PEER-REVIEWED JOURNAL OF COMPUTER SCIENCE (PRJCS)

ISSN Online :

Open Access Scholarly Journal

Artificial Intelligence-Driven 6G Networks and Intelligent Radio Access

Sandra Charly

Lecturer, Department of Computer Engineering, Holy Grace Polytechnic College, Mala, Kerala, India.

Article information

Received: 12th April 2026
Received in revised form: 27th April 2026
Accepted: 14th May 2026
Available online: 9th June 2026

Volume: 1
Issue: 6
DOI: https://doi.org/10.5281/zenodo.20536861

Abstract

Sixth-generation (6G) wireless networks are entering the standardisation horizon for the early 2030s, with research roadmaps already published by 3GPP, ITU-R, and major industrial alliances. Unlike previous generations, 6G is being designed as an AI-native system in which machine learning is integrated into the air interface, the radio access network, and the core. This paper surveys the architectural vision of 6G, key enabling technologies sub-terahertz spectrum, reconfigurable intelligent surfaces (RIS), cell-free massive MIMO, AI-RAN, network digital twins, and semantic communications and the role of artificial intelligence at each layer. We discuss energy efficiency, spectrum sharing, integrated sensing and communication, and the security implications of pervasive learning components. Open research problems related to standardisation, explainability, and sustainable deployment are highlighted.

.

Keywords: - 6G, AI-RAN, Reconfigurable Intelligent Surfaces, Semantic Communications, Machine Learning, Open RAN, Integrated Sensing and Communication, Network Digital Twin.

I. INTRODUCTION

Each generation of mobile networks has been defined by a small number of headline capabilities: 1G voice, 2G messaging, 3G mobile internet, 4G mobile broadband, 5G ultra-reliable low-latency communications and massive connectivity. 6G is expected to deliver peak data rates approaching one terabit per second, sub-millisecond latency, and seamless integration of communication, sensing, and intelligence [1], [2]. The ITU-R framework for IMT-2030 [3] defines six usage scenarios that include immersive communication, hyperreliable and low-latency communication, ubiquitous connectