



## Review Article

# AI-Driven Terahertz 6G Wireless Communication Systems: From Hardware Design to Network Intelligence

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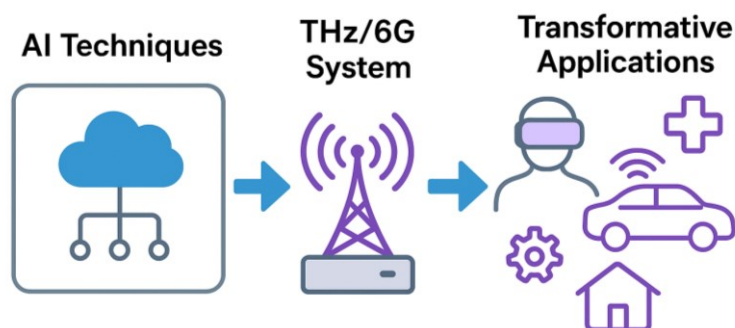
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**Abstract-** The rapid growth of data-intensive applications, such as immersive extended reality and autonomous systems, is driving wireless networks beyond the capabilities of fifth-generation (5G) systems. Sixth-generation (6G) communication, leveraging the terahertz (THz) spectrum (0.1–10 THz), promises terabit-per-second data rates, ultra-low latency, and massive device connectivity. Yet, THz systems face critical barriers including severe propagation loss, hardware constraints, and complex spectrum management. Artificial intelligence (AI) has emerged as a key enabler to address these challenges by enhancing channel modeling, adaptive beamforming, interference mitigation, and intelligent resource allocation. This review critically examines AI-driven THz 6G wireless communication systems, covering fundamentals of THz propagation, AI integration into hardware design, and network intelligence. Representative machine learning and deep learning models are analyzed, supported by schematic frameworks and comparative summaries, to highlight their applications and limitations. Emerging approaches, including federated learning, graph neural networks, explainable AI, and physics-informed modeling, are also discussed, underscoring their role in building resilient and energy-efficient networks. The paper identifies major open issues in hardware feasibility, energy consumption, data availability, and system security, before outlining future research pathways. Recommendations emphasize lightweight AI models, hybrid physics-informed frameworks, security-aware algorithms, and accelerated standardization. By bridging electrical engineering and computer science, AI-driven THz 6G networks are poised to form the backbone of future wireless ecosystems and enable transformative applications across Industry 5.0, healthcare, and immersive digital environments.

## Graphical Abstract

### AI-Driven Terahertz 6G Wireless Communication Systems



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## Article Key Information

**Keywords:** Terahertz communication, 6G, artificial intelligence, deep learning, network intelligence, beamforming, resource allocation.

**Received:** 27th June 2025 **Revised:** 7th August 2025 **Accepted:** 24th September 2025 **Published:** 30th September 2025

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## 1.0 Introduction

The relentless evolution of wireless communications from 4G to 5G has substantially elevated data rates, reduced latency, and expanded connectivity. However, emerging use cases such as augmented and virtual reality, holographic communications, digital twins, and massive Internet of Things (IoT) ecosystems are outpacing existing capabilities. To meet these demands, sixth-generation (6G) networks are turning to the terahertz (THz) frequency range (0.1–10 THz) for its abundant untapped bandwidth, offering the potential for terabit-per-second speeds and sub-millisecond latencies [1,2].

Despite its promise, THz communication faces substantial technical challenges. At these frequencies, atmospheric absorption, particularly by water vapor, and minimal diffraction result in excessive path loss, severely limiting communication range [3]. Additionally, non-line-of-sight (NLoS) situations further deteriorate signal quality. Compounding these issues, existing channel models optimized for sub-6 GHz and millimeter-wave bands are inadequate for accurately characterizing THz propagation, necessitating advanced modeling techniques [2].

On the hardware front, the design and fabrication of systems operating at THz frequencies, encompassing antennas, RF front-ends, and transceivers, remain a nascent field. Materials such as graphene and indium phosphide, despite their potential, are still being explored for feasibility and mass manufacture. Concurrently, photonic generation, frequency multipliers, and ultra-fast signal processing circuitry introduce complexity and elevate costs, while raising thermal management and energy-efficiency concerns [4].

Amid these challenges, Artificial Intelligence (AI), notably Machine Learning (ML) and Deep Learning (DL), is emerging as a transformative force. AI methods excel in learning complex, nonlinear relationships, enabling dynamic beamforming, channel forecasting, adaptive resource allocation, and resilient interference management, often exceeding traditional heuristic approaches in performance [5]. Early studies already demonstrate the potential of AI in key THz communication tasks, including beam alignment, channel estimation, scheduling, and MAC-layer optimization [5,6].

