for sensing and communication tasks. DMs generate high-fidelity ISAC data, perform denoising, and model robust distributions under noisy networks [97]. They perform well for radio map estimation, channel reconstruction, and secure signal generation, and provide realistic datasets. Finally, transformers and LLMs play a crucial role in semantic and multimodal ISAC by enabling the interpretation of high-dimensional sensing, communication, and contextual data [186], [187], [188]. They also optimize predictive beamforming, multi-target detection, semantic feature extraction, and the creation of semantic DTs, and enhance resource allocations. The integration of LLMs in ISAC enables meaning-driven insights by bridging raw sensor data with actionable insights.

As summarized in Table 9, under the common constraint of high-fidelity perception in dynamic wireless environments, transformers and LLMs are the preferred GenAI models for ISAC due to their ability to perform context-aware multimodal interpretation, semantic feature extraction, and predictive beamforming.

DTs: DTs generate virtual representations of physical networks, which enable the real-time optimization of 6G performance within ISAC systems [24]. DTs provide a robust framework for modeling, simulation, and prediction, and thus

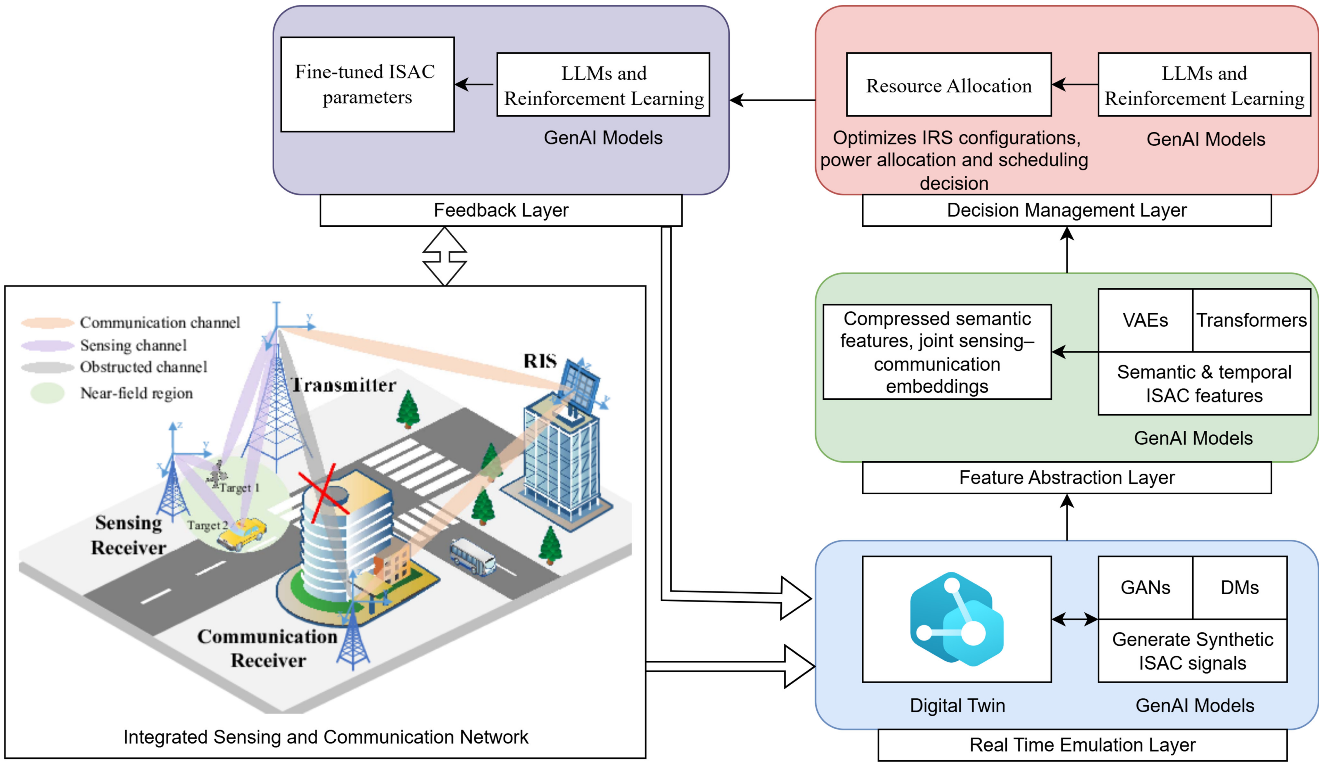

FIGURE 7. Synergic framework for the interplay of GenAI and DT for ISAC network.

TABLE 10. GenAI-driven layered framework for ISAC with DT integration.

Layer	Functionality	GenAI Models Used
Real-Time Emulation Layer	Emulate dynamic ISAC channels with fading, noise, and interference for DT synchronization.	GANs, DMs
Feature Abstraction Layer	Extracts latent semantic features and compresses multimodal ISAC data.	VAEs, Transformers
Decision Management Layer	Optimizes allocation of resources for joint sensing and communication.	LLMs, RL
Feedback Layer	Refines DT models by aligning virtual and physical ISAC environments.	LLMs, RL

effectively address the challenges arising from highly mobile and dynamic network conditions. For example, a DT-enabled ISAC framework can facilitate the smooth integration of heterogeneous sensing data. It enables accurate environmental awareness, which leads to informed decision-making that is necessary for effective interference management and resource allocation [135]. DTs also improve ISAC reliability by maintaining high-fidelity synchronized data from the physical layer, which improves interference mitigation and channel estimation techniques [190].

Additionally, DTs provide dynamic management of resources across multiple domains, ensuring the scalability of ISAC operations and addressing data synchronization and latency issues [191]. The capability of DTs to infer information regarding wireless sensing channels also helps to optimize ISAC systems. For example, DTs can emulate and predict NLoS directions or provide partial channel information that can help optimize joint communication and sensing beamforming designs. These capabilities allow DTs to enhance sensing performance across LoS as well as NLoS scenarios. DTs provide a unified platform for real-time optimization, reliability, and security, which affirms their critical architectural role in the advancement of ISAC-enabled 6G networks.

