Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 6, December 2026, pp. 4943~4952
ISSN: 2302-9285, DOI: 10.11591/eei.v15i6.13537

Artificial intelligence for next-generation 6G technologies and networks

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Article Info

Article history:

Received May 31, 2026
Revised Sep 12, 2026
Accepted Oct 4, 2026

Keywords:

AI-radio access network
Artificial intelligence
Integrated sensing and communication
Machine learning
Massive multiple-input multiple-output
Reconfigurable intelligent surface
Sixth-generation

ABSTRACT

Sixth-generation (6G) networks require extreme data rates, ultra-low latency, pervasive sensing, energy-aware operation, and massive intelligent connectivity. This review examines artificial intelligence (AI) and machine learning (ML) as enabling mechanisms for AI-native 6G networks. It synthesizes third generation partnership project (3GPP) progress, AI-radio access network (AI-RAN), radio-resource management, mobility and coverage optimization, massive multiple-input multiple-output (MIMO), integrated sensing and communication (ISAC), semantic communication, reconfigurable intelligent surfaces (RIS), non-terrestrial networks (NTNs), edge intelligence, and security. The review contributes an AI-native taxonomy based on embedded intelligence, closed-loop learning, distributed inference, heterogeneity awareness, trustworthy autonomy, critically compares benefits, constraints, deployment settings, and research gaps. The evidence indicates that AI must be designed as a resource-constrained and trustworthy component of radio, edge, and management planes, rather than used only as an external optimizer.

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1. INTRODUCTION

Wireless networks are moving from fifth-generation (5G) enhancement toward sixth-generation (6G) systems that must support terabit-class throughput, sub-millisecond latency, integrated sensing, massive connectivity, and service-aware automation. These requirements enlarge the optimization space beyond what fixed rules and purely model-based algorithms can handle in real time. Artificial intelligence–radio access network (AI-RAN), integrated sensing and communication (ISAC), and large-scale optimization studies show that AI and machine learning (ML) are becoming central to 6G design rather than optional network-management add-ons [1]-[3].

The need for intelligence is strongest where the radio environment is highly dynamic. Massive multiple-input multiple-output (MIMO), cell-free architectures, terahertz links, reconfigurable intelligent surfaces (RIS), ambient internet of things (IoT), non-terrestrial networks (NTN), and AI-assisted physical-layer processing all require rapid estimation, prediction, and coordinated control [4]-[9]. Earlier AI/ML surveys for 5G and beyond established the value of data-driven network control; 6G extends that idea by embedding learning mechanisms into the protocol stack, edge-cloud architecture, and radio environment itself [10], [11].

This review addresses a gap in existing AI-enabled 6G surveys: most treat individual technologies or individual learning techniques separately, whereas deployment decisions require a cross-layer view that links AI-RAN control loops with physical-layer intelligence, edge execution, trustworthy governance, and heterogeneous terrestrial, aerial, and satellite operation. Its novelty is the AI-native taxonomy that organizes these issues around where intelligence is placed, how feedback is closed, where inference is executed, which services are supported, and how trustworthy operation is assured. The review therefore emphasizes engineering trade-offs, not only technology descriptions.

The main contributions are threefold: i) a cross-layer AI-native taxonomy that connects standardization, RAN control, physical-layer intelligence, edge intelligence, and environment-aware operation; ii) a structured comparison of the benefits, limitations, deployment scenarios, and unresolved challenges of leading AI-based 6G technologies; and iii) a critical synthesis of practical constraints, including latency, energy consumption, data governance, model robustness, explainability, and implementation cost.

The review methodology adopted for this study was through a structured narrative review of peer-reviewed journals, conference papers as well as other relevant publications, third generation partnership project (3GPP) technical report (TR) and specifications, and major 6G research-project outputs published mainly from 2020 to 2025, supplemented by foundational studies where required for technical context. Searches combined terms such as "6G", "AI-RAN", "machine learning", "radio resource management", "massive MIMO", "ISAC", "RIS", "semantic communication", "non-terrestrial networks", "edge intelligence", and "trustworthy AI". Sources were retained when they provided direct technical evidence, a standards contribution, a deployment-relevant evaluation, or a clearly defined research challenge; duplicate, off-topic, and purely promotional sources were excluded. The selected publications/works were then grouped by network function and assessed against latency, reliability, energy, security, scalability, and deployment feasibility.