This convergence of electronic engineering (hardware and antenna systems), computer science (ML/DL algorithms), and communication systems (protocol design, networking) establishes a uniquely interdisciplinary research frontier. Despite growing interest in these individual facets, no existing review comprehensively unifies them within an AI-driven THz 6G framework.

Some prior works provide partial coverage. For instance, Jiang et al. systematically review THz communication and sensing technologies in 6G, spanning propagation, channel modeling, devices, beamforming, and testbeds [1]. Boulogeorgos et al. investigate the role of ML across various network layers in THz communications [6]. Nevertheless, neither integrates hardware design, AI-enabled signal processing, and network intelligence into a cohesive narrative.

To address this gap, this review paper titled “AI-Driven Terahertz 6G Wireless Communication Systems: From Hardware Design to Network Intelligence” provides a holistic survey across the following axes:

- i Fundamentals and challenges of THz communication in 6G, including propagation characteristics, hardware constraints, and application scenarios.
- ii AI-enhanced hardware innovations, encompassing ML-augmented antenna and transceiver architectures and energy-efficient circuit design.
- iii Application of AI to THz channel modeling and processing, featuring deep learning-based estimation, reinforcement learning for spectrum control, and advanced signal detection.
- iv AI-driven network intelligence, such as optimized resource allocation, mobility control, federated learning frameworks, and security mechanisms.
- v Emerging application domains, including smart infrastructure, health systems, autonomous platforms, XR, and holographic interfaces.
- vi Current limitations and research opportunities, spanning hardware scalability, data availability, privacy, and standards.
- vii Future directions, such as quantum-inspired AI, edge intelligence, sustainable architectures, reconfigurable surfaces, and hybrid optical-THz systems.

This structured review aims to guide both researchers and practitioners through the evolving landscape of AI-enabled THz systems, paving the path from conceptual progress to practical deployment.

## 2.0 Fundamentals of Terahertz Communications and Challenges

The terahertz (THz) frequency band spans roughly 0.1 to 10 THz and is considered a frontier for future 6G wireless communication systems, enabling unprecedented capacities through expansive bandwidth [7]. Despite its promise, the THz band presents distinct propagation, hardware, and system challenges that must be thoroughly understood to harness its full potential.

To illustrate the operational spectrum and architecture of terahertz communication systems, Figure 1 presents a schematic model of THz communications, highlighting the frequency range, transceiver components, and propagation environment. Figure 1 provides readers with a visual reference for the fundamental concepts and challenges discussed.

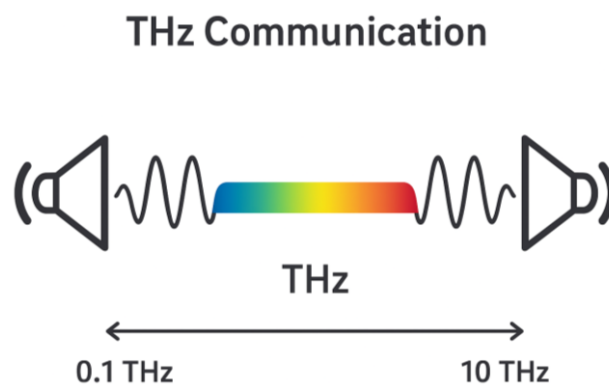


Figure 1. Schematic illustration of a terahertz (THz) communication model, showing the frequency spectrum, transceiver components, and propagation environment.

### 2.1 Propagation Characteristics and Channel Modeling

At THz frequencies, both spreading loss and molecular absorption increase significantly, resulting in severe path loss that poses a formidable barrier to long-range communication. Analytical models show that propagation over just 10 m can incur over 100 dB of free-space path loss, rendering traditional communication strategies ineffective [8]. Moreover, molecular resonances, particularly involving water vapor and oxygen, generate frequency-selective absorption peaks, effectively creating spectral transmission “windows” that fluctuate with environmental conditions [9,10].

THz channels are highly sparse, with minimal multipath due to negligible diffraction and limited scattering, which challenges the design of robust NLoS communication systems. Indoor measurements reveal that reflected NLoS links often suffer attenuation exceeding 10 dB, substantially reducing coverage continuity [11]. Sophisticated channel models that integrate line-of-sight (LOS), reflection, diffuse scattering, and molecular absorption phenomena are essential for accurate simulation and system planning [12].

Environmental factors such as weather also play a critical role. Studies have documented how rain, fog, and airborne particulates can exacerbate signal attenuation. One evaluation indicates that while terahertz links outperform free-space optical channels in fog conditions, all-weather resilience remains a significant design constraint, especially for extended outdoor links [13]. Additionally, atmospheric turbulence can introduce intensity fluctuations (scintillation), further complicating link stability and reliability [13].