Interplay: The integration of GenAI and DTs is crucial for ISAC applications in 6G networks. GenAI effectively predicts network demands, which helps in the intelligent allocation of communication and sensing resources. Moreover, the synthetic data generated by GenAI is used by the DTs for creating accurate replicas of the physical network. This interplay allows ISAC systems to manage complex and dynamic environments in an effective manner and at the same time ensures the efficient utilization of resources within heterogeneous 6G networks. The following section discusses how this GenAI- and DT-assisted ISAC framework can effectively optimize 6G network performance.

1) *Real-Time Emulation Layer:* In the real-time emulation layer, DTs are employed for creating virtual models of the ISAC network communication and sensing parameters, such as CSI, multimodal data, and interference patterns. This virtual environment enables the system to simulate various scenarios, ultimately facilitating the joint optimization of sensing and communication parameters. Moreover, GANs generate synthetic radar echoes, interference patterns, wireless propagation patterns, and joint communication–sensing channel states, enabling the simulation of realistic dynamic ISAC conditions. Conditional GANs can also be incorporated to generate ISAC environment characteristics tailored to specific interference or mobility scenarios. It also mitigates the DT synchronization challenges by generating realistic synthetic data, reducing the need for continuous high-volume data exchange between the physical ISAC network and the DT. On the other hand, DMs can also be employed to learn the stochastic variations of the ISAC network, such as noise, fading, and mobility, by learning the probability distributions of joint sensing–communication signals. This approach allows the system to generate high-fidelity synthetic signals that can model various radar and communication parameters, including transmission power, beamforming techniques, waveform selection, and resource allocation in the time-frequency domain.
2) *Feature Abstraction Layer:* The feature abstraction layer is used to encode high-dimensional ISAC data, such as CSI or radar measurements, into compact latent representations. VAEs and transformers are incorporated for dimensionality reduction to extract semantic-rich features, allowing the framework to process useful information while discarding redundant or noisy data. The abstraction of useful information facilitates the efficient allocation of resources for beamforming, power control, and interference management. Contrarily, the sensing data extraction provides valuable insights into mobility patterns, environmental variations, and object detection. This feature abstraction process enables efficient feature extraction, denoising, and uncertainty modeling, and allows subsequent layers, such as decision-making, to operate on high-quality, information-rich inputs for accurate analysis and system optimization.
3) *Decision-Making Layer:* This layer interprets the abstracted features from the feature abstraction layer to generate context-aware actions in ISAC systems. Initially, transformers and VAEs are used to decode sequential and temporal dependencies in the latent features, which enables predictions of mobility patterns, channel dynamics, and traffic demands. LLMs are incorporated in this layer for semantic understanding in order to perform task-oriented reasoning, adaptive resource allocation, and context-aware scheduling. RL frameworks can be employed to further optimize the decisions by learning such policies that maximize long-term rewards, such as reliability, throughput, or sensing accuracy, under dynamic network conditions. From a communication perspective, this combination enables the adjustments of dynamic beamforming to maximize throughput, enhance signal quality, and minimize interference. For sensing tasks, it optimizes radar parameters to ensure accurate detection and tracking of objects in complex environments. These models together can enable real-time adaptation to changing conditions, such as user mobility, interference, and environmental variations, thereby ensuring an adaptive and intelligent ISAC operation.
4) *Feedback Validation Layer:*The feedback validation layer uses LLMs and RL to fine-tune ISAC configurations based on deviations between physical and virtual environments. The DT environment helps in comparing the performance of real-world metrics with the outcomes of the simulated ISAC network to ensure alignment with operational needs. RL is incorporated in this layer for learning optimal policies for beamforming, waveform design, and resource allocation. These adjustments in real time optimize sensing and communication functions and ensure robust performance in highly dynamic environments. ISAC systems utilize feedback loops to refine configurations so as to improve SNR and resource allocation.

Security: GenAI models significantly enhance ISAC network security through advanced capabilities like encoding, adaptive beamforming, channel estimation, and anomaly signal identification [97]. Specifically, models such as GANs and DMs can learn complex wireless propagation environments to accurately predict channel states and thus facilitate more secure communication that is resilient to spoofing or jamming attacks. Furthermore, GANs can generate synthetic data in ISAC to detect malicious signal injections in real time, which in turn helps the network in quickly responding to adversarial threats [194].

These GenAI techniques are further improved by DTs, which provide high-fidelity virtual replicas of the ISAC physical environment to facilitate real-time threat mitigation [195]. DTs can simulate the impact of potential attacks on beamforming strategies, channel conditions, and sensing performance through continuous synchronization with the real-world ISAC communication and sensing data. This virtual testing capability allows ISAC systems to timely predict vulnerabilities, such as misconfigured encoding strategies or identifying weak links in beam alignment. The interplay of GenAI and DTs increases robustness against threats and ensures that ISAC systems offer reliable communication and highly accurate sensing under adversarial scenarios.

D. ARTIFICIAL INTELLIGENCE-GENERATED CONTENT

AIGC is anticipated to be a core application within 6G networks that will promote immersive user engagement and automated content generation in various domains, notably

TABLE 11. GenAI models and applications in AIGC for 6G.

GenAI Model	Applications in AIGC for 6G	References
GANs and DMs	High-fidelity image and video generation for immersive applications such as VR/AR and smart city simulations.	[18]
VAEs and FGMs	Data compression and efficient content distribution for adaptive video streaming and scalable delivery across heterogeneous devices.	[18]
LLMs	Generation of diverse, high-quality, and context-aware content; semantic communication scenarios; resource-aware scheduling; adaptive configuration of communication environments.	[184], [192], [193]

the metaverse, holographic systems, and AR/VR [18]. AIGC reduces dependence on pre-stored data and enhances the scalability of content delivery by enabling on-demand generation of high-fidelity digital assets, interactive avatars, and adaptive streaming content. AIGC enables edge devices and network nodes to autonomously generate and adapt media streams in latency-sensitive applications such as XR and real-time collaboration, thereby minimizing bandwidth requirements and ensuring seamless user experiences [184], [196]. Moreover, in large-scale 6G ecosystems, AIGC can support context-aware and personalized services to increase communication efficiency by embedding semantic meaning into generated content rather than transmitting raw data. This positions AIGC as a key enabler for next-generation digital services and immersive environments in 6G. In the following, we discuss the role of GenAI models in enabling AIGC for 6G applications.

