Future of Connectivity: A Comprehensive Review of Innovations and Challenges in 7G Smart Networks

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Future of Connectivity: A Comprehensive Review of Innovations and Challenges in 7G Smart Networks

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ABSTRACT The evolution from 1G to 6G networks has transformed global communication, progressing from basic voice calls in 1G to the immersive, AI-enabled experiences of 6G. As emerging AI-driven applications like autonomous systems, the Internet of Everything (IoE), and immersive technologies demand unprecedented capabilities, 7G networks are set to redefine connectivity by overcoming the limitations of earlier generations. This paper comprehensively reviews the innovations and challenges in 7G networks, focusing on integrating advanced AI and machine learning paradigms such as meta-learning, incremental learning, distributed intelligence, and reinforcement learning to enhance adaptability, resource allocation, and edge performance. The review also examines the role of Large Language Models (LLMs) in enabling real-time actionable intelligence and optimizing edge devices within 7G. The paper highlights the use of technologies, including blockchain for decentralized security, quantum computing for robust encryption, terahertz communication for ultra-fast data transfer, zero-energy solutions for sustainability, and generative AI for intelligent network optimization and automation. By addressing these challenges and exploring cutting-edge strategies, this paper envisions 7G networks as the foundation for a secure, intelligent, and sustainable digital future, equipped to combat emerging cyber warfare threats, enhance resilience against technological disruptions, and support innovations across smart cities, autonomous systems, healthcare, and industrial IoT.

INDEX TERMS 7G networks, intelligent networking, machine learning, AI, LLM, wireless, terahertz communication, meta-learning, self-sustaining, security, XAI, explainable AI, distributed intelligence, edge performance, real-time actionable intelligence, generative AI.

I. INTRODUCTION

NETWORK technologies are advancing rapidly, and the demand for faster and more reliable communication is growing [1], [2], [3], [4]. While 5G networks are being used worldwide, there are limits to how much they can handle, especially with new applications that need high-speed connections and almost no delay [5], [6]. This is where 7G networks come in, promising to solve these issues by offering faster, more efficient, and wider-reaching communication systems, as shown in Figure 1. This review explores what 7G will bring, helping researchers, businesses, and decision-makers to understand its potential. With a global push for energy-saving technologies, it's important to consider how 7G can support greener and smarter solutions [7]. The evolution of wireless technologies has been a remarkable journey marked by significant advancements, each generation building upon its predecessor to meet the growing demands for connectivity, speed, and functionality [8]. Before the advent of 1G, communication was primarily facilitated through wired systems, which limited user mobility and accessibility [9]. These networks have evolved over several generations, beginning with basic mobile communication systems and progressing to modern technologies like 4G and 5G. Wireless networks operate through Radio Frequency (RF) signals and sophisticated networking protocols to enable communication across smartphones, tablets, IoT devices, and computers [10].

FIGURE 1. Advancements of 7G network, including cutting-edge network capabilities and technological integration innovations.

Early wireless communication systems utilized Amplitude Modulation (AM) and Frequency Modulation (FM) to transmit analog signals over radio frequencies [11]. These initial experiments laid the groundwork for understanding radio wave propagation, signal encoding, and the challenges of interference and attenuation [12]. Over the decades, each new generation of mobile networks–from 1G to the latest 5G–has ushered in transformative changes, expanding the speed and reliability of communication and its global accessibility [13].

As we edge closer to an era dominated by hyper-connectivity, advanced AI, and ubiquitous data exchange, the limitations of existing networks become apparent. In response, we are now looking beyond 5G and 6G toward developing 7G networks. 7G is anticipated to revolutionize communication further by integrating advanced technologies such as quantum computing, edge intelligence, and green energy systems, marking a pivotal shift in network architectures' scope and capability [14].

A. KEY BREAKTHROUGHS AND TECHNOLOGICAL ADVANCEMENTS

The key breakthroughs and technological advancements from 1G to 6G show a remarkable transformation in mobile communication [8]. 1G (1980s) introduced analog voice transmission, while 2G (1990s) revolutionized connectivity with digital communication, SMS, and encryption. The advent of 3G (2000s) brought mobile Internet, video calls, and packet-switching technology, paving the way for 4G (2010s), which introduced LTE, high-speed broadband, app ecosystems, and seamless streaming. 5G (2020s) marked a significant leap with millimeter-wave technology, massive MIMO, network slicing [15], and ultra-low latency, enabling smart cities, IoT, AR/VR, and autonomous systems. Looking forward, 6G (2030s) aims to push the boundaries with AI-native networks, terahertz (THz) communication, quantum security, holographic communication, and Brain-Computer Interfaces (BCI), delivering speeds up to 1 Tbps and merging the digital and physical worlds for unprecedented connectivity. Currently, 7G network technology remains in the research and development phase, with no standardized definitions or specifications established. It is currently a theoretical concept with no commercially available networks. Most experts anticipate its potential rollout around the 2030s, as further research is required to develop the necessary technologies and standards. Table 1 comprehensively compares key breakthroughs and technological advancements across network generations from 1G to 7G. Table 2 presents the key differences between 6G and 7G technologies, especially in artificial intelligence, quantum communication, and terahertz communication.

B. MOTIVATION FOR 7G NETWORK INNOVATIONS

The rapid evolution of communication technology has significantly changed how people connect, work, and live. As each generation of mobile networks has introduced new capabilities, the demand for faster, more reliable, and more efficient connectivity continues to grow. With the rise of the Internet of Things (IoT), smart cities, autonomous vehicles, and immersive technologies like Virtual Reality (VR) and Augmented Reality (AR), it is becoming clear that existing networks are struggling to meet the ever-increasing demand [16]. 7G networks aim to address these challenges by providing an advanced infrastructure beyond what 5G and 6G can offer [17]. One of the primary motivations for developing 7G is to support the seamless integration of emerging technologies, including AI, robotics, and quantum computing, into everyday life. The need for real-time processing, minimal latency, and massive data handling requires a next-generation network capable of handling the complexities of future technologies [18]. 7G networks are motivated by a more sustainable and efficient communication system. As we move toward a future where billions of devices are interconnected, energy consumption becomes a major concern. 7G networks are expected to incorporate energy-efficient mechanisms to reduce the environmental impact of network operations, supporting global efforts toward green technology [1].

C. 7G: EVOLUTION BEYOND 5G AND 6G

While 5G networks are still in the early stages of global deployment, their scalability, spectrum efficiency, and geographic coverage limitations are already becoming apparent [19]. The shift toward 6G[1] is expected to address some of these issues by offering even higher data rates, improved latency, and enhanced integration of AI in managing network functions. The demand for more comprehensive solutions encompassing terrestrial, aerial, and satellite networks will only intensify as communication technologies advance. Figure 2 shows the progression of wireless communication

[1]https://www.wipro.com/engineering/can-ai-take-off-without-6g/

TABLE 1. Comprehensive comparison of key breakthroughs and technological advancements across network generations from 1G to 7G.

Parameter	1G	2G	3G	4G	5G	6G	7G
Key Breakthroughs	Analog voice calls	Digital voice, SMS, Encryption	Mobile internet, Video calls	High-speed broadband, Streaming, VoLTE	IoT, AR/VR, Smart cities, Ultra-low latency	AI-native networks, Quantum security, Holographic communication	Quantum-powered networking, Interplanetary communication, Fully autonomous systems
Technological Advancements	AMPS, NMT, TACS	GSM, CDMA, Circuit-switched data	UMTS, WCDMA, Packet-switching, HSPA	LTE, OFDM, Massive MIMO, Cloud services	mmWave, Network slicing, Edge computing, Beamforming	Terahertz (THz) spectrum, BCI, Digital twins	Quantum computing, AI-driven self-evolving networks, Satellite-based global coverage, Brain-to-brain communication
Speed	∼2.4 kbps	Up to 64 kbps	2 Mbps – 42 Mbps	100 Mbps – 1 Gbps	Up to 10 Gbps	Up to 1 Tbps	Potentially Up to 1.5 to 2 Tbps (Quantum-based data transfer)

Abbreviations: AMPS = Advanced Mobile Phone System, BCI = Brain-Computer Interface, CDMA = Code Division Multiple Access, GSM = Global System for Mobile Communications, LTE = Long Term Evolution, MIMO = Multiple-Input Multiple-Output, NMT = Nordic Mobile Telephony, OFDM = Orthogonal Frequency Division Multiplexing, UMTS = Universal Mobile Telecommunications System, VoLTE = Voice over LTE, WCDMA = Wideband Code Division Multiple Access.

TABLE 2. Key differences between 6G and 7G in terms of artificial intelligence, quantum communication, and terahertz communication.

Parameter	6G	7G
AI Integration	Deep Reinforcement Learning (DRL), Federated Learning (FL), and Swarm AI for network optimization, latency reduction, and security.	Artificial General Intelligence (AGI) and Neuro-Symbolic AI for fully autonomous, self-learning, and self-healing networks.
Quantum Communication	Quantum Key Distribution (QKD) for ultra-secure encryption against classical cyber threats.	Quantum Entanglement-based Instant Communication (QEIC) and Quantum Teleportation for real-time interplanetary and deep-space networking.
Terahertz (THz) Communication	Operates in the 100 GHz – 1 THz range, enabling high-speed wireless connections for urban areas, automated factories, and high-density environments.	Expands to 1 – 10 THz, supporting high-fidelity holographic calls, metaverse experiences, and AI-powered data streaming with zero lag.
Network Speed	Theoretical max speed: 1 Tbps.	Theoretical max speed: 1.5 – 2 Tbps, enabling remote AI processing, real-time interstellar communication, and near-instant cloud computing.
Holographic & XR Integration	AI-driven volumetric video streaming for ultra-HD AR/VR applications in industries, education, and entertainment.	Light Field Holography & Quantum-Enhanced XR (QEXR) for real-time, high-fidelity holographic interactions with zero latency.
Satellite Integration (Including Starlink)	Starlink and other LEO constellations extend high-speed internet coverage to remote and underserved areas, supporting global 6G connectivity.	Starlink 2.0 & AI-Optimized Quantum Satellites enable global and interplanetary communication, leveraging quantum mesh networking for deep-space missions.
Smart Cities & IoT	AI-managed transportation, IoT-driven energy grids, and predictive analytics for disaster management.	Self-sustaining AI-powered smart cities with Quantum AI-controlled infrastructure, bio-digital human-AI interfaces, and zero-energy smart grids.
Computing Power	Edge AI + Cloud AI for decentralized data processing, reducing latency and improving efficiency.	Quantum Computing & AGI Integration, enabling real-time AI decision-making, self-learning networks, and instant problem-solving at a planetary scale.
Bio-Digital Integration	Early-stage Brain-Computer Interfaces (BCIs) for medical applications and brainwave-driven prosthetics.	Advanced Neural Mesh BCIs for telepathic communication, direct AI-to-human interfacing, and cognitive augmentation.
Interplanetary Communication	Space-based internet using LEO constellations like Starlink and OneWeb for extended Earth-wide coverage.	Quantum-based interstellar networking, using quantum memory teleportation & entangled particles for real-time data transfer across planets.
Sustainability & Energy Efficiency	AI-based self-healing networks optimize power consumption and enable sustainable network management.	Zero-Energy AI Networks, powered by Quantum Energy Harvesting (QEH) & Wireless Power Transmission (WPT), making traditional power sources obsolete.

Abbreviations: AGI = Artificial General Intelligence, BCI = Brain-Computer Interface, DRL = Deep Reinforcement Learning, FL = Federated Learning, LEO = Low Earth Orbit, QEIC = Quantum Entanglement-based Instant Communication, QEXR = Quantum-Enhanced XR, QKD = Quantum Key Distribution, QEH = Quantum Energy Harvesting, WPT = Wireless Power Transmission.

technologies from 5G to 7G, illustrating significant improvements in key parameters. For instance, the Downlink (DL) Peak Rate improves from 20 Gbps in 5G to 1 Tbps in 6G and further to 1.5-2 Tbps in 7G. The 1.5-2 Tbps peak rate for 7G is based on THz spectrum expansion [20], ultra-massive MIMO [21], Reconfigurable Intelligent Surfaces (RIS) [22], and AI-driven network management [23]. THz frequencies (0.3-3 THz) provide extreme bandwidth, and advanced modulation (1024-QAM, holographic beamforming) improves spectral efficiency. Ultra-massive MIMO (1000+ antennas) enables spatial multiplexing, while RIS optimizes signal propagation to counter THz attenuation [24]. AI-driven resource allocation and edge computing improve speed consistency. These factors align with Shannon's theorem and

FIGURE 2. The requirement of wireless communication technology from 5G to 6G and 7G, highlighting key advancements in data rate, energy efficiency, latency, security, and AI integration.

the historical trend of 10x speed jumps per generation [25]. Assuming spectrum availability, low-power THz transceivers, and optimized network orchestration, 7G could achieve 1.5-2 Tbps by 2035-2040 [26], [27]. Latency is reduced from 1 msec in 5G to 0.1 msec in 6G and less than 0.1 msec in 7G. Energy consumption is minimized from 10-100 pJ/bit in 5G to near-zero in 7G, and localization precision advances from 10 cm on 2D in 5G to sub-millimeter precision in 7G. 7G focuses on quantum and blockchain security, real-time holography, and energy-harvesting capabilities. 7G is poised to transcend the limitations of 5G and 6G by creating a network architecture capable of delivering seamless, ubiquitous connectivity across terrestrial, oceanic, and space environments [28]. This convergence of multiple layers of communication–land-based, airborne, and space-based is crucial to achieving the ultra-reliable, low-latency communication necessary for mission-critical applications. Unlike 5G and 6G, which rely heavily on spectrum allocation and advanced modulation techniques, 7G uses cutting-edge technologies such as Terahertz (THz) communication, quantum networking, and fully autonomous AI-driven resource management to maximize efficiency and minimize latency [29], [30]. One of the primary goals of 7G is to create a holistic communication environment where data can be accessed, transmitted, and processed in real-time, regardless of the user's location or the application's complexity. Whether facilitating real-time remote surgery, supporting fully autonomous fleets of vehicles, or enabling instantaneous global financial transactions, 7G networks will be foundational to the continued growth and innovation of industries that rely on ultra-reliable communication infrastructures. Figure 3 shows the next frontier in communication technology. 7G networks power a new era of connectivity by integrating AI, Quantum Computing, Blockchain, IoT, and Terahertz Communication Alongside Edge, Fog, and Space-Based Networks, revolutionizing Global Interactions with 6G Coexistence and Advanced Distributed Ledger Technologies [31], [32].

D. CONTRIBUTION

The paper's contribution focuses on integrating innovative technologies such as AI-driven machine learning, blockchain, quantum computing, and zero-energy solutions to enable secure, intelligent, and sustainable 7G networks. It explores the evolution of wireless networks, highlights transformative applications of 7G, and addresses the challenges and future research directions required to realize this vision. The contribution of the paper is as follows:

- The paper offers a comprehensive review of the evolution from 1G to 7G networks, particularly emphasizing advancements in connectivity, speed, latency, and the integration of AI and machine learning technologies.
- It explores the role of AI and machine learning paradigms, such as meta-learning, incremental learning, and reinforcement learning, in enhancing adaptability, resource allocation, and edge performance for 7G networks.

TABLE 3. List of abbreviations and their meanings used in the paper.

Abbreviation	Meaning	Abbreviation	Meaning	Abbreviation	Meaning
AIM	Adaptive Intelligence Modules	AKA	Authentication and Key Agreement	AM	Amplitude Modulation
AR	Augmented Reality	ATL	Adaptive Transfer Learning	BCI	Brain-Computer Interface
BERT	Bidirectional Encoder Representations from Transformers	BQC	Blind Quantum Computing	CDMA	Code Division Multiple Access
CMOS	Complementary Metal-Oxide-Semiconductor	CNNs	Convolutional Neural Networks	CS	Compressed Sensing
CTCS	Convolution-based Transfer Learning CS	DDL	Distributed Deep Learning	DDoS	Distributed Denial of Service
DL	Downlink	DLT	Distributed Ledger Technology	DMMA-FL	Decomposition and Meta-Deep Reinforcement Learning Algorithm
DP	Differential Privacy	DPoS	Delegated Proof of Stake	eMBB	Enhanced Mobile Broadband
ECC	Elliptic Curve Cryptography	EEG	Electroencephalography	EAP	Extensible Authentication Protocol
EPC	Evolved Packet Core	EMG	Electromyography	EWC	Elastic Weight Consolidation
FIDS	Federated Intrusion Detection Systems	FLAN-T5	Fine-tuned Language Net T5	FM	Frequency Modulation
FDMA	Frequency Division Multiple Access	GaAs	Gallium Arsenide	GaN	Gallium Nitride
GANs	Generative Adversarial Networks	GMSK	Gaussian Minimum Shift Keying	GNNs	Graph Neural Networks
GPT	Generative Pre-trained Transformer	GSM	Global System for Mobile	HAPS	High-Altitude Platform Stations
HHL	Harrow-Hassidim-Lloyd	HE	Homomorphic Encryption	HD	High Definition
HSFL	Hybrid Split and Federated Learning	IBN	Intent-Based Networking	IDS	Intrusion Detection Systems
IoE	Internet of Everything	IoT	Internet of Things	IRS	Intelligent Reflecting Surfaces
LEO	Low-Earth Orbit	LDP	Local Differential Privacy	LightGBM	Light Gradient Boosting Machine
LNF	Low Noise Figure	LP	Linear Programming	LTE	Long-Term Evolution
LSTMs	Long Short-Term Memory networks	MAML	Model-Agnostic Meta-Learning	MBBP	Meta-Learning-Based Beam Prediction
MDP	Markov Decision Process	MIMO	Multiple-Input Multiple-Output	MITM	Man-In-The-Middle
mmWave	Millimeter-Wave	MLS	Metric Learning using Scale Functions	MOS	Metal-Oxide-Semiconductor
MSDCNN	Multi-Scale Dilated CNN	NR	Neural Receivers	NRX	Universal Neural Receivers
NTN	Non-Terrestrial Networks	OAM	Orbital Angular Momentum	O-RAN	Open Radio Access Network
OFDM	Orthogonal Frequency Division Multiplexing	PBFT	Practical Byzantine Fault Tolerance	PoS	Proof of Stake
PoW	Proof of Work	QoS	Quality of Service	QAM	Quadrature Amplitude Modulation
QBER	Quantum Bit Error Rate	QKD	Quantum Key Distribution	QPSK	Quadrature Phase Shift Keying
RIS	Reconfigurable Intelligent Surfaces	RL	Reinforcement Learning	RLHF	Learning with Human Feedback
RRM	Radio Resource Management	SAGIN	Space-Air-Ground Integrated Networks	SEL	Split Edge Learning
SIM	Subscriber Identity Module	SiGe	Silicon-Germanium	SL	Split Learning
SMPC	Secure Multi-Party Computation	SMS	Short Message Service	SNR	Signal-to-Noise Ratio
S5A	Secure 5G Architecture	S-ITS	Smart Intelligent Transportation Systems	TBps	Terabits per Second
TDMA	Time Division Multiple Access	THz	Terahertz	TL	Transfer Learning
UAVs	Unmanned Aerial Vehicles	UWB	Ultra-Wideband	URLLC	Ultra-Reliable Low-Latency Communication
VAEs	Variational Autoencoders	VLC	Visible Light Communication	VR	Virtual Reality
WCDMA	Wideband Code Division Multiple Access	XAI	Explainable Artificial Intelligence	XR	eXtended Reality
ZKP	Zero-Knowledge Proof				

- The study investigates using blockchain, quantum computing, and zero-energy solutions as critical enablers for building secure, decentralized, and energy-efficient 7G networks.
- It highlights the potential of Large Language Models (LLMs) and ambient intelligence as transformative technologies for achieving hyper-connectivity and real-time actionable intelligence.

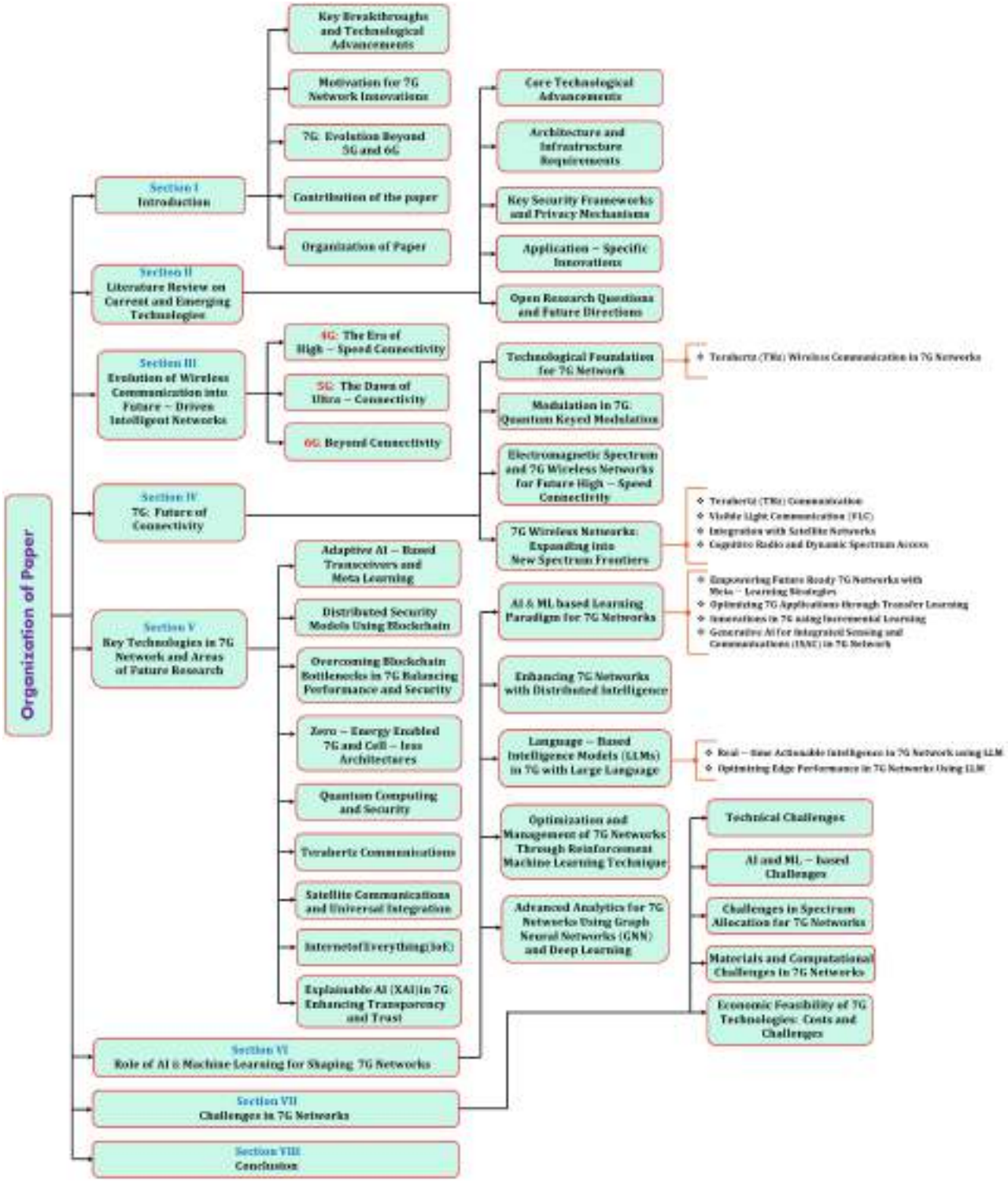

FIGURE 4. Detailed organization of the content flow used in the paper.

- Key challenges such as data privacy in federated learning, computational burdens in split learning, adversarial risks to incremental learning, and the complexities of LLMs are analyzed, offering essential insights into the 7G development process.
- The paper proposes solutions to address emerging cybersecurity threats, including post-quantum cryptography and blockchain-based privacy frameworks.
- The study examines transformative 7G applications, including smart cities, autonomous vehicles, industrial

FIGURE 3. Envisioning the Future of 7G Networks: Integrating AI, Quantum Computing, IoT, and Blockchain for a Hyper-Connected World.

IoT, and immersive technologies, and their potential to revolutionize various sectors.

- It investigates the convergence of terrestrial, aerial, and satellite networks as a key strategy for achieving global, seamless connectivity.
- Future research directions are identified, focusing on sustainable infrastructure, intelligent energy harvesting, and the deployment of ambient intelligence for enhancing 7G networks.
- The roles of Explainable AI (XAI) and edge computing in enabling real-time analytics, efficient resource management, and enhanced decision-making in 7G networks are discussed.

E. ORGANIZATION

The rest of the paper is organized as follows: In Section II, we review the evolution of wireless communication from 1G to 7G, focusing on technological advancements such as AI integration, quantum networking, and terahertz communication and their applications in smart cities and healthcare. In Section III, detailed key milestones from 1G to 7G are analyzed, highlighting the role of AI and automation in building future-driven intelligent networks. Section IV explores the foundational technologies of 7G, including green networking, quantum communication, and satellite integration, emphasizing their significance in achieving hyper-connectivity. In Section V, key technologies driving 7G, such as adaptive AI-based transceivers, blockchain security, and XAI, are analyzed alongside areas for future research like energy efficiency and decentralized frameworks are presented. Section VI discusses the overview of how AI and ML technologies are key to enabling the next generation of 7G networks. It concentrates on how advanced AI techniques like meta-learning, transfer learning, large language models, split learning, and incremental learning contribute to the adaptability, efficiency, and scalability of 7G systems. In Section VII, challenges in 7G, including spectrum management, material requirements, and sustainability issues, are identified, with innovative solutions proposed. Finally, Section VIII concludes the paper by summarizing the key contributions, emphasizing the transformative potential of 7G networks, and suggesting future research directions. The detailed organization of the paper is organized in Figure 4. Table 3 shows the list of abbreviations and their meanings used in the paper.

II. LITERATURE REVIEW ON CURRENT AND EMERGING TECHNOLOGIES

The evolution of wireless communication networks has reached a pivotal point with the progression from 4G to 5G, and now to 6G, each generation bringing forward new technologies and capabilities that enable faster, more reliable, and more intelligent connectivity [29], [33]. While 4G laid the foundation for mobile broadband, 5G introduced significantly higher data speeds, ultra-low latency, and enhanced connectivity for many devices [34]. As we continue to build on these advancements, 6G is expected to push further boundaries with innovations such as advanced AI integration [35], hyper-connectivity [36], and terahertz and quantum communication technologies [37], [38]. Following the advancements in 5G and the ongoing developments in 6G, 7G networks are anticipated to introduce transformative technologies such as terahertz communications [39], quantum networking [37], and highly adaptive network management [40]. These innovations promise to support unprecedented levels of device connectivity, ultra-low latency, and energy-efficient solutions adapted to meet the needs of future applications like immersive AR/VR experiences, autonomous transportation, and real-time healthcare systems [41], [42].