The remainder of the paper is organized as follows. Section 2 reviews AI/ML standardization and introduces the AI-native design principles. Section 3 examines AI/ML-enabled 6G technologies and their practical trade-offs. Section 4 compares the major technology areas, discusses open challenges and deployment scenarios, and identifies future research directions. Section 5 presents the conclusion summarizes the review's findings, limitations, and implications.

2. AI/ML STANDARDIZATION AND AI-NATIVE DESIGN

This section establishes the standards and design foundation for the AI-native 6G discussion. It first explains how 3GPP has moved from network automation toward AI/ML support for radio access functions, then connects that standardization path to the design principles required for autonomous, trustworthy, and adaptive 6G operation.

2.1. 3GPP standardization and artificial intelligence–radio access

The standardization path toward AI-assisted networks began with network automation and data exposure. 3GPP TR 23.791 studied enablers for network automation in 5G, while technical specification (TS) 32.500 defined self-organizing network concepts and requirements for telecommunication management [12], [13]. More recently, TR 38.843 studied AI/ML for the new radio (NR) air interface and identified use cases such as channel state information (CSI) feedback enhancement, beam management, and positioning improvement [14]. These documents indicate a shift from isolated vendor-specific AI functions toward standardized cooperation among devices, base stations, and management entities.

AI-RAN extends this standardization trend by treating intelligence as part of the radio access network. Instead of applying ML only after data have been collected, AI-native operation uses learning to assist mobility control, energy saving, load balancing, spectrum allocation, and network slicing. Autonomous RAN and network digital-twin studies further show how a model of the network can be used to test decisions before they are applied to live infrastructure [1], [11], [15].

2.2. Design principles for artificial intelligence-native sixth-generation

Five design principles are important for AI-native 6G. First, intelligence should be embedded into network functions instead of being treated as an external optimizer. Second, the network should operate with closed feedback loops that sense, learn, decide, and adapt. Third, learning should be distributed across devices, base stations, edge servers, and cloud platforms to reduce latency and protect local data. Fourth, models must handle heterogeneous services, including broadband access, ultra-reliable low-latency communications (URLLC), massive machine-type communications (mMTC), sensing, and NTN connectivity. Fifth, the decisions made by AI systems must be secure, explainable, and reliable enough for critical infrastructure [3], [16]-[19]. Figure 1 positions embedded intelligence, closed-loop learning,

distributed inference, service heterogeneity, and trustworthy autonomy as the design criteria distinguishing AI-native 6G from conventional AI-assisted optimization.