GenAI: GenAI holds a pivotal position in 6G system design and drives the efficient management of network resources, synthesizes diverse data modalities, and ensures the integrated functionality across communication, sensing, and computational capabilities [21]. GenAI models, including GANs, LLMs, and ChatGPT, can produce realistic synthetic datasets, which effectively mimic complex traffic, user behaviors, and wireless environments, and substantially support the design and simulation of 6G networks for AIGC [184]. GANs and DMs are particularly effective for generating high-fidelity videos and images, highly applicable to AIGC scenarios within 6G networks. VAEs and FGMs can optimize data compression and efficient content distribution, providing scalable frameworks for adaptive and bandwidth-efficient delivery of video streaming data across heterogeneous devices and networks [18].

GANs also generate data for training AI models in such a way that the users' privacy is preserved. This unlocks new possibilities for AIGC in privacy-constrained and resource-limited settings [26]. GenAI models, particularly LLMs, are pivotal in advancing AIGC capabilities for 6G networks by enabling the generation of diverse, high-quality, and context-aware content while optimizing network resources [184]. Deploying LLM models such as ChatGPT at the network edge enhances AIGC services in 6G by providing real-time contextual and semantic understanding of user inputs [26]. By efficiently allocating computational resources, optimizing user allocation, and selecting AIGC service providers with sufficient resources, GenAI improves bandwidth utilization and network efficiency [21]. LLMs further enhance AIGC by generating communication scenarios and network configurations tailored to real-world conditions, such as channel modeling and environmental simulations. LLMs can also leverage textual prompts to dynamically model diverse communication environments and optimize configurations. This addresses the influence of external factors, such as vehicular traffic and channel conditions, on network performance. This synergy between AIGC and LLMs shows their exceptional potential to achieve adaptive, robust, and resource-efficient 6G networks [192], [193].

As highlighted in Table 11, under the common constraint of high-quality, context-aware content generation across heterogeneous 6G networks, GANs, DMs, and LLMs are the preferred GenAI models for AIGC due to their ability to generate immersive multimedia content, perform semantic reasoning, and support adaptive content delivery.

DTs: DT enhances AIGC by providing real-time synchronization between physical and virtual environments, and thereby enables dynamic resource allocation and efficient content creation [10]. DTs permit the modeling of real-world network conditions and user behaviors in a virtual space, facilitating immersive and context-aware AIGC applications, such as the metaverse and smart cities. In 6G networks, DTs optimize the network and content generation processes through continuous monitoring, fault detection, and predictive maintenance. For instance, DTs in space-air-ground integrated networks synchronize UAV-collected data with core networks to enhance AIGC services with efficient resource management and reduced energy consumption [197]. Furthermore, in healthcare, the creation of personalized medical content via human DTs facilitates the generation of data on rare diseases and the delivery of customized services. This approach ultimately results in improvements in personalized healthcare and medical training [10]. This interplay between DTs and AIGC enables more efficient, scalable, and responsive 6G networks by ensuring high-quality content generation and optimized network performance.

Interplay: The interplay between GenAI and DT frameworks for AIGC is shown in Fig. 9. In the context of 6G network design, this framework is essential for optimizing content generation and resource management across diverse and distributed applications. There are four

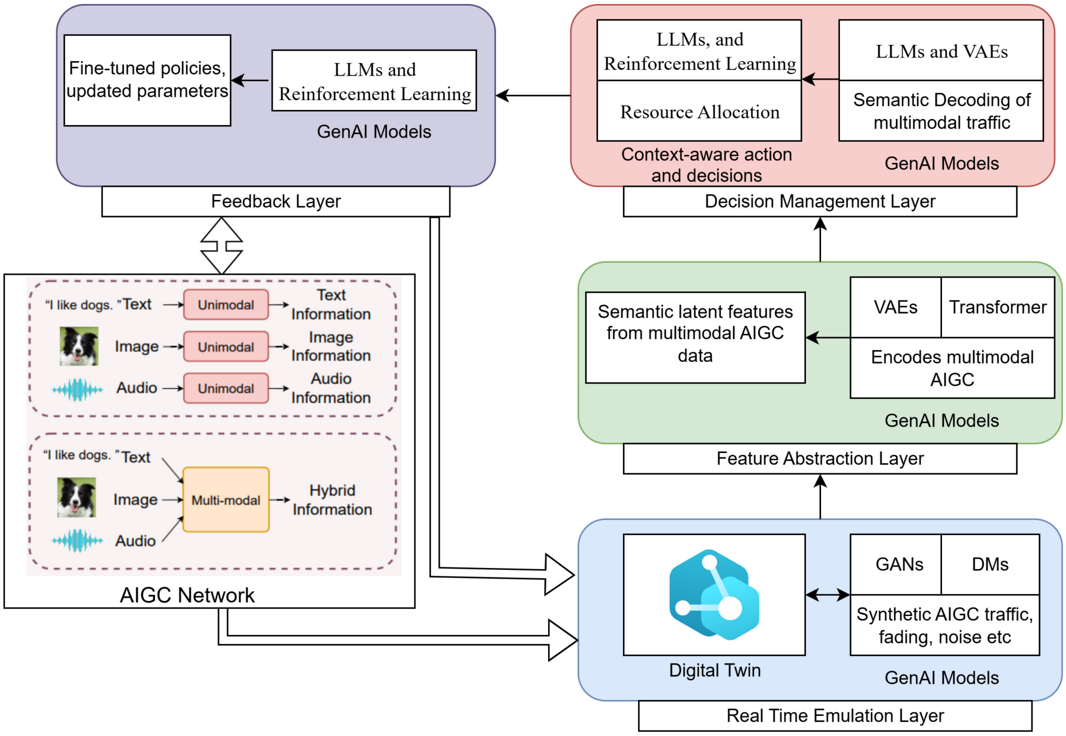

FIGURE 8. Interplay of GenAI and DTs for performance optimization and security of AIGC network.