The literature review is structured as follows. First, we have examined the *core technological advancements from 4G to 7G*, including the innovations introduced in each generation, such as AI integration, quantum communication, and terahertz frequency usage. Next, we have analyzed the *architecture and infrastructure requirements* that support these technologies, followed by a discussion of the *key security frameworks and privacy mechanisms* that address the evolving challenges in next-generation networks. We have then explored *application-specific innovations* across these network generations, focusing on smart cities, autonomous systems, and healthcare. In the end, we have discussed the *open research questions and future directions for 7G*, highlighting areas requiring further exploration and the anticipated trajectory of global research and development in this field. Figure 5 illustrates a structured framework for the literature review, beginning with core technological advancements and progressing through key aspects such as architectural and infrastructure requirements, security frameworks, and application-specific innovations. The pathway

highlights the evolution from fundamental developments in 4G towards emerging technologies in 7G. It systematically addresses security and privacy concerns while incorporating innovative applications. The review concludes with open research questions and future directions, finding a way to explore next-generation communication technologies further. Table 4 shows the comparative analysis of key parameters across wireless network generations from 1G to 7G, highlighting advancements in frequency bands, data rates, security features, and emerging technologies like quantum key distribution and holographic communication in 7G. It also identifies parameters unique to 7G for next-generation connectivity and intelligence. Figure 6 shows a circular dendrogram that categorizes research papers based on technologies like 4G, 5G, and 6G. It is labeled with author names and journal details while color-coded to represent papers such as Architecture, Survey, and Roadmap. This visualization is utilized in the literature review to highlight current and emerging technologies systematically.

A. CORE TECHNOLOGICAL ADVANCEMENTS

The evolution of wireless communication networks from 4G to 7G involves groundbreaking technological innovations transforming how we interact with the digital world. The introduction of 4G networks marked a significant shift in mobile communications, offering much faster data rates and broader coverage than previous generations [43], [44]. This enabled the widespread use of high-definition video streaming, video calls, and mobile Internet applications [45]. Key technologies like LTE (Long-Term Evolution) and Orthogonal Frequency Division Multiplexing (OFDM) allowed 4G to deliver high-speed Internet and data connectivity while supporting the massive growth of smartphones and mobile applications [46]. Building on 4G, 5G networks aim to provide a new level of connectivity with millimeter-wave frequencies, massive Multiple-Input Multiple-Output (MIMO), and network slicing [47]. These innovations enable enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC), and Ultra-Reliable Low-Latency Communication (URLLC) [48], [49]. 5G's ability to handle many connected devices, alongside its potential to support applications such as autonomous vehicles, smart cities, and AR, places it as a transformative technology in the connectivity landscape [50]. 6G is expected to harness the power of terahertz frequencies, quantum communication, and artificial intelligence to create a truly immersive and intelligent connectivity infrastructure [15], [29], [51]. Innovations in 6G include holographic communications, real-time sensory interaction (the tactile Internet), and eXtended Reality (XR) integration [28], [52]. With 6G, networks will support data rates of up to 1 Tbps, ensuring faster, more reliable, and ultra-low-latency connections for mission-critical applications [53], [54]. The future of connectivity, 7G, will likely push the limits of wireless communication even further, relying on quantum networks, ambient intelligence, and advanced telepresence [55]. It is expected that 7G will provide ultra-secure communications through Quantum Key Distribution (QKD) and support massive device connectivity at even greater speeds and efficiency [56]. Key technologies will include advanced spectrum management utilizing THz bands and machine learning for self-organizing networks. The era of 7G will lay the groundwork for autonomous systems, real-time healthcare, and ambient intelligence [57], [58].

B. ARCHITECTURE AND INFRASTRUCTURE REQUIREMENTS

Each generation of wireless technology requires a new approach to network architecture and infrastructure to accommodate the growing demands of global connectivity. The architecture of 4G networks focuses on providing wide-area coverage with a central control system that manages data transmission across vast distances [59]. This was based on IP-based networks, where data, voice, and multimedia services were integrated using Evolved Packet Core (EPC) architecture [60]. The primary infrastructure for 4G consisted of base stations, evolved NodeBs, and core routers to handle the increased data traffic [61]. With the advent of 5G, the network architecture has evolved to incorporate cloud-native technologies and edge computing to provide low-latency services. 5G NR (New Radio) and 5G Core networks (5GC) form the backbone of this generation, with network slicing being one of the key enablers to provide customized services to different industries [62], [63]. The infrastructure requires small cells, millimeter-wave antennas, and high-speed fiber optic links to support higher data rates and better coverage in urban and dense areas. The infrastructure for 6G will include multi-layered networks that combine terrestrial and non-terrestrial communication, such as satellites, drones, and High-Altitude Platforms (HAPs) [64], [65], [66]. These networks require advanced AI-driven orchestration for dynamic network management, distributed edge computing, and quantum communication infrastructure. Smart antennas and dynamic spectrum management will also play key roles in meeting the capacity and latency demands of 6G applications [67], [68]. The architecture for 7G will integrate quantum computing and advanced artificial intelligence to support highly intelligent, self-healing, and self-optimizing networks [29], [69]. New infrastructure elements such as nano-satellites, molecular communications, and swarm-based computing might be required to ensure seamless global coverage and ultra-low latency. AI-driven network management will be essential to handle the enormous amount of real-time data flowing from billions of connected devices [29], [70].

C. KEY SECURITY FRAMEWORKS AND PRIVACY MECHANISMS

As connectivity becomes more pervasive, security and privacy become even more critical in every generation of mobile

FIGURE 5. Structured Pathway of Literature Review: From Core Technological Advancements to Future Research Directions.

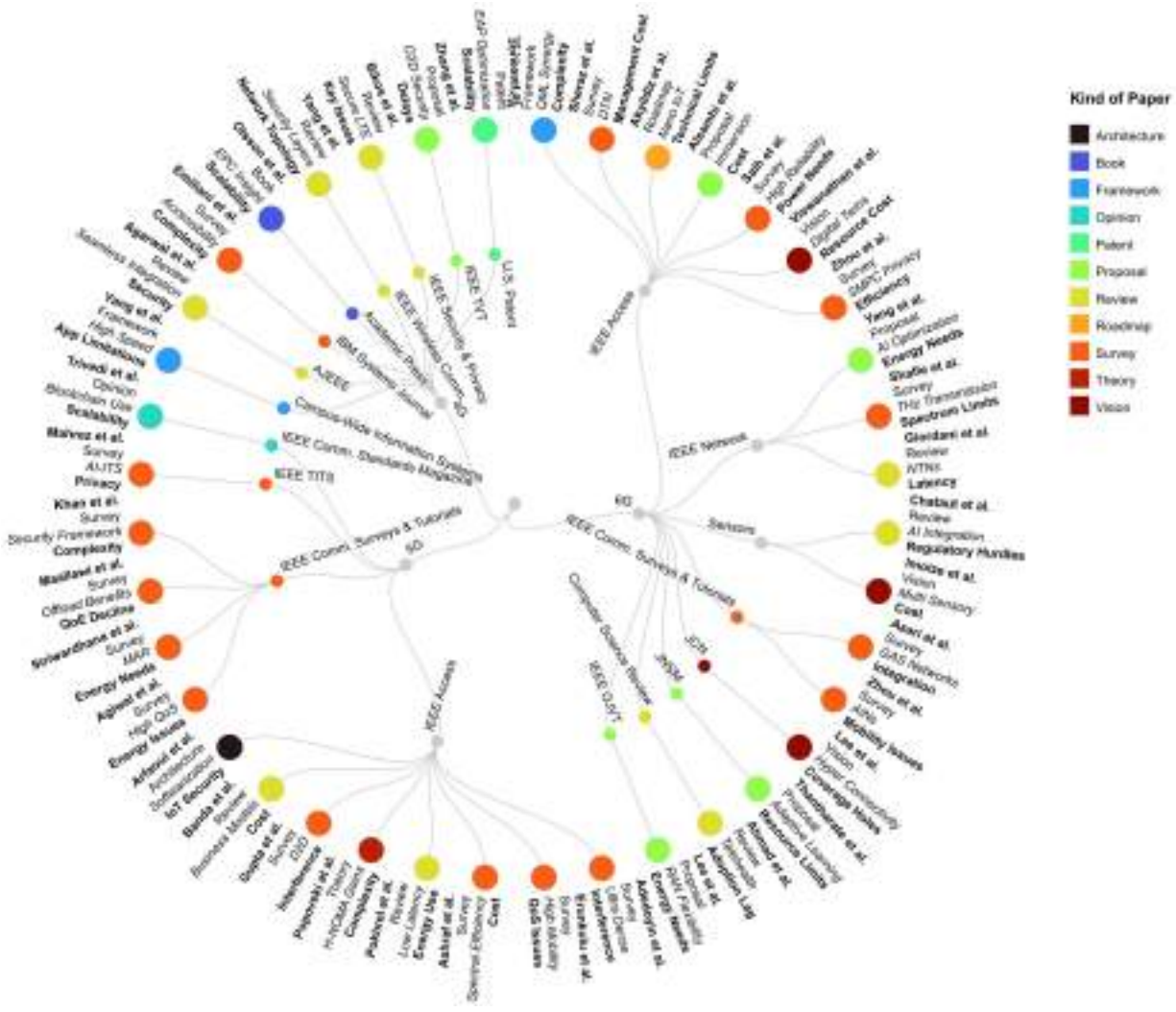

FIGURE 6. Circular dendrogram categorizing research papers based on technologies like 4G, 5G, and 6G, labeled with author names and journal details, and color-coded by the type of paper used in the literature review on current and emerging technologies.

networks [71]. In 4G, security was primarily based on end-to-end data encryption and authentication through Subscriber Identity Module (SIM) cards [72], [73]. While secure, these methods were not designed to address modern threats' increasing complexity and scale. Authentication protocols such as Extensible Authentication Protocol - Authentication and Key Agreement (EAP-AKA) were used [74]. Still, vulnerabilities in these protocols led to concerns about

TABLE 4. Comprehensive comparison of key parameters across network generations from 1G to 7G.

Parameter	1G	2G	3G	4G	5G	6G	7G
Frequency Band	800-900 MHz	900-1800 MHz	2100 MHz	800, 1800, 2600 MHz	Sub-6 GHz, mmWave (24-100 GHz)	100 GHz - 10 THz	1 THz - 100 THz
Channel Bandwidth	30 kHz	200 kHz	5 MHz	Up to 20 MHz	Up to 400 MHz (mmWave)	Up to 1 THz	Up to 10 THz
Modulation Scheme	FM	GMSK	QPSK	64-QAM	256-QAM	Advanced Modulation Techniques (e.g., Higher-order QAM)	Advanced Quantum Keyed Modulation
Handoff Mechanism	Hard Handoff	Soft Handoff	Hard Handoff	Seamless Handoff	Ultra-reliable Low-latency Handoff	AI-driven Seamless Handoff	AI-driven Intelligent Handoff
Capacity	∼1000 users	∼1200 users/cell	∼2000 users/cell	∼1000 users/cell	1 million devices/sq.km	Up to 10 million devices/sq.km	Up to 100 million devices/sq.km
Security	Minimal, prone to eavesdropping	Improved, supports encryption	Improved, stronger encryption standards	Enhanced security, EPC	End-to-end encryption	AI-based Threat Detection	Quantum Encryption, AI Threat Mitigation
Maximum Data Rate	2.4 kbps (Voice only)	Up to 64 kbps	Up to 2 Mbps (Stationary Mode)	Up to 100 Mbps (DL), 50 Mbps (UL)	Up to 10 Gbps (DL), 1 Gbps (UL)	Up to 1 Tbps (DL), 100 Gbps (UL)	Up to 10 Tbps (DL), 1 Tbps (UL)
Range	10-30 km/cell	10-20 km/cell	5-10 km/cell	2-5 km/cell	500m (mmWave), several km (Sub-6 GHz)	Several km with advanced beamforming	Extensive coverage with holographic beamforming
Power Control	Limited, high power consumption	Enhanced, reduced power consumption	Enhanced interference reduction	Advanced power control algorithms	Beamforming with power optimization	Intelligent power management	Energy harvesting with intelligent management
Call Handoff	Abrupt, frequent drops	Smooth, reduced drops	Support for seamless mobility	Enhanced QoS traffic prioritization	Highly flexible QoS frameworks	Ultra-flexible QoS support	QoS for immersive applications (e.g., AR/VR)
QKD	NA	NA	NA	NA	NA	NA	Implemented
AI-driven Network Orchestration	NA	NA	NA	NA	NA	Partial Support	Fully Integrated
Nano-Satellite Integration	NA	NA	NA	NA	NA	Experimental	Fully Enabled
Holographic Communication	NA	NA	NA	NA	NA	Experimental	Fully Enabled
Ambient Intelligence for Smart Devices	NA	NA	NA	NA	NA	Initial Stages	Fully Enabled

Abbreviations: AI = Artificial Intelligence, AMPS = Advanced Mobile Phone System, CDMA = Code Division Multiple Access, DL = Downlink, EPC = Evolved Packet Core, GMSK = Gaussian Minimum Shift Keying, LTE = Long Term Evolution, MIMO = Multiple-Input Multiple-Output, mmWave = Millimeter Wave, NA = Not Applicable, OFDM = Orthogonal Frequency Division Multiplexing, QAM = Quadrature Amplitude Modulation, QKD = Quantum Key Distribution, QoS = Quality of Service, QPSK = Quadrature Phase Shift Keying, THz = Terahertz, UL = Uplink, WCDMA = Wideband Code Division Multiple Access.

potential security breaches, particularly in user data privacy and network integrity. With 5G, a stronger emphasis on privacy and identity management is needed due to the scale of IoT devices and the criticality of services being connected to the network [75]. Advanced encryption techniques, Secure Multi-Party Computation (SMPC), and zero-knowledge proofs are introduced to protect sensitive data [76]. End-to-end security protocols such as Secure 5G Architecture (S5A) aim to secure communication across various use cases, ranging from industrial IoT to autonomous systems [77]. Network slicing also introduces challenges for segment-specific security models [78]. In 6G, security will move beyond traditional encryption models, using quantum cryptography to create unbreakable security through QKD [79]. The integration of AI will detect anomalous behavior in real-time, enabling proactive defense mechanisms. The security framework will be designed for distributed networks, ensuring data integrity is maintained across heterogeneous communication channels and networks. Security in 7G will rely heavily on quantum networks and ambient intelligence for continuous monitoring and authentication [80], [81]. Quantum encryption and blockchain-based security protocols will likely create more decentralized security systems that respond to real-time threats [82]. Privacy-preserving protocols and trusted computing environments will protect user data even in ultra-connected, intelligent environments.

D. APPLICATION-SPECIFIC INNOVATIONS

The various applications of wireless networks continue to evolve as new generations of mobile technology offer new possibilities for different industries [83], [84]. 4G networks enabled the growth of mobile apps, HD video streaming, social media, and e-commerce platforms [45], [85]. It was crucial for enabling the mobile-first revolution, where

FIGURE 7. Exploring open research questions and future directions in 7G through the lens of the word cloud.

smartphones became the primary devices for accessing the Internet and digital services. Industries such as entertainment, retail, and transportation began to see the transformative potential of always-connected applications [62]. 5G supports mission-critical applications such as autonomous vehicles, smart cities, smart agriculture, and industrial automation. With ultra-low latency, it facilitates real-time control for robotics, precision agriculture, and Augmented/Virtual Reality (AR/VR) applications [86]. The integration of IoT in industries like healthcare, manufacturing, and logistics has accelerated, enabling innovative solutions such as remote surgery, predictive maintenance, and asset tracking [87]. 6G will surpass what 5G offers, enabling hyperconnectivity and immersive technologies like holographic communications and mixed-reality environments [88], [89]. It will support applications that require massive data throughput, including real-time immersive AR/VR for education, entertainment, and communication, smart healthcare systems with real-time diagnostics, and autonomous fleets of drones and vehicles [90], [91]. The applications of 7G will be transformative, supporting a world of ambient intelligence. 7G networks will enable real-time, fully immersive environments where virtual and physical realities merge seamlessly [92]. Potential applications include advanced telepresence for meetings and conferences, real-time collaborative work environments, and hyper-precise smart cities with self-organizing infrastructure and resource management systems [93]. Figure 7 shows the open research questions and future directions in 7G technologies. It highlights critical themes such as scalability, interoperability, advanced sensing, and security, representing pivotal areas of exploration. These research questions and future directions encapsulate the innovative pathways required to shape the next generation of communication networks.

E. OPEN RESEARCH QUESTIONS AND FUTURE DIRECTIONS

As each generation of wireless technology unfolds, numerous research challenges and opportunities must be addressed to ensure continued innovation and growth [94]. For 5G to fully realize its potential, further research is needed to improve network slicing, optimize millimeter-wave spectrum utilization, and integrate AI-based network management [95]. Security challenges around IoT and network privacy are also areas requiring significant attention. As we move into 6G, questions around quantum communication, terahertz spectrum management, and AI integration in network management must be addressed [37]. Research on integrating terrestrial and non-terrestrial networks and AI-driven cybersecurity will be crucial to enable the seamless experience envisioned for 6G [28]. For 7G, open research questions include the viability of ambient intelligence in networks, quantum-based communication protocols, and managing nano-communications [96]. 7G challenges integrating self-learning, self-healing networks that can operate autonomously. Energy efficiency, sustainability, and global coverage remain critical research areas for future generations of wireless networks [97].

III. EVOLUTION OF WIRELESS COMMUNICATION INTO FUTURE-DRIVEN INTELLIGENT NETWORKS

Wireless communication has undergone significant transformations since its inception, from simple analog systems to advanced digital networks that enable high-speed data transfer and seamless connectivity [43]. This evolution reflects the dynamic nature of technological advancements and the increasing demands of users for more efficient, reliable, and intelligent communication systems. In this section, we have explored the key milestones in the evolution of wireless communication and the trajectory toward future-driven intelligent networks. Figure 8 shows the evolution of mobile network technologies from 1G to 7G, showcasing the advancements in features such as communication speed, connectivity, and integration with AI and automation. The timeline highlights key milestones, from analog cellular technology in the 1980s to the anticipated seamless integration of AI in 7G networks by 2035. Early developments in wireless communication trace back to the late 19th century, primarily driven by the efforts of pioneers such as Heinrich Hertz and Guglielmo Marconi [98]. Hertz's experiments in the 1880s demonstrated the existence of electromagnetic waves, laying the foundation for wireless technology. 1895 Marconi successfully transmitted the first radio signal over a distance, marking a significant communication milestone [99]. The technology evolved rapidly with the introduction of AM and FM in the early 20th century, enabling clearer transmission

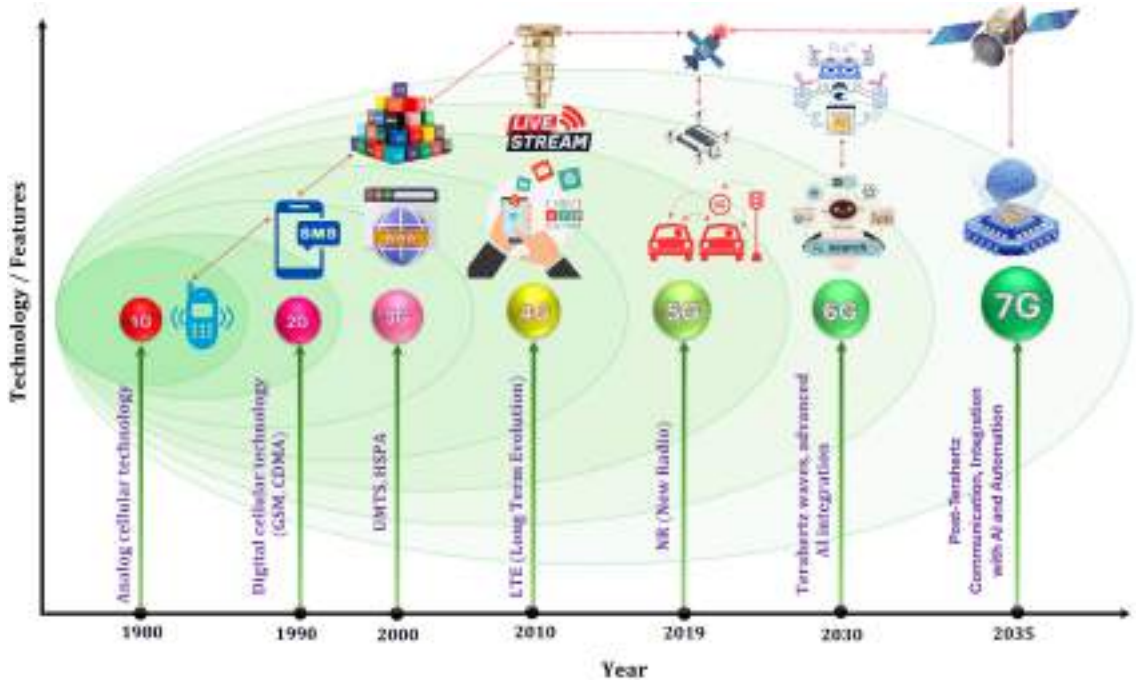

FIGURE 8. Evolution of cellular networks from 1G analog in 1980 to 7G with AI-driven, post-terahertz communication projected by 2035.

of sound and voice. During World War I, wireless communication proved crucial for military operations, leading to advancements in equipment and protocols [10], [100]. The post-war period saw the commercialization of radio broadcasting, which further popularized the technology. By the 1930s, the development of television began to integrate wireless transmission, expanding the scope of communication [101]. These foundational advancements paved the way for the future of wireless communication, influencing various technologies we rely on today [102].

The evolution of wireless communication, from the transformative advancements of 4G to the groundbreaking capabilities of 5G and the visionary horizon of 6G, is shaping future-driven intelligent networks. Each generation has progressively enhanced speed, connectivity, and efficiency, enabling a hyper-connected world. Integrating intelligent systems is a key driver in this transformation, where advanced technologies play a pivotal role [103]. For instance, in 5G, intelligent algorithms optimize network traffic and ensure low-latency, reliable connections [104]. 6G envisions deeper integration, utilizing intelligent systems for predictive maintenance, dynamic resource allocation, and real-time decision-making [105]. These technologies power applications like autonomous vehicles, personalized healthcare, and immersive virtual experiences, establishing intelligent connectivity as the backbone of future communication networks. We have covered this evolution from 4G to 6G, demonstrating how intelligence has been the cornerstone of transforming communication systems into future-driven intelligent networks. The following illustrates this progression and its impact on shaping the future of connectivity.

A. 4G: THE ERA OF HIGH-SPEED CONNECTIVITY

Fourth-generation (4G) mobile communication systems, introduced in the late 2000s, represent a significant leap forward in wireless technology, focusing on providing high-speed data services and seamless connectivity [43], [106]. 4G networks support many multimedia applications, enabling mobile broadband access and enhanced user experiences [107].

- *Technological Foundation: Long-Term Evolution (LTE):* The primary technology behind 4G is LTE, which utilizes a flat architecture and Orthogonal Frequency-Division Multiplexing (OFDM) for efficient data transmission [108].
- *Modulation in 4G: 64-QAM (Quadrature Amplitude Modulation):* 4G networks predominantly use 64-QAM to enhance data transmission efficiency, allowing for the transmission of 6 bits per symbol [109].
- *Capacity and Frequency Reuse:* 4G networks utilize advanced frequency reuse techniques to maximize capacity [110].
- *Limitations of 4G Systems:* While 4G technologies significantly improved mobile communication, they also had limitations.

    1) *Coverage Limitations:* In rural areas, coverage may be inconsistent due to geographical challenges.
    2) *High Infrastructure Requirements:* Building the necessary infrastructure requires substantial investment.
    3) *Interference Issues:* Increased user density can lead to interference, affecting quality.

4) *Complexity of Standards:* Variations in LTE standards across regions can complicate deployment.

B. 5G: THE DAWN OF ULTRA-CONNECTIVITY

Fifth-generation (5G) mobile communication systems, which began to roll out in the late 2010s, aim to revolutionize connectivity by enabling ultra-reliable, low-latency communication and massive machine-type communications [111]. 5G networks are designed to support an increasingly interconnected world with enhanced capabilities for IoT, AR, and high-definition video streaming [50], [112], [113], [114].

- *Technological Foundation: New Radio (NR):* The key technology behind 5G is NR, which employs a flexible air interface and supports a wide range of frequency bands, including sub-6 GHz and millimeter waves (mmWave) [115], [116], [117].
- *Capacity and Frequency Reuse:* 5G networks use advanced frequency reuse techniques to enhance capacity significantly [110].
- *Limitations of 5G Systems:* Despite its advanced capabilities, 5G technologies face certain challenges:
  1) *Coverage Challenges:* mmWave signals have limited range and penetration capabilities.
  2) *Infrastructure Costs:* The deployment of 5G infrastructure requires significant investment.
  3) *Device Compatibility:* Not all existing devices support 5G technology, requiring new hardware.
  4) *Interference Management:* High-frequency bands are susceptible to interference from obstacles and weather conditions.

C. 6G: BEYOND CONNECTIVITY

Sixth-generation (6G) mobile communication systems, expected to emerge around 2030, aim to surpass the capabilities of 5G by providing unprecedented levels of connectivity, speed, and versatility [105], [118]. 6G is anticipated to explore advanced technologies such as terahertz (THz) communication, integrated AI, and enhanced holographic applications to create a fully immersive and interconnected environment [28], [119].

- *Technological Foundation: Terahertz Communication:* 6G networks will utilize terahertz frequencies, ranging from 100 GHz to 10 THz, to achieve ultra-high data rates and ultra-reliable low-latency communication [53], [120], [121].
- *Modulation in 6G: Higher-Order QAM:* 6G networks are expected to utilize advanced modulation techniques, such as 1024-QAM, to enhance data throughput further [109].
- *Capacity and Frequency Reuse:* 6G networks will explore advanced frequency reuse and dynamic spectrum access techniques to enhance capacity exponentially [118], [122].
- *Limitations of 6G Systems:* Although 6G technologies promise remarkable advancements, they will encounter certain challenges [123]. Figure 9 shows a detailed comparison between the specific problems encountered in 6G and 7G networks, such as massive data processing, network latency, spectrum shortage, energy consumption, and security threats–and their respective solutions anticipated in 7G networks. These solutions include advanced technologies like edge computing, AI-driven network management, quantum communication protocols, blockchain-based security frameworks, and green communication technologies [124], [125].
  1) *Infrastructure Requirements:* The deployment of THz infrastructure necessitates significant technological innovations and investments.
  2) *Regulatory Concerns:* Spectrum allocation for THz frequencies may face regulatory hurdles.
  3) *Device Evolution:* The development of compatible devices will require extensive research and development.
  4) *Health Concerns:* Potential health effects of THz radiation will need thorough investigation.

IV. 7G: FUTURE OF CONNECTIVITY

Seventh-generation (7G) mobile communication systems, anticipated to emerge around 2035, are expected to revolutionize the concept of connectivity by integrating advanced technologies such as quantum communication, artificial intelligence, and pervasive sensing capabilities [126], [127]. 7G aims to achieve seamless connectivity across multiple domains, facilitating Ultra-Reliable Low-Latency Communications (URLLC) and immersive experiences for users and devices alike [29], [55]. Figure 10 highlights essential tools and frameworks for 7G networks, including Quantum Communication Simulators, Edge and Fog Computing Frameworks, Satellite and Next-Generation Network Simulators, AI/ML Modeling Platforms, Blockchain Auditing Tools, and IoT Data Aggregation Platforms, critical for advancing communication, analytics, and security in 7G ecosystems. Using radar charts, Figure 11 compares key performance metrics across 5G, 6G, and 7G network generations. For 5G, the metrics include a peak downlink of 10–20 Gbps, peak uplink of 1 Gbps, latency around 10 ms, energy consumption of 10–100 pJ/bit, connection density of 10^6 devices/km^2, and spectral efficiency of 30 bps/Hz. In 6G, values improve with a peak downlink of 1 Tbps, peak uplink of 100 Gbps, latency under 0.1 ms, energy consumption of 1 pJ/bit, connection density of 10^7 devices/km^2, and spectral efficiency of 100 bps/Hz. The 7G network further enhances these with a peak downlink of 1.5–2 Tbps, peak uplink of 1 Tbps, near-zero latency, energy consumption of near-zero pJ/bit, connection density of 10^8 devices/km^2, and spectral efficiency of 1000 bps/Hz.