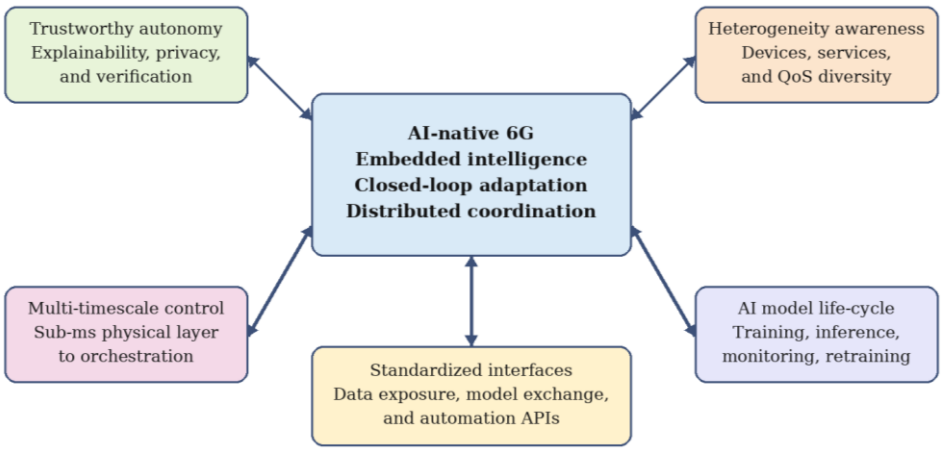


Figure 1. Design principles and control loops for AI-native 6G systems

3. ARTIFICIAL INTELLIGENCE/MACHINE LEARNING-ENABLED 6G TECHNOLOGIES

Building on the standardization and design principles discussed above, this section examines the main 6G technology areas where AI/ML is expected to have the greatest operational impact. The discussion moves from network-level functions such as coverage, mobility, spectrum, and quality of service (QoS) management to physical-layer intelligence, ISAC, semantic communication, RIS, NTN, and environment-aware operation. Figure 2 links sensing, RAN, edge, cloud, and orchestration functions, identifying where AI decisions can be executed and verified.

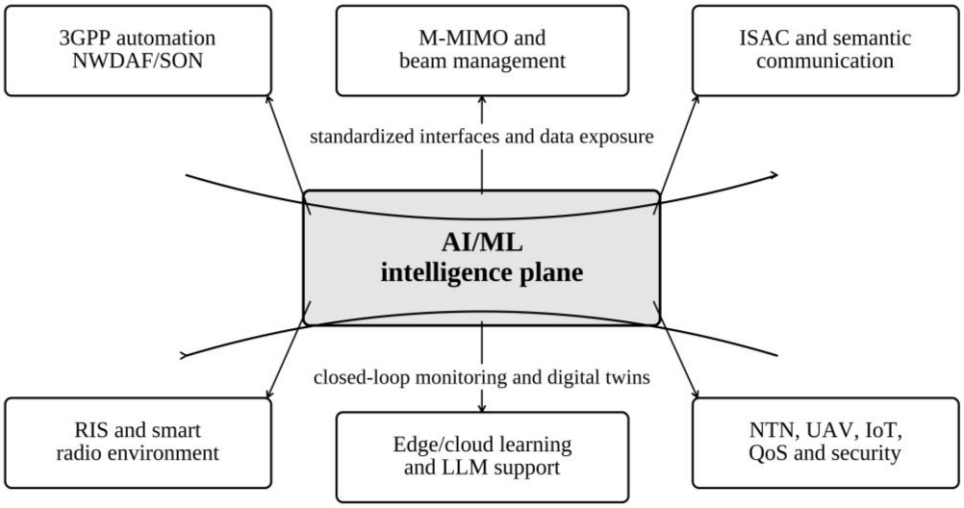


Figure 2. AI-native 6G architecture and enabling technologies

3.1. Coverage, mobility, spectrum, and quality of service management

Coverage and mobility management provide a practical bridge between legacy cellular optimization and AI-native 6G. Earlier work on dynamic channel borrowing, long-term evolution (LTE) physical-layer procedures, discontinuous transmission, call admission control, and VoLTE QoS evaluation established the importance of resource coordination, interference management, and service guarantees [20]-[24]. These foundations remain relevant because 6G networks will still need to support mobility, admission decisions, and heterogeneous QoS under changing channel and traffic conditions.

AI/ML adds prediction and adaptation to these functions. AI-enabled spectrum management supports spectrum sensing, resource allocation, and adaptive access policies for future networks [25]. Learning-based handover, velocity-aware handover self-optimization, unmanned aerial vehicle (UAV)-assisted coverage optimization, and particle swarm optimization–backpropagation–Kriging (PSO-BP-Kriging) coverage detection illustrate how data-driven methods improve coverage planning and mobility robustness [26]-[29]. Green 6G resource-management studies and deep reinforcement learning (DRL)-based vehicular resource allocation further show how energy use, latency, and reliability can be jointly optimized [30], [31]. Figure 3 shows how monitored measurements become predictions and resource-control actions. Figure 4 details the closed loop of data collection, learning, model update, inference, control, and post-action evaluation.

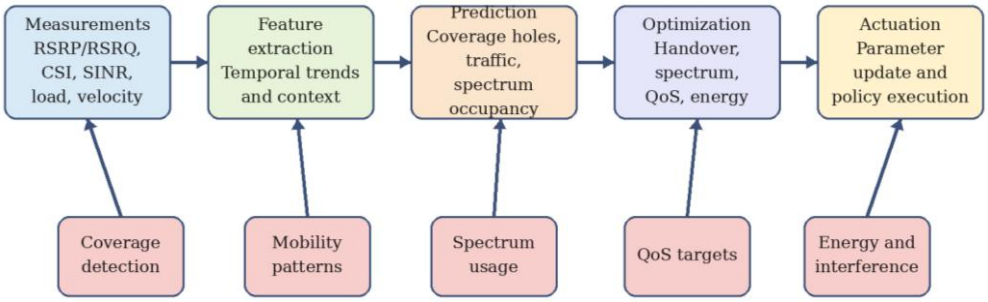


Figure 3. AI/ML workflow for coverage, mobility, spectrum, and QoS optimization

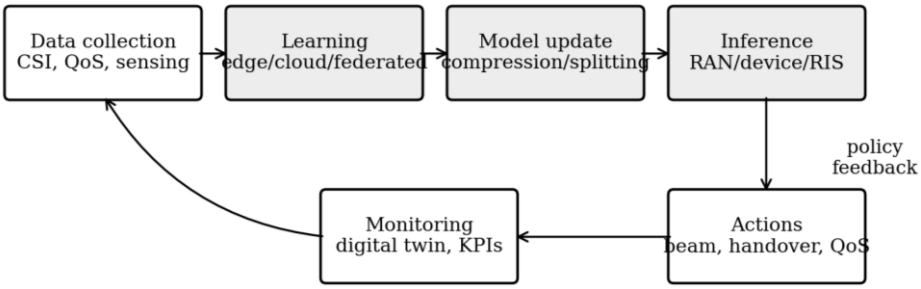


Figure 4. Closed-loop AI/ML workflow for 6G radio-resource management

3.2. Massive multiple-input multiple-output, channel estimation, and physical-layer intelligence

Massive MIMO remains a core 6G technology because large antenna arrays can increase spectral efficiency, reliability, and spatial multiplexing. However, the scale of channel estimation, precoding, user scheduling, and beam management makes manual or exhaustive optimization impractical [4], [5]. Deep learning can assist channel estimation and CSI feedback, while automatic modulation recognition, deep unfolding, and deep learning-aided physical-layer (PHY) architectures show how signal processing can be combined with trainable models [9], [32], [33]. Automatic modulation recognition in fading channels is another useful physical-layer application because it improves signal classification and adaptive radio control [34].

The same approach supports reliability and energy objectives. Hybrid beamforming with deep learning can help balance spectral, energy efficiency, and deep learning for URLLC can reduce decision latency where deterministic response is required [35], [36]. However, these gains depend on representative training data, affordable CSI acquisition, and inference that fits within the latency and energy budget. Large models can shift computation and memory pressure to the edge, while highly optimized models may lose robustness when propagation or traffic conditions change. In edge deployments, distributed deep neural networks can scale resources quickly for 5G/6G services [18], but feasibility must be evaluated with end-to-end metrics such as inference time, control-loop latency, energy per decision, reliability, and performance degradation under distribution shift. Figure 5 couples channel estimation, CSI feedback, beam selection, and reliability-oriented physical-layer control for AI-enabled massive MIMO.

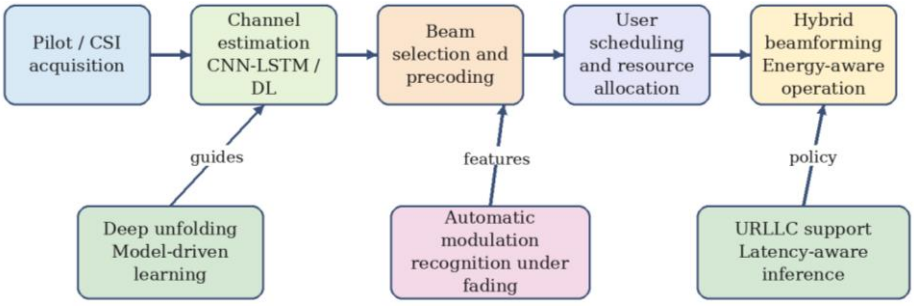


Figure 5. AI-enabled massive MIMO and physical-layer processing pipeline

3.3. Integrated sensing and communication, semantic communication, and edge intelligence

ISAC changes the role of the waveform by allowing communication and sensing to share spectrum, hardware, and signal processing. AI/ML can support this integration by learning the trade-off between sensing accuracy, communication throughput, beam selection, and interference control [2]. Semantic communication extends the same idea by prioritizing the meaning and task relevance of transmitted information instead of transmitting all bits with equal importance [37].