TABLE 12. Interplay of GenAI and DT for AIGC-6G networks.

Layer	Functionality	GenAI Models Used
Real-Time Emulation	Generates synthetic multimodal AIGC traffic (text, audio, video), models network conditions (fading, interference, mobility).	GANs, DMs
Feature Abstraction	Encodes raw multimodal AIGC data into latent semantic-aware features (intent, QoE-critical factors) for efficient processing.	VAEs, Transformers
Decision Management	Decodes semantic features, optimizes resource allocation, scheduling, and network configurations using adaptive policies.	LLMs, RL
Feedback	Compares decision outputs with physical AIGC network performance, fine-tunes policies, and aligns virtual-physical models.	LLMs, RL

fundamental layers of this framework, which directly address key challenges, including data synchronization, high-fidelity modeling, and generalization, thus enabling the seamless generation of context-aware, real-time content within 6G-enabled environments. A summary of these layers is provided in Table 12.

1) *Real-Time Emulation Layer:* The real-time emulation layer generates a dynamic virtual representation of the AIGC network, which represents network states, user behavior, multimedia content, and variations in network traffic. To ensure accurate representation of dynamic network traffic, this layer emulates real-time network behaviors and conditions that adhere to stringent QoS requirements, such as ultra-low latency, high throughput, and reliable synchronization. This layer uses GenAI models like GANs to synthesize AIGC content that encompasses not only traditional media (audio, video, images) but also semantic data that encapsulates high-level, context-specific information to enhance communication efficiency. This layer also generates synthetic content to address the data scarcity challenges, particularly in complex, data-intensive applications where real-time, high-quality data is essential. Furthermore, DMs learn the stochastic variations in time-varying mobility, interference, and fading to simulate realistic network traffic patterns, user mobility, and environmental variations. The maintenance cost of DT models is substantially reduced by aligning AIGC-generated content with dynamic network conditions. This directly enhances the performance, scalability, and user experience of 6G applications in different areas such as immersive VR/AR and smart cities.

2) *Feature Abstraction Layer:* The feature abstraction layer encodes high-dimensional multimodal AIGC traffic into low-dimensional compact latent representations for efficient processing. The layer integrates a knowledge base of semantic communications, which

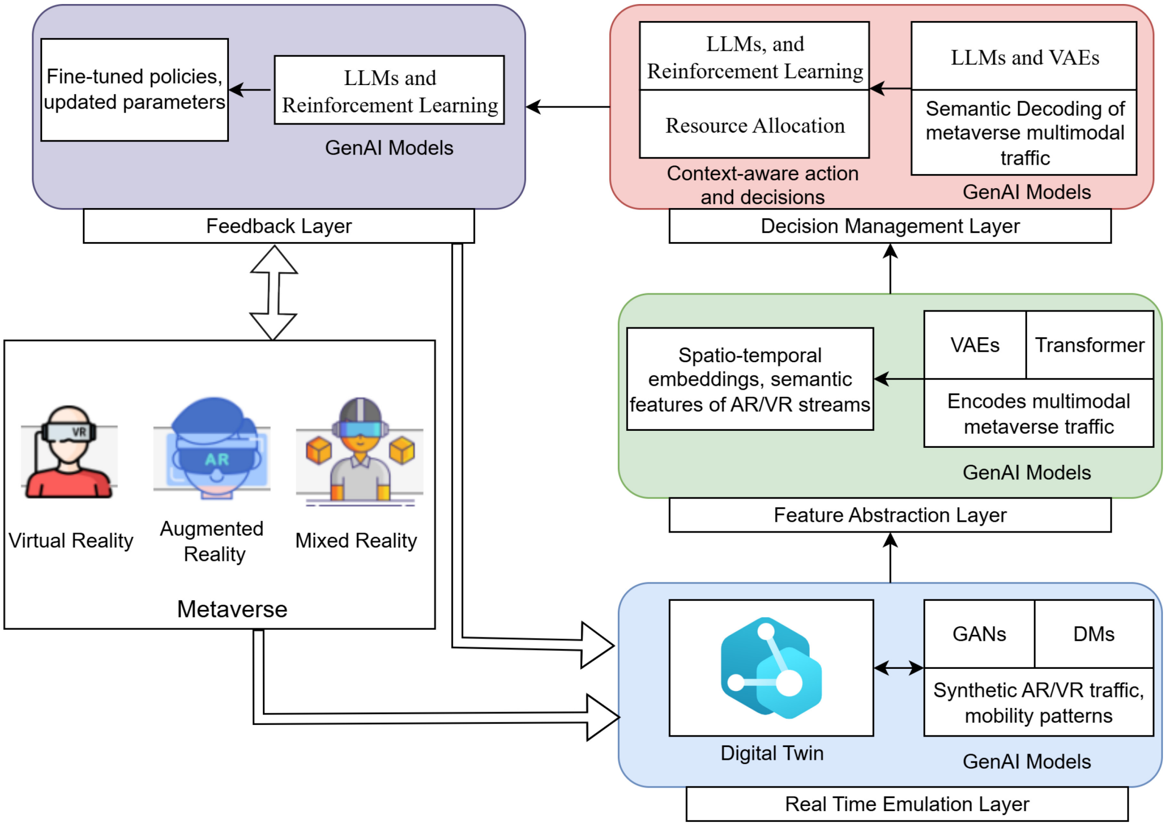

FIGURE 9. **Interplay of GenAI and DTs for metaverse applications.**

leverages past network insights to refine content generation and encoding. GenAI models, such as VAEs and transformers, compress high-dimensional, raw multimodal data into low-dimensional representations while preserving critical relationships, including traffic patterns and mobility characteristics. This abstraction process ensures that the multimodal AIGC traffic from the status emulation layer is effectively translated into actionable content for network optimization, and effectively supports real-time, adaptive content generation and the evolving needs of 6G applications.