## 2.2 Hardware Design and Implementation Challenges

On the hardware front, generating and processing THz signals remains technologically arduous. Traditional electronic components often struggle to operate efficiently at such high frequencies. Novel materials like graphene, indium phosphide, and photonic sources are under investigation, but scalable, cost-effective fabrication is yet to be realized [14]. Switching to photonic or frequency-multiplier-based transmitters also introduces complexity, size constraints, and thermal management challenges, all of which hinder real-world deployment [15].

Antenna arrays tailored for THz frequencies must be ultra-compact, capable of generating ultra-massive MIMO (UM-MIMO) beamforming gains while managing heat dissipation and power consumption. Hybrid beamforming architectures—combining analog and digital precoding—have been proposed to strike a balance between performance and hardware complexity, avoiding the power-hungry full-digital implementations [16]. However, these systems must contend with the beam squint effect, a significant problem in wideband THz systems where beam directions vary with frequency, eroding array gain [16].

The link coverage is heavily constrained by distance-dependent path loss, making precise beam alignment essential. Techniques like reconfigurable intelligent surfaces (RIS) have been explored to redirect THz signals around obstacles, yet their practical integration remains in early research stages [16]. Moreover, the physical integration of such components, transceivers, antennas, and wavefront controllers into compact, energy-efficient platforms remains a formidable engineering pursuit.

## 2.3 Measurement, Channel Sounding, and Testbeds

Characterizing THz channels in real-world environments requires advanced channel sounding tools. Conventional vector network analyzers (VNAs) struggle with synchronization over long distances, limiting their applicability in mobile or dynamic environments [17]. Alternative methods like sliding correlator channel sounders, which compress wideband measurements into manageable signals, face synchronization and precision challenges, especially over extended links without wired calibration [17].

Experimental endeavors have succeeded in mapping channel characteristics in offices, corridors, and urban microcells, but dynamic or outdoor NLoS environments remain underexplored. Recent efforts, such as IEEE Communications Magazine, represent advances by covering various scenarios, indoor, data centers, and even nanoscale on-chip channels, yet highlight that comprehensive, multi-dimensional channel databases are still lacking [18]. Table 1 presents a summary of the key challenges.

Table 1: Summary of Key Challenges

Category	Key Challenges
Propagation	Severe path loss; molecular absorption; sparse NLoS channels.
Hardware	THz signal generation; component fabrication; thermal issues.
Beamforming	Power-hungry digital systems; beam squint; RIS integration issues.
Measurement	Synchronization, dynamic scenario testing, and a lack of comprehensive data.

The THz band offers extraordinary capacity for 6G wireless communication, but this potential is contingent on overcoming unique propagation impairments, developing advanced hardware, managing beam alignment, and executing accurate channel characterization. These challenges underline the importance of integrating AI-driven approaches from adaptive beamforming to real-time channel prediction to enable practical, high-performance THz systems.

### 3.0 Role of AI in Wireless Communication, Leading to Terahertz Networks

Artificial intelligence (AI) has emerged as a key enabler of next-generation wireless communication systems, offering solutions to the complex problems of dynamic spectrum allocation, massive connectivity, and adaptive resource management. While 5G networks already incorporate limited AI capabilities in radio resource optimization, 6G and beyond are expected to rely heavily on AI across nearly every layer of the communication stack [19]. The high dimensionality and dynamic nature of terahertz (THz) communication channels make AI indispensable for overcoming traditional design bottlenecks in hardware, channel modeling, and adaptive beamforming [20].

To illustrate the conceptual role of artificial intelligence in next-generation wireless systems, **Figure 2 presents the schematic integration framework**, where the THz/6G communication environment serves as the input domain, AI techniques operate as the intelligence core, and network intelligence emerges as the output, enabling adaptive and optimized system performance.

#### AI Integration Framework for THz/6G Systems

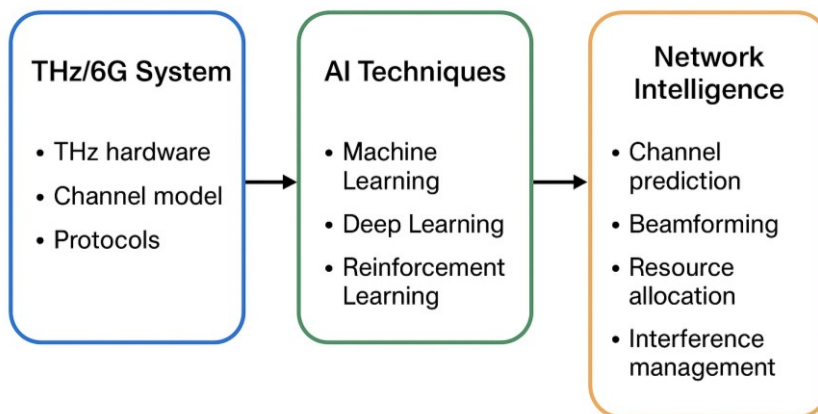


Figure 2: Schematic framework showing the integration of AI techniques in THz/6G wireless systems to enable adaptive and intelligent network operations.