Large language models and edge intelligence can support semantic interpretation, network orchestration, and context-aware services, but their size, energy consumption, and data exposure create deployment challenges. Mobile edge intelligence approaches, split inference, compression, and federated learning can reduce these constraints [17]. Ambient IoT and security surveys also show that 6G devices will have different energy, processing, and trust requirements, so AI models must be lightweight, adaptive, and secure [6], [38]. In telehealth, the priority is dependable latency and privacy rather than peak throughput; in autonomous driving, the primary concern is robust, rapidly validated decisions under mobility; and in immersive or metaverse services, the trade-off is between edge-rendering load, throughput, and energy. Security remains a cross-layer issue: earlier work on KASUMI and 3GPP encryption illustrates the long history of cellular security, while recent UAV-enabled intrusion-detection work shows how AI can support real-time protection in 6G scenarios [19], [39]. Figure 6 shows how sensing context and task relevance connect semantic encoding, ISAC, and edge intelligence to guide meaning-aware communication.

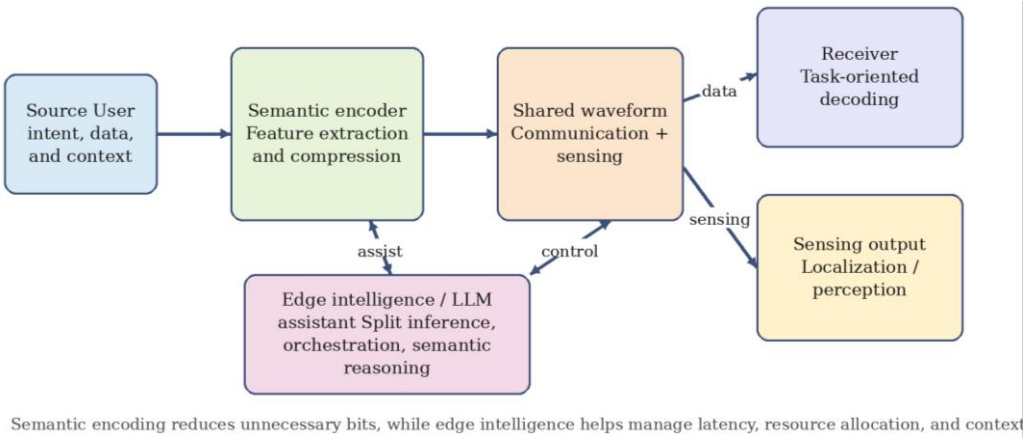


Figure 6. ISAC, semantic communication, and edge intelligence in 6G

3.4. Reconfigurable intelligent surfaces, non-terrestrial networks, and environment-aware operation

RIS technology supports the creation of smart radio environments by controlling reflections from many nearly passive elements. This can improve coverage, spatial multiplexing, and energy efficiency, but it also creates high-dimensional phase-control and channel-estimation problems [8]. Learning-based PHY design and convolutional neural network–long short-term memory (CNN-LSTM) channel estimation for RIS-non-orthogonal multiple access (RIS-NOMA) networks show how AI can reduce the practical burden of modeling cascaded channels and configuring surfaces under time-varying conditions [9], [40].