3) *Decision Making Layer:* The decision-making layer integrates VAEs, transformers, and DMs to efficiently manage AIGC traffic for real-time resource allocation in 6G networks. LLMs interpret high-level service requests and translate them into semantic-aware network policies. They also support multimodal reasoning and help in aligning the user's intent with network control. Furthermore, semantic-aware features from LLMs are leveraged by RL to optimize scheduling, power allocation, and RIS configurations in order to produce adaptive network control policies for real-time AIGC network optimization.

4) *Feedback Validation Layer:* This layer verifies the accuracy and relevance of AIGC-generated content by comparing it with the real-time data obtained from the DT models. It incorporates LLMs and RL agents to compare these virtual decisions with real-time data from the physical AIGC network. Based on this comparison, the models fine-tune policies and update resource management and configuration strategies to reduce discrepancies between predicted and actual network performance, thereby ensuring semantic-aware optimization across the 6G AIGC system. For example, in the case of edge computing applications, it ensures that the proposed configurations match real-world traffic conditions and mobility patterns. This validation mechanism guarantees the reliability, adaptability, and scalability of the AIGC-generated content across diverse 6G environments.

Security: The integration of GenAI and DT technologies is essential for securing 6G AIGC networks [115], [198]. The increasing decentralization of 6G networks notably increases the risks of adversarial attacks, data poisoning, and unauthorized access. This vulnerability is particularly critical for applications that depend on real-time AIGC content generation, e.g., autonomous systems, smart cities, and the metaverse. GenAI models, including LLMs, dynamically generate multimodal traffic, but robust security mechanisms are still essential due to the vulnerability of these models to cyber threats. A synchronized intelligent framework for real-time monitoring, validation, and anomaly detection is established by embedding DTs into the AIGC ecosystem, which ensures that both the content and network resources are secure and fully compliant.

DTs simulate the behaviors of distributed AIGC applications and monitor deviations from expected traffic patterns to enhance network security. DTs can proactively detect different attack types by synchronizing the virtual and physical network states in real time. For example, if any anomaly is detected in the virtual model, RL and federated learning techniques can be used to take the necessary security measures while preserving user privacy. Additionally, GenAI-based adversarial training can be utilized to generate synthetic attack scenarios, which enables the continuous improvement of AI models for effective threat detection and mitigation. This interplay between GenAI and DTs not only enhances intrusion detection but also fortifies AIGC networks against emerging cyber threats and thereby ensures a resilient and self-adaptive security mechanism in 6G distributed environments.

VI. INTERPLAY OF GENAI AND DTs FOR THE METAVERSE

Metaverse is a groundbreaking concept that integrates the real and virtual worlds and uses holographic displays, AR, and VR technologies for enabling its users to generate and customize their own content and experiences [13]. Beyond this integration, the metaverse also offers a dynamic digital space wherein users can continuously create content with the help of smart devices and wearables. This special attribute extends the potential applications of the metaverse into various sectors such as education, healthcare, and industrial manufacturing. Taking the rapid development of the metaverse's technical infrastructure into account, it can be anticipated that it will soon transform daily lives by enabling immersive virtual interactions. Nevertheless, the successful implementation of these immersive experiences is heavily dependent on the robust capabilities of 6G networks. The capacity of 6G to provide high data transfer rates, ultra-low latency, and guaranteed reliability is critical for the effective functioning of the metaverse immersive applications [207].

Within 6G network architectures, the role of AR is to integrate digital elements with the physical environment to generate interactive and highly immersive user experiences. This capability is engineered to support real-time, high-fidelity applications, such as remote collaboration platforms, advanced gaming, and interactive educational systems. However, the widespread implementation of AR presents several significant technical challenges, such as data synchronization, high-fidelity modeling, and generalization across diverse network conditions [13]. Achieving a truly seamless user experience requires extremely low network latency, usually less than 1 *ms*. This critical performance threshold is necessary to ensure the high level of responsiveness required for effectively merging and stabilizing the virtual and physical environments [145]. VR is positioned as a primary driver of 6G development, which requires performance metrics that exceed current network capabilities to support deep immersion. The 6G architectural design for VR applications mandates the convergence of URLLC, mMTC, and eMBB to jointly achieve seamless network integration and extreme data throughput [208].

The intricate demands of the metaverse, specifically those that are used by AR, VR, and holographic technologies, need transformative enablers within 6G networks. These components are critical for supporting the necessary high throughput for multi-dimensional content and enabling instantaneous data synchronization that is essential for real-time operation. Holographic communication also requires advanced rendering techniques to achieve fully immersive experiences. Effective network optimization and resource management are crucial for addressing interoperability among devices and meeting the diverse demands of users in the metaverse [13].

GenAI: The combination of GenAI and the metaverse is expected to transform 6G networks. This integration will create very immersive and smart applications that need extremely reliable, fast communication and high bandwidth [64], [98]. GenAI significantly improves the AR/VR experiences [10], [204] by using GenAI models such as GANs [199], VAEs [201], transformer-based architectures, and LLMs [205] to create and adapt virtual content instantly. Table 13 provides a summary of the applications of these models in the metaverse.

The integration of GenAI models with AR/VR technologies results in the creation of highly realistic synthetic data. Specifically, outputs like photorealistic 3D assets and complex dynamic virtual environments are utilized to advance AI model training, optimize system capabilities, and facilitate content generation in real time [13]. GANs and DMs, in particular, have shown exceptional results in generating lifelike avatars, spatially consistent environments, and adaptive textures that respond seamlessly to user interactions and thus enable immersive applications, such as remote collaboration, industrial simulations, and next-generation entertainment [200]. Furthermore, VAEs play a pivotal role in learning compact latent representations of multimodal data, thereby improving generalization capabilities and compression efficiency, which are essential for large-scale, bandwidth-constrained AR/VR applications [202].

Besides content generation, transformer models and LLMs also substantially improve real-time contextual awareness in AR environments. This enhancement is achieved by facilitating multimodal interactions, advanced natural language processing, and automated intelligent content labeling, alongside their content generation capabilities [203]. These functionalities are essential in specific applications, such as medical training assisted by AI. In this context, the dynamic generation of instructional overlays and the provision of real-time feedback serve to enhance both procedural learning and clinical decision-making skills.

Beyond enhancing content realism and contextual intelligence, GenAI-driven optimization strategies are also instrumental in achieving efficient resource allocation within

TABLE 13. GenAI models and their applications in the metaverse.

GenAI Model	Applications in the Metaverse (6G)	References
GANs	Generation of avatars, photorealistic 3D assets, and dynamic textures; enhancing virtual environments for AR/VR-based remote collaboration, entertainment, and industrial simulations.	[13], [199], [200]
VAEs	Learning compact latent representations for multimodal AR/VR data for improving compression efficiency.	[201], [202]
DMs	Learning spatiotemporal relationships to synthesize high-fidelity virtual scenes and adaptive textures.	[98], [200]
Transformers	Enabling real-time contextual adaptation, multimodal fusion, and intelligent annotation in AR environments.	[203], [204]
LLMs	Providing semantic understanding and reasoning for context-aware metaverse interactions, conversational avatars, and dynamic content generation in XR applications.	[10], [205]
Neural Radiance Fields	High-fidelity scene rendering and optimization of computational and bandwidth resources in distributed AR/VR environments.	[20], [206]

the 6G ecosystem. Techniques such as neural radiance fields (NeRFs) render high-fidelity scenes while minimizing computational and bandwidth overhead, which leads to optimized performance of AR/VR applications in distributed network environments [206]. These advancements establish GenAI as a fundamental technology for AR and VR within 6G networks. GenAI facilitates the seamless connection of digital and physical spaces by providing real-time interaction, adaptability, and efficient resource usage [20].

As summarized in Table 13, GenAI models such as GANs, DMs, and LLMs are the preferred choices for metaverse applications operating within 6G networks. This preference is driven by the stringent constraint of requiring low-latency, high-fidelity content generation and interaction within real-time XR environments. These models are specifically chosen for their ability to deliver photorealistic 3D content synthesis, perform context-aware semantic reasoning, and facilitate spatiotemporal scene adaptation.

DTs: DTs optimize the AR and VR applications within the 6G metaverse through improved network design, efficient resource allocation, and enhanced security [2]. DTs enable rapid prototyping and virtual simulations, which support strategic placement of network resources (nodes, access points) and ensure optimal performance for AR and VR applications [129], [130]. Real-time data from the physical world is utilized in DT technology to create realistic AR experiences. In addition, DTs adjust network parameters to optimize bandwidth and ensure consistent service quality. DTs also provide sophisticated virtual environments for VR applications that enable network designers to simulate and optimize network behaviors, such as bandwidth allocation and latency, and also ensure high-quality VR experiences [209]. The analysis and testing of network configurations and resource allocation strategies in a virtual environment are more efficient in terms of both time and cost. Furthermore, DTs improve user experiences through such predictive models that optimize resources in real-time, reduce latency, and ensure smooth interactions. It needs to be noted that DTs not just optimize performance but also ensure a resilient and adaptive 6G infrastructure for AR and VR applications through continuous system monitoring, anomaly detections, and threat mitigation [137], [210].

Interplay: The interplay between GenAI and DTs is essential to obtain optimal resource allocation and high performance in 6G metaverse applications. Metaverse data, i.e., user behavior and device performance, is collected in real-time and used as an input for GenAI models, which generate synthetic datasets to improve DT simulations. These simulations depend on high-fidelity modeling to accurately predict network performance and optimize resource allocation [211], [212]. Fig. 9 shows the significance of GenAI-DT for metaverse applications.

The following discussion explores the role of the GenAI-DT-based framework in optimizing 6G network performance. It specifically highlights the framework's ability to create immersive experiences while ensuring robust network security. Table 14 summarizes the role of different layers in the GenAI-DT-based framework.

1) *Real-Time Emulation Layer:* This layer generates a virtual representation of the physical metaverse environment, which captures immersive interaction parameters such as haptics, gaze, and gestures as well as network states (including jitter, bandwidth, and latency), and user mobility patterns. GANs generate synthetic AR/VR traffic, including interactive events, holographic frames, and avatars, which play an important role in addressing DT synchronization issues for AR/VR metaverse services. Furthermore, DMs enhance this by modeling stochastic variations, such as multi-user dynamics, interference, and rendering delays to ensure high-fidelity emulation of real-world uncertainty.
2) *Feature Abstraction Layer:* The feature abstraction layer transforms complex time-series AR/VR data, i.e., spatial audio, video, haptic feedback, and motion tracking, to compact latent representations. For holographic communications, it employs a semantic encoding technique to prioritize and compress essential 3D

TABLE 14. GenAI–DT layered framework for metaverse (AR/VR) services.

Layer	Functionality	GenAI Models Used
Real-Time Emulation	Generate synthetic AR/VR traffic, emulate mobility and latency, bridge DT synchronization gaps.	GANs, DMs
Feature Abstraction	Encode multimodal AR/VR data into compact semantic embeddings, while preserving spatial features and temporal patterns.	VAEs, Transformers
Decision Management	Decode embeddings, derive QoS/QoE descriptors, optimize scheduling, and resource control.	LLMs, RL
Feedback	Compare DT and physical KPIs, fine-tune control policies, update DT with synthesized corner cases.	LLMs, RL

data in order to reduce bandwidth consumption while maintaining visual fidelity. In AR applications, it processes real-time spatial and environmental data to optimize object placement, interaction tracking, and latency minimization for ensuring seamless user experiences. For VR, this layer enables multi-sensory data fusion in which visual, auditory, and haptic signals are integrated to enhance immersion while reducing unnecessary data transmission. VAEs are incorporated to reduce high-dimensional multimodal data into low-dimensional representations while preserving semantic fidelity, traffic patterns, and mobility characteristics. Transformers further enhance feature extraction by capturing spatial-temporal dependencies across modalities, thereby ensuring consistency between user motion and rendered immersive scenes. This process creates a well-structured representation of multimodal data that reduces communication overhead while retaining immersive fidelity for the decision-making layer.