#### 3.1 AI in Current Wireless Systems

AI techniques such as reinforcement learning (RL), deep learning (DL), and federated learning (FL) are increasingly being applied in existing 5G systems for traffic prediction, handover management, interference mitigation, and channel estimation. For example, deep neural networks (DNNs) have been successfully used to improve channel state information (CSI) prediction, outperforming conventional model-based approaches in highly dynamic environments [21]. Similarly, RL algorithms have been deployed for adaptive spectrum allocation in cognitive radio networks, demonstrating near-optimal performance in uncertain spectrum environments [22]. These advancements illustrate how AI can efficiently manage scarce wireless resources by learning and adapting to the environment without explicit programming.

The energy efficiency challenge of wireless systems also benefits from AI integration. Deep reinforcement learning (DRL) models have been shown to optimize energy-harvesting relay systems by balancing throughput and power constraints, providing insights into how AI can improve sustainability in large-scale deployments [23].

As the number of devices in the Internet of Things (IoT) expands into billions, AI-driven automation becomes essential for maintaining quality of service (QoS) and latency guarantees.

### 3.2 Extending AI Applications to Terahertz Communications

The transition to THz communications magnifies existing wireless challenges, such as beam alignment, mobility management, and channel estimation, due to the ultra-narrow beams and high propagation losses characteristic of this spectrum [24]. Conventional optimization methods that rely on closed-form models fail to scale under the multi-dimensional uncertainty of THz environments. AI offers an attractive alternative by learning patterns from high-dimensional channel measurements, predicting optimal beamforming strategies, and adapting to rapidly changing propagation conditions.

For instance, convolutional neural networks (CNNs) have been employed to predict beam directions directly from user location data and environmental features, reducing alignment overheads in THz massive MIMO systems [25]. Likewise, graph neural networks (GNNs) have shown promise in capturing the topological structure of THz networks, particularly in RIS-assisted scenarios, where spatial correlations among reflection elements can be modeled more effectively than with conventional statistical tools [26].

Another emerging application lies in THz channel estimation. Traditional pilot-based estimation is impractical at very high frequencies due to excessive overhead. Recent studies show that unsupervised deep learning approaches can infer channel state information directly from raw received signals, achieving significant accuracy improvements over linear estimators [27].

### 3.3 AI-Driven Security and Resource Management in THz

In addition to performance optimization, AI is critical for ensuring security and resilience in THz networks. The high capacity of THz links makes them a potential target for jamming, spoofing, and eavesdropping. AI-enabled intrusion detection systems, trained on large-scale traffic datasets, can identify abnormal patterns in real time and implement proactive countermeasures [28]. Furthermore, reinforcement learning models can be used for secure beamforming, dynamically reconfiguring antenna arrays to minimize information leakage in the presence of malicious users.

Resource management is another area where AI can enhance THz networks. Unlike sub-6 GHz and mmWave bands, where spectrum allocation is relatively well understood, the THz band requires dynamic frequency selection due to frequency-selective absorption windows. AI models, particularly federated learning frameworks, enable collaborative optimization across distributed base stations without requiring centralized training, reducing overhead and preserving user privacy [29].

### 3.4 Towards AI-Native Terahertz Networks

The integration of AI in THz communications is not just an enhancement, but a necessity. Future AI-native networks will treat machine learning models as integral components of the communication protocol, enabling self-optimizing and self-healing systems. For example, AI-powered digital twins are being investigated to simulate THz environments in real time, providing predictive control and faster adaptation than conventional feedback loops [30].

In summary, the role of AI in wireless communications is rapidly evolving from an optimization tool in 5G to a core enabler in 6G THz networks. By addressing challenges in beam alignment, channel estimation, resource allocation, and security, AI is poised to transform THz systems into highly adaptive, resilient, and efficient communication platforms.

## 4.0 Deep Learning Approaches in Terahertz 6G Wireless Systems

### 4.1 Overview

Deep learning (DL), a subset of artificial intelligence, has emerged as a transformative enabler in wireless communications, particularly in the context of terahertz (THz) 6G systems. Unlike traditional model-based methods, DL architectures can autonomously learn complex non-linear mappings from large datasets, making them highly suitable for the challenging propagation and hardware constraints of THz bands [31]. The ultra-broad bandwidth, susceptibility to blockages, and highly directional beam characteristics in THz systems require advanced learning frameworks that can address channel estimation, beam management, modulation classification, and resource allocation simultaneously [32].

In the following subsections, we present the key areas where DL techniques are being applied in THz-enabled 6G communication systems, highlight their comparative performance, and critically analyze open challenges.