Environment-aware 6G communication also requires knowledge of geography, mobility, blockage, and propagation history. Channel knowledge maps can represent such information and support proactive link adaptation [41]. In NTN, on-board radio-resource management for satellites can benefit from neuromorphic computing because spacecraft have strict energy and processing constraints [42]. UAV-assisted coverage and Hexa-X studies highlight coordinated terrestrial, aerial, and satellite operation [11], [28]. Complementary foundations include 6G architectures [43], wireless sensor networks for environmental monitoring under energy and processing constraints [44], and fixed-wireless planning at 3.5 and 28 GHz under foliage and atmospheric losses [45]. The latter two sources provide deployment context, not evidence of AI gains; deep-learning methods are reviewed separately [46]. Broader 6G visions, AI roadmaps, high-frequency links, channel models, and the IMT-2030 framework place these methods in a common deployment context [47]-[52]. The practical limitation is that maps, twins, RIS states, and satellite links may be stale or costly to update; robust deployment therefore requires uncertainty estimation, fallback control policies, and explicit accounting for signaling and operational cost. Figure 7 shows how geographic and propagation knowledge guides RIS and NTN configuration. Table 1 compares the benefits, limitations, deployment scenarios, and open challenges of the reviewed technology areas.

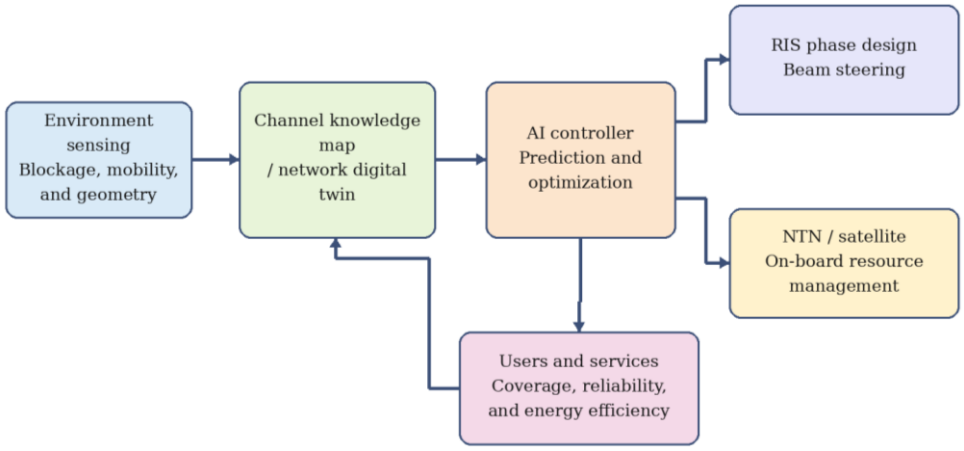


Figure 7. Environment-aware 6G operation using RIS, NTN, and channel knowledge maps

Table 1. Comparison of major AI-based 6G technology areas, practical benefits, limitations, deployment scenarios, and open challenges

Technology area	AI-enabled benefit	Key limitation	Deployment scenario	Remaining challenge
AI-RAN and resource management	Predictive scheduling, load balancing, and QoS adaptation	Data drift and control-loop overhead	Dense urban broadband and private networks	Safe online learning and interoperability
Massive MIMO and PHY intelligence	Faster CSI estimation, beam selection, and interference control	Training-data dependence and CSI cost	High-mobility broadband and URLLC	Generalization, explainability, and latency-bound inference
ISAC, semantic, and edge intelligence	Task-aware transmission and sensing-communication co-design	Model size, privacy exposure, and energy use	Autonomous driving, telehealth, and immersive services	Joint evaluation of task accuracy, latency, and energy
RIS, NTN, and environment awareness	Proactive propagation control and extended coverage	State acquisition, signaling overhead, and model staleness	Remote coverage, satellites, and UAV-assisted access	Robust operation under uncertainty and multi-domain coordination
Trustworthy AI and security	Anomaly detection and policy enforcement across layers	Adversarial data, opaque models, and governance burden	Critical infrastructure and enterprise 6G	Auditable model life-cycle management and resilience

4. OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite its potential, AI-native 6G faces several open challenges. First, data quality, governance, and representativeness remain unresolved: models trained on narrow channel, mobility, or traffic conditions can fail in unfamiliar environments, while private network data cannot always be centralized for training. Federated learning and digital twins can help, but they introduce synchronization, verification, communication, and trust overhead [3], [15], [16]. Second, there is a tension between model accuracy and deployability.

Physical-layer and mobility decisions may require sub-millisecond or millisecond responses, whereas powerful models can impose unacceptable computation, memory, cooling, and energy costs. Edge intelligence, model compression, split learning, and distributed inference must therefore be evaluated against a complete budget of inference time, signaling overhead, energy per decision, reliability, and cost [17], [18], [30].