3) *Decision-Making Layer:* The decision management layer uses the simplified, high-level features provided by the abstraction layer to generate specific, executable system control commands. VAE takes these abstracted semantic features as input. It processes and transforms these features to directly generate the necessary actionable parameters for the AR/VR system, such as tuning spatial accuracy, setting rendering priorities, or defining latency constraints. This layer integrates LLMs to perform semantic decoding, while RL agents are used for dynamically learning optimal policies for resource allocation. LLMs and RL facilitate the context-aware adaptation of both network and compute resources. This coordinated process is essential for balancing the stringent immersive QoE demands across heterogeneous multimodal traffic.

4) *Feedback Validation Layer:* The feedback validation layer incorporates LLMs and RL to fine-tune metaverse applications. For this purpose, it establishes a real-time feedback loop between DTs and the physical 6G metaverse network. Specifically for holographic applications, this layer evaluates how the network handles the transmission of vast amounts of holographic data in real time. It uses RL for learning optimal bandwidth allocation, caching mechanisms, and rendering strategies to maintain high-fidelity projections with minimal latency. This layer ensures smooth and responsive operation within AR/VR environments by confirming the accuracy of motion tracking, maintaining multi-user synchronization, and optimizing the adaptive rendering models driven by AI.

Security: The integration of GenAI models and DT technologies in 6G networks considerably boosts the security for AR and VR applications [103]. AR and VR environments require real-time data synchronization, seamless user interactions, and robust protection against cyber threats due to their immersive nature and extensive use of sensitive user data. The virtual replicas of AR/VR systems created by DT technology enable real-time monitoring, simulation, and testing. These DTs and AI generative tools can function together to proactively identify vulnerabilities and mitigate potential risks [115], [198]. For instance, DTs establish the operational baselines of AR/VR systems while GenAI models continuously analyze deviations from these baselines to detect anomalies such as unauthorized access or abnormal data behavior. This interaction ensures data integrity and offers protection against potential security breaches in different scenarios.

GenAI models like GANs can generate synthetic data and challenging adversarial scenarios for the DT environment, which enable robustness evaluation of AR/VR systems [115]. This function is important for simulating specific cyberattacks (e.g., man-in-the-middle and spoofing) against AR/VR communication. DTs can analyze current security defenses and propose targeted improvements. Moreover, GenAI helps in developing flexible security policies by analyzing user interactions and environmental data within AR/VR systems. These policies dynamically adjust access controls, communication encryption, and multi-factor authentication to secure real-time user experiences in 6G networks. Furthermore, GenAI and DTs together help to mitigate user privacy concerns by enabling intelligent monitoring of data. This integration maintains the operational integrity of AR/VR applications while simultaneously bolstering security, especially in sensitive sectors such as healthcare, virtual tourism, and online education.

TABLE 15. Summary of challenges and future directions in the interplay of GenAI and DTs for 6G-enabling technologies and the metaverse.

Area	Challenges	Future Research Directions
AI Safety & Explainability [213], [214]	Integration of LLMs in DT-driven 6G systems raises concerns about trust, transparency, and accountability. The black-box nature of LLMs leads to biased outputs, hallucinations, and security vulnerabilities. Additionally, AI-generated synthetic data can introduce erroneous optimizations in 6G networks.	Developing explainable AI (XAI) frameworks tailored for LLM-based DTs to enhance interpretability. Implementing AI red teaming strategies to assess model vulnerabilities and incorporating risk-aware AI architectures for robust and mission-critical deployments.
Interoperability & Standardization [215]	Lack of standardized protocols, interfaces, and data formats for integrating DTs with GenAI models across heterogeneous 6G infrastructures. Inconsistencies in AI governance and cross-platform compatibility hinder large-scale adoption.	Establishing global interoperability standards for AI-driven DTs in 6G. Developing modular AI architectures and open-source frameworks that enable seamless interaction across different industries, such as smart healthcare, IoT, and autonomous systems.
Scalability & Energy Efficiency [34], [216]	The computational overhead of large-scale GenAI models (e.g., transformers) increases energy consumption, making them unsuitable for resource-constrained 6G environments. The rise of ultra-dense networks in 6G further exacerbates scalability challenges.	Designing energy-efficient GenAI architectures with adaptive resource utilization for real-time inference. Leveraging hardware accelerators, model compression techniques (quantization, pruning), and federated learning to enhance sustainability.
Semantic Multimodal Traffic [217], [218]	The integration of DTs and GenAI for semantic communication introduces challenges in real-time processing, multimodal fusion, and contextual reasoning. Metaverse applications demand ultra-low latency and high accuracy in semantic interpretation.	Developing interoperable semantic frameworks for distributed 6G applications. Exploring agentic LLMs and advanced transformer-based architectures to improve semantic awareness, personalization, and decision-making in metaverse-driven 6G scenarios.

A. SUMMARY OF LESSONS LEARNED

GenAI supports accurate simulations and predictive modeling by creating synthetic data. Additionally, DTs create virtual replicas that dynamically adjust network parameters to optimize immersive experiences. Furthermore, GenAI synthesizes high-fidelity 3D content, videos, images, and textual data that increases user engagement within the metaverse environment. The integration of GenAI and DTs not only improves performance but also increases the security of the 6G metaverse environment against evolving threats through proactive threat detection and the implementation of adaptive defense strategies.

VII. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

While the integration of GenAI and DTs is vital for the efficient development of 6G networks within the metaverse, this synergy also introduces specific challenges. Table 15 summarizes the current open issues and difficulties associated with this interplay.