To better contextualize the spectrum of artificial intelligence techniques deployed in terahertz 6G wireless systems, Figure 3 provides a schematic taxonomy that maps the roles of machine learning and deep learning approaches across hardware optimization, spectrum management, and network intelligence. This broader framework lays the foundation for the detailed discussion of representative deep learning models summarized in Table 2.

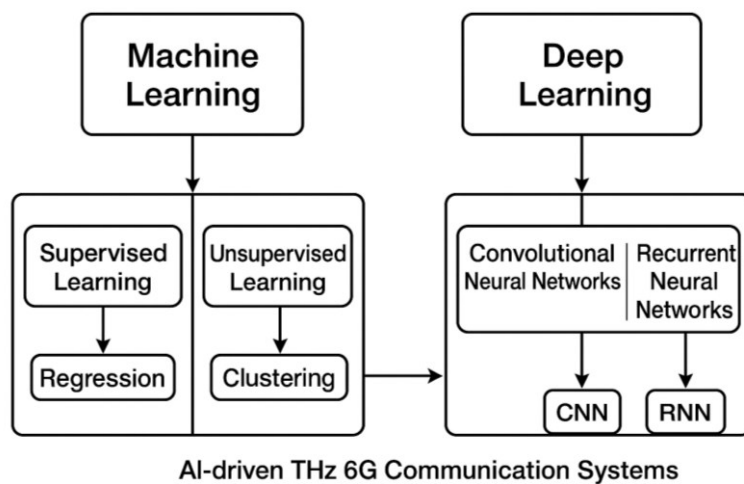


Figure 3 is the schematic overview of machine learning and deep learning approaches for AI-driven 6G/THz communication systems (taxonomy/comparison)

### 4.2 Applications of Deep Learning in THz/6G

#### 4.2.1 Channel Estimation and Modeling

THz channels exhibit high frequency selectivity, molecular absorption losses, and sparsity in the time–frequency domain. Conventional channel estimation methods, such as least squares (LS) and minimum mean square error (MMSE), struggle in high-dimensional THz scenarios [33]. DL-based models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated superior performance by exploiting the sparsity and temporal correlations of THz channels [34]. For instance, deep autoencoders can reconstruct incomplete channel state information (CSI) with lower pilot overheads [35].

#### 4.2.2 Beamforming and Beam Tracking

Beam alignment is critical in THz links due to highly directional antennas. Traditional exhaustive search is computationally prohibitive. DL models, particularly reinforcement learning (RL)-assisted deep Q-networks (DQNs), have been proposed for fast beam alignment and adaptive tracking under mobility conditions [36]. Hybrid beamforming strategies enhanced by DL have also been shown to minimize power consumption while maintaining high spectral efficiency [37].

#### 4.2.3 Modulation Classification and Signal Detection

In THz systems, high-order modulation schemes (e.g., 256-QAM, OTFS) are necessary for ultra-high throughput but are sensitive to noise and hardware impairments. DL-based classifiers, particularly CNNs and long short-term memory (LSTM) networks, outperform traditional likelihood-based detectors by learning directly from raw I/Q samples [38]. These approaches are robust to nonlinear distortions and hardware imperfections [39].

#### 4.2.4 Spectrum Management and Interference Mitigation

The dense deployment of THz small cells in 6G raises severe interference management issues. DL models can dynamically predict spectrum usage, identify interference patterns, and allocate spectrum resources more efficiently than rule-based methods [40]. Generative adversarial networks (GANs) have also been applied to synthesize spectrum occupancy data for training, reducing the dependency on costly real-world measurements [41].

#### 4.2.5 Resource Allocation and QoS Optimization

DL is also applied to optimize resource allocation in multi-user THz systems, balancing throughput, latency, and reliability. Multi-agent reinforcement learning (MARL) approaches enable distributed agents (e.g., base stations or devices) to cooperate in allocating spectrum and power under highly dynamic THz conditions [42]. This capability is crucial for ensuring end-to-end quality of service (QoS) in mission-critical 6G applications such as holographic communications and remote surgery [43].

### 4.3 Comparative Analysis of DL Approaches

**Table 2** summarizes representative deep learning models applied to core THz/6G tasks, comparing their objectives, architectures, and observed limitations.

**Table 2: Representative Deep Learning Approaches in THz/6G Communication Systems**

Application Area	DL Model Used	Key Advantage	Limitation/Challenge	Ref.
Channel Estimation	CNN, Autoencoders	Robust CSI recovery with reduced pilot overhead	Requires large labeled datasets	[33–35]
Beamforming & Tracking	DQN, RL-based models	Fast alignment, adaptive under mobility	High training complexity	[36,37]
Modulation Classification	CNN, LSTM	High accuracy, robust to nonlinear distortion	Sensitive to adversarial perturbations	[38,39]
Spectrum Management	GANs, RNNs	Efficient interference prediction & spectrum use	Synthetic data may lack realism	[40,41]
Resource Allocation	MARL, DNNs	Improved QoS trade-offs in multi-user scenarios	Convergence time in dynamic networks	[42,43]