A. TECHNOLOGICAL FOUNDATION FOR 7G NETWORK

The technological foundation of 7G networks includes a wide range of advancements aimed at achieving hyper-connectivity, ultra-low latency, and sustainable operations [29]. Central

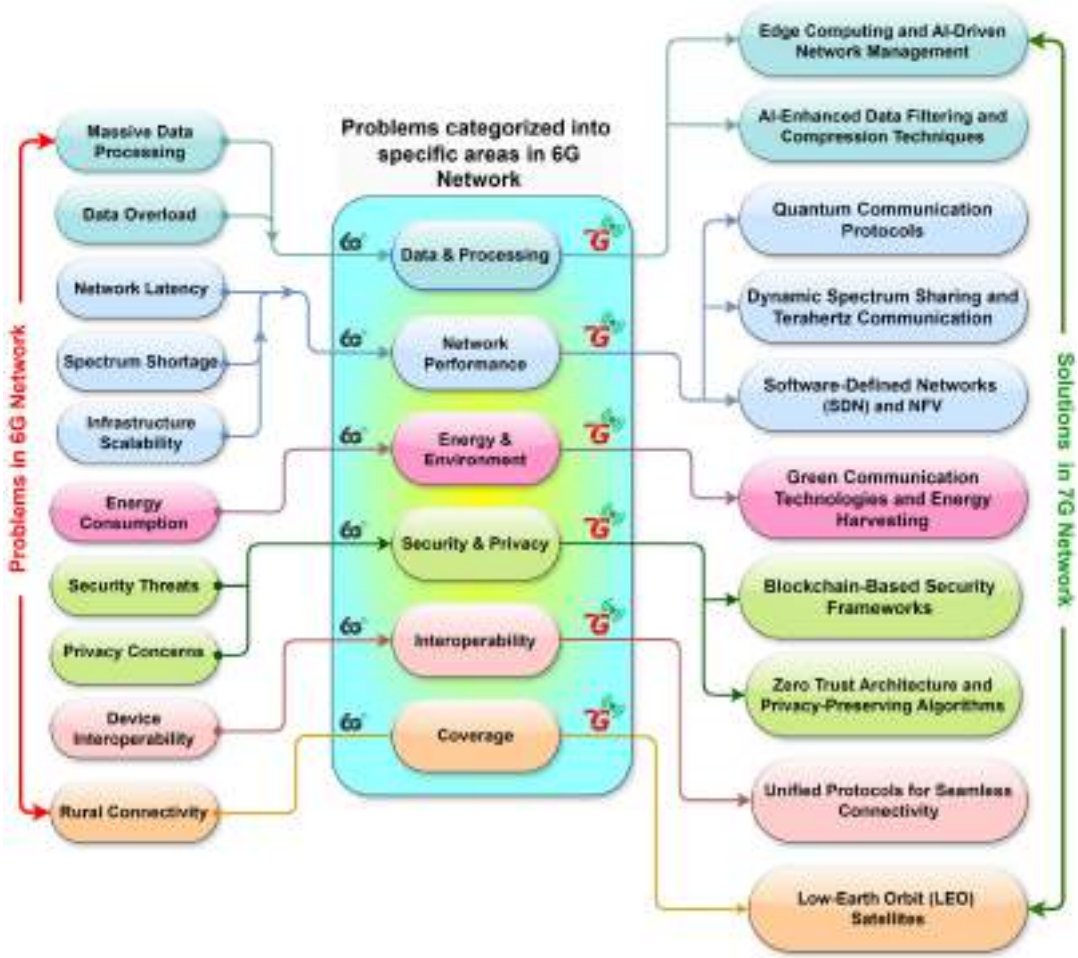

FIGURE 9. Comparison of 6G network challenges with 7G network solutions, highlighting advancements in data processing, network performance, security, energy efficiency, and rural connectivity.

to this development are terahertz (THz) frequencies, which enable unparalleled data transmission speeds and immense bandwidth, supporting applications such as immersive AR/VR, holographic communication, and real-time analytics [124]. Prime global connectivity is made possible through the integration of satellite and aerial networks, including Low-Earth Orbit (LEO) satellites, High-Altitude Platform Stations (HAPS), and Autonomous aerial vehicles (AAVs), ensuring coverage in remote or disaster-prone regions. Quantum technologies like QKD and quantum computing offer enhanced security with unbreakable encryption and efficient optimization of network resources [129], [130]. Green networking practices, including adopting renewable energy sources and energy-efficient devices, reflect a strong commitment to sustainability [131]. The Internet of Everything (IoE) paradigm expands connectivity to integrate humans, devices, and biological systems, supported by the advanced edge and fog computing architectures [132]. Blockchain and decentralized systems ensure secure identity management, operational transparency, and the development of decentralized autonomous networks [133]. Artificial intelligence and machine learning provide real-time network optimization, fault detection, and predictive maintenance [134]. 7G will revolutionize communication with multi-sensory platforms that transmit touch, taste, and smell, offering transformative experiences in industries like telemedicine and entertainment [135], [136].

Figure 12 shows the core technological pillars for the development of 7G networks, including Blockchain and Decentralized Systems, Green and Sustainable Networking, Internet of Everything (IoE), Multi-Sensor Communication, Artificial Intelligence and Machine Learning, Quantum Technologies, Terahertz Wireless Communication, and Satellite and Aerial Integration. Each technology is crucial in advancing connectivity, efficiency, and sustainability in next-generation networks.

1) TERAHERTZ (THZ) WIRELESS COMMUNICATION IN 7G NETWORKS

Terahertz (THz) wireless communication is a cornerstone of 7G networks, significantly surpassing the capabilities of 6G by utilizing frequencies in the 0.1 THz to 10 THz

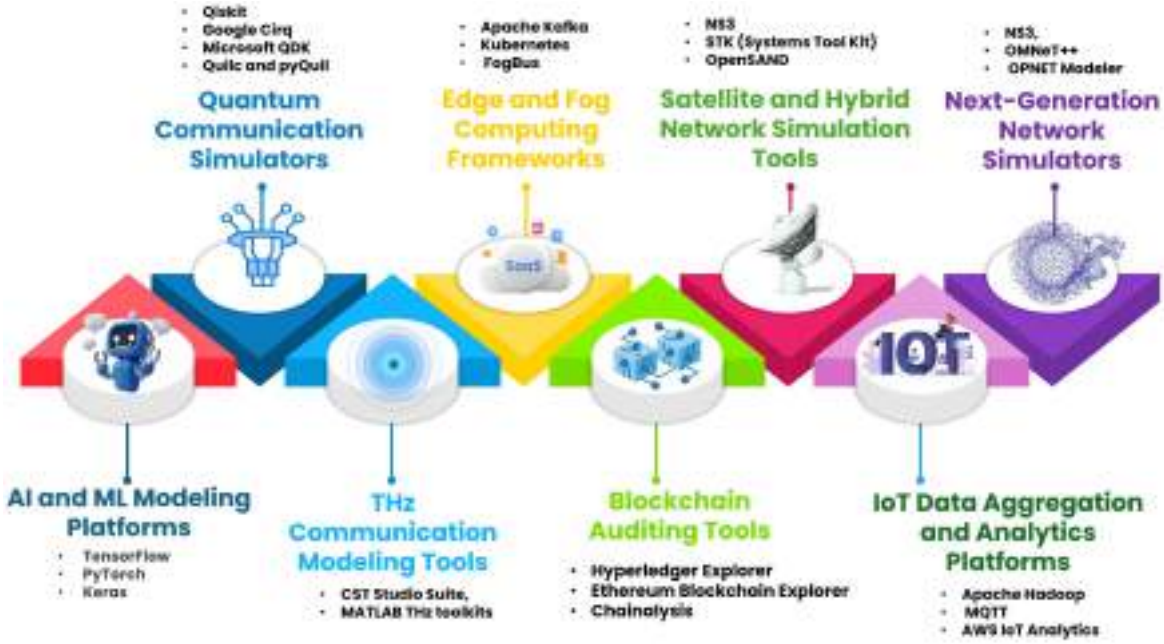

FIGURE 10. Essential tools and frameworks driving the development of 7G networks, including Quantum Simulators, AI/ML Platforms, Blockchain Auditing, and IoT Analytics.

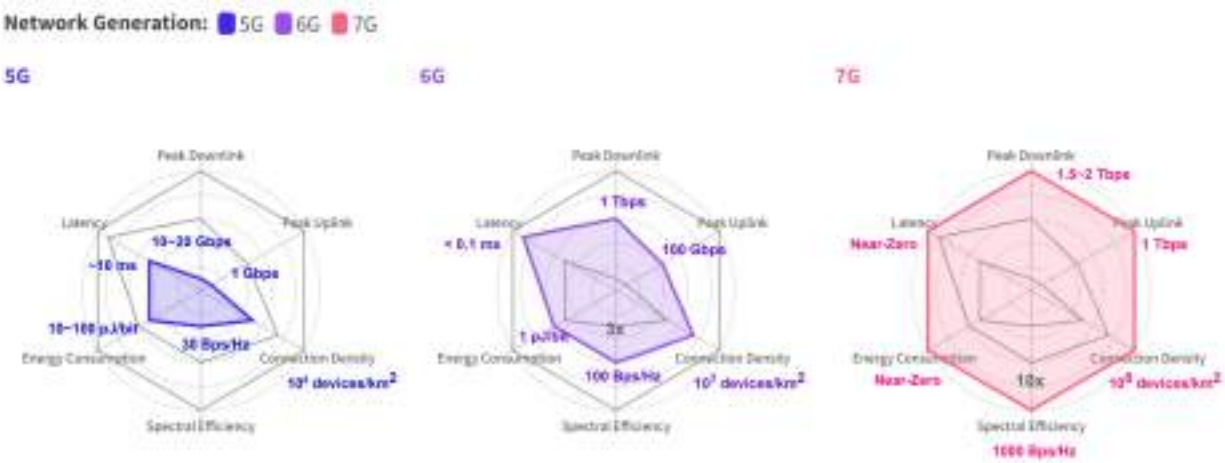

FIGURE 11. Comparison of key performance metrics across 5G, 6G, and 7G network generations using radar charts [128], showing parameters such as peak downlink, peak uplink, latency, energy consumption, connection density, and spectral efficiency.

TABLE 5. Comparison of THz wireless communication in 6G and 7G networks.

Feature	6G Networks (Sub-THz)	7G Networks (Full THz)	Required Changes for 7G
Frequency Range (GHz)	100–300	300–10,000	Development of THz-compatible hardware and protocols
Bandwidth (B)	10 GHz	100 GHz	Multi-band aggregation to achieve 100 GHz
Data Rate (R) (Gbps)	Up to 1,000	10^4 (10 Tbps)	Advanced modulation to achieve 10^4 Gbps
Latency (T) (ms)	$T < 1$	$T \approx 0.1$	Real-time optimization for $T < 0.1$ ms
Path Loss ($A(d)$) (dB)	$A(10) \approx 80$	$A(10) > 100$	Use of RIS to reduce $A(d)$ by $> 20\%$
Signal-to-Noise Ratio (SNR) (dB)	SNR ≈ 30	SNR > 40	Improved beamforming for SNR > 40
Energy Efficiency (J/bit)	10^{-10}	10^{-12}	Efficient transceivers for 10^{-12} J/bit

range [137]. The wider spectrum in the THz range allows for substantial increases in B, enabling data rates beyond 10 Tbps. Higher frequencies also introduce challenges such as increased attenuation (A), defined as:

$$A(d) = A_0 + 10 \cdot \gamma \cdot \log_{10}(d), \tag{1}$$

where A_0 is the free-space path loss, γ is the attenuation factor, and d represents the distance. Overcoming such

FIGURE 12. Technological Foundation for the Future of Connectivity through Advancements in 7G Networks.

challenges in 7G necessitates innovations in advanced beamforming, Reconfigurable Intelligent Surfaces (RIS), and high-precision antenna arrays. Table 5 shows the detailed comparison of key parameters in THz communication for 6G and 7G networks, alongside the required changes for 7G networks. The challenges and changes required in 7G networks are necessary to handle future demands in mobile communication, such as huge increases in data traffic, very low latency, and global connectivity [138]. With the rise of applications like autonomous vehicles, remote surgery, and IoT, 7G networks must improve in areas like bandwidth, energy efficiency, and network coverage [124]. Integrating new technologies like AI, quantum computing, and strong security measures will help protect sensitive data and ensure privacy. Network slicing, automation, and self-optimization will also be important to provide tailored solutions and manage the network efficiently [139]. These changes will ensure that 7G networks can deliver reliable, high-performance services across various industries and work smoothly worldwide. Several technological advancements are necessary to realize the full potential of THz communication in 7G. i.

1) *Frequency Range (GHz):* Transitioning from 100–300 GHz to 300–10,000 GHz requires the development of THz-compatible hardware and communication protocols to handle the ultra-high-frequency spectrum efficiently.
2) *Bandwidth (B):* To achieve a bandwidth of 100 GHz, multi-band aggregation techniques are essential. This approach helps the available spectrum more effectively, enabling data throughput to reach the desired 100 GHz range.
3) *Data Rate (R) (Gbps):* Achieving data rates of up to 10 Tbps (104 Gbps) demands advanced modulation schemes. High-capacity modulation techniques, such as Orbital Angular Momentum (OAM) and ultra-dense constellations, are essential for the necessary throughput for future communication systems.
4) *Latency (T) (ms):* To reduce latency to sub-millisecond levels $T \approx 0.1$ ms, real-time optimization techniques need to be implemented. This includes minimizing transmission delays and optimizing network protocols to achieve ultra-low latency for critical applications.
5) *Path Loss (A(d)) (dB):* At higher frequencies, path loss increases significantly. To mitigate this, techniques like RIS and ultra-dense networks are critical in reducing path loss by more than 20% to maintain reliable communication.
6) *Signal-to-Noise Ratio (SNR) (dB):* Achieving an SNR greater than $40dB$ is essential for ensuring robust communication. This can be accomplished by deploying advanced beamforming techniques, enhancing signal quality, and improving network reliability.
7) *Energy Efficiency (J/bit):* To address the growing demand for energy-efficient systems, low-power THz transceivers and efficient energy harvesting mechanisms must be integrated into the system design to minimize energy consumption while maintaining high performance.

B. MODULATION IN 7G: QUANTUM KEYED MODULATION

7G networks are expected to utilize quantum-key modulation techniques, enhancing data throughput and security [140]. The mathematical representation can be expressed as:

$$s(t) = A \cdot \cos\left(2\pi f_c t + \phi(t) + \theta_q\right) \tag{2}$$

where A is the amplitude, f_c is the carrier frequency, $\phi(t)$ represents the phase, and θ_q represents the quantum key information.

C. ELECTROMAGNETIC SPECTRUM AND 7G WIRELESS NETWORKS FOR FUTURE HIGH-SPEED CONNECTIVITY

The development of 7G wireless networks is poised to revolutionize high-speed connectivity by integrating advanced technologies and pushing the limits of communication systems [141]. At the heart of 7G is the efficient utilization of the electromagnetic spectrum, which is critical for achieving the ultra-high data rates, low latencies, and large-scale device connections expected from future networks [142]. The electromagnetic spectrum refers to the range of all types of electromagnetic radiation, as shown in Figure 13, categorized by wavelength or frequency. It includes radio waves, microwaves, infrared, visible light, ultraviolet, X-rays, and gamma rays. The specific portion of the spectrum used for wireless communications is primarily in the RF and microwave ranges.

- *Radio Waves:* The lowest-frequency waves are used for wireless communication, ranging from 3 kHz to 300 GHz. Most modern mobile networks, including 5G, rely heavily on the RF spectrum for transmitting data [141].

- *Microwaves:* Higher-frequency waves, from 300 MHz to 300 GHz, are used for shorter-range communication and more data-intensive applications [143].

D. 7G WIRELESS NETWORKS: EXPANDING INTO NEW SPECTRUM FRONTIERS

By pushing beyond traditional RF and microwave frequencies and into the terahertz (THz) and Visible Light Communication (VLC) bands, 7G wireless networks seek to revolutionize connectivity. Adopting the THz spectrum, which spans from 300 GHz to 3 THz, is expected to allow a wide range of applications, from ultra-low-latency industrial automation to real-time holographic communication, and enable previously unheard-of data speeds [141]. Using these high-frequency bands has several difficulties, including the requirement for sophisticated transceiver equipment, considerable attenuation, and a limited propagation distance. Concurrently, including VLC presents a chance for data transmission and dual-purpose illumination; nonetheless, it necessitates effective modulation strategies and smooth communication with conventional networks [30]. These advancements highlight the critical role of spectrum innovation in realizing the transformative potential of 7G networks while addressing technical, regulatory, and operational complexities [17]. Table 6 provides a detailed analysis of spectrum usage in 7G wireless networks, highlighting key parameters such as bandwidth potential, range, energy consumption, and deployment costs across THz, VLC, and satellite spectrums. It demonstrates the technological advancements and associated challenges in integrating these diverse spectrums into a unified network.

The vision for 7G wireless networks goes beyond the capabilities of current 5G and 6G technologies. Key characteristics of 7G include:

- *Terahertz Communications:* 7G will explore the terahertz spectrum for ultra-high-speed data transmission. While the terahertz band offers enormous bandwidth and data rates up to several terabits per second (Tbps), it suffers from high atmospheric attenuation, requiring advanced beamforming and short-range, line-of-sight communication technologies to maximize performance [144].
- *Visible Light Communication (VLC):* Alongside RF and microwave communication, visible light communication is expected to play a role in 7G networks. VLC utilizes the visible portion of the electromagnetic spectrum for data transmission using LEDs and photodetectors, making it a promising solution for indoor, high-speed connectivity [145], [146].
- *Integration with Satellite Networks:* To achieve global coverage, 7G networks will integrate with satellite communications, particularly exploring LEO satellite constellations [147], [148]. This will expand the use of spectrum outside Earth's atmosphere and deliver high-speed Internet even to remote areas.
- *Cognitive Radio and Dynamic Spectrum Access:* Cognitive radio technology enables more efficient use of the electromagnetic spectrum by allowing devices to detect and utilize unused frequencies intelligently [149], [150]. This dynamic spectrum access reduces interference and optimizes bandwidth usage, which is essential for the dense device environments envisioned for 7G.

V. KEY TECHNOLOGIES IN 7G NETWORK AND AREAS OF FUTURE RESEARCH

The development of 7G networks brings forward a transformative landscape of key technologies and potential areas of future research, aiming to redefine global connectivity standards [151], [152]. At the forefront of these advancements is the utilization of terahertz (THz) communication, offering unparalleled data rates in the terabit-per-second (Tbps) range but demanding innovations in transceiver design, beamforming techniques, and strategies to overcome high atmospheric attenuation. VLC is emerging as a complementary technology, exploring LED-based systems for high-speed indoor connectivity while addressing challenges in modulation efficiency and integration with existing wireless networks [145], [153]. Satellite communication, particularly through LEO constellations, is pivotal in ensuring global coverage, pushing research into minimizing latency, enhancing spectral efficiency, and developing cost-effective deployment strategies [154]. Cognitive radio and dynamic spectrum [155] access technologies are critical for optimizing spectrum usage in increasingly dense device environments, requiring further exploration into machine-learning-driven spectrum management algorithms [156]. Energy-efficient communication is a central theme, prompting research into low-power hardware, advanced network protocols, and renewable energy integration to reduce the environmental impact of 7G deployments [157]. Addressing security and privacy concerns, especially in quantum-resistant encryption and resilient network architectures, remains vital for ensuring robust and secure connectivity [158]. Together, these technologies and research directions signify the revolutionary potential of 7G networks while underscoring the multidisciplinary efforts required to overcome technical, regulatory, and operational challenges.

Figure 14 shows the key technologies and future research areas shaping 7G networks. These include adaptive AI-based transceivers, distributed security models using blockchain, zero-energy, cell-less architectures, and quantum computing for enhanced security. It also highlights advancements like terahertz communications, satellite integration, IoE, and generative AI for 7G innovations. Table 7 comprehensively analyzes key technologies driving 7G networks, highlighting their unique features, challenges, potential solutions, and applications. The following is the area for developing 7G networks and the corresponding area for future research.

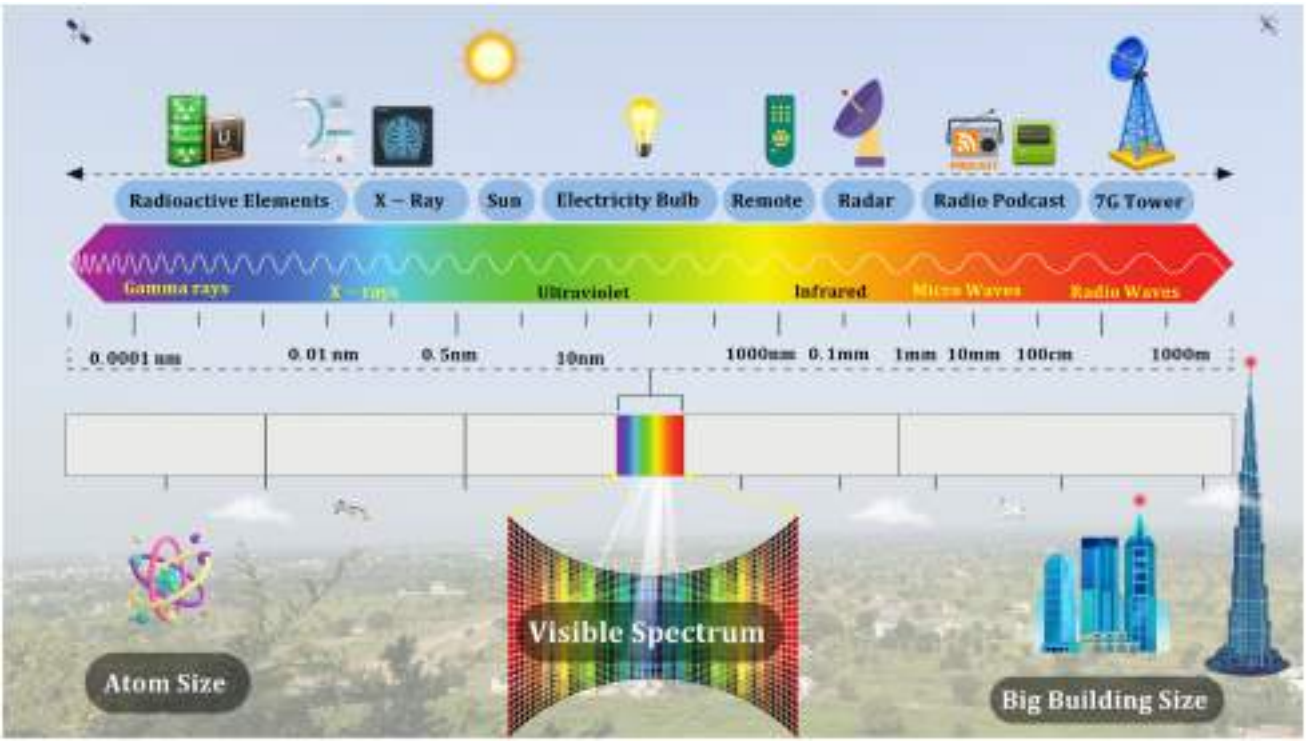

FIGURE 13. Electromagnetic spectrum showing wave types from gamma rays to radio waves, including 7G technology, with the visible spectrum highlighted.

TABLE 6. Analysis of spectrum usage in 7G wireless networks.

Parameter	THz Spectrum (300 GHz - 3 THz)	VLC Spectrum (430 THz - 770 THz)	Integration with Satellite Networks
Bandwidth Potential	1–10 Tbps	100 Mbps–1 Gbps	100 Mbps–1 Gbps
Range	1–10 meters	Up to 30 meters	500–36,000 km (depending on satellite orbit)
Key Challenges	Attenuation: 50 dB/km	Requires 100% line-of-sight clarity	Latency: 10–50 ms
Applications	Industrial IoT, holographic communication	IoT, smart lighting, indoor navigation	Rural connectivity, emergency communication
Technological Requirements	Beamforming: Efficiency > 90%	LEDs: Efficiency 80–90%, Photodetector gain > 50 dB	LEO satellite constellations: Altitude 500–2,000 km
Energy Consumption	Power usage: 5–10 W per transceiver	LED power: < 20 W for indoor environments	Satellite power: 1–5 kW per satellite
Deployment Cost	$50–100 million per THz infrastructure unit	$20–50 million per large-scale VLC setup	$100 million–$500 million per satellite
Propagation Medium	Free space: Loss 40–60 dB over 10 meters	Optical path: Loss 10–20 dB	Space-to-ground: Loss 100–120 dB
Latency	< 1 ms	1–5 ms	10–50 ms
Interference Management	Noise cancellation: 30–40 dB suppression	RF interference: Near zero	Cross-link beam precision: 95%

A. ADAPTIVE AI-BASED TRANSCEIVERS AND META LEARNING

Adaptive AI-based transceivers and meta-learning represent cutting-edge advancements in wireless communication, especially for 7G networks used in Smart Intelligent Transportation Systems (S-ITS). Figure 15 shows an advanced 7G network that uses adaptive AI-based transceivers and meta-learning for efficient communication in smart transportation systems. Red lines show the satellite communication links, while blue lines highlight AI-assisted data relays enabling real-time connectivity between devices. The Adaptive Intelligence Modules (AIM) ensure dynamic decision-making, and the meta-learning drone network facilitates predictive analytics for seamless operations. Together, these components demonstrate the transformative potential of 7G in enabling intelligent and responsive infrastructure where the demand for ultra-fast, reliable, and efficient communication systems is crucial [159], [160], [161]. These transceivers utilize Artificial Intelligence (AI) algorithms to dynamically adjust to changing network conditions, including interference, channel variations, and traffic demands, ensuring optimal signal transmission and reception [162].

FIGURE 14. Comprehensive Overview of Emerging Technologies in 7G Networks and Key Areas for Future Research and Development.

Unlike traditional static systems, AI-based transceivers can continuously learn and adapt to environmental factors, enhancing the system's overall performance in real-time [53]. This adaptability allows for smarter beamforming, resource allocation, and power control, essential for maximizing throughput and minimizing latency in high-frequency bands such as terahertz (THz) and VLC. Meta-learning, an advanced subset of machine learning, adds another layer of intelligence to these systems by enabling the transceivers to quickly adapt to new environments and tasks with minimal data, learning from a wide range of experiences [163]. Meta-learning can optimize AI models more effectively, allowing transceivers to generalize from past experiences and apply learned knowledge to new scenarios with minimal retraining [164]. This is particularly beneficial for 7G networks facing diverse challenges, such as network congestion, interference from multiple devices, and varying signal conditions. Combining adaptive AI-based transceivers with meta-learning can transform communication networks by enhancing efficiency, reducing energy consumption, and improving the overall user experience in an increasingly complex and dynamic wireless environment [165].