A. AI SAFETY, TRUST, AND EXPLAINABILITY

Integrating GenAI, particularly LLMs, into DT-driven 6G systems raises severe concerns regarding AI safety, trustworthiness, and explainability [213]. LLMs and multimodal AI models can generate network policies, automate decision-making procedures, and optimize traffic flow. However, risks such as biased outputs, hallucinations, and adversarial vulnerabilities occur due to their black-box nature [214]. Moreover, unverified AI-generated synthetic data may cause inaccurate network optimizations or unexpected security risks.

Future Directions: It is important to enhance the explainable AI (XAI) frameworks that are tailored for LLM-based DTs to ensure improved transparency and trust in AI-driven 6G applications. Researchers should pay attention to robust AI validation techniques and AI red teaming strategies to rigorously test LLMs for vulnerabilities before deploying within mission-critical scenarios. It is also crucial to develop risk-aware AI architectures to reduce potential unintended consequences arising from autonomous network operations and DT-based simulation environments.

B. INTEROPERABILITY AND STANDARDIZATION

The integration of DTs and GenAI across varied 6G infrastructures is significantly hindered due to the lack of standardized interfaces, communication protocols, and data formats [215]. The lack of cohesion within the AI ecosystem acts as a constraint that impedes cross-platform functionality, security policy consistency, and network management. Thus, the scalability and deployment of AI-driven DTs across various industries are eventually restricted by this fragmentation.

Future Directions: Cross-industry standardization is essential for guaranteeing the interoperability of integrated DT-GenAI systems. Future research should focus on developing open-source frameworks and modular AI architectures to ensure the interoperability of DTs across varied 6G network applications, including smart healthcare and autonomous transport. Moreover, collaborative AI governance frameworks involving industry, academia, and regulatory bodies will play a vital part in shaping global policies for AI-driven 6G standardization.

C. SCALABILITY AND ENERGY-EFFICIENCY

Several scalability and energy-efficiency-related challenges arise when DT and GenAI are integrated for 6G applications [34], [216]. The high computational requirements of large-scale GenAI models, such as transformers, can result in significant energy consumption, which limits their suitability for deployment in resource-constrained 6G environments. This energy efficiency constraint poses risks to the sustainability of operations, especially with the expected increase in connected devices and the variety of data types within 6G networks.

Future Directions: Research should investigate how to integrate GenAI effectively with the underlying frameworks of distributed Software-Defined Networking (SDN) and federated learning. This configuration can optimize energy consumption by dynamically adjusting the resource usage in accordance with the real-time network conditions. It is crucial to employ hardware accelerators and model compression techniques (i.e., quantization and pruning) to effectively integrate GenAI models into DT frameworks. These methods significantly reduce the required computational load. The use of wireless federated learning is intended to enhance communication efficiency and reduce energy use. This process is critical for enabling smooth collaboration and minimizing the energy cost associated with the training and updating of models across multiple DTs. The strategic focus on these domains will empower the interaction between DTs and GenAI and will contribute significantly to the long-term sustainability of 6G technologies and immersive metaverse environments.

D. SEMANTIC MULTIMODAL TRAFFIC

The successful application of DTs and GenAI in semantic contexts faces several critical challenges that require attention [217]. A primary problem is the need to establish robust semantic protocols capable of accurately interpreting and unifying the diverse data streams originating from both DT and GenAI systems [218]. It is important to maintain real-time processing and achieve minimal latency for dynamic environments, such as smart cities and autonomous transportation systems. Furthermore, effective decision-making, particularly in complex scenarios demanding nuanced interactions, relies fundamentally on a high degree of contextual understanding. Finally, the integrated use of DTs and GenAI is constrained by the management of large datasets produced by metaverse applications. Consequently, the focus must be on developing advanced models that simultaneously maintain situational awareness and efficiently yield valuable insights.

Future Directions: Future research efforts should concentrate on developing interoperable and semantic frameworks for distributed 6G applications that can enable seamless data exchange across diverse systems and foster collaboration and integration. The second critical research direction is to explore agentic LLMs and transformer architectures to advance semantic communication and contextual comprehension [219]. Researchers can effectively overcome the challenges inherent in integrating DTs and GenAI by investigating how these advanced models can improve user interactions, deliver personalized experiences, and facilitate complex decision-making within metaverse applications. Finally, these initiatives are essential to develop innovative solutions that support practical semantic applications in the evolving 6G environment.

E. CHALLENGES OF DTs WITHOUT GENAI IN 6G APPLICATIONS

Even though DTs provide a virtualized representation of network elements, their standalone use in 6G applications encounters several limitations. These include difficulty in modeling high-dimensional and dynamic channels for RIS, restricted semantic feature abstraction for semantic communication, limited adaptability in ISAC scenarios, and scalability bottlenecks for data-intensive applications such as AIGC and the metaverse. Such constraints limit the capability of DTs to achieve real-time context-aware optimization within the extremely dynamic 6G environments.

Future Directions: A critical area of research is to investigate the systematic shortcomings of DTs when deployed without GenAI and subsequently identify how tailored GMs can resolve these deficiencies. For example, DMs and GANs may enhance high-dimensional modeling, VAEs can improve semantic feature compression, and LLMs can support adaptive reasoning across diverse contexts. Investigating these synergies will lay the foundation for robust DT–GenAI frameworks that enable adaptive learning, semantic reasoning, and massive-scale intelligent resource management for 6G applications.

VIII. CONCLUSION

The need for low-latency, intelligent, and context-aware connectivity in 6G networks creates major challenges for optimizing network performance and security. This paper examines this issue by focusing on the integration of GenAI models (such as GANs, DMs, VAEs, and LLMs) with DTs, demonstrating how this combination can boost resource allocation, network efficiency, and security. A GenAI-enabled DT framework is proposed to show how different GenAI models can support various 6G applications, including semantic communications, the metaverse, ISAC, AIGC, and RIS. Finally, the work identifies key research challenges and future directions needed to develop resilient, intelligent, and adaptive 6G networks.

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