### 4.4 Critical Discussion

While DL has demonstrated remarkable progress in tackling key THz/6G challenges, several gaps remain. First, the data-hungry nature of DL models is problematic in THz systems, where measurement campaigns are costly and datasets are scarce. Synthetic data generation via GANs and transfer learning are promising but raises

concerns about realism and generalizability [41]. Second, DL models often function as black boxes, limiting explainability and trustworthiness in mission-critical 6G applications [44]. Third, the high computational complexity of DL models may not be feasible for real-time applications at the network edge, requiring model compression and edge–cloud cooperation [45]. Finally, security vulnerabilities in DL models themselves, such as susceptibility to adversarial attacks, pose risks when deployed in THz networks [46].

Therefore, future research must focus on developing lightweight, explainable, and secure DL architectures that can be deployed in resource-constrained THz devices while ensuring reliability.

## 5.0 Emerging Directions in AI-driven Terahertz 6G Wireless Communication Systems

The rapid integration of AI into terahertz (THz)-enabled 6G networks has opened up multiple research frontiers that extend beyond conventional deep learning techniques. To ensure that future wireless communication systems meet the stringent demands of ultra-high data rates, low latency, scalability, and robustness, novel paradigms in distributed intelligence, advanced neural architectures, explainability, and sustainability are gaining traction. This section critically surveys the most promising directions.

### 5.1 Federated Learning for Privacy-Preserving THz/6G

Federated learning (FL) distributes the model training process across multiple edge devices while keeping raw data local. This approach is particularly relevant for THz/6G applications where sensitive user data (e.g., channel state information, localization signals) cannot always be shared with central servers. FL reduces communication overhead, preserves privacy, and leverages distributed edge computing resources for model updates. Challenges include handling non-independent and identically distributed (non-IID) data across devices and communication-efficient model aggregation. Recent works demonstrate FL-based solutions for THz beamforming, channel estimation, and resource allocation in highly dynamic wireless environments [47–49].

### 5.2 Graph Neural Networks for Network Topology-Aware Intelligence

The massive device density in 6G requires network representations that can capture spatial and topological dependencies. Graph neural networks (GNNs) offer a natural way to model user association, interference, and routing in THz networks. By representing nodes as devices and edges as communication links, GNNs enable distributed optimization of routing, spectrum allocation, and interference management. GNN-driven models have been shown to outperform traditional optimization in ultra-dense networks by learning scalable representations that adapt to varying topologies [50–52].

### 5.3 Transformers for Sequence Modeling in Dynamic THz Environments

While recurrent neural networks and convolutional neural networks have dominated wireless applications, transformer architectures are emerging as powerful alternatives for sequence modeling and spatiotemporal tasks. Their self-attention mechanism enables modeling of long-range dependencies, making them suitable for predicting THz channel variations, adaptive beam tracking, and dynamic traffic forecasting. Initial studies demonstrate that transformers outperform LSTMs in mobility prediction and beam alignment under highly dynamic conditions [53,54].

### 5.4 Explainable AI (XAI) for Trustworthy Wireless Intelligence

The opaque nature of deep learning models poses significant challenges for their adoption in critical THz/6G applications, particularly in autonomous driving, healthcare, and industrial automation. Explainable AI (XAI) provides mechanisms to interpret decisions made by neural networks, improving transparency, accountability, and regulatory compliance. Integrating XAI into THz/6G systems can help operators diagnose channel misclassifications, detect adversarial attacks, and verify compliance with service-level agreements. Early research highlights the feasibility of combining XAI with reinforcement learning and signal classification tasks in wireless networks [55–57].

## 5.5 Green AI for Sustainable THz/6G Networks

The energy consumption of AI-driven models poses a major barrier to scalable deployment in THz/6G, given the large number of devices and base stations. Green AI emphasizes energy-efficient neural architectures, lightweight training, and carbon-aware computing. Techniques such as pruning, quantization, knowledge distillation, and neuromorphic computing are being explored to reduce the energy footprint of AI in 6G networks. Integrating energy efficiency as a primary design objective will be crucial for the sustainable deployment of AI in future wireless systems [58–60].

## 5.6 Integration of Emerging AI Paradigms with THz Hardware

Future research must also address the co-design of AI algorithms with THz hardware systems. AI-assisted intelligent metasurfaces, reconfigurable intelligent surfaces (RIS), and hybrid analog-digital architectures can benefit from adaptive optimization enabled by AI models. Co-design strategies can optimize end-to-end system performance while addressing hardware imperfections such as nonlinearities, phase noise, and limited resolution in THz circuits [61,62].