B. DISTRIBUTED SECURITY MODELS USING BLOCKCHAIN

Distributed blockchain security models represent a revolutionary approach to securing data and communications in decentralized environments [181], [182]. Blockchain, characterized by its immutable, distributed ledger and cryptographic protocols, ensures transparency, traceability, and tamper-proof operations [183]. These characteristics make blockchain a natural fit for creating resilient security frameworks, particularly in distributed systems where trust between parties is paramount. Unlike traditional centralized security models, blockchain's decentralized architecture eliminates single points of failure, enhancing resistance to cyberattacks [184]. It facilitates secure identity management, data sharing, and authentication mechanisms across a network of participants without requiring intermediaries. As the world embraces advanced technologies such as 7G networks, blockchain-based distributed security models hold the potential to address complex challenges such as data breaches, unauthorized access, and privacy concerns in high-speed, low-latency communication infrastructures [185]. As 7G evolves to support applications like immersive telepresence and autonomous ecosystems, blockchain-based security models protect sensitive data and maintain stakeholder trust [186], [187]. The following points highlight the key aspects of how blockchain facilitates distributed security in 7G.

- *Decentralized Data Security:* Blockchain provides a decentralized ledger, ensuring data integrity and preventing unauthorized modifications [188]. Decentralized Data Security in 7G networks relies on blockchain's distributed ledger technology to ensure secure, tamper-proof data management across a vast, interconnected infrastructure [189]. As 7G networks involve billions of devices with ultra-low latency and high throughput requirements, traditional centralized security models struggle with scalability, bottlenecks, and single points of failure. Blockchain addresses these issues by replicating data across multiple nodes, using consensus mechanisms like Proof of Stake (PoS) to validate transactions and ensure data integrity through cryptographic hashing [190]. Each data block is linked to its predecessor, ensuring tampering is

TABLE 7. Analysis of key technologies and future research in 7G networks.

Technology	Key Feature	Challenges	Potential Solutions	Applications
Adaptive AI-Based Transceivers [166]–[168]	Self-learning signal processing	Real-time adaptability in complex networks	Meta-learning, reinforcement learning	Autonomous networks, edge devices
Distributed Security Models Using Blockchain [169], [170]	Decentralized authentication	Scalability, latency issues	Hybrid blockchain frameworks	Decentralized IoT security
Zero-Energy 7G and Cell-less Architectures [171]–[173]	Energy Harvesting, D2D comm.	Limited energy sources, interference	Advanced materials, efficient protocols	Environmental monitoring, rural coverage
Quantum Computing and Security [130], [174], [175]	Quantum-resistant encryption	High hardware complexity, cost	Quantum Key Distribution (QKD)	Critical infrastructure, financial systems, UAV Networking
Terahertz Communications [176]	Tbps data rates	Atmospheric attenuation, hardware design	Beamforming, advanced antenna arrays	High-speed wireless access
Satellite Communications [154], [177]	Global coverage, low latency	Deployment costs, spectral efficiency	Low-cost satellites, AI for traffic management	Remote connectivity, disaster recovery
Internet of Everything (IoE) [178], [179]	Massive device connectivity	Interoperability, data overload	Edge computing, unified protocols	Smart cities, industrial automation
Generative AI for 7G [180]	Network optimization, analytics	Model scalability, real-time learning	Adaptive AI-based models	Predictive maintenance, fraud prevention

easily detectable. Public and private key cryptography facilitates secure authentication and communication between devices, while smart contracts automatically enforce security policies such as access control and anomaly detection. This decentralized structure eliminates the need for a central authority, enabling trustless interactions, and ensures that 7G networks can handle the high demands of applications like IoT, autonomous vehicles, and real-time healthcare while maintaining confidentiality, integrity, and data availability [191].

- *Immutable Record Keeping:* Immutable Record Keeping in 7G networks uses blockchain's decentralized and tamper-resistant nature to ensure that all data transactions are securely recorded and preserved [192]. Traditional centralized systems are vulnerable to data manipulation or loss in environments where data integrity is critical, such as autonomous vehicle communication or healthcare systems. Blockchain overcomes these challenges by creating a chain of blocks linked to its predecessor using cryptographic hashes, making it virtually impossible to alter records without detection [193]. Once data is added to the blockchain, it is immutable, meaning it cannot be modified or erased, ensuring a trustworthy, auditable trail of all transactions. This immutability is crucial for applications in 7G networks that require high accountability, such as financial transactions, sensor data collection, or regulatory compliance, as it guarantees data authenticity and prevents malicious tampering [194]. By ensuring that records are permanently stored and verifiable, blockchain enables secure and transparent data management, fostering trust across all stakeholders in the 7G ecosystem [195].
- *Smart Contracts for Automation:* Smart Contracts for Automation in 7G networks enable the self-execution of predefined security protocols and transactions without intermediaries. These contracts are deployed on the blockchain and automatically enforce agreed-upon conditions when certain criteria are met [196], [197]. In a highly connected 7G environment, where devices and systems must operate with minimal latency, smart contracts eliminate centralized control, ensuring that authentication, access control, and data sharing are automated and executed securely [198], [199]. Once a smart contract is deployed, it runs autonomously, reducing human intervention and the risk of errors or malicious alterations. For example, a smart contract can automatically grant access to a device or validate a transaction based on real-time data inputs, ensuring efficient compliance with security policies [200]. This automation not only accelerates processes but also enhances the security and reliability of the network by removing vulnerabilities introduced by centralized decision-making, making it an essential tool for managing the complex and dynamic nature of 7G networks [139], [198].
- *Resilience Against Attacks:* Resilience Against Attacks in 7G networks is enhanced through blockchain's decentralized structure, which significantly reduces the risk of single points of failure that traditional centralized systems are vulnerable to [195]. In 7G, where millions of devices are interconnected, ensuring continuous, secure operation is critical. Blockchain provides resilience by distributing data across multiple nodes, so even if one or more nodes are compromised, the system remains functional and secure. Consensus mechanisms, such as Proof of Stake (PoS), ensure that all transactions are validated by multiple participants, making it difficult for malicious actors to alter the network without the consensus of the majority [201]. The immutability of blockchain records prevents tampering with transaction data, offering a robust defense against attacks like Distributed Denial of Service (DDoS) and Man-In-The-Middle (MITM) attacks [202]. This decentralized

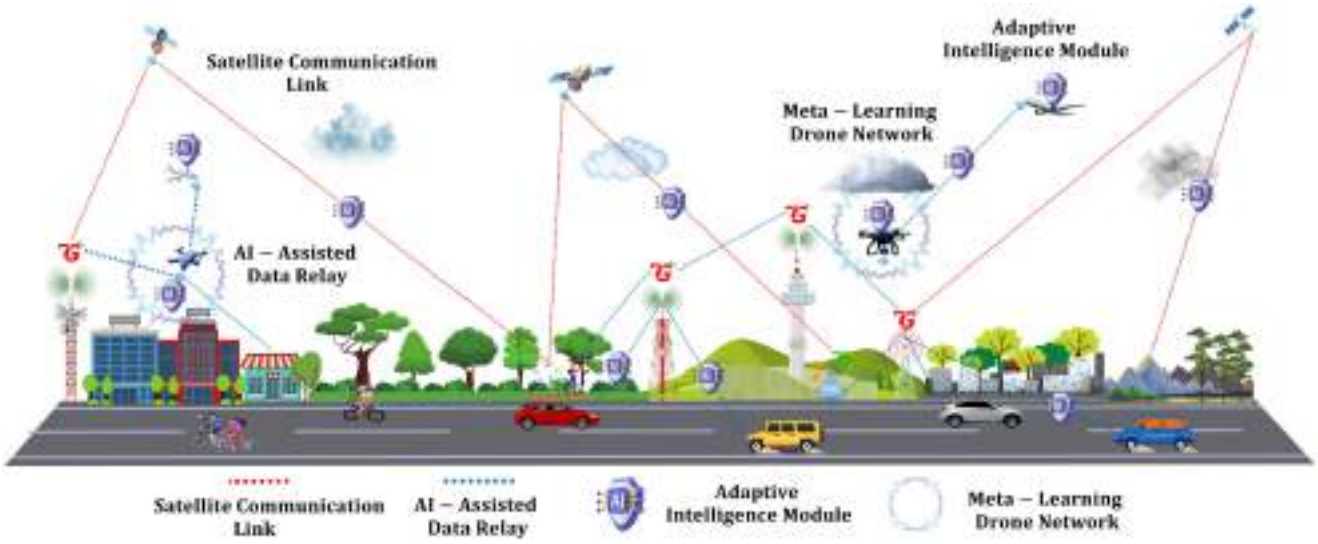

FIGURE 15. Adaptive AI-Driven Communication and Meta-Learning Networks Powered by 7G Technology for Smart Intelligent Transportation Systems (S-ITS).

approach enhances the network's ability to withstand disruptions, maintain uptime, and protect sensitive data, ensuring the security and reliability of 7G services even in the face of sophisticated cyber threats [203].

- *Secure Authentication:* Blockchain enables robust identity management using cryptographic techniques, ensuring trusted communication between devices [204]. Secure Authentication in 7G networks is achieved through the blockchain's cryptographic protocols, which ensure that only authorized devices and users can access network resources [185]. In 7G, where many devices are interconnected, traditional authentication methods may struggle with scalability and vulnerability to spoofing or unauthorized access. Blockchain mitigates these challenges using public and private key cryptography, assigning each device a unique cryptographic identity [201], [205]. This identity is used to authenticate devices and users before allowing access to the network, ensuring that only legitimate entities can participate. Blockchain's decentralized nature eliminates the need for centralized authentication servers, reducing the risk of single points of failure [184], [206]. Multi-factor authentication (MFA) can also be integrated into blockchain-based systems, adding an extra layer of security by requiring users to provide additional verification forms [207], [208]. By ensuring secure and transparent authentication mechanisms, blockchain helps protect 7G networks from unauthorized access and cyberattacks while enabling trustless communication between devices in a highly dynamic environment [209].
- *Efficient Resource Allocation:* Blockchain can optimize resource sharing securely in 7G's hyper-connected ecosystems [55]. Efficient Resource Allocation in 7G networks using blockchain optimizes the distribution of resources such as bandwidth, storage, and processing power based on real-time demand [210]. In this environment, where devices and services generate varying demand levels, blockchain ensures that resources are allocated dynamically and fairly. Equation (3) represents the efficient resource allocation.

$$R_i = \frac{D_i}{\sum_{j=1}^{n} D_j} \times A_t \tag{3}$$

where R_i is the allocated resource for device or service i in the 7G network, D_i is the demand for device or service i, and A_t is the total available resources at time t (e.g., total available bandwidth or computational power). The equation ensures that resources are distributed proportionally according to each device's or service's demand, allowing high-priority services, such as autonomous vehicles or real-time healthcare applications, to receive the necessary resources. Blockchain's decentralized structure verifies and tracks resource allocation in real-time, ensuring transparency and preventing bottlenecks [211]. By removing the need for centralized control, blockchain enables efficient, scalable, and transparent resource management in 7G networks, ensuring optimal performance and preventing over-subscription across the entire system. Algorithm 1 shows an efficient resource allocation strategy using blockchain in 7G networks. It calculates the resource distribution based on the demand from each device, ensuring optimal utilization of available resources while maintaining an immutable record of transactions in the blockchain ledger. It includes dynamic adjustments based on real-time feedback to improve resource allocation performance.

Algorithm 1 Real Time Efficient Resource Allocation Algorithm Using Blockchain for 7G Networks

Input: Demand vector $\mathbf{D}(t) = [D_1(t), D_2(t), \ldots, D_n(t)]$ and Available Resources A_t at time t
Output: Allocated Resources $\mathbf{R}(t) = [R_1(t), R_2(t), \ldots, R_n(t)]$ and Updated Blockchain Ledger L
Function EfficientResourceAllocation($\mathbf{D}(t)$, A_t)
begin
  Initialize $t = 0$;
  Input demand vector $\mathbf{D}(0)$ and available resources A_0;
  foreach *device* i *in* $\{1, 2, \ldots, n\}$ **do**
    if $D_i(t) > 0$ **then**
      $R_i(t) \leftarrow \frac{D_i(t)}{\sum_{i=1}^{n} D_i(t)} \times A_t$;
  total_allocation $\leftarrow \sum_{i=1}^{n} R_i(t)$;
  if *total_allocation* $== A_t$ **then**
    Store transaction in blockchain ledger;
    Transaction $T_i = (R_i(t), D_i(t), t, signature_i)$;
    Append T_i to blockchain ledger L;
  else
    Trigger Reallocation;
    foreach *device* i **do**
      Recalculate $R_i(t) \leftarrow \frac{D_i(t)}{\sum_{i=1}^{n} D_i(t)} \times A_t$;
  if *Demand changes for any device* i **then**
    Recalculate $R_i(t+1) = \frac{D_i(t+1)}{\sum_{i=1}^{n} D_i(t+1)} \times A_t$;
  Feedback Adjustment:
  foreach *device* i **do**
    if *Feedback indicates performance issues* **then**
      Adjust $R_i(t+1) \leftarrow R_i(t) + \alpha \times (F_i(t) - D_i(t))$;
  Return $\mathbf{R}(t)$ and Updated Ledger L;

- *Data Privacy and Trust:* In 7G networks, data privacy and trust are crucial in the face of the growing complexity of connected devices and vast amounts of data [212]. Distributed blockchain security models address these concerns using decentralized architectures, ensuring that data is not stored in a single vulnerable location [213]. Cryptographic techniques such as asymmetric encryption (e.g., Rivest-Shamir-Adleman (RSA) and Elliptic Curve Cryptography (ECC)) ensure data confidentiality, while hash functions (e.g., Secure Hash Algorithm (SHA)-256) preserve data integrity and prevent tampering [214]. Consensus algorithms like Proof of Stake (PoS) and Practical Byzantine Fault Tolerance (PBFT) play a key role in ensuring trust, as they require network participants to agree on the validity of transactions, thereby preventing malicious actors from manipulating the system [215]. Zero-knowledge proofs (ZKPs) provide privacy by allowing data validation without revealing the data itself [216]. Together, these blockchain algorithms enable robust data privacy through encryption and hashing while maintaining trust through consensus and verifiable transactions, making them essential for securing data in 7G networks.
- *Scalability for Massive IoT:* Blockchain frameworks can handle the large-scale connectivity and transactions required in 7G networks [217]. Scalability for massive IoT in 7G networks is a critical challenge, given the sheer number of devices and their vast volume of data [218]. Blockchain offers a scalable solution by providing a decentralized, distributed ledger that can handle many devices without the bottlenecks associated with centralized systems [211], [219]. Using lightweight consensus algorithms such as Delegated Proof of Stake (DPoS) or sharding, blockchain networks can efficiently process a high throughput of transactions, ensuring IoT devices can securely communicate and share data without overwhelming the system [220], [221]. Creating sidechains or layer-2 solutions on top of the main blockchain enhances scalability by offloading some transaction processing while maintaining the primary network's security and integrity [222].

Scalability issues of blockchain in 7G networks revolve around high transaction throughput, ultra-low latency, and integration with decentralized applications. Due to consensus mechanisms like Proof of Work (PoW), traditional blockchain networks face bottlenecks, leading to delays and inefficiencies [201]. In a 7G environment, solutions such as sharding, layer-2 scaling (e.g., rollups, state channels), and advanced consensus models (e.g., Proof of Stake, Directed Acyclic Graphs) will be important for handling massive data volumes in real-time [223]. However, technical feasibility depends on optimizing smart contract execution, reducing computational overhead, and ensuring interoperability with AI-driven and edge-computing-based 7G architectures. The practical deployment will require balancing decentralization, security, and network efficiency to support blockchain-driven services in ultra-fast 7G ecosystems.

C. OVERCOMING BLOCKCHAIN BOTTLENECKS IN 7G BALANCING PERFORMANCE AND SECURITY

As 7G networks evolve to support ultra-high-speed communication, massive device connectivity, and real-time data processing, the integration of blockchain faces significant performance bottlenecks due to its inherent decentralization, high computational demands, and scalability limitations [124]. The dynamic nature of 7G networks, characterized by frequent topology changes, adaptive routing, and intelligent resource allocation, exacerbates these challenges, requiring blockchain to enhance its efficiency while maintaining security and decentralization [224]. Several advancements are being explored to overcome these bottlenecks. These include sharding techniques to parallelize transactions, layer-2 scaling solutions like state channels and rollups, and hybrid consensus mechanisms that balance security with transaction throughput. Integrating AI and edge computing in blockchain networks can optimize resource allocation, reduce latency, and improve adaptability in highly dynamic environments [225]. By harnessing these innovations, blockchain can maintain its core strengths of security, transparency, and immutability while efficiently supporting the high-speed, dynamic, and intelligent infrastructure of 7G networks, ultimately ensuring a balance between performance and security [226]. The following

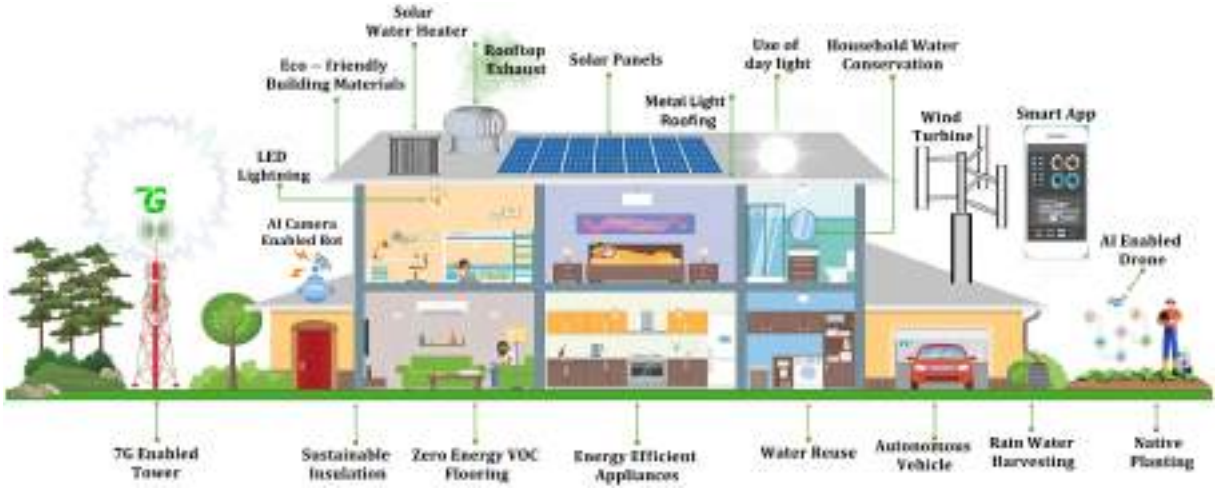

FIGURE 16. Eco-Friendly Zero-Energy Home Integrated with 7G Network and AI-Driven Smart Systems for Sustainable Living.

points show how blockchain technology can overcome performance bottlenecks while improving security to strike a balance in high-dynamism 7G networks:

- **Quantum Cryptography for Secure Blockchain Transactions:** 7G integrates QKD to enhance blockchain security, reducing computational overhead from traditional encryption. Quantum-resistant cryptographic algorithms prevent attacks, ensuring blockchain integrity against quantum computing threats.
- **AI-Enhanced Blockchain Optimization:** AI dynamically adjusts consensus mechanisms, optimizing transaction validation and reducing congestion. Predictive models improve smart contract execution, minimizing redundant computations and increasing blockchain efficiency.
- **Edge and Fog Computing for Decentralized Processing:** 7G networks use edge and fog computing to process blockchain transactions locally, reducing latency and improving throughput. Offloading computations to edge nodes decreases reliance on centralized processing, enhancing the speed of decentralized networks.
- **Terahertz (THz) Spectrum for Faster Blockchain Data Transmission:** Ultra-high-speed data transfer in the THz spectrum accelerates block propagation, reducing delays in transaction confirmation. Enhanced bandwidth allows for real-time blockchain synchronization across global networks.
- **Blockchain Sharding for Improved Scalability:** 7G supports blockchain sharding, enabling parallel processing of transactions across multiple smaller chains. Sharding reduces the load on individual nodes, significantly improving the blockchain's scalability and transaction throughput.
- **Holographic and Smart Meta-Surface Communication for Blockchain Efficiency:** Holographic networking optimizes blockchain data routing, ensuring faster block validation and consensus execution. Smart meta-surfaces minimize network interference, improving blockchain node communication and reducing synchronization delays.
- **AI-Driven Consensus Mechanisms for Energy Efficiency:** Advanced AI-powered PoS and hybrid consensus models reduce computational overhead while maintaining security. Adaptive consensus mechanisms adjust dynamically to network conditions, balancing speed, security, and energy consumption.

D. ZERO-ENERGY ENABLED 7G AND CELL-LESS ARCHITECTURES

The evolution from 5G to 6G and then to 7G represents a progressive leap in mobile network architectures, each generation aiming to address the growing demands for higher efficiency, faster speeds, and more sustainable operations [227]. In comparison, while 5G networks focus on enhancing mobile broadband, ultra-reliable low-latency communication, and massive machine-type communications, they still rely heavily on traditional cell-based architecture and centralized base stations [228], [229], which can lead to increased energy consumption and infrastructure requirements. In contrast, 6G introduces more advanced features such as integrated AI-driven networks, immersive experiences through holography and mixed reality, and broader use of terahertz (THz) frequencies for ultra-high-speed data transfer [124], [172], [230]. 6G networks still face challenges in terms of energy consumption due to the dense infrastructure and high-performance hardware required to manage the increased data traffic and complexity [231]. 7G, on the other hand, takes a transformative approach by incorporating Zero-energy-enabled solutions and cell-less architectures, which significantly differ from both 5G and 6G designs [171]. While 5G and 6G networks are still heavily reliant on centralized cell towers and energy-intensive infrastructure, 7G networks aim for a radical

shift, enabling self-sustaining networks powered primarily by renewable energy sources such as solar or wind. Zero-Energy Enabled 7G networks achieve this through energy harvesting techniques, AI-driven power management, and advanced storage systems, drastically reducing the operational energy requirements compared to 5G and 6G systems [90], [133]. Figure 16 shows a Zero-Energy home effectively integrated with a 7G-enabled network tower, facilitating ultra-fast, low-latency connectivity for efficient smart systems. This setup ensures real-time management of AI-driven devices like autonomous vehicles, energy-efficient appliances, and AI-enabled drones, promoting sustainability and enhanced living standards. The Cell-less Architecture of 7G, where networks no longer rely on traditional cellular towers and instead use distributed nodes and dynamic spectrum allocation [105], further reduces the energy footprint [28], [172]. In 5G and 6G, the dependence on centralized base stations still makes these networks less energy-efficient compared to the decentralized, energy-optimized 7G design, which minimizes the need for power-hungry infrastructure. 7G's reliance on low-power nodes for communication, equipped with technologies like distributed beamforming and intelligent routing, ensures ultra-efficient spectrum utilization without the need for fixed cell boundaries, marking a sharp contrast to the cell-based designs in 5G and 6G [37], [232]. This makes 7G more energy-efficient and increases scalability, as the network can dynamically adapt to traffic demands and environmental conditions without significant infrastructure overhead. Thus, while 5G and 6G represent important steps toward more efficient, high-speed networks, 7G offers a visionary shift towards energy sustainability, autonomy, and a radically new architecture that optimizes performance and environmental impact [233].

E. QUANTUM COMPUTING AND SECURITY

Quantum computing holds transformative potential for enhancing security and efficiency in 7G networks, addressing critical shortcomings of previous generations such as 4G, 5G, and 6G [14]. While 4G networks struggled with data overload and susceptibility to cyberattacks, 5G improved latency and connectivity but faced privacy and quantum-resilient encryption challenges [241]. 6G aims to provide terahertz bandwidth and integration of AI-driven applications but remains vulnerable to emerging quantum threats due to its reliance on classical cryptographic algorithms [205]. Quantum computing in 7G networks overcomes these limitations by enabling quantum-safe encryption, ultra-fast data processing, and secure key distribution through QKD [126]. This ensures robust security frameworks that protect massive IoT ecosystems, critical infrastructure, and user privacy, paving the way for resilient and future-proof communication systems. Table 8 highlights quantum security algorithms for 7G networks, focusing on their technical aspects, challenges, and applications. Algorithms like BB84 and E91 ensure secure key distribution, while Quantum Random Number Generator (QRNG) and lattice cryptography enhance randomness and scalability. It also covers Grover's and Shor's algorithm resistance, which is critical for securing cryptosystems, and Limited Vision Quantum Computing (BQC), which supports privacy-preserving computations despite hardware limitations.

Quantum computing's integration into 7G networks depends on technical feasibility and practical deployment challenges. While quantum algorithms offer advantages in ultra-fast computation, network optimization, and QKD for unbreakable encryption, current quantum hardware faces limitations in qubit stability, error correction, and large-scale deployment [129]. Practical landing possibilities remain constrained by the lack of fault-tolerant quantum processors and reliable quantum networking infrastructure. Hybrid quantum-classical models may serve as transitional solutions, but full-scale implementation in 7G networks requires breakthroughs in quantum error correction, scalable qubit architectures, and interoperability with classical systems [242].

Quantum communication transforms data transmission by ensuring ultra-secure and high-speed connectivity [130], [243]. Key advancements, such as dynamic resource allocation and AI-driven optimization, harness quantum technologies to enhance efficiency. Within 7G networks, quantum communication is essential across multiple key areas, including:

- *Quantum Resource Allocation Optimization Through Superposition and Entanglement:* 7G networks require highly dynamic and adaptive resource allocation to manage ultra-dense environments, intelligent connectivity, and real-time autonomous applications. Classical optimization methods such as Linear Programming (LP) and Game Theory face computational inefficiencies due to the complexity of large-scale networks [244]. Quantum computing uses superposition and entanglement and allows simultaneous evaluation of multiple resource allocation states, significantly improving efficiency [56], [243]. In classical networks, resource allocation problems are typically formulated as convex optimization [245]. Quantum Approximate Optimization Algorithm (QAOA) enhances this process by transforming the optimization problem into a Hamiltonian formulation [246]:

$$H = H_C + H_M \tag{4}$$

  where H_C encodes the cost function, and H_M applies mixing terms that allow quantum states to explore multiple solutions. The system evolves according to the time-dependent Schrödinger equation [247]:

$$i\hbar \frac{d}{dt}|\psi(t)\rangle = H|\psi(t)\rangle. \tag{5}$$

  This quantum-driven optimization approach enables 7G networks to dynamically allocate resources with reduced

TABLE 8. Technical analysis of quantum security algorithms for 7G networks

Algorithm/Technique	Input Requirements	Key Features	Challenges	7G Use Case
BB84 Protocol (QKD) [234]	Quantum states (polarized photons)	Secure key exchange; detects eavesdropping	Sensitive to noise and transmission loss	Dynamic encryption for IoT devices
E91 Protocol (Entanglement-Based QKD) [235]	Entangled photon pairs	Improved security using entanglement	Requires entanglement generation devices	Quantum-safe communications for UAVs
Post-Quantum Lattice Cryptography [236]	Large-dimensional lattice structures	Resistant to Shor's algorithm; scalable	Computationally intensive for mobile nodes	Securing 7G IoT ecosystem
Quantum-Resistant Signatures (CRYSTALS-DILITHIUM) [237]	Polynomial-based signatures	Compact and quantum-safe digital signatures	May require higher bandwidth for key sizes	Authentication for 7G edge devices
Quantum Random Number Generators (QRNG) [238]	Photonic quantum devices	Unpredictable keys, high randomness entropy	Requires integration into existing hardware	Key generation for secure network access
Grover's Algorithm [56]	Large search spaces for symmetric keys	Reduces search complexity to $O(\sqrt{N})$	Potential vulnerability for weak hash algorithms	Authentication and anomaly detection
Shor's Algorithm Resistance [139]	Cryptosystems with large (>2048-bit) keys	Protects against quantum factorization	High computational overhead for long keys	Protecting 7G blockchain and identity data
Blind Quantum Computing (BQC) [240]	Quantum states for computation offloading	Secure delegation of computations to quantum servers	Limited by current quantum hardware	Privacy-preserving computations in 7G edge computing

computational complexity, ensuring efficient bandwidth distribution and real-time decision-making.