Third, resilience and security require more than conceptual safeguards. Training data, models, and inference results can be manipulated, and opaque decisions are difficult to validate in safety-critical services. Practical deployments need model monitoring, uncertainty thresholds, fallback rule-based control, secure update mechanisms, and clear accountability for model life-cycle decisions [19], [38], [39]. These issues are especially important in autonomous driving, telehealth, industrial control, and non-terrestrial coverage, where failure costs are high and infrastructure resources are heterogeneous.

Future work should focus on standardized datasets, interoperable AI interfaces, trustworthy model life-cycle management, and unified evaluation metrics for latency, energy, reliability, security, and operational cost. The evidence reviewed here also points to a need for comparative field trials and reproducible simulations that report not only accuracy or throughput but also robustness to distribution shift, control-loop stability, inference energy, signaling burden, and recovery behavior. Standards work on automation and AI/ML air interfaces provides a foundation, but practical validation is still required across terrestrial, aerial, satellite, and edge-cloud systems [12]-[14]. Figure 8 groups the deployment barriers and research priorities that determine whether laboratory AI methods become scalable, trustworthy systems.

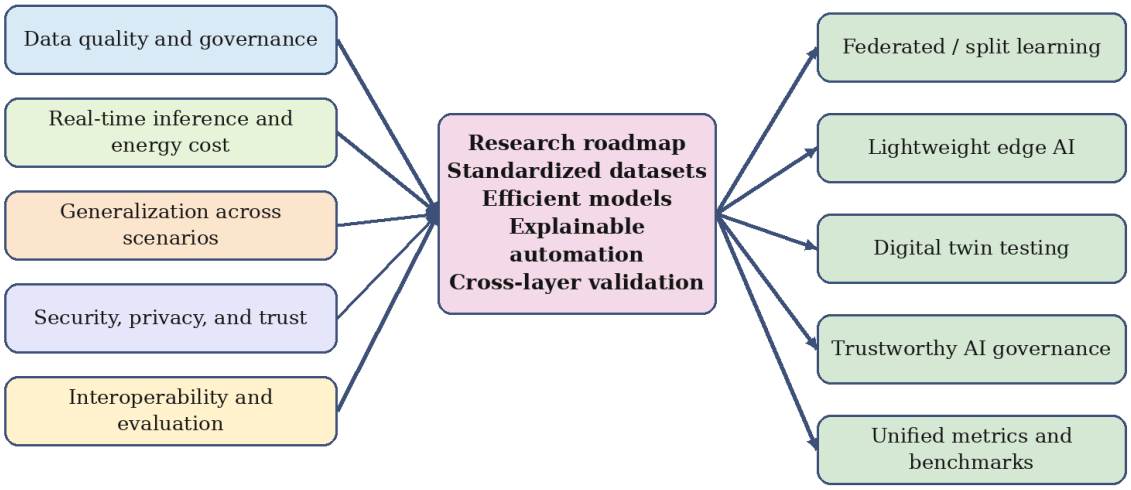


Figure 8. Open challenges and future research directions for AI-native 6G

5. CONCLUSION

This paper reviewed AI and ML as enabling technologies for next-generation 6G networks and introduced an AI-native taxonomy that links embedded intelligence, closed-loop learning, distributed inference, heterogeneity awareness, and trustworthy autonomy. The synthesis shows that AI can support network automation, spectrum management, mobility, QoS, massive MIMO, ISAC, semantic communication, RIS, NTN, edge intelligence, and security; however, benefits are conditional on representative data, latency-bounded inference, energy-aware execution, resilient control, and accountable governance. The main limitation of this review is that it synthesizes published evidence rather than reporting a new experimental campaign, so the identified trade-offs should be validated through comparable simulations, testbeds, and field deployments. Future research should prioritize reproducible cross-layer evaluation and safe deployment practices that make AI-native 6G both technically effective and operationally trustworthy.

ACKNOWLEDGMENT

The authors acknowledge their respective institutions for providing an enabling research environment for this review.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Joseph M. Mom	✓	✓		✓	✓		✓			✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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