# 6.0 Challenges, Open Issues, and Future Research Directions

## 6.1 Overview

Despite the remarkable potential of AI-driven Terahertz (THz) 6G wireless systems, multiple unresolved challenges hinder large-scale deployment. These challenges arise from the fundamental physics of THz propagation, the complexity of AI models, energy efficiency concerns, and the need for standardization and interoperability. Addressing these gaps requires interdisciplinary research that unifies communication theory, AI/ML/DL techniques, and system-level optimization [63,64].

## 6.2 Key Challenges and Open Issues

### 6.2.1 Propagation and Channel Modeling

THz waves suffer from severe path loss, molecular absorption, and sensitivity to blockages, complicating accurate channel modeling and estimation [65]. Current deep learning-based channel predictors struggle with generalization across environments and lack transferability from simulation to real-world scenarios [66]. Future research should emphasize physics-informed AI models that integrate electromagnetic theory with machine learning [67].

### 6.2.2 Hardware Limitations and Integration

Realizing AI-driven THz hardware requires ultra-fast ADC/DACs, reconfigurable antenna arrays, and intelligent RF frontends. Present hardware architectures are energy-hungry, costly, and difficult to scale [68]. Integration of intelligent reflecting surfaces (IRSs) and massive MIMO systems at THz bands introduces additional signal processing burdens [69]. Future directions include neuromorphic processors, photonics-based THz transceivers, and AI-optimized hardware co-design [70].

### 6.2.3 AI Model Complexity and Data Limitations

Large-scale AI/DL models (e.g., CNNs, GNNs, Transformers) demand significant data and computational resources, raising scalability and real-time processing concerns [71]. Data scarcity at THz frequencies makes supervised training impractical, while privacy concerns limit data sharing. Promising solutions include federated learning, self-supervised learning, and synthetic data generation [72,73].

### 6.2.4 Security and Robustness of AI Models

AI models used for channel estimation, beamforming, and resource allocation are vulnerable to adversarial attacks and data poisoning [74]. Unlike classical security risks, these attacks target the ML pipeline directly. Open issues include developing robust training paradigms, explainable AI for security-critical tasks, and AI-augmented cryptography [75].

### 6.2.5 Energy Efficiency and Sustainability

With billions of devices expected in 6G, energy sustainability is a pressing issue. AI training and inference significantly increase carbon footprints, raising concerns about the environmental impact of large-scale deployments [76]. Green AI, leveraging model compression, pruning, quantization, and energy-aware scheduling, is crucial to align THz 6G with sustainable development goals (SDGs) [77].

### 6.2.6 Standardization, Interoperability, and Deployment

The lack of global standards for THz frequency bands and AI-driven communication frameworks hinders industrial adoption [78]. Current regulatory frameworks mainly focus on sub-6 GHz and mmWave bands, leaving THz largely uncharted. Future work should involve multi-stakeholder collaborations among academia, industry, and standardization bodies to ensure seamless interoperability and backward compatibility [79].

## 6.3 Future Research Directions

Future research in AI-driven Terahertz 6G systems is expected to evolve along several complementary directions that collectively address the fundamental limitations identified earlier. One promising avenue is the development of physics-informed neural networks that embed Maxwell's equations and electromagnetic theory directly into AI architectures, thereby enabling more accurate and generalizable THz channel modeling. At the same time, cross-layer optimization using advanced reinforcement learning techniques will become increasingly important, allowing the physical, MAC, and network layers to be jointly optimized rather than treated in isolation.

Another emerging direction involves edge intelligence, where lightweight AI models are deployed at the network edge to enable real-time inference with minimal latency and reduced dependence on centralized data centers. This trend aligns closely with the demand for ultra-reliable low-latency communications in 6G applications. Security considerations will also shape the research agenda, with efforts focusing on the design of explainable and adversarially robust machine learning models that can protect AI-driven THz systems from malicious attacks while ensuring transparency in decision-making.

Equally critical is the pursuit of energy-efficient and sustainable solutions, often referred to as "Green AI." This includes techniques such as model compression, pruning, and quantization, as well as energy-aware scheduling that collectively reduce the environmental footprint of training and deploying large AI models in THz networks. Finally, there is an urgent need for coordinated efforts in standardization and policy development, where academia, industry, and regulatory bodies collaborate to define global protocols for AI-driven THz systems. Such frameworks must ensure interoperability, backward compatibility, and regulatory clarity, thereby laying the foundation for scalable and secure deployment of future 6G networks.

To provide a consolidated view of the critical research gaps, Table 3 summarizes the major challenges in AI-driven terahertz 6G systems, highlights their current limitations, and outlines promising research pathways that can guide future investigations.

Table 3: Summary of Key Challenges, Current Limitations, and Future Research Pathways

Challenge	Current Limitation	Promising Research Direction
Terahertz Channel Modeling	Existing statistical and ray-tracing models lack accuracy in dynamic environments and mobility conditions.	Development of hybrid physics-informed and AI-based models incorporating real-time environmental awareness.