- *QKD Security Through Entropy and Probability:* Security in 7G networks must withstand future quantum-based attacks, which can compromise classical encryption. QKD ensures unbreakable security using the principles of quantum mechanics, particularly Heisenberg's uncertainty principle and the no-cloning theorem [175]. The security of QKD is analyzed through the Quantum Bit Error Rate (QBER), defined as:

$$QBER = \frac{N_{\text{error}}}{N_{\text{total}}} \tag{6}$$

where N_{error} is the number of erroneous bits detected, and N_{total} is the total number of transmitted bits. A higher QBER indicates possible eavesdropping attempts. The entropy of the key exchange process is determined using:

$$H(X|E) = H(X) - I(X;E), \tag{7}$$

where $H(X)$ represents the entropy of the key, and $I(X;E)$ is the information leakage to an eavesdropper. The Holevo bound places an upper limit on the accessible information available to an attacker:

$$I(X;E) \leq S(\rho_E) - \sum_x p_x S\left(\rho_E^x\right). \tag{8}$$

These quantum security mechanisms ensure that 7G networks remain resilient against cyber threats, providing secure communication for applications requiring high-level encryption, such as financial transactions, autonomous vehicle networks, and critical infrastructure.

- *Quantum Teleportation Latency-Free Communication:* Latency is a critical factor in 7G networks, affecting applications such as real-time control systems, remote surgeries, and autonomous vehicles [248]. Quantum teleportation offers a revolutionary approach by enabling instantaneous state transfer using quantum entanglement, eliminating classical propagation delays [37]. Quantum teleportation relies on Bell state representation:

$$|\Phi^+\rangle = \frac{|00\rangle + |11\rangle}{\sqrt{2}}, \quad |\Phi^-\rangle = \frac{|00\rangle - |11\rangle}{\sqrt{2}}. \tag{9}$$

When Alice and Bob share an entangled state, Alice can encode an arbitrary quantum state:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle. \tag{10}$$

Alice measures her qubit and transmits classical information to Bob, who applies a corresponding unitary operation:

$$U = \begin{cases} I, & \text{if Alice measures } |\Phi^+\rangle \\ \sigma_x, & \text{if Alice measures } |\Phi^-\rangle \\ \sigma_z, & \text{if Alice measures } |\Psi^+\rangle \\ \sigma_x\sigma_z, & \text{if Alice measures } |\Psi^-\rangle \end{cases} \tag{11}$$

where σ_x and σ_z are Pauli matrices. This allows quantum information to be transferred instantaneously, making ultra-low latency applications viable in 7G networks.

- *Quantum-Assisted AI and Statistical Learning in 7G:* AI plays a significant role in 7G for real-time data analytics, traffic prediction, and self-optimizing networks [249]. Classical machine learning relies on solving large linear systems:

$$A\mathbf{x} = \mathbf{b}, \tag{12}$$

where A is an $n \times n$ matrix. The classical solution requires $O(n^3)$ operations, but quantum-assisted AI using the Harrow-Hassidim-Lloyd (HHL) algorithm

solves this in $O(\log n)$ time [250]. The eigenvalue decomposition allows for exponential speedup:

$$A = V\Lambda V^{-1}, \quad x = A^{-1}b = V\Lambda^{-1}V^{-1}b. \tag{13}$$

This enables real-time optimization in 7G networks, significantly improving performance for intelligent decision-making applications.

Integrating quantum computing into 7G networks faces significant technical and economic challenges. The high cost, scalability issues, and energy demands of quantum systems create barriers to widespread adoption, requiring further research and innovation to make them practical for real-world deployment. The following will show the key technical bottlenecks and economic costs of quantum computing in 7G networks.

- **Qubit Stability and Error Correction:** Quantum computing in 7G networks requires highly stable qubits, but their susceptibility to decoherence and noise leads to high error rates, demanding complex error correction mechanisms.
- **High Infrastructure and Deployment Costs:** Quantum computing hardware, including cryogenic cooling systems [251] and specialized materials, is extremely expensive, making large-scale integration into 7G networks economically challenging.
- **Limited Scalability for Real-Time Processing:** Scaling quantum processors to handle real-time 7G network optimization and data processing is difficult due to constraints in qubit connectivity and quantum gate fidelity.
- **Energy-Intensive Operations:** While quantum computing promises efficiency, maintaining quantum coherence in a 7G network environment requires significant power, increasing energy consumption concerns.
- **Uncertain Commercial Viability:** The long timeline for quantum computing advancements makes its immediate integration into 7G networks uncertain, raising concerns about return on investment for telecom companies.

F. TERAHERTZ COMMUNICATIONS

Terahertz (THz) communications in 7G networks mark a substantial leap over 4G, 5G, and even the emerging 6G technologies, primarily by utilizing frequencies between 0.1 THz and 10 THz, enabling unprecedented data rates up to several terabits per second (Tbps) [126]. Unlike 4G, which operates below 6 GHz and is constrained to megabits per second (Mbps), and 5G, which expands into millimeter waves (24–100 GHz) with gigabits per second (Gbps) speeds, THz waves use ultra-wide bandwidths to achieve exponential growth in spectral efficiency [118]. THz frequencies in 7G enable micro and nano-scale applications, including nanosensor networks, which are unattainable with 5G or 6G [252]. While 6G aims to operate in the sub-THz range (100–300 GHz), its range and penetration are significantly limited compared to THz in 7G, where beamforming and massive antenna arrays mitigate such limitations [253]. For 7G, the bandwidth B increases dramatically in the THz range, achieving much higher R than 6G. In atmospheric attenuation in THz bands, described by $\alpha(f, T, p)$, where f is frequency, T is temperature, and p is pressure, poses challenges addressed through intelligent relay systems and adaptive modulation techniques. Unlike 4G's reliance on centralized architectures and 5G's edge computing extensions, 7G with THz incorporates decentralized processing and real-time AI-assisted dynamic resource allocation [254]. This enables seamless support for ultra-dense environments, holographic communications, and multi-sensory telepresence, positioning 7G and THz communications as transformative technologies for future connectivity.

The deployment of terahertz (THz) communication in 7G networks introduces new concerns regarding its potential effects on human health. THz waves operate at extremely high frequencies, interacting with biological tissues in ways that may impact cellular structures and physiological functions. The following are the key health impacts of terahertz communication in the 7G network:

- **Biological Effects of Terahertz Radiation:** Terahertz (THz) radiation primarily affects biological tissues through molecular interactions. Its high-frequency waves can cause molecular vibrations, leading to localized heating and potential structural changes in proteins and cells. Since THz waves do not penetrate deeply, their effects are concentrated on surface tissues like the skin and eyes [255].
- **Health Concerns and Safety Standards:** Exposure to THz radiation raises concerns about long-term biological impacts, particularly regarding thermal effects and molecular disturbances. High-frequency radiation can alter normal physiological functions by influencing cellular activities. Safety standards are being developed to regulate permissible exposure levels and prevent excessive absorption of THz waves [255].
- **Potential Risks to Human Cells and DNA:** THz waves may influence DNA stability by inducing molecular vibrations, which could impact genetic material and cellular repair mechanisms. Repeated exposure could cause cellular stress, potentially affecting biological processes such as cell division and protein synthesis. While THz radiation is non-ionizing, its high-frequency interactions raise concerns about genetic alterations [256].
- **Impact on Skin and Eyes:** The skin, being the first point of contact, absorbs THz radiation, which may lead to heating effects and tissue alterations. Prolonged exposure could affect skin hydration, collagen structure, and barrier functions. The eyes, particularly the cornea, are vulnerable to THz radiation, potentially leading to changes in ocular tissues that may impact vision [257].

- **Neurological and Physiological Effects:** THz waves may interact with nerve cells, influencing neural activity and possibly affecting cognitive functions. There are concerns that exposure could alter metabolic processes, immune responses, and hormone regulation. Changes in nervous system function due to THz interactions could also impact coordination, reflexes, and neurological health [258].
- **Molecular Absorption Effect:** THz radiation is strongly absorbed by polar molecules, such as water and biomolecules, in the human body [259]. This absorption can lead to vibrational excitation, influencing molecular structures and biological functions. The interaction of THz waves with biomolecules may alter chemical reactions, protein folding, and enzymatic activities, potentially affecting cellular function.

A key enabler of 7G is terahertz (THz) communication, which operates in the frequency range of 0.1–10 THz, providing ultra-wideband spectrum for unprecedented data speeds. However, deploying THz communication in real-world 7G networks presents several challenges:

- **Limited Penetration Through Obstacles:** THz waves cannot easily pass through walls, buildings, or human bodies, necessitating a dense deployment of base stations and relay networks for continuous connectivity.
- **High Hardware Complexity and Cost:** THz transceivers and antennas require advanced materials like graphene and plasmonics, increasing production costs and challenging large-scale deployment.
- **Environmental Sensitivity:** Rain, fog, and dust cause severe attenuation of THz signals, reducing their reliability for outdoor applications and requiring adaptive channel reconfiguration.
- **High Energy Consumption and Heat Dissipation:** THz communication demands significant power, leading to excessive energy consumption and overheating issues that require efficient thermal management.
- **Interference and Spectrum Allocation:** THz frequencies need careful spectrum management to avoid interference with satellite, military, and scientific applications, requiring AI-driven frequency optimization.
- **Security and Privacy Concerns:** While highly directional, THz signals are vulnerable to jamming and blockage, necessitating advanced security solutions like quantum encryption and blockchain authentication.
- **Standardization and Regulatory Challenges:** Global standards for THz spectrum allocation, transmission power, and interference management are still evolving, creating challenges for international deployment.
- **Integration with 7G Network Architecture:** THz communication must work alongside AI-driven intelligent networks, reconfigurable intelligent surfaces (RIS), and hybrid wireless solutions for seamless 7G connectivity.

G. SATELLITE COMMUNICATIONS AND UNIVERSAL INTEGRATION

Satellite communications and universal integration represent pivotal advancements in the evolution of the 7G network aimed at achieving seamless global connectivity [260], [261]. Unlike 4G, which primarily relies on terrestrial infrastructure with limited satellite involvement for specific use cases, and 5G, which introduces Low Earth Orbit (LEO) satellites to extend coverage in remote regions [262], 7G is expected to integrate satellites into its architecture as a core component fully. This integration will support ubiquitous communication by combining terrestrial, aerial, and satellite networks into a unified framework, enabling continuous coverage across oceans, rural landscapes, and polar regions. While 6G moves closer to this goal by exploring the potential of high-throughput satellites and hybrid networking, its satellite capabilities often remain auxiliary rather than intrinsic to its framework [66]. In 7G, satellite networks will transition from a complementary role to a foundational infrastructure, driven by technological innovations in AI, edge computing, terahertz (THz) communications, quantum networking, and Reconfigurable Intelligent Surfaces (RIS) [263]. Unlike 6G, where satellites primarily serve as an extension for remote coverage, 7G will deeply integrate space-based communication with terrestrial and aerial networks, forming a truly ubiquitous, intelligent, and global network [264], [265]. This shift is made possible by AI-driven network orchestration, allowing dynamic spectrum allocation, predictive load balancing, and real-time optimization of data routing across terrestrial and Non-Terrestrial Networks (NTN).

Projects like Starlink,[2] OneWeb,[3] and Amazon Kuiper[4] already demonstrate the feasibility of large-scale, Low-Earth Orbit (LEO) constellations with high-throughput, low-latency capabilities. Nevertheless, 7G will take this further by utilizing advanced Inter-Satellite Links (ISLs) that create a self-sufficient space-based mesh network, reducing dependency on ground stations and improving real-time global coverage. The convergence of quantum communications and satellite technology will enable highly secure, ultra-reliable transmissions essential for defense, financial, and critical infrastructure applications [260].

Beyond infrastructure, emerging applications such as immersive holographic communications, space-based IoT, and AI-driven predictive analytics for climate monitoring, disaster response, and autonomous vehicle ecosystems will rely on the enhanced role of satellites [172]. In addition, satellite networks in 7G will integrate with Autonomous aerial vehicles (AAVs) and High-Altitude Platform Stations (HAPS) to create a multi-layered communication environment, ensuring connectivity even in highly dynamic or extreme conditions [266]. As these innovations unfold,

[2]https://www.starlink.com/technology
[3]https://oneweb.net/our-network
[4]https://www.aboutamazon.com/what-we-do/devices-services/project-kuiper

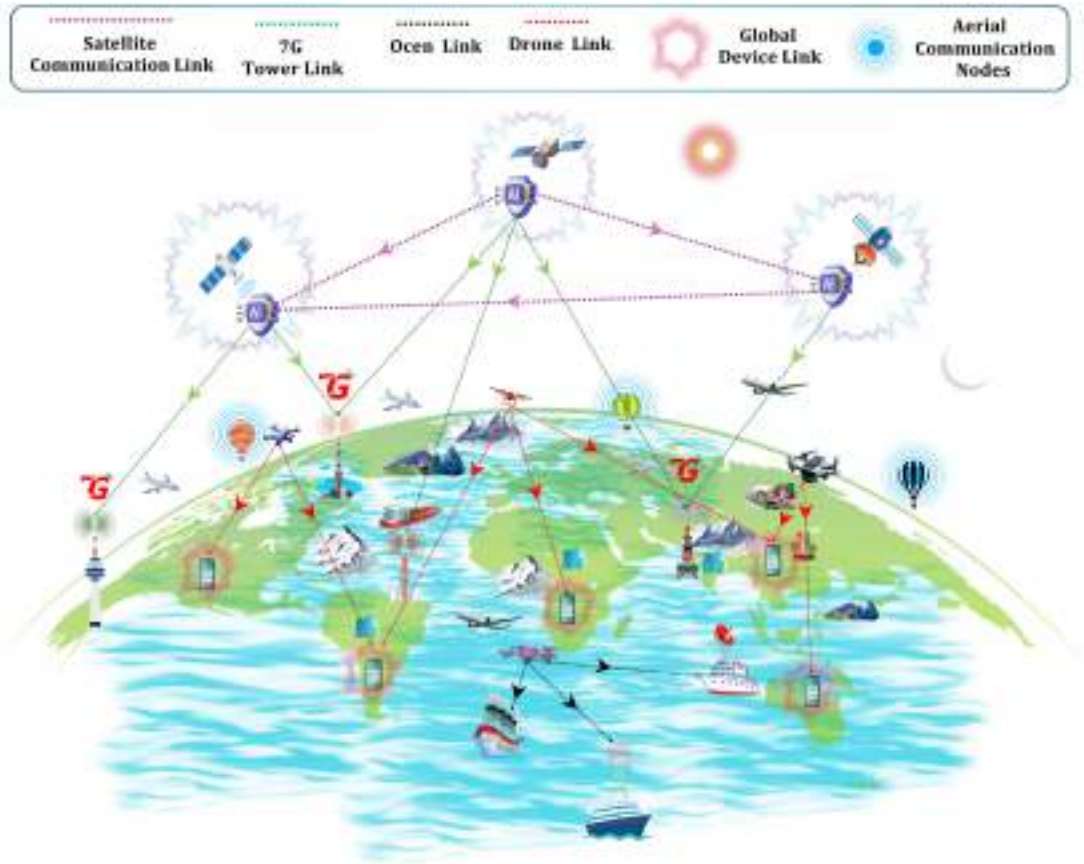

FIGURE 17. Satellite Communications and Universal Integration Powered by 7G and AI: A unified network connecting terrestrial, aerial, and maritime systems through satellites, 7G towers, drones, and AI-driven technologies for real-time global connectivity.

satellites will no longer be secondary components but key enablers of a seamless, intelligent, omnipresent communication framework that defines the 7G era.

- **Role of Satellite Networks in 7G:** 7G is set to revolutionize global connectivity by integrating advanced satellite networks into its architecture. Unlike previous generations, which relied heavily on terrestrial infrastructure, 7G will harness the power of LEO satellite constellations such as those deployed by Starlink to enable seamless, high-speed, and ultra-low latency communication worldwide [267].
- **Technological Innovations in 7G Satellite Networks:** The technological advancements in 7G will optimize satellite networks through next-generation low-latency connectivity, AI-driven beamforming, and quantum-enhanced security. Unlike traditional geostationary satellites at 35,786 km, which cause latencies of over 600 ms, 7G will utilize LEO satellites at 550 km, reducing latency to 25 ms and enabling real-time applications like streaming, gaming, and video calls. AI-driven dynamic beamforming will optimize bandwidth allocation, reduce congestion, and improve efficiency. Also, 7G will integrate quantum encryption and AI-based anomaly detection to enhance security in satellite communications [126].
- **Architectural Optimization for 7G Integration:** 7G will optimize satellite network architectures by utilizing multi-layered hybrid networks, mesh-based satellite constellations, and edge computing at the satellite level. By efficiently integrating terrestrial and non-terrestrial networks (NTN), 7G will ensure continuous, high-speed connectivity in rural, remote, and disaster-stricken areas. Like Starlink, interconnected satellite mesh networks will enhance resilience and data transmission speeds without relying solely on ground stations. Onboard AI processing will enable satellites to perform real-time computations closer to the user, reducing the need for centralized data processing and minimizing latency [268].
- **Emerging 7G Applications Enabled by Satellites:** With enhanced satellite integration, 7G will enable applications previously unattainable with traditional satellite networks, including global 3D holographic communications, AI-driven smart cities, immersive technologies, and advanced disaster recovery networks. Ultra-low latency satellite connections will support real-time holographic interactions, eliminating communication delays across continents. Intelligent satellite networks will provide continuous IoT connectivity, powering autonomous vehicles, remote industrial automation, and AI-driven smart grids. High-bandwidth

XR applications, including AR/VR and metaverse interactions, will be accessible worldwide without reliance on fiber-optic networks. 7G's satellite backbone will facilitate rapid deployment of emergency networks in disaster-stricken or unconnected regions, ensuring efficient coordination of humanitarian aid [269].

7G envisions satellites to eliminate the digital divide, offering high-speed, low-latency connectivity and ensuring universal service access. 7G is anticipated to incorporate advanced satellite capabilities, such as dynamic resource allocation, real-time data processing, and direct-to-device communication without intermediary ground stations, which surpasses the dependence on intermediary infrastructures seen in earlier generations [270]. By achieving tight integration between satellites and terrestrial networks, 7G sets the stage for robust interoperability, secure connections, and global scalability, marking a significant departure from the fragmented approaches of 4G, 5G, and the transitional improvements in 6G [271]. The following points show the innovations in satellite communications and how 7G networks adopted them for universal integration. Figure 17 shows the comprehensive framework of global connectivity enabled by AI-powered satellite communications and 7G network. The illustration emphasizes the integration of terrestrial, aerial, and maritime networks through advanced communication infrastructures. Key elements include inter-satellite links for global data synchronization, ground-to-satellite communication for real-time data transmission, and 7G towers facilitating ultra-fast connectivity for smart devices and IoT systems.

- *Comprehensive Global Coverage:* 7G integrates satellites with terrestrial and aerial networks to provide seamless global connectivity, bridging the digital divide [265]. This approach ensures uninterrupted communication in remote areas, including oceans and polar regions, unlike 4G's reliance on terrestrial towers and 5G's limited satellite use.
- *Direct-to-Device Quantum Communication:* By incorporating quantum technologies, 7G enables secure direct-to-device communication via satellites. QKD ensures tamper-proof encryption, providing unparalleled security [272]. This marks a significant improvement over 6G's preliminary exploration of quantum technology, making it a central element in 7G's secure architecture.
- *Edge Computing for Real-Time Processing:* 7G integrates edge computing into satellite and terrestrial systems, enabling real-time data processing at the network's edge [273]. Unlike earlier networks, where most processing occurs in centralized data centers, 7G reduces latency and bandwidth usage by performing computations closer to the source.
- *Network Optimization through Predictive Technologies:* Predictive technologies optimize network performance, satellite positioning, and resource allocation in 7G networks [274]. These systems anticipate demand, dynamically adjust bandwidth, and efficiently manage traffic, offering improved performance compared to 5G and 6G static systems.
- *Dynamic Resource Allocation with Quantum Computing:* Quantum computing in 7G drives dynamic resource allocation by analyzing massive datasets with unparalleled speed [275]. This ensures efficient bandwidth and processing power distribution, enabling the network to handle global demands while maintaining energy efficiency.
- *Unified Network Infrastructure:* Through integrating advanced technologies, 7G combines terrestrial, aerial, and satellite networks into a cohesive system [276], [277]. This ensures seamless transitions between communication layers, supporting diverse applications such as autonomous vehicles, smart cities, and global IoT.

H. INTERNET OF EVERYTHING (IOE)

The Internet of Everything (IoE) represents a transformative paradigm where people, processes, data, and things are interconnected to create intelligent, adaptive systems that enhance decision-making and automation [278]. In 4G, IoE was in its nascent stage. It was limited by low data speeds, high latency, and the inability to support massive device connectivity, which restricted its applications to basic smart devices and industrial automation [279]. With 5G, IoE gained momentum through improved speeds, reduced latency, and higher device density, enabling advancements in smart homes, connected vehicles, and industrial IoT [132], [280]. The scope remained constrained to specific regions due to its reliance on terrestrial networks. The transition to 6G introduced edge computing and AI integration, enhancing IoE by enabling localized real-time processing and expanding applications like remote healthcare and autonomous systems [281]. 6G's dependence on fragmented hybrid networks still limited its universal reach. In contrast, 7G will redefine IoE by integrating satellite, aerial, and terrestrial networks into a unified framework that ensures global connectivity, even in remote areas [282]. It will enable real-time, low-latency communication between billions of devices and leverage advanced technologies like quantum computing and AI to process and analyze data instantaneously at scale. This will drive the next wave of IoE applications, including fully autonomous supply chains, global smart city ecosystems, and interconnected environmental monitoring systems, far surpassing the capabilities of its predecessors. 7G will propel IoE to its full potential by ensuring ubiquitous connectivity and intelligent resource allocation, creating a truly interconnected world [283]. Table 9 shows the details of various sensors used in IoE applications across 4G to 7G networks, focusing on their technical capabilities. It includes key parameters such as precision, range, response time, and environmental adaptability. AI integration capability and security compliance are marked to highlight the suitability of each sensor for modern network applications.

TABLE 9. Sensor technologies and applications for Internet of Everything (IoE) in 4G, 5G, 6G, and 7G networks.

Sensor Name	Application Field	Purpose	Network Technology	Precision	Range (meters)	Response Time (ms)	Environmental Adaptability (°C)	AI Integration Capability	Security Compliance Level
LiDAR	Autonomous Vehicles	Obstacle Detection, Navigation	5G/6G	±2 cm	100-200	0.1	-20 to 85	✓	✓
Thermal Imaging Sensor	Healthcare	Patient Monitoring, Thermal Screening	4G/5G	±0.5°C	0.5-3	0.5	-10 to 60	✓	✓
MEMS Accelerometer	Industrial Automation	Vibration Analysis	4G/5G/6G	±0.01 g	0.1-2	0.01	-40 to 125	✓	✗
pH Sensor	Agriculture	Soil Quality Monitoring	4G/5G	±0.1 pH	0.05-0.2	0.05	-10 to 50	✗	✗
Smart Camera	Smart Surveillance	Facial Recognition, Traffic Monitoring	5G/6G	±0.001 pixels	50-300	0.1	-10 to 50	✓	✓
Gas Sensor (CO2)	Environmental Monitoring	Air Quality Measurement	4G/5G/6G	±10 ppm	0.1-50	0.2	-40 to 85	✓	✓
Radar	Transportation	Speed Detection, Weather Monitoring	5G/6G	±1 m/s	0.2-200	0.05	-40 to 125	✓	✓
Quantum Sensor	Quantum Communication	Quantum State Measurement	7G	$\pm 10^{-9}$	0.01-1	0.001	-20 to 60	✓	✓
Optical Fiber Sensor	Smart Cities	Structural Health Monitoring	6G/7G	±0.001 mm	0.1-1000	0.02	-40 to 85	✓	✓
Bioelectric Sensor	Wearable Technology	Heart Rate, EMG, EEG Measurement	5G/6G/7G	±0.01 mV	0.01-0.5	0.01	0 to 50	✓	✓
RFID Sensor	Logistics and Inventory	Real-Time Asset Tracking	4G/5G	±0.5 m	0.01-100	0.02	-20 to 85	✓	✓
Piezoelectric Sensor	Energy Harvesting	Vibration-Based Power Generation	5G/6G/7G	±0.1 µm	0.01-5	0.01	-40 to 125	✓	✗
Humidity Sensor	Agriculture and Smart Homes	Environmental Humidity Monitoring	4G/5G	±2%	0.1-10	0.15	-10 to 50	✗	✓
Ultrasonic Sensor	Automotive and Robotics	Obstacle Detection, Depth Measurement	4G/5G/6G	±0.1 cm	0.05-10	0.01	-40 to 85	✓	✓
IR Sensor	Consumer Electronics	Motion Detection, Proximity Sensing	4G/5G	±0.1 cm	0.01-2	0.005	-20 to 60	✗	✗
Biosensors (Glucose)	Healthcare	Continuous Glucose Monitoring	5G/6G	±2 mg/dL	0.01-0.1	0.1	0 to 50	✓	✓

I. EXPLAINABLE AI (XAI) IN 7G: ENHANCING TRANSPARENCY AND TRUST

Generative AI is poised to become a cornerstone of 7G networks, enabling hyper-realistic simulations, personalized digital services, and real-time content generation with minimal latency [284]. Unlike 4G, 5G, and even 6G, which provide significant advancements in connectivity and data processing, these networks fall short in key areas critical to Generative AI's full potential [23]. For example, 4G lacks the bandwidth and low-latency characteristics necessary to handle large-scale AI models efficiently, making it unsuitable for real-time generative applications such as autonomous systems or immersive XR experiences. While 5G improves on these limitations, its edge computing capabilities and network slicing still struggle with the vast computational demands and ultra-high bandwidth requirements of next-generation Generative AI tasks like holographic communications or AI-driven robotics [285]. Even 6G, though incorporating AI at the core of its infrastructure, may face challenges in areas such as real-time quantum AI or distributed neural network training due to its reliance on evolving hardware and software ecosystems.

7G, in contrast, integrates AI deeply into its infrastructure, using native AI-driven optimizations like automated decision-making, self-healing networks, and AI-accelerated data compression. Generative AI in 7G benefits from enhanced capabilities like quantum AI for solving large-scale optimization problems, neuromorphic computing for more energy-efficient and adaptive AI models, and bio-inspired AI for advanced problem-solving [286]. These technologies support applications such as real-time language synthesis, predictive healthcare simulations, and fully autonomous vehicles.

Future AI developments for 7G are expected to include explainable AI (XAI) to enhance transparency and trust, swarm AI for managing complex, interconnected systems, and hyper-efficient AI models designed to operate on ultra-low-power devices [287]. The advent of ethical AI will play a pivotal role, ensuring that AI systems in 7G prioritize user safety, privacy, and inclusivity, paving the way for a more intelligent, connected future.

Explainable AI (XAI) is a critical component of the 7G network infrastructure, designed to ensure transparency, accountability, and trust in AI-driven decisions [288]. Unlike traditional "closed box" AI systems, XAI in 7G provides

FIGURE 18. Explainable AI (XAI) in 7G: Redefining Transparency and Trust through Real-Time Interpretability, Blockchain Integration, and Neuromorphic Advancements.

clear, interpretable insights into how AI models generate predictions or outcomes [289]. This is particularly crucial for applications such as healthcare diagnostics, autonomous transportation, and financial risk assessment, where understanding the rationale behind decisions is essential. By integrating XAI, 7G enables users and stakeholders to evaluate AI outputs better, fostering greater adoption of advanced AI systems in sensitive and critical domains. 7G networks are inherently designed to integrate AI at every level, from core infrastructure to edge devices. This enables seamless deployment of advanced AI models, such as Explainable AI (XAI), for real-time interpretability and decision-making [290]. Figure 18 shows the transformative role of Explainable AI (XAI) in 7G networks, emphasizing enhanced transparency and trust. It highlights key innovations such as real-time interpretability, blockchain integration, and neuromorphic computing for advanced data processing. These advancements ensure cross-domain compatibility, self-healing networks, and quantum-powered model transparency, paving the way for dynamic and decentralized XAI systems. Using XAI natively, 7G optimizes resource allocation and enhances system adaptability, ensuring superior performance across various applications, as shown below.

- *Real-Time Interpretability:* 7G harnesses its ultra-low latency (<1 ms) and high bandwidth (>1 Tbps) capabilities to deliver real-time explanations for AI-driven decisions [28]. This is vital for applications such as autonomous vehicles, where split-second decisions can save lives. AI system navigating a self-driving car can instantly explain why it brakes or changes lanes, ensuring safety and user confidence. In healthcare, real-time interpretability allows AI-powered diagnostics to explain anomalies in medical imaging or justify treatment recommendations, enabling trust between medical professionals and patients [291].
- *Decentralized XAI Systems:* 7G implements distributed AI architectures that bring XAI capabilities closer to the network edge [292]. Localized models can process and interpret data on-site without relying on centralized servers. For instance, wearable health devices can provide immediate feedback and explanations about vital signs, ensuring patient privacy and reducing dependency on external systems. Similarly, in smart cities, localized XAI enables quick and interpretable decisions for managing traffic lights or responding to emergencies tailored to the immediate context of a situation [293].
- *Enhanced Data Processing with Neuromorphic Computing:* Neuromorphic processors in 7G mimic the human brain's neural structure, offering energy-efficient AI computation [294]. This allows complex XAI models to run on low-power edge devices like IoT sensors, drones, or wearables. For example, a neuromorphic processor in a smart home device can explain its decision to adjust temperature or lighting based on user behavior patterns, all while consuming minimal power. These processors make XAI scalable across billions of interconnected devices within 7G's IoE ecosystem [295].
- *Quantum Computing for Model Transparency:* Quantum computing integrated into 7G accelerates the analysis of large-scale AI models, enabling clearer and more detailed explanations. Quantum AI can dissect complex decision-making processes, such as those used in predictive analytics for stock market trends or disaster management [296]. The quantum-enhanced XAI model could explain why it predicts a specific financial crash or hurricane trajectory, providing stakeholders with confidence in its accuracy and reasoning.
- *Integration with Blockchain:* 7G networks use blockchain technology to ensure that AI explanations and decision logs are securely recorded and tamper-proof. This is particularly important for sensitive applications like financial fraud detection or legal adjudications, where audit trails are essential [297]. Blockchain-secured XAI systems in banking can provide transparent justifications for flagging fraudulent transactions while retaining immutable records for compliance and regulatory purposes.
- *Dynamic Network Slicing for XAI Applications:* 7G enables dynamic allocation of network resources to XAI applications using network slicing. This ensures critical use cases, such as AI-driven medical diagnostics or emergency response systems, receive priority bandwidth and computational power access [298]. For instance, during a crisis, 7G can allocate slices to XAI systems managing disaster relief logistics, ensuring rapid, interpretable decisions on resource allocation and response strategies.
- *XAI-Driven Self-Healing Networks:* With self-healing capabilities powered by XAI, 7G can detect and resolve network issues autonomously while providing interpretable insights into the cause and resolution of faults [299]. If a node fails in a smart grid, the network can automatically reroute resources while explaining the

issue to operators in real-time. This improves network reliability and builds trust in automated processes.

- *Cross-Domain Compatibility:* XAI in 7G operates across diverse sectors, including healthcare, finance, transportation, and education. Its cross-domain compatibility ensures consistent explainability regardless of the application [298]. For instance, XAI can justify a diagnosis in a healthcare setting, explain stock predictions in finance, or clarify traffic optimization decisions in smart cities, adapting to the unique requirements of each domain.

VI. ROLE OF AI AND MACHINE LEARNING FOR SHAPING 7G NETWORKS

The emergence of 7G networks marks a transformative era in wireless communication, driven by the need to meet unprecedented demands for uninterrupted connectivity, ultra-low latency, and intelligent network operations. As the digital world increasingly relies on hyper-connected ecosystems, 7G networks are envisioned to support applications like immersive metaverses, real-time augmented reality, autonomous systems, and large-scale IoT deployments [300].

These networks must provide high-speed data transmission and incorporate intelligence to manage future applications' complex and dynamic requirements. Advanced technologies like Artificial Intelligence (AI) and Machine Learning (ML) are indispensable in this evolution, enabling 7G to achieve unparalleled adaptability and efficiency [92]. Meta-learning, often called "learning to learn", allows 7G systems to adapt to new environments or tasks with minimal retraining dynamically, ensuring real-time responsiveness [301], [302]. Transfer learning facilitates the reuse of pre-trained models, reducing computational overhead and enabling knowledge transfer across diverse network scenarios [303]. Large Language Models (LLMs), known for processing and analyzing vast amounts of data, can be integrated into 7G at the edge, enabling real-time decision-making and enhanced contextual understanding for edge devices [304]. Split learning, by distributing the model training process between devices and the cloud, ensures data privacy and reduces the computational burden on individual devices, making it a critical component for secure and efficient edge intelligence [300]. Incremental learning further enhances 7G's adaptability by allowing systems to evolve continuously, updating their models with new data without retraining from scratch [305]. These AI and ML approaches collectively empower 7G networks to become faster, more reliable, and smarter, enabling them to address the diverse and dynamic challenges of the near future with unprecedented efficiency. Figure 19 shows the key components of AI and ML driving the evolution of 7G networks. It highlights learning paradigms like meta-learning and incremental learning, distributed intelligence with federated approaches, and language-based intelligence through large language models. it uses optimization techniques and advanced analytics, including deep learning and graph neural networks, as fundamental enablers for next-generation network capabilities.

A. AI & ML BASED LEARNING PARADIGM FOR 7G NETWORKS

7G networks evolve, and their intelligence must keep pace with the unprecedented demands of hyper-connectivity, ultra-low latency, and various real-time applications, including immersive augmented reality, autonomous systems, and advanced IoT ecosystems [306]. These networks' vast scale and complexity require innovative solutions to ensure adaptability, efficient resource utilization, and continuous learning in dynamic environments. Advanced paradigms such as Meta-Learning, Transfer Learning, and Incremental Learning are key enablers in this context, addressing the unique challenges posed by 7G [307].

1) EMPOWERING FUTURE-READY 7G NETWORKS WITH META-LEARNING STRATEGIES

Empowering future-ready 7G networks with meta-learning strategies involves addressing key challenges such as data imbalance, non-Independent and Identically Distributed (non-IID) data, resource constraints, and rapid adaptation in dynamic environments [314], [315]. Federated Meta-Learning (FML) ensures data privacy by training models locally and sharing only optimized parameters, while digital twins simulate network behavior for improved system testing [316]. Reinforcement learning-based meta-samplers enhance Intrusion Detection Systems (IDS) by balancing datasets in skewed data scenarios [317]. Techniques like the Decomposition and Meta-Deep Reinforcement Learning Algorithm (DMMA-FL) optimize multi-objective federated learning for satellite systems, using CNNs and LSTMs for spatial-temporal feature extraction, achieving Pareto-optimal solutions [309]. Frameworks like Model-Agnostic Meta-Learning (MAML) and Meta-Transfer Metric Learning using Scale Functions (MLS) improve the adaptability of Neural Receivers (NRXs) and time series classifiers by enabling rapid adaptation to new configurations, reducing Bit Error Rates (BER) and enhancing feature extraction [318]. These strategies drive advancements in applications such as wireless traffic prediction and beamforming, where Meta-Learning-Driven Beam Prediction Algorithms (MBBP) enhance millimeter-wave (mmWave) performance, and Reconfigurable Intelligent Surfaces (RIS) optimize spectral efficiency. Ensemble meta-models for intrusion detection, including Random Forest, LightGBM, and AdaBoosting, improve accuracy and reduce false alarms. Meta-learning's flexibility also addresses challenges like data dimension mismatches and distribution shifts, ensuring power savings and performance improvements in diverse 7G configurations. These approaches collectively empower 7G networks to be adaptable, energy-efficient, and secure, fostering a robust and scalable architecture for next-generation communication systems. Table 10 summarizes various meta-learning techniques for 7G networks, focusing on methodologies, addressing challenges, and key applications.

FIGURE 19. Core Pillars of AI and ML Advancements for Enabling Intelligent, Scalable, and Efficient 7G Network Systems.

TABLE 10. Technical analysis of meta-learning techniques for 7G networks.

Techniques	Challenges Addressed in 6G	Methodology	Metrics for Evaluation	7G Use Case
Federated Meta-Learning	Data imbalance, non-IID data, privacy concerns [308]	Local training on devices, optimized parameter aggregation, clustering	Accuracy, convergence speed	Intrusion Detection systems (IDS) with scalable and privacy-preserving models
DMMA-FL (Meta-Deep Reinforcement Learning)	Asynchronous communication, resource constraints, straggler issues [309]	Actor-critic networks, CNNs, LSTMs, weighted aggregation	Training latency, communication overhead, scalability index	Resource allocation and efficient federated learning for satellite-based 7G infrastructures
Model-Agnostic Meta-Learning (MAML)	Distribution shifts, diverse configurations in real-world tasks [310]	Pre-trained meta-parameters, rapid fine-tuning with minimal data	Bit error rate (BER), energy efficiency, adaptation time	Universal Neural Receivers (NRX) for adapting to dynamic transmitter configurations
MLS (Meta-Transfer Metric Learning)	Limited labeled data, high computational costs [311]	Multi-Scale Dilated CNN (MSDCNN), triplet-loss optimization, scale functions	Few-shot learning accuracy, convergence rate	Time series classification for applications like traffic accident detection
Zero-Padding in Meta-Learning	Dimension mismatch in heterogeneous networks [312]	Input standardization via padding to handle varying data dimensions	Input compatibility, configuration flexibility	Seamless operation across diverse transmitter setups (e.g., antennas, modulation orders)
MBBP (Meta-Learning-Based Beam Prediction)	Limited data for mmWave beam prediction, dual-band adaptation [164]	Bi-level optimization using sub-6GHz CSI for mmWave beam prediction	Prediction accuracy, spectral efficiency, training overhead reduction	Efficient and scalable beamforming in dual-band 7G networks
Stacking Ensemble Learning	Data imbalance, high false alarm rates in IDS [313]	Integration of multiple classifiers with decision tree meta-classifier	Detection accuracy, false positive/negative rates	Robust IDS with high detection accuracy in multi-class scenarios
Meta-learning for RIS Optimization	High pilot overhead, channel acquisition challenges [160]	Inductive bias training, adaptive phase shift optimization	Spectral Efficiency (SE), convergence rate	Adaptive beamforming and spectral optimization for Reconfigurable Intelligent Surfaces (RIS)

Techniques such as MAML and MLS facilitate rapid adaptation and efficient training, while methods like Federated Meta-Learning and stacking ensemble learning enhance data privacy and improve detection accuracy in complex environments. These approaches find applications ranging from intrusion detection systems to adaptive beamforming for Reconfigurable Intelligent Surfaces (RIS), highlighting meta-learning's transformative impact on optimizing 7G systems.

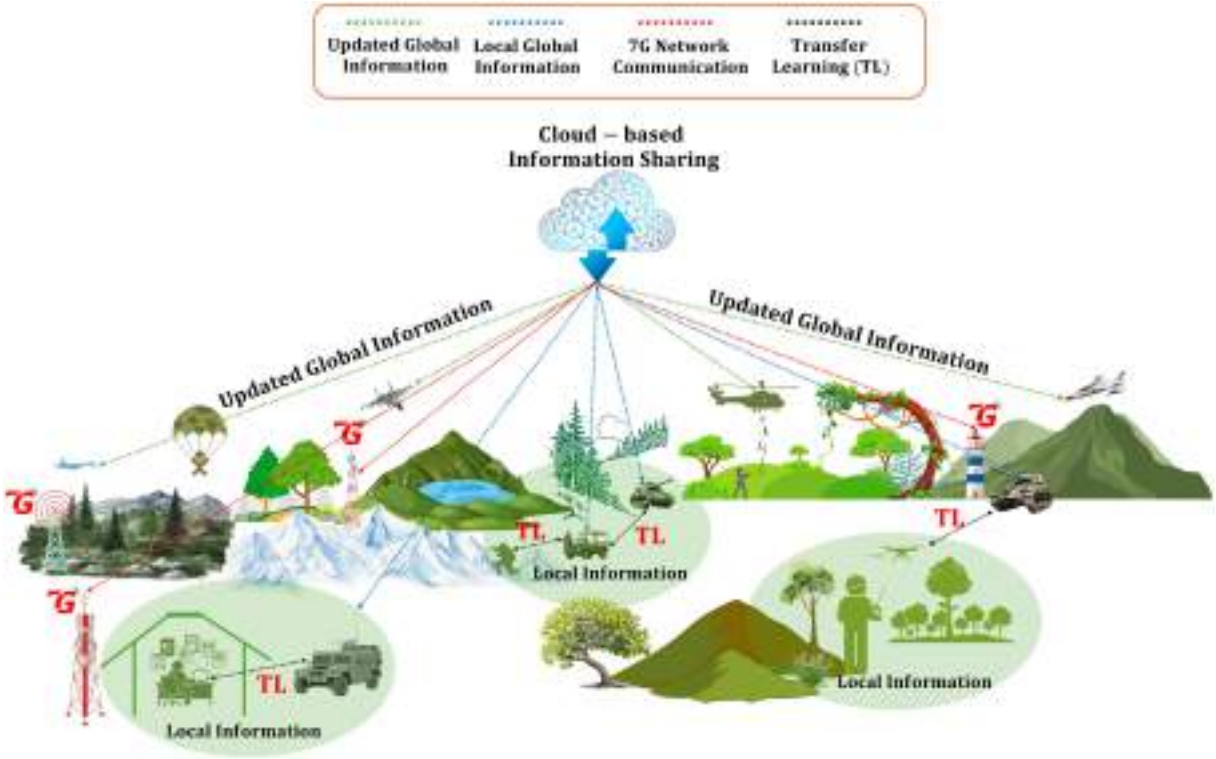

FIGURE 20. Cloud-based information sharing utilizing Transfer Learning (TL) and 7G network communication for synchronized global and local operations in military warfare.

2) OPTIMIZING 7G APPLICATIONS THROUGH TRANSFER LEARNING

Integrating transfer learning into 7G applications is vital to address the complexities of unprecedented data volumes, varied network requirements, and the need for real-time decision-making [319]. Transfer learning enables the reuse of pre-trained models across domains, significantly enhancing efficiency, reducing training costs, and accelerating the deployment of intelligent solutions [320]. This approach ensures adaptability and scalability, which are critical for the success of 7G networks in delivering unified and innovative services. The transition from 6G to 7G networks challenges ensuring adaptive and efficient connectivity through Intelligent Defined Networks (IDNs). Transfer learning plays a vital role by reusing pre-trained models within distributed learning frameworks, enabling faster adaptation and scalability. This approach addresses the stringent requirements of 7G's dynamic and decentralized ecosystem [321]. The evolution to 7G-enabled Internet of Vehicles (IoV) introduces new challenges in ensuring secure, efficient, and adaptive learning processes. Transfer learning enhances data quality, accelerates learning, and reduces computational demands, making it integral to smart driving and other 7G IoV applications. Utilizing blockchain for decentralized reputation management ensures reliability in model sharing, addressing security concerns in the 7G IoV ecosystem [322]. The transition to 7G networks and the Internet of Things (IoT) brings a significant increase in data complexity and volume, similar to the challenges of 6G. Transfer learning-based Compressed Sensing (CS) models, such as Convolution-based Transfer Learning CS (CTCS), optimize signal reconstruction by utilizing pre-trained models to handle small sample data efficiently. This method, proven effective with UWB radar and Mnist datasets, outperforms traditional reconstruction algorithms, enhancing recovery performance in the 7G-IoT ecosystem under various noise levels, measurement numbers, and signal sparsities [323]. In 7G networks, the rapid changes in network conditions and the need for dynamic Radio Resource Management (RRM) make it challenging for Reinforcement Learning (RL) algorithms to converge quickly. Transfer learning (TL) is crucial in overcoming this limitation by enabling RL agents to adapt faster to the constantly evolving 7G environment. With the Open Radio Access Network (O-RAN) integration in 7G, TL allows Mobile Network Operators (MNOs) to make real-time adjustments to RL models, ensuring efficient management of radio resources. TL accelerates convergence, helping RL agents perform more efficiently in 7G networks, enabling faster adaptation to network priorities and service-level agreement changes [323]. Figure 20 shows the cloud-based information-sharing framework using Transfer Learning (TL) and 7G network communication to support military operations. It highlights the reuse of pre-trained models for efficient decision-making, reduced training costs, and faster adaptability in dynamic environments. This approach ensures secure communication, rapid resource management,

and scalability, meeting the demands of modern military networks.

3) INNOVATIONS IN 7G USING INCREMENTAL LEARNING

The evolution of mobile networks from 1G to 7G introduces unprecedented challenges in data processing and network optimization. Incremental learning enables continuous adaptation to new data. It offers a promising solution for enhancing 7G networks by improving real-time decision-making and resource allocation and efficiently managing evolving technologies and user demands [324]. Incremental learning is crucial for adapting to modern wireless communication systems' dynamic and evolving nature, especially in 7G networks. As user demands, network conditions, and device behaviors continuously change, traditional models may struggle to keep up. Incremental learning allows continuous adaptation without retraining from scratch by progressively enabling systems to integrate new information. This capability ensures that 7G networks remain efficient and intelligent, particularly in optimizing critical components like Radio Frequency (RF) power amplifiers, while maintaining high performance across diverse and unpredictable scenarios [325].

4) GENERATIVE AI FOR INTEGRATED SENSING AND COMMUNICATIONS (ISAC) IN 7G NETWORK

Generative AI enhances Integrated Sensing and Communications (ISAC) in 7G networks by enabling intelligent signal processing, environment-aware communication, and adaptive resource allocation [326]. It improves sensing accuracy by generating high-fidelity synthetic data for training models, aiding in object detection, localization, and environmental mapping. Generative AI optimizes spectrum utilization by predicting network demand and dynamically adjusting communication parameters [327]. This integration ensures better connectivity, enhanced security, and efficient network operations, making 7G networks more resilient and adaptive to real-world scenarios. The following shows how Generative AI contributes to 7G ISAC:

- *Enhanced Sensing Accuracy:* Generates synthetic training data for object detection, localization, and environmental mapping.
- *Intelligent Signal Processing:* Improves noise reduction, interference management, and adaptive filtering.
- *Dynamic Spectrum Allocation:* Predicts network demand and optimizes spectrum usage in real-time.
- *Autonomous Network Management:* Supports self-optimizing and self-healing networks.
- *Security Enhancement:* Simulates potential cyber threats and strengthens intrusion detection.
- *Better Connectivity* Facilitates robust, low-latency communication for emerging applications like holographic telepresence and IoT.

B. ENHANCING 7G NETWORKS WITH DISTRIBUTED INTELLIGENCE

7G networks, with their various devices and massive connectivity, can adopt Hybrid Split and Federated Learning (HSFL) to optimize machine learning. Combining the strengths of Federated Learning's decentralized model training and Split Learning's reduced computational load, HSFL ensures higher accuracy and lower communication overhead. This approach is crucial for handling the diverse capabilities of 7G devices, enabling scalable and privacy-preserving AI applications [328]. Future intelligent devices in beyond-5G networks require ultra-low communication delay and high Quality of Service (QoS), which can be achieved through Space-Air-Ground Integrated Networks (SAGIN). SAGIN expands coverage and enhances connectivity for intelligent applications by integrating satellite, aerial, and terrestrial networks. Federated Learning offers an innovative solution for resource management and transmission strategies in SAGIN, ensuring security and user privacy while addressing dynamic network challenges. This method can optimize various objectives, as demonstrated in a case study on federated reinforcement learning for traffic offloading in SAGIN [329]. As 7G networks evolve towards ultra-connected intelligent systems, integrating Federated Learning with mobile edge computing faces challenges due to resource-constrained IoT devices. Split Learning (SL) offers a solution by offloading major training tasks to servers, enhancing data privacy while supporting efficient model training. A customized architecture for Split Edge Learning (SEL) addresses key design issues like resource-efficient frameworks, multi-edge collaboration for model placement, and migration while highlighting open problems such as convergence analysis and label privacy preservation in 7G environments [330]. As 7G networks aim to support the Internet of Everything (IoE), Distributed Deep Learning (DDL) can be crucial in enhancing intelligence generation. With ultra-reliable and low-latency communication (uRLLC), 7G can further boost DDL performance, driving IoE development. Traditional DDL designs often focus on isolated areas, resulting in fragmented intelligence, and are vulnerable to data privacy and execution issues due to centralized management. A novel BC-escorted 7G-based DDL design is proposed to address these challenges, incorporating system-wide uRLLC, non-homogeneous edge devices, two-tier parameter aggregation, and BC consensus for secure model training. This approach improves accuracy and latency compared to Cloud-based and P2P-based DDLs [331].

C. LANGUAGE-BASED INTELLIGENCE IN 7G WITH LARGE LANGUAGE MODELS (LLMS)

Language-based intelligence in 7G networks, powered by Large Language Models (LLMs), is set to transform communication systems by improving the efficiency and intelligence of network management, user interactions, and service customization [332]. With the rapid increase in data and the growing complexity of 7G networks, LLMs can

FIGURE 21. Application of Language-Based Intelligence in 7G with Large Language Models.

FIGURE 22. 7G Enabled Multimodal LLM Framework for Real-Time Actionable Intelligence.

process large amounts of real-time linguistic information, enabling advanced features like predictive analytics, automated troubleshooting, and dynamic resource optimization. These models can support smooth communication between humans and machines, creating a more intuitive and responsive user experience. LLMs will be important in making smarter decisions, improving security through natural language processing for anomaly detection, and enhancing the network's ability to adapt to the changing needs of future communication systems [333]. LLMs, such as OpenAI's GPT series, Google's BERT, and similar models, represent the pinnacle of artificial intelligence in Natural Language Processing (NLP) [334], [335]. These models are trained on extensive datasets to understand, generate, and manipulate human language. Their ability to comprehend context, infer meaning, and adapt to various linguistic cues makes them ideal candidates for integration with 7G networks. The implementation of LLMs in 7G infrastructure would not only enhance the user experience but also enable advanced network management techniques. One of the most compelling aspects of LLMs is their ability to process massive amounts of data and extract meaningful insights in real-time [336]. This capability is essential for 7G networks, which are expected to handle an exponentially greater volume of data and a more diverse range of applications, from IoT devices to high-definition immersive media. By using LLMs to interpret both structured and unstructured data within the network, 7G can ensure more efficient resource allocation, reduced latency, and better service quality. By harnessing the inherent capabilities of LLMs, such as contextual understanding and adaptability, 7G networks can achieve efficient communication between edge devices and the core network. Besides their role in 7G-enabled multimodal LLM frameworks for real-time actionable intelligence, LLMs have several other applications in intelligent network operations and performance optimization. These include dynamic resource management, predictive analytics, and adaptive decision-making, which contribute to enhancing network efficiency. Their application in optimizing edge performance remains crucial for 7G networks, where ultra-low latency and reliability are paramount. Figure 21 shows the various applications of LLMs in intelligent network operations and performance optimization.

1) REAL-TIME ACTIONABLE INTELLIGENCE IN 7G NETWORK USING LLM

Real-time actionable intelligence in 7G networks, powered by Large Language Models (LLM), is essential to meet the demands of ultra-low latency and seamless communication [337]. 7G will support an increasingly complex environment where immediate data processing and decision-making are crucial for autonomous systems, smart cities, and critical infrastructure applications. LLMs enable real-time insights from vast data streams, ensuring optimal network performance, efficiency, and responsiveness in this high-speed, interconnected landscape. Figure 22 shows a 7G-enabled multimodal LLM framework that processes and integrates inputs from multiple modalities like text (T), audio (A), video (V), and IoT sensor data (I). Each data type is encoded into high-dimensional embeddings, represented as $E_T \in \mathbb{R}^{d_T}$, $E_A \in \mathbb{R}^{d_A}$, $E_V \in \mathbb{R}^{d_V}$, and $E_I \in \mathbb{R}^{d_I}$, where d_T, d_A, d_V, and d_I are the respective dimensions of each modality. These embeddings are processed by the *LLM Embedding Alignment* module, which projects them into a shared latent space $E_{aligned} \in \mathbb{R}^d$ through transformation functions represented by equation (14) which ensuring cross-modal compatibility.

$$\Phi_m(E_m) \rightarrow \mathbb{R}^d, \quad \text{for } m \in \{T, A, V, I\}, \tag{14}$$

The alignment minimizes the *modality gap* by optimizing a loss function using equation (15).

$$\mathcal{L}_{align} = \sum_{m,n} \text{sim}(\Phi_m(E_m), \Phi_n(E_n)), \tag{15}$$

where *sim* is a similarity metric (e.g., cosine similarity) between modality pairs m and n. The LLM processes the unified embeddings $E_{aligned}$, $\mathcal{F}_{LLM}$, which operates on the aligned embeddings and the 7G-enabled control instructions C_{7G}, represented by equation (16).

$$R = \mathcal{F}_{LLM}\left(E_{aligned}, C_{7G}\right), \tag{16}$$

where R is the Real-Time Actionable Response (RTAR). This framework highlights integrating high-speed, low-latency 7G capabilities with multimodal processing, allowing the LLM to generate intelligent decisions and predictions in real-time.