Hardware Constraints	High propagation losses, limited power efficiency, and difficulty in fabricating low-cost THz transceivers.	Exploration of novel semiconductor materials (e.g., graphene, III-V compounds) and AI-driven adaptive beamforming.
Spectrum and Resource Management	Inefficient allocation due to non-stationary THz channels and high interference levels.	Deep reinforcement learning for cross-layer spectrum allocation and dynamic resource scheduling.
Security and Privacy	Vulnerability to adversarial attacks, spoofing, and jamming in ultra-dense THz/6G networks.	Design of adversarially robust and explainable AI models for secure, transparent decision-making.
Latency and Reliability	Edge-cloud dependence increases latency; centralized AI models limit real-time responsiveness.	Edge intelligence with lightweight AI models for real-time decision-making closer to users.
Energy Efficiency	Training and deployment of large AI models increase energy footprint, conflicting with green networking goals.	“Green AI” techniques including pruning, quantization, and energy-aware scheduling for sustainable THz/6G systems.
Standardization and Interoperability	Lack of unified global frameworks for THz spectrum allocation and AI-driven protocol design.	Cross-industry collaboration on standardization bodies to ensure interoperability, scalability, and regulatory compliance.

In addition to the tabular summary, Figure 4 presents a visual roadmap of the challenges, limitations, and future research directions in AI-driven terahertz 6G wireless systems, mapping the interconnections across technical, security, hardware, and policy dimensions to complement the insights provided in Table 3.

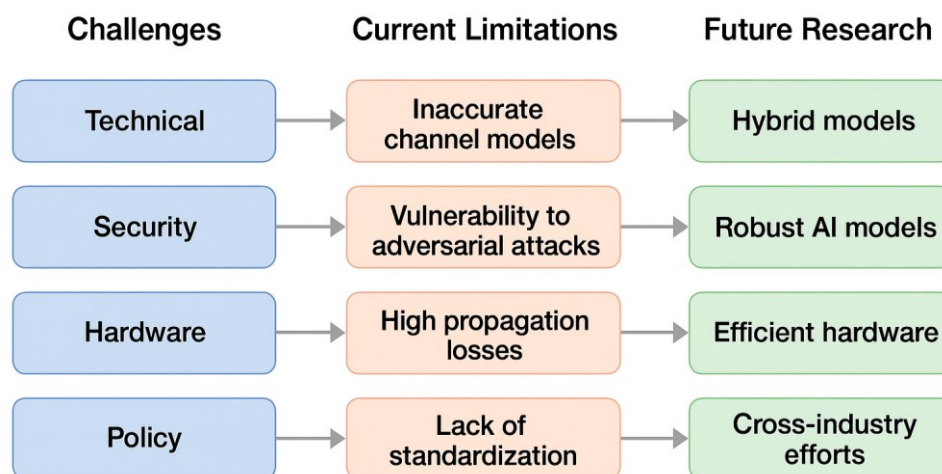


Figure 4: Schematic figure of challenges and future research directions in AI-driven terahertz 6G wireless systems, showing interconnections across technical, hardware, security, and policy dimensions.

## 7.0 Conclusion and Recommendations

Artificial intelligence is indispensable for realizing the potential of THz 6G systems. AI enables adaptive beamforming, efficient resource allocation, and intelligent network management, overcoming traditional hardware and propagation constraints. Nevertheless, challenges in hardware design, energy consumption, data requirements, and security must be addressed.

We recommend four key directions: first, develop physics-informed and hybrid AI models to improve channel predictions; second, design lightweight and energy-efficient algorithms; third, implement security-aware AI frameworks to ensure resilience; and fourth, accelerate collaborative standardization and policy-making to

guarantee interoperability. By aligning AI innovations with sustainable engineering and cooperative policy frameworks, robust, intelligent, and energy-efficient THz 6G infrastructures can be realized, supporting transformative applications such as XR, autonomous systems, and Industry 5.0.

## Declarations

### Funding:

The authors received no specific funding for this study.

### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

### Ethical Approval

Not applicable, as this study did not involve human participants or animal experiments.

### Consent to Participate

Not applicable.

### Consent for Publication

All authors consent to the publication of this manuscript in its current form.

### Availability of Data and Materials

All data generated or analyzed during this study are included in this published article.

### Authors' Contributions:

**Celestine Mbakaan** conceptualized the study and supervised the overall project. **Kpelai Justin A** conducted the literature review and drafted Sections 2.0–4.0. **Tyavnande Moses, I** contributed to the writing of Sections 5.0–6.0 and compiled the references. All authors reviewed, edited, and approved the final manuscript.

### Acknowledgments:

The authors gratefully acknowledge the constructive feedback from peer reviewers, which significantly improved the quality of this manuscript.

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