2) OPTIMIZING EDGE PERFORMANCE IN 7G NETWORKS USING LLM

The rapid evolution of 7G networks introduces unprecedented demands for optimizing edge performance to meet ultra-low latency requirements, reliable connectivity, and enhanced user experiences. Integrating advanced technologies has become critical, focusing on achieving uninterrupted communication. Large Language Models (LLMs) offer transformative potential, enabling intelligent resource management, real-time data analysis, and dynamic decision-making at the network edge [338]. Integrating advanced cognitive technologies in 7G networks will redefine connectivity, emphasizing reliability, adaptability, and ultra-low latency. Cognitive models address performance degradation by utilizing LLMs with Context-Enhanced Reasoning Chains (CERC), achieving higher accuracy in real-world scenarios like holographic communications. LLMs will also improve edge device performance by providing real-time, context-aware processing and optimizing decision-making at the network's edge [337]. These advancements highlight 7G's potential for intelligent, self-optimizing network infrastructures. Table 11 provides a detailed analysis of the strategies utilizing LLMs in 7G networks for edge devices. It highlights specific LLM algorithms/models, their intended purposes, quantifiable impacts on latency, throughput, energy efficiency, scalability, and implementation challenges.

Optimizing edge device performance in 7G networks involves balancing three critical metrics: latency (L), throughput (T), and resource efficiency (R_e). Latency measures the delay in transmitting and processing data, throughput represents the system's capacity to handle data traffic, and resource efficiency quantifies the effective utilization of computational and communication resources [339]. Latency can be expressed as the sum of transmission and processing delays as shown in equation (17).

$$L = \frac{d}{b} + \frac{C_p}{P_e} \tag{17}$$

where d is the size of the data, b is the allocated bandwidth, C_p is the computational complexity of the task, and P_e is the processing efficiency of the edge node in the 7G network. Resource efficiency is defined using equation (18).

$$R_e = \frac{U_r}{R_{\text{total}}} \tag{18}$$

where U_r represents utilized resources and R_{total} denotes the total available resources. The network must ensure $R_e \geq \gamma$, where γ is a predefined threshold. LLMs bring advanced capabilities for predictive analysis, enabling dynamic resource allocation, workload partitioning, and real-time traffic prediction. One of the key contributions of LLM in a 7G network is *workload partitioning*, where computational tasks are segmented into smaller units to ensure efficient processing. The objective is to minimize the cumulative latency using equation (19).

$$\text{Minimize: } \sum_{i=1}^{k} \frac{d_i}{b_i}, \quad \text{Subject to: } b_i \leq B_{\max} \tag{19}$$

where d_i and b_i are the data size and bandwidth allocated to the i-th task, respectively, and $B_{\max}$ is the maximum available bandwidth of the 7G network. This segmentation ensures optimal resource utilization and reduces processing delays. Another essential function of LLMs in 7G networks is dynamic resource allocation, where resources are distributed in real-time based on demand. The allocation vector $\mathbf{A} = [a_1, a_2, \ldots, a_k]$ is computed to maximize efficiency shown in equation (20).

$$a_i = \arg\max \frac{U_{r,i}}{R_{i,\text{total}}}, \quad a_i \leq 1 \tag{20}$$

Here, a_i represents the fraction of resources allocated to the i-th task. By dynamically reallocating resources, LLMs ensure that edge nodes operate near their optimal capacity, maintaining high-performance levels under varying conditions. Resources allocation in LLMs effectively predicts traffic patterns, a critical aspect of managing fluctuating network loads. Traffic prediction is achieved using autoregressive models, where the future traffic load (X_t) is forecasted based on historical data represented by equation (21).

$$X_t = \sum_{j=1}^{n} \beta_j \cdot X_{t-j} + \epsilon_t \tag{21}$$

Here, β_j are the learned coefficients, and ϵ_t is the prediction error. Accurate predictions allow the network to proactively allocate resources, prevent congestion, and maintain optimal performance. Integrating LLMs into 7G networks facilitates formulating a multi-objective optimization that balances the latency minimization, throughput maximization, and resource efficiency, which is represented by equation (22).

$$\text{Maximize: } \mathbf{F}(\mathbf{x}) = [T, -L, R_e], \quad \text{Subject to: } \mathbf{x} \in \mathcal{D} \tag{22}$$

where $\mathbf{x}$ represents decision variables such as data size, bandwidth, and processing power, while $\mathcal{D}$ defines the feasible domain constrained by 7G network limitations. Solving this optimization problem ensures that the network meets the

TABLE 11. Technical analysis of LLM strategies in 7G networks for edge devices.

Attribute	7G-Adaptive LLM Strategies	Purpose	Impact	Challenges
Latency Reduction	Transformer-based Models (e.g., GPT, BERT)	Localized, real-time data processing	Reduces latency to <5 ms	High computational demand and memory-intensive operations at edge devices
Throughput Optimization	Long Short-Term Memory (LSTM), GRU	Traffic prediction and dynamic load balancing	Increases throughput by 30-50%	Requires real-time, high-quality data for accurate predictions
Resource Utilization	Reinforcement Learning (RL)	Optimal allocation of bandwidth and resources	Utilizes >80% of available resources	Convergence time for large-scale problems can delay results
Energy Efficiency	Neural Architecture Search (NAS), Lightweight LLMs	Predictive workload and energy distribution	Reduces power consumption by 20-35%	Computational complexity for heterogeneous device modeling
Security	Anomaly Detection Models (e.g., Autoencoders)	Identifying and handling security threats	Detects 90%+ anomalies proactively	Dependency on extensive labeled datasets for training
Personalization	Few-shot and Zero-shot Learning (e.g., GPT-3, T5)	User-specific recommendations and applications	Improves user satisfaction by 40-60%	Balancing personalization and data privacy regulations
Scalability	Distributed LLM Frameworks (e.g., FLAN-T5, Bloom)	Efficiently manage billions of IoT devices	Supports millions of devices simultaneously	Integration challenges with legacy protocols
Fault Prediction	Predictive Maintenance Models (e.g., BERT-based)	Anticipate failures and schedule maintenance	Reduces downtime by 25-40%	Requires consistent and complete diagnostic data streams
Real-time decision-making	Attention Mechanisms, RL-based LLMs	Adaptive real-time system adjustments	Improve response time for critical systems	Trade-off between decision speed and accuracy

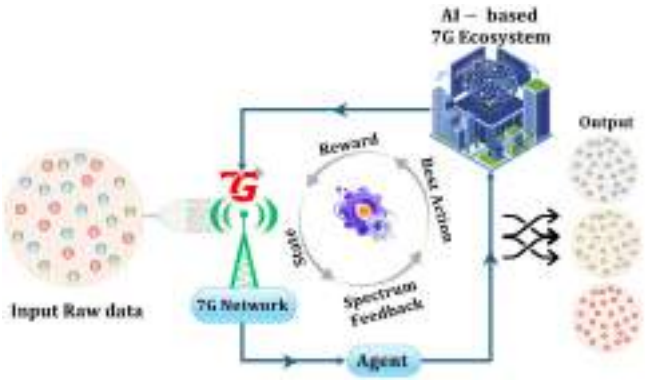

FIGURE 23. Reinforcement Learning-Based Optimization in AI-Driven 7G Ecosystem: From Raw Data to Intelligent Decisions for Smooth Connectivity.

various demands of modern applications while adhering to physical and operational constraints. The practical implications of LLM in 7G network integration extend across various applications. For instance, in vehicular networks, LLMs enable real-time traffic prediction and intelligent routing, reducing delays and enhancing safety. In IoT ecosystems, it optimizes the processing and communication of massive data streams, ensuring efficient operation. Similarly, LLMs facilitate unexpected experiences in AR and VR by minimizing latency and maximizing throughput.

D. OPTIMIZATION AND MANAGEMENT OF 7G NETWORKS THROUGH REINFORCEMENT MACHINE LEARNING TECHNIQUE

Reinforcement Learning (RL) is important in optimizing and managing 7G networks using dynamic spectrum allocation, energy efficiency, and ultra-low latency challenges [340], [341]. RL demonstrates exceptional adaptability by learning from interactions with the environment, enabling real-time optimization of network slicing, resource allocation, and traffic routing. It ensures smooth mobility management by predicting user movements and optimizing handovers while enhancing security through advanced anomaly detection mechanisms [342]. With edge computing integration, RL reduces latency and enhances scalability, making it a suitable solution for the complexity of 7G networks. These intelligent strategies are crucial for ensuring the efficient operation and reliability of 7G networks [343]. Figure 23 shows the application of Reinforcement Learning in optimizing the AI-driven 7G ecosystem. It demonstrates how raw input data is processed through the 7G network, where the RL agent interacts with the environment by receiving states and rewards to determine the best actions. The feedback loop enhances network performance, ensuring smooth connectivity and efficient resource management, leading to refined outputs designed to meet varied requirements. RL uses a dynamic state-action-reward mechanism for optimizing and managing 7G networks, effectively adapting to complex and evolving environments [344]. This mechanism involves user density, mobility patterns, spectrum availability, and environmental conditions. Traditional methods often fall short, but RL frames these challenges as a Markov Decision Process (MDP) [345], represented by the tuple (S, A, P, R, γ), where S denotes the state space, capturing real-time 7G network metrics such as throughput, latency, and signal strength. A represents the action space, including decisions like spectrum allocation and routing adjustments. $P(s'|s, a)$ is the transition probability of moving

from state s to state s' after action a. $R(s, a)$ is the reward function, guiding the agent to optimize performance metrics. $\gamma \in [0, 1]$ is the discount factor, determining the importance of future rewards.

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right] \tag{23}$$

RL aims to find the optimal policy π^* that maximizes the cumulative discounted reward ($\mathbb{E}$) as shown in equation (23). Dynamic spectrum allocation in 7G networks involves allocating frequency bands dynamically to minimize interference and maximize utilization. The reward function for this task can be expressed by equation (24), where U_i represents the 7G spectrum utilization for user i, I_{ij} denotes interference between users i and j, η_i is the priority weight of user i, λ is a penalty factor for interference.

$$R(s, a) = \sum_{i=1}^{N} \eta_i U_i - \lambda \sum_{j=1}^{M} I_{ij} \tag{24}$$

In energy efficiency optimization, RL agents minimize the total power consumption while maintaining Quality of Service (QoS). The power allocated to each base station P_i is optimized under the constraint $C_i \geq C_{\min}$, where C_i denotes coverage and $C_{\min}$ is the minimum acceptable coverage threshold. The reward function is represented by equation (25).

$$R(s, a) = -\sum_{i} P_i + \mu \sum_{i} \mathbf{1}(C_i \geq C_{\min}) \tag{25}$$

where $\mathbf{1}(C_i \geq C_{\min})$ is the indicator function, P_i is the power consumption, and μ is a constant that acts as a scaling factor or weight in the reward function.

Mobility management in 7G, particularly during high-speed scenarios, involves predicting user movement and optimizing handovers to minimize disruptions. The reward function for handover optimization is represented by equation (26).

$$R(s, a) = -H - \beta Q \tag{26}$$

where H represents the handover cost, Q is the QoS degradation during handover, and β balances the trade-off between these metrics. Traffic routing optimization ensures efficient data packet transmission by balancing latency and throughput and is calculated by equation (27).

$$R(s, a) = T - \alpha L \tag{27}$$

where T is the network throughput, L is the latency, and α is the weight controlling the trade-off.

E. ADVANCED ANALYTICS FOR 7G NETWORKS USING GRAPH NEURAL NETWORKS (GNN) AND DEEP LEARNING

Advanced analytics for 7G networks utilizes the power of Graph Neural Networks (GNNs) and Deep Learning to address the unique challenges introduced by these next-generation communication systems. With 7G networks offering ultra-fast speeds, near-zero latency, and effortless connectivity for intelligent devices, traditional methods struggle to process the complex, dynamic data they generate [346]. GNNs excel in capturing intricate relationships within network topologies, while Deep Learning provides hierarchical feature extraction for predictive analytics, resource optimization, and anomaly detection [12]. Together, these technologies enable intelligent, adaptive solutions that unlock the full potential of 7G networks, ensuring their efficiency, scalability, and reliability. Applications of GNNs in RF spectrum sensing for 7G networks enable precise and adaptive management of the complex and dynamic wireless environments characteristic of next-generation systems [347].

FIGURE 24. 7G-powered GNN framework for efficient spectrum sensing, management, and secure communication.

Figure 24 shows the 7G-enabled GNN framework for advanced RF spectrum sensing and management. The 7G Base Station Tower is the central hub, connected to the Spectrum Coordination Center via a high-speed 7G Link for real-time data processing and decision-making. The framework incorporates multiple GNN modules for *Cooperative Sensing*, *Dynamic Sensing*, and *Secure Cooperative Sensing*, ensuring efficient spectrum allocation and interference mitigation. A dedicated module for Latent Node Identification addresses hidden node problems, enhancing network reliability. The system identifies Malicious Users and secures communication between the Spectrum Participants, optimizing resource utilization and maintaining robust 7G connectivity. In 7G networks, the wireless environment is modeled as a graph $G = (V, E)$, where V represents nodes such as transmitters, receivers, or frequency bands, and E captures the edges or relationships like interference patterns or connectivity. Each node v is associated with features $h_v^{(k)}$, representing its state at iteration k, while edge features e_{uv} encode pairwise relationships, such as signal interference or proximity between nodes u and v. Equation (28) shows the *Node Embedding Update Equation for Message Passing* in

GNN.

$$h_v^{(k+1)} = \phi\left(h_v^{(k)}, \sum_{u \in \mathcal{N}(v)} \psi\left(h_u^{(k)}, e_{uv}\right)\right), \tag{28}$$

where $h_v^{(k)}$ denotes the feature vector or embedding of node v at iteration k, and $\mathcal{N}(v)$ represents the set of neighboring nodes directly connected to node v. The term e_{uv} corresponds to the feature of the edge between nodes u and v, which encodes their relationship, such as interference or connectivity strength. The function ϕ is a learnable transformation that aggregates and updates the node features, while ψ is a learnable function that processes and transforms the information from neighboring nodes and their connecting edges. It enables the iterative refinement of node embeddings by aggregating information from a node's neighbors, weighted by their connections. It captures local and global dependencies in the graph, ensuring that each node's representation is enriched with contextual knowledge from the network.

This mechanism is integral for 7G networks' real-time tasks, such as spectrum occupancy detection, interference classification, and dynamic frequency allocation. Using ultra-low latency, massive connectivity, and computational power of 7G, GNNs can analyze and adapt to spectrum usage patterns on the fly. This ensures optimal resource allocation, enhances spectral efficiency, and minimizes co-channel interference, supporting the vast connectivity demands of 7G-enabled smart consumer electronic devices. GNNs become a cornerstone for RF spectrum sensing and resource management in the 7G ecosystem by embedding these advanced capabilities [348].

VII. CHALLENGES IN 7G NETWORKS

The development of 7G networks presents unprecedented challenges due to the reliance on cutting-edge technologies and the demand for unparalleled performance. We have categorized the challenges in developing 7G networks into five primary categories, as given below.

- Technical Challenges
- AI and ML-based Challenges
- Spectrum Allocation Challenges
- Materials and Computational Challenges
- Economic Feasibility of 7G Technologies: Costs and Challenges

These challenges represent a multifaceted roadmap for realizing the vision of 7G, balancing technological innovation with intelligent and adaptive solutions.

In Table 12, we have compiled references from the literature review to compare relevant existing surveys, highlighting key aspects of various network technologies. This structured comparison demonstrates how our paper surpasses prior studies by addressing more comprehensive challenges, integrating cutting-edge advancements, and proposing novel research directions. By analyzing enabling technologies, applications, and future trends, our study provides a more holistic and forward-looking perspective than previous works.

FIGURE 25. Technical Challenges in 7G Networks.

A. TECHNICAL CHALLENGES

The technical challenges include a wide array of critical aspects fundamental to achieving the ambitious objectives of 7G. These include Spectrum and Interference Management, focusing on efficient allocation and coexistence of various frequency bands, and High Power and Highly Integrated Devices, emphasizing the development of energy-efficient yet highly capable hardware. Additional technical concerns involve advancements in Enabling Devices and Semiconductor Technologies to meet the demands of ultra-fast and reliable communication, Antenna Design for optimizing signal propagation, and innovative Modulation and Multiplexing Techniques to maximize data throughput. Challenges such as Transceivers and Noise Management for minimizing signal distortion, integrating Quantum Technologies for unprecedented computational capabilities, and addressing Environmental Impact through sustainable practices are equally significant. The use of terahertz (THz) frequencies introduces spectrum scarcity and interference issues compounded by atmospheric absorption and the need for precise THz beam management and modeling [349], [350], [351]. Enhancing physical layer security against quantum and advanced cyber threats adds further complexity [124]. Advanced materials like GaAs, GaN, InP, SiGe, and CMOS are required for high-power, highly integrated devices [352] that ensure efficient performance at THz frequencies, but these materials also pose manufacturing and scalability challenges. Antenna design innovations, including Intelligent Reflecting Surfaces (IRS), Orbital Angular Momentum (OAM) systems, and lens antennas, are essential for efficient signal transmission and reception, requiring breakthroughs in design and fabrication [231]. New modulation techniques, such as OAM multiplexing and full-duplex communication, aim to

TABLE 12. Comparative analysis of various network technologies, highlighting key aspects across different studies.

Authors	Technology Generation	Key Technologies	Focus Area	Challenges Discussed	Approach	Applications	Future Research Directions
Chataut *et al.* [29]	6G	AI, ML, Quantum, THz	AI-Driven 6G Networks	Scalability, Security	Self-Optimizing Networks	Smart Cities, Autonomous Systems	AI-Driven 6G Optimization
Adedoyin *et al.* [33]	5G	Ultra-Dense Networks, Network Slicing	5G Technology Integration	Interference, Energy Consumption	Intelligent Management Techniques	IoT, Smart Infrastructure	Adaptive Network Slicing
Erunkulu *et al.* [34]	5G	mMTC, eMBB, URLLC	5G Use Cases	Latency, Scalability	Spectrum Optimization	Industrial IoT, Smart Applications	5G Channel Characterization
Yang *et al.* [35]	6G	AI, Edge Computing	AI-Enabled 6G Networks	Mobility, Spectrum Management	Intelligent Network Layers	Smart Applications	AI-Driven Network Optimization
Lee *et al.* [36]	6G	Massive MIMO, Non-Terrestrial Networks	Hyper-Connectivity	Coverage, Data Rate	Distributed Intelligence	IoT, Smart Infrastructure	Fully Integrated Networks
Nawaz *et al.* [37]	6G	Quantum ML, AI	Quantum Computing in 6G	Computational Complexity	Quantum-Assisted ML	Edge AI, Low-Latency Systems	Quantum ML Applications
Shafie *et al.* [39]	6G	THz Communications	THz for Beyond 5G	High-Frequency Band Challenges	THz Beamforming	High-Speed Wireless	THz Spectrum Standardization
Thantharate *et al.* [40]	6G	Adaptive Learning, Network Slicing	6G Resource Management	Load Estimation, Scalability	Transfer Learning	Network Slicing, Smart Networks	Intelligent Resource Management
Ahmad *et al.* [41]	6G	XR, IoT, Big Data	6G in Healthcare	Scalability, Security	AI-Driven Healthcare Services	Telehealth, Remote Surgery	Healthcare 6G Convergence
Agiwal *et al.* [43]	5G	Massive MIMO, mmWave	5G Network Evolution	QoS, Energy Efficiency	Beamforming, Spatial Multiplexing	5G Network Capacity	MIMO for 5G Evolution
Yang *et al.* [45]	4G	Mobile Applications	4G Wireless Networks	Latency, Traffic Symmetry	Application Framework	Augmented Reality, m-Health	Future Mobile Applications
Agarwal *et al.* [46]	4G	LTE, WiMAX	4G Evolution	Security, Integration	All-IP Architecture	Mobile Broadband, IoT	Future 4G Enhancements
Ashraf *et al.* [279]	5G	Modular Antenna Arrays	Scalable MIMO Networks	Performance Optimization	Beamforming, Spatial Multiplexing	5G Network Capacity	MIMO for 5G Evolution
Pokhrel *et al.* [48]	5G	URLLC, mMTC	Critical mMTC	Latency, Scalability	Network Slicing	Factory Automation, IoT	Hybrid URLLC-mMTC Integration
Popovski *et al.* [49]	5G	eMBB, mMTC, URLLC	5G Network Slicing	Reliability, Resource Allocation	H-NOMA, Non-Orthogonal Slicing	IoT, Industrial Automation	Future NOMA-Based 5G Networks
Future of Connectivity (Our)	**7G**	**AI, Quantum, THz, Edge Computing**	**Next-Gen 7G Networks**	**All Challenges Addressed**	**Comprehensive AI-Optimized Approach**	**Smart Cities, IoT, Autonomous Systems**	**Full 7G Ecosystem Development**

Abbreviations: AI = Artificial Intelligence, ML = Machine Learning, THz = Terahertz, mMTC = massive Machine Type Communication, eMBB = enhanced Mobile Broadband, URLLC = Ultra-Reliable Low Latency Communication, QoS = Quality of Service, MIMO = Multiple-Input Multiple-Output, XR = Extended Reality, IoT = Internet of Things, mmWave = Millimeter Wave, LTE = Long-Term Evolution, WiMAX = Worldwide Interoperability for Microwave Access, NOMA = Non-Orthogonal Multiple Access, H-NOMA = Hybrid Non-Orthogonal Multiple Access, IP = Internet Protocol, m-Health = Mobile Health.

maximize spectral efficiency but demand highly sophisticated hardware and software integration. Low Noise Figure (LNF) transceivers capable of handling ultra-wideband signals [353] remain a significant technical hurdle. The materials, technologies, and architectures used in 5G and 6G fall short of addressing these demands, necessitating a paradigm shift in network design and implementation. Figure 25 shows the key challenges for 7G networks, encompassing spectrum management, advanced materials, antenna design, modulation techniques, transceiver optimization, quantum integration, and environmental sustainability.

- *Spectrum and Interference Management:* THz frequencies suffer from high atmospheric absorption, signal degradation, and interference, requiring advanced beam management and modeling techniques that are not fully developed. 5G and 6G operate primarily in the sub-6 GHz and mmWave bands with lower attenuation issues. They lack the required technologies for THz frequency utilization and cannot meet the demands of ultra-high spectral efficiency.
- *High Power and Highly Integrated Devices:* Devices operating at THz frequencies require materials like

FIGURE 26. AI and ML-based Challenges in 7G Networks for the Upcoming Future.

GaAs, GaN, and InP for high-power applications [354], which are costly and difficult to integrate. Heat dissipation and energy efficiency are also significant hurdles. 5G and 6G rely heavily on CMOS and SiGe for lower-frequency operations. These materials are unsuitable for the high-power demands of THz frequencies, and their energy efficiency decreases with increasing frequencies.

- *Enabling Devices and Semiconductor Advancements:* Developing semiconductors that can withstand ultra-high-frequency operations' thermal and electrical stresses requires innovation in material science and device architecture. Current 5G and 6G semiconductor technologies are optimized for mmWave and sub-6 GHz bands, limiting their application for THz operations.
- *Antenna Design:* Novel designs like IRS, OAM, and lens antennas are required for efficient THz signal propagation [355], which involves overcoming significant design, fabrication, and deployment challenges. Antennas in 5G and 6G are optimized for mmWave and sub-6 GHz operations, lacking the capability to manage THz signals or integrate OAM technologies efficiently.
- *Modulation and Multiplexing Techniques:* Advanced modulation schemes like OAM multiplexing and full-duplex communication are computationally intensive and require ultra-precise hardware synchronization [356]. 5G and 6G primarily use OFDM and other conventional multiplexing techniques, which are inadequate for handling the complexity and spectral efficiency demands of 7G.
- *Transceivers and Noise Management:* Designing low-noise figure (NF) transceivers that can handle wideband signals without compromising signal integrity requires significant innovation in circuit design. Transceivers in 5G and 6G are not optimized for THz communication's noise levels and bandwidth demands, limiting their performance at higher frequencies.
- *Integration of Quantum Technologies:* Incorporating quantum cryptography and sensing into 7G networks is still in its infancy, requiring breakthroughs in both theoretical frameworks and practical implementations. Quantum technologies were not a focus in 5G and 6G networks, leaving a gap in their ability to address next-generation security and sensing needs.
- *Environmental Impact:* The energy and material demands of 7G infrastructure could significantly increase the carbon footprint, necessitating sustainable and efficient solutions [357]. While 5G and 6G have made strides toward energy efficiency, their environmental impact still falls short of the standards needed for 7G.

B. AI/ML-BASED CHALLENGES AND SOLUTIONS

AI AI and ML are at the forefront of revolutionizing the capabilities of next-generation networks, with 7G networks being no exception [15]. These technologies enable intelligent decision-making, resource optimization, and adaptive learning in highly dynamic and decentralized environments. In the 7G era, integrating AI and ML is pivotal to achieving ultra-low latency, enhanced connectivity, and sustainable energy efficiency. Cutting-edge techniques such as Federated Learning, Split Learning, Incremental Learning, LLMs, Reinforcement Learning, and Transfer Learning are critical to meeting the demands of distributed intelligence and real-time adaptability in 7G networks. These methodologies empower networks to process data locally, optimize bandwidth usage, and enhance security, ensuring user experiences even in highly heterogeneous and resource-constrained environments. Adaptive AI transceivers utilize machine learning

TABLE 13. Overview of AI and ML techniques, their contributions, and associated challenges in 7G network advancements.

AI/ML Technique/Model	Role in 7G Network	Potential Applications in 7G	Advantages	Challenges	Energy Efficiency	Security & Privacy Contributions	Future Prospects in 7G
Explainable AI (XAI)	Ensures transparency and accountability	Network performance optimization	Builds trust, supports debugging	Limited scalability in complex models	Optimized	Enhances system integrity	Promising for trust-building in automated decisions
Federated Learning (FL)	Distributed model training without data sharing	Personalized QoS adjustments, traffic optimization	High user privacy, bandwidth savings	High communication costs	Energy Efficient	Robust against data breaches	Integral for adaptive, user-centric networks
Split Learning	Secure collaborative learning across devices	Hierarchical system optimizations	Preserves data locality	High dependency on stable connections	Moderately Efficient	Ensures compliance with data laws	Scalable for edge-dominant network deployments
Reinforcement Learning (RL)	Enables autonomous network configuration	Spectrum allocation, energy routing	Self-optimizing systems	Requires extensive training time	Balanced	Improves resilience to network dynamics	Expanding to proactive resource management
Graph Neural Networks (GNN)	Enhances network topology analysis	Predictive maintenance, routing optimizations	Captures intricate relationships	Computationally intensive for large graphs	Balanced	Effective in multi-layered systems	Essential for optimizing dense IoT environments
Transfer Learning (TL)	Leverages pre-trained models for efficient learning	Rapid model deployment, cross-domain applications	Faster learning with fewer data requirements	Requires domain adaptation	Energy Efficient	Reduces data exposure across domains	Promises to reduce time-to-deployment in 7G
Meta-learning	Fast adaptation to new network scenarios	Rapid protocol adjustments, error prediction	Highly flexible in dynamic contexts	Challenging to implement for all domains	Moderately Efficient	Enables customization at scale	Central to on-the-fly decision optimization
Self-supervised learning	Utilizes unlabeled data effectively	Noise reduction, proactive fault detection	Reduces dependence on labeled datasets	Prone to unstable convergence	Balanced	Improves fault tolerance	Key enabler for reducing manual interventions
Generative Models (GANs, VAEs)	simulate realistic network scenarios	Testing, and training under variable conditions	Supports robust system evaluations	High risk of overfitting and mode collapse	Moderately Efficient	Facilitate secure testing environments	Speeds up experimentation cycles in virtual environments
LLM (Large Language Models)	Enables natural language understanding and interaction	Advanced customer support, conversational agents	Superior handling of complex queries	Resource-heavy for real-time systems	Energy Consuming	Medium	Transforming human-machine interaction and automation
Incremental Learning	Adapts to new data without forgetting old knowledge	Real-time data updates, adaptive services	Minimizes catastrophic forgetting	Complex to manage data drift and bias	Moderately Efficient	Enhances adaptability to evolving data	Crucial for dynamic, long-term network optimization

algorithms to dynamically optimize signal processing, spectrum allocation, and energy efficiency in 7G networks. By integrating meta-learning, these transceivers can rapidly adapt to changing network conditions, improving real-time decision-making and reducing latency. This combination enhances self-optimization, fault tolerance, and intelligent resource management, making 7G networks more resilient and efficient. It enables smooth communication across environments, from terrestrial to space-based networks, supporting next-generation applications. Figure 26 shows the critical AI and ML-based challenges in developing 7G networks. Each challenge is tied to a specific learning paradigm, such as Federated Learning faces data privacy and security issues, Split Learning encounters computational overheads, Incremental Learning struggles with scalability and adaptability, Large Language Models (LLMs) demand efficient contextual understanding, Reinforcement Learning needs optimization for resource allocation, and Transfer Learning grapples with knowledge transfer inefficiencies. Table 13 shows the role of various AI and ML techniques in advancing 7G networks, highlighting their unique contributions, potential applications, and associated challenges. It provides a detailed comparison of their advantages, energy efficiency, and security contributions, offering insights into their relevance for future 7G developments.

1) DATA PRIVACY, SECURITY CHALLENGES AND SOLUTIONS IN FEDERATED LEARNING FOR 7G NETWORKS

Federated learning in 7G networks introduces profound security challenges that demand analytical consideration of vulnerabilities and their impact [358]. While promoting data privacy by keeping raw data on devices, the decentralized nature of federated learning inadvertently exposes models to inference attacks. These attacks exploit shared gradients or model updates to deduce sensitive information about training data, often revealing user-specific patterns without direct access to the data. Poisoning attacks further complicate

security, where malicious clients inject incorrect or biased data to alter the model's decision boundaries, as seen in label flipping or backdoor attacks, undermining the model's reliability. The heterogeneity of devices in 7G networks amplifies these risks; devices differ significantly in computational power, connectivity (ranging from 3G to 7G), and energy capacity, leading to stragglers or compromised nodes that attackers can exploit [359]. Although essential, privacy-preserving techniques like secure multiparty computation and differential privacy often introduce system efficiency and model accuracy trade-offs. The massive scale of 7G networks, encompassing millions of devices generating non-identical data distributions, makes it challenging to maintain statistical robustness and communication efficiency. These challenges underline the critical need for advanced cryptographic measures, anomaly detection mechanisms, and adaptive federated learning frameworks to ensure data security and model performance in next-generation networks.

The security and privacy challenges introduced by Federated Learning (FL) in 7G networks necessitate robust solutions to protect model integrity, ensure user data confidentiality, and enhance resilience against adversarial attacks. The following key solutions have been explored to address these challenges:

- **Advanced Cryptographic Techniques for Secure Federated Learning:** To counteract inference attacks and data leakage in 7G networks, cryptographic techniques enhance the security and privacy of FL. Homomorphic Encryption (HE) enables computations on encrypted data without decryption, ensuring model updates remain confidential across ultra-fast, low-latency 7G communication channels [182]. Secure Multiparty Computation (SMPC) allows multiple entities to collaboratively compute functions without revealing their inputs, securing gradient exchanges between edge devices and central servers [360]. Zero-knowledge proofs (ZKP) verify model updates without exposing underlying data, handling risks of poisoning and inference attacks in AI-driven 7G environments [361]. These cryptographic methods enhance privacy-preserving FL, ensuring secure decentralized intelligence in next-generation networks.
- **Differential Privacy for User Data Protection:** The decentralized nature of federated learning in 7G networks makes Differential Privacy (DP) essential for preventing adversaries from extracting sensitive information [362]. Local Differential Privacy (LDP) enhances security by adding noise to model updates before transmission, ensuring individual data protection while maintaining utility for global learning [363]. Adaptive Noise Injection dynamically adjusts noise levels based on real-time adversarial risks, optimizing the trade-off between accuracy and privacy in 7G-enabled FL systems [364]. These techniques collectively enhance user data protection in next-generation networks.
- **Byzantine-Resilient Aggregation Mechanisms:** Byzantine-Resilient Aggregation Mechanisms are essential for defending 7G-enabled federated learning against poisoning attacks and malicious model updates [365]. Krum and Trimmed Mean Aggregation enhances robustness by filtering out outlier model updates, ensuring only reliable gradients contribute to the global model [366]. Blockchain-based Federated Learning uses Distributed Ledger Technology (DLT) to securely record transactions, maintaining transparency and integrity in model updates [367]. Trust-based Client Selection prioritizes reliable clients using reputation scores, reducing the influence of malicious nodes [368]. These mechanisms collectively enhance the security and resilience of federated learning in next-generation networks.
- **Anomaly Detection and Intrusion Detection Systems (IDS):** Anomaly Detection and Intrusion Detection Systems (IDS) play a crucial role in securing federated learning in 7G networks by identifying malicious behavior and ensuring robust model performance [369]. AI-powered Intrusion Detection Systems (AI-IDS) utilize deep learning to analyze model updates for suspicious patterns indicative of adversarial attacks [370]. Decentralized Federated Intrusion Detection Systems (FIDS) enable multiple edge nodes to detect security threats in real-time using anomaly detection techniques collaboratively [371]. Adaptive Thresholding for Attack Prevention adjusts detection thresholds based on historical attack patterns, enhancing model resilience in heterogeneous 7G environments [372]. These mechanisms collectively reinforce security against evolving cyber threats.

2) SPLIT LEARNING'S COMPUTATIONAL CHALLENGES AND SOLUTIONS IN EMERGING 7G NETWORKS

Split Learning (SL), a privacy-preserving distributed machine learning approach, is increasingly relevant for emerging 7G networks. Yet, its implementation encounters several computational burdens, particularly with resource-constrained devices like IoT sensors, smartphones, and smart consumer electronics [373]. These challenges must be addressed to enable effective integration into hyper-dense 7G environments. The following computational burdens are identified in 7G networks.

- Devices like IoT sensors and AR/VR equipment, with limited computational capacity, face challenges in handling forward propagation, backpropagation, and high-dimensional data.
- Frequent data exchanges between devices and servers for gradient synchronization and activation transmission lead to increased computational and communication overhead.
- Expanding the number of participants in 7G networks amplifies the complexity of synchronizing split layers and aggregating updates.

- Security techniques such as homomorphic encryption and secure multi-party computation, essential for preserving privacy, impose significant computational strain.
- Adaptive split layer partitioning, necessary for accommodating devices with heterogeneous capabilities, introduces additional real-time computational demands.
- The variability in computational power across devices results in latency disparities, creating straggler effects and requiring redundant computations to maintain synchronization.

To enable efficient implementation of SL in 7G networks, addressing computational burdens is essential. The following solutions focus on reducing resource constraints, improving communication efficiency, and ensuring learning across heterogeneous devices in the 7G ecosystem.

- **Edge-Assisted Split Learning for Computational Offloading:** Resource-constrained devices such as IoT sensors, AR/VR systems, and smart sensors often struggle with high computational demands. Edge computing addresses this challenge by offloading model processing to nearby edge servers, optimizing efficiency in 7G networks [374]. Hierarchical SL Architecture enables intermediate edge nodes to process initial model layers before transmitting activations to the cloud server, reducing the computational burden on weaker devices. Dynamic Task Allocation utilizes AI-driven load-balancing mechanisms to assign complex tasks to high-power edge nodes while reserving lightweight operations for constrained devices [375]. This approach minimizes latency, enhances real-time learning capabilities, and improves system performance.
- **Communication-Efficient Split Learning via Model Compression:** Frequent data exchanges between devices and servers in SL generate significant communication overhead, particularly in hyper-dense 7G networks [376]. To solve this issue, Activation Compression employs quantization, sparsification, and dimensionality reduction to decrease the size of transmitted activation maps, minimizing bandwidth usage. Selective Activation Sharing prioritizes high-impact features instead of transmitting all activations, effectively reducing communication load while maintaining model accuracy. Federated Distillation for Split Learning integrates knowledge distillation with SL, enabling lightweight student models on low-power devices to learn from a more powerful server model [377]. These optimizations enhance communication efficiency and reduce transmission delays in 7G networks.
- **Adaptive Split Layer Partitioning for Heterogeneous Devices:** Heterogeneous devices in 7G networks exhibit varying processing capabilities, often causing straggler effects where slower devices delay the learning process. Dynamic Layer Partitioning utilizes AI-driven models to adjust layer split points in real-time based on device computational power, network conditions, and workload distribution to address this challenge. Multi-tier split Learning adopts a hybrid SL approach, where edge devices perform partial training while deeper layers are offloaded to more powerful cloud or edge servers, preventing excessive computational strain on weaker devices [378]. This solution facilitates adaptation to device heterogeneity, eliminating bottlenecks and maintaining synchronization in 7G-enabled SL frameworks.

3) CHALLENGES AND SOLUTIONS OF INCREMENTAL LEARNING UNDER ADVERSARIAL ATTACKS IN 7G SCENARIOS

Incremental learning is emerging as a crucial paradigm for adapting machine learning models in real-time to evolving data in 7G network environments [379]. These networks, characterized by hyper-dense deployments, ultra-low latency, and consistent connectivity, make robust incremental learning vital for applications ranging from autonomous systems to network security. Yet, adversarial attacks exploit the distributed and dynamic nature of 7G networks to compromise model stability and accuracy [300]. The following points show the computational and security challenges of incremental learning under adversarial conditions.

- Devices like autonomous vehicles and smart appliances face difficulties in real-time model adaptation while addressing adversarial vulnerabilities.
- Adversarial attacks, especially closed box variants, exploit limited knowledge about model parameters to introduce instability, posing significant challenges to defense mechanisms.
- Restrictions on data sharing due to privacy concerns block the ability to train models incrementally without losing knowledge of previously learned data.
- The rapid influx of data in 7G systems complicates deploying continual learning strategies while maintaining real-time responsiveness.
- Incremental learning frameworks often fail to ensure robustness against unforeseen data distributions introduced by adversarial manipulations.
- Security mechanisms, such as model distillation and transfer learning, though useful against attacks, introduce additional computational demands that strain resource-constrained systems in 7G networks.

The following shows the possible solutions to address the challenges of incremental learning under adversarial attacks in 7G networks. These solutions enhance model security, preserve data privacy, and ensure adaptability in hyper-connected and ultra-low latency 7G environments.

- **Adversarial Training with Dynamic Regularization:** Enhances model resilience by continuously learning from adversarial examples while reducing catastrophic forgetting, ensuring stability in evolving 7G scenarios.

- **Real-time Adversarial Detection:** Utilizes AI-driven anomaly detection mechanisms to identify and neutralize adversarial manipulations dynamically, preventing model corruption in real-time learning.
- **Federated Knowledge Distillation:** Enables privacy-preserving incremental learning by allowing lightweight models to gain knowledge from a global model without sharing raw data, reducing security risks.
- **Elastic Weight Consolidation (EWC):** Preserves previously learned knowledge while adapting to new data, preventing catastrophic forgetting and ensuring robust continual learning in adversarial conditions.
- **Resource-aware Learning Strategies:** Dynamically optimizes computational resource allocation based on network conditions and device capabilities, ensuring real-time incremental learning efficiency in 7G environments.

4) CHALLENGES AND SOLUTIONS OF CONTEXTUAL UNDERSTANDING WITH LLMS IN 7G NETWORKS

LLMs are set to transform 7G networks by enabling advanced contextual understanding, real-time decision-making, and integrated interactions across distributed systems [286]. Despite their promise, deploying LLMs in the 7G ecosystem presents substantial challenges stemming from the complexity of networks, security vulnerabilities, and scalability demands. Recent studies and analysis show that the following challenges have been observed in the 7G network.

- *Adversarial Vulnerabilities:* LLMs in 7G scenarios face sophisticated adversarial attacks, such as prompt injection and backdoor manipulation, which exploit the contextual nature of LLMs to manipulate responses or compromise systems [380]. For instance, a malicious actor might inject hidden triggers into user queries, causing the model to output sensitive system configurations or execute unintended actions.
- *Bias and Fairness in Contextual Outputs:* Biases ingrained in training data can lead to unfair or contextually inappropriate outputs, particularly in sensitive applications like autonomous driving or healthcare [381]. For example, biased outputs in medical decision-making could disproportionately disadvantage underrepresented populations, undermining the credibility of LLMs in critical 7G services.
- *Privacy Risks in Distributed Systems:* In decentralized 7G networks, privacy concerns are heightened as LLMs interact across multiple nodes [144]. Membership inference attacks, where attackers deduce whether specific data records were used in training, are a significant threat. For instance, such attacks could expose individual location data from traffic systems in a smart city use case.
- *Integration with Edge-Cloud Continuum:* Maintaining consistent, contextual understanding in the edge-cloud continuum of 7G networks is challenging due to synchronization issues and the need for secure, low-latency data exchanges [187]. For example, an LLM deployed on an edge device for autonomous vehicle navigation may fail to provide timely instructions if the data flow between the edge and cloud is disrupted.
- *Real-Time Adaptability:* The ultra-low latency requirements of 7G networks demand LLMs to adapt dynamically to changing contexts. During a network outage, an LLM must immediately adjust its contextual understanding to manage traffic rerouting in a smart transportation system [382]. Current LLMs often struggle to achieve this level of adaptability in real-time.
- *Security in Intent-Based Networking (IBN):* As IBN automates network configurations, compromised LLMs could generate harmful configurations, such as rerouting sensitive data through malicious nodes [383]. For example, an attacker exploiting intent translation might redirect financial transaction data to unauthorized locations, compromising user privacy and security.
- *Scalability in Autonomous LLM Swarms:* Distributed LLM swarms for contextual understanding in 7G networks face challenges maintaining secure inter-agent communication [166]. Blockchain integration can help, but it introduces overheads. Blockchain-based swarm managing network security might experience delays in consensus, affecting the system's responsiveness during a cyberattack.

The following solution addresses the challenges of contextual understanding with LLMs in 7G networks. These solutions focus on improving security, ensuring fairness, enhancing privacy, and optimizing real-time adaptability in dynamic 7G environments.

- **Adversarial Defense Mechanisms for LLMs:** Implementing adversarial training, prompt filtering, and anomaly detection helps reduce prompt injection and backdoor attacks, ensuring robust and secure contextual understanding in 7G networks.
- **Bias Mitigation through Adaptive Fine-Tuning:** Utilizing fairness-aware training, Reinforcement Learning with Human Feedback (RLHF), and dynamic bias correction ensure LLM outputs remain unbiased and contextually appropriate, particularly in critical domains like healthcare and autonomous driving.
- **Privacy-Preserving Techniques for Distributed LLMs:** Deploying federated learning with differential privacy, homomorphic encryption, and decentralized access controls protects sensitive data from membership inference attacks and enhances security in distributed 7G environments.
- **Edge-Cloud Synchronization with Low-Latency Context Adaptation:** Implementing edge-aware LLM architectures with proactive caching, context prediction, and bandwidth-efficient updates ensures smooth real-time decision-making across the edge-cloud continuum in 7G networks.

- **Intent Verification in Intent-Based Networking (IBN):** Employing LLM-powered intent validation, blockchain-backed policy enforcement, and AI-driven anomaly detection prevents malicious intent translations, safeguarding automated network configurations from exploitation.

5) CHALLENGES AND SOLUTIONS OF REINFORCEMENT LEARNING IN 7G RESOURCE ALLOCATION

Reinforcement Learning (RL) in 7G resource allocation introduces a range of complex challenges, particularly in dynamic, heterogeneous environments where various service requirements such as Ultra-Reliable Low-Latency Communication (URLLC), enhanced Mobile Broadband (eMBB), and massive Machine-Type Communication (mMTC) coexist [384]. The high dimensionality of state-action spaces in RL-based resource allocation models, especially in multi-agent settings, significantly increases computational overhead and complicates convergence [385]. Balancing diverse Quality of Service (QoS) needs, such as the ultra-low latency for URLLC and high data throughput for eMBB, requires careful design of reward functions, which must incentivize resource efficiency without compromising service performance [386]. The inherent real-time constraints in 7G, coupled with frequent fluctuations in traffic and network conditions, exacerbate the difficulty of deploying RL models, as they demand rapid adaptation to maintain optimal resource utilization. 7G-enabled edge devices and base stations, where RL is often deployed, face hardware limitations such as constrained computational power and energy efficiency, posing barriers to the scalability and practical implementation of complex RL algorithms [28]. These challenges necessitate innovations in lightweight, distributed RL approaches and advanced coordination mechanisms to enable efficient, adaptive, and scalable resource allocation in next-generation 7G networks.

To overcome the challenges of RL in 7G resource allocation, solutions must focus on efficiency, adaptability, and scalability. Implementing lightweight and distributed RL frameworks, such as edge-based federated RL and decentralized learning architectures, can reduce computational strain by distributing learning across multiple nodes. Adaptive reward function designs that dynamically balance latency, throughput, and energy efficiency enable RL models to optimize resource allocation for various URLLC, eMBB, and mMTC services [387]. Traffic-aware RL models incorporating Graph Neural Networks (GNNs) and meta-learning can quickly adapt to network fluctuations while maintaining low-latency performance to enhance real-time decision-making [388]. Deploying efficient model compression techniques like knowledge distillation, sparsification, and quantization allows RL models to function effectively on resource-constrained 7G edge devices without sacrificing accuracy. Integrating hybrid AI-driven coordination mechanisms and combining reinforcement learning with supervised and unsupervised learning enhances predictive resource allocation and ensures stable convergence in multi-agent RL environments [389]. These advancements will enable scalable, adaptive, and efficient RL-based resource allocation in next-generation 7G networks.

6) WARFARE-INSPIRED CHALLENGES AND SOLUTIONS IN TRANSFER LEARNING FOR 7G NETWORKS

Warfare in modern scenarios is advancing rapidly with the integration of AI-enabled robots, 7G-enabled drones, and automated tanks [390]. All are interconnected through advanced 7G networks powered by Transfer Learning (TL). These systems rely on real-time data transfer and cloud-based architectures for efficient communication and operational precision. AI-enabled robots perform reconnaissance, logistics, and combat support tasks, while 7G-enabled drones enhance surveillance and strike capabilities through ultra-low latency and high-speed data transmission [391]. Automated tanks equipped with AI make autonomous decisions for navigation and targeting, further augmenting battlefield efficiency. Challenges like managing high mobility, frequent handovers in dense deployment zones, and high signal attenuation due to smaller coverage areas are significant. TL-powered algorithms address these by dynamically predicting future serving cells, optimizing handover triggers, and significantly reducing retraining times, even when new AAVs or automated systems are integrated [392]. Ensuring secure and reliable communication in adversarial environments, maintaining energy efficiency, and adapting to unforeseen disruptions in data flow are critical obstacles. Despite these difficulties, AI and 7G integration provide a transformative framework for achieving real-time situational awareness, faster decision-making, and superior operational resilience on the battlefield.

Addressing the challenges of AI-enabled warfare in 7G networks requires intelligent handover optimization through AI-driven predictive models to minimize latency in dense deployment zones. Adaptive Transfer Learning (ATL) enables continual learning, allowing autonomous systems to quickly adapt to new environments and reduce retraining overhead [393]. Resilient communication protocols, including blockchain-based federated learning and secure multiparty computation, ensure encrypted, tamper-proof data exchanges in adversarial conditions. Energy-efficient AI architectures utilize low-power deep learning models and edge AI optimizations to extend the operational life of autonomous units. Robust signal processing techniques, such as advanced beamforming and Intelligent Reconfigurable Surfaces (IRS), reduce high signal attenuation for stable connectivity in battlefield environments [394]. AI-powered self-healing networks detect and counteract failures in real-time, enhancing resilience against jamming and cyber threats [395]. By integrating these solutions, AI-enabled warfare in 7G networks can achieve superior situational

awareness, rapid decision-making, and enhanced operational efficiency.

C. CHALLENGES IN SPECTRUM ALLOCATION FOR 7G NETWORKS

The demand for ultra-high-speed connectivity, the high density of devices, and the variety of use cases necessitating effective and dynamic spectrum management are the main causes of spectrum allocation challenges for 7G networks [396]. Technical challenges, including signal attenuation, a short transmission distance, and heightened susceptibility to interference, arise from integrating terahertz (THz) and millimeter-wave (mm-wave) frequencies, essential for reaching 7G's performance objectives [397]. Additional challenges include managing cross-border spectrum harmonization, addressing regulatory and licensing issues, and guaranteeing fair spectrum distribution among parties [254]. The emergence of heterogeneous networks and multi-access edge computing makes spectrum sharing even more difficult, necessitating sophisticated strategies like cognitive radio and spectrum sensing to maximize utilization during real-time interference mitigation. These difficulties highlight the necessity of creative spectrum management techniques to fully utilize the potential of 7G networks. The following challenges show the need for spectrum management strategies to address technical, regulatory, and operational issues for fully realizing the potential of 7G networks [398].

- *Spectrum Congestion:* As more devices connect to global networks, the RF and microwave bands are becoming increasingly congested, limiting available bandwidth for high-speed communication.
- *High-Frequency Usage:* To counteract this, 7G networks are expected to push into the terahertz (THz) band of the electromagnetic spectrum (300 GHz to 3 THz). These extremely high frequencies enable higher data rates but present challenges in range, attenuation, and hardware complexity.
- *Regulatory Complexities:* Managing cross-border spectrum harmonization and ensuring equitable distribution among stakeholders adds significant regulatory hurdles.
- *Interference and Sharing:* The rise of heterogeneous networks and multi-access edge computing complicates real-time spectrum sharing and increases the risk of interference.
- *Dynamic Spectrum Allocation:* Allocating spectrum dynamically for diverse applications, from autonomous vehicles to smart cities, requires sophisticated algorithms and real-time management techniques.
- *Energy Efficiency:* High-frequency spectrum usage demands energy-efficient hardware and network designs to mitigate the power consumption of devices operating at THz frequencies.
- *Hardware Limitations:* Developing reliable, cost-effective transceivers and antennas capable of operating at THz frequencies remains a technical challenge.
- *Propagation Issues:* High-frequency waves are more susceptible to obstacles, weather conditions, and environmental factors, necessitating advanced beamforming and relay technologies.
- *Security Vulnerabilities:* The shared spectrum increases the risk of eavesdropping and other security threats, requiring robust encryption and secure communication protocols.

D. MATERIALS AND COMPUTATIONAL CHALLENGES IN 7G NETWORKS

The rapid advancement of 7G wireless networks and quantum computing is pushing the limits of modern technology, relying heavily on breakthroughs in materials science [399]. Terahertz (THz) communications promise ultra-high-speed data transmission for 7G but face fundamental material challenges, while quantum computing demands highly specialized materials for stable qubit implementation [400]. Overcoming these challenges is crucial for the next generation of communication and computation technologies. Following are the key material science challenges in Terahertz communications and the physical implementation of quantum computing:

- **Terahertz Communications in 7G:** High atmospheric attenuation necessitates low-loss metamaterials and graphene-based conductors. Efficient THz sources, such as Quantum Cascade Lasers (QCLs), require semiconductors with high carrier mobility [401]. Miniaturization of THz antennas demands plasmonic materials and 2D structures, while thermal and mechanical stability issues call for high-conductivity materials like SiC and h-BN [402].
- **Quantum Computing Implementation:** Superconducting qubits need ultra-pure niobium and aluminum for enhanced coherence [403]. Topological qubits rely on Majorana-supporting materials like topological insulators, while semiconductor qubits struggle with decoherence, requiring precise fabrication. Photonic qubits depend on advanced nonlinear optical materials for integrated quantum networks [404].
- **7G and Quantum Computing Synergy:** Quantum cryptography could enhance 7G security, while advancements in THz-optical materials may facilitate hybrid classical-quantum networks [405]. AI-driven material discovery is critical for optimizing THz and quantum technologies for future innovations [406].

The future of 7G networks relies on solving material challenges in Terahertz communication for high-speed data transfer and quantum computing for secure encryption and processing. Innovations in nanomaterials, superconductors, and topological materials will drive the integration of these technologies, enabling ultra-fast, intelligent, and resilient communication systems.

E. ECONOMIC FEASIBILITY OF 7G TECHNOLOGIES: COSTS AND CHALLENGES

The development of 7G networks integrates advanced technologies such as Terahertz (THz) communication, quantum computing, and blockchain to enhance speed, security, and efficiency [29]. These technologies require significant investment in materials, fabrication, and infrastructure, making their economic feasibility a critical factor in real-world deployment. The costs associated with THz components, quantum computing hardware, and blockchain energy consumption must be carefully evaluated to ensure scalable and sustainable 7G implementation [55]. Following are the key economic challenges associated with deploying 7G networks.

- **Cost of Terahertz Communication:** The high cost of THz communication stems from the need for advanced low-loss materials, specialized semiconductor technologies, and infrastructure upgrades to support high-frequency signal transmission. Developing efficient and scalable THz components remains a key economic challenge.
- **Quantum Computing Expenses:** Quantum computing, essential for secure data processing in 7G, requires expensive cryogenic cooling, precise qubit fabrication, and advanced error correction mechanisms. The scalability of quantum systems and cost reduction in hardware development will determine its feasibility in real-world deployment.
- **Blockchain and Computational Efficiency:** While blockchain offers secure and decentralized frameworks for 7G, its economic viability depends on balancing security with computational efficiency. The high energy consumption and processing costs must be optimized for large-scale implementation without compromising network performance.
- **Economic Feasibility of 7G Technologies:** The affordability of 7G depends on advancements in material science, cost-effective fabrication, and scalable deployment strategies. Reducing production costs and improving efficiency in THz communication, quantum computing, and blockchain will be crucial for the widespread adoption of 7G networks.

VIII. CONCLUSION

In this paper, we have examined the transformative potential of 7G networks, offering a comprehensive review of their foundational technologies, innovations, and associated challenges. We highlighted key advancements, including terahertz communication, quantum computing, green networking, and AI-driven optimizations, while exploring their applications across sectors such as smart cities, healthcare, and autonomous systems. We emphasized the essential role of XAI, meta-learning, incremental learning, and reinforcement LLMs in promoting transparency, trust, and effective decision-making, positioning these AI techniques as crucial enablers for adaptive and intelligent networks. Challenges related to energy efficiency, spectrum management, and sustainable infrastructure were discussed, with proposed solutions to address these obstacles. The paper demonstrates how 7G networks will lay the foundation for a hyper-connected, intelligent, and sustainable digital ecosystem. By integrating cutting-edge technologies and overcoming key barriers, these networks will facilitate efficient communication across terrestrial, aerial, and satellite systems, ensuring security, scalability, and inclusivity. Future research directions focus on refining enabling technologies, enhancing XAI integration, and developing robust regulatory frameworks, all essential for unlocking the full potential of 7G and reshaping the future of global connectivity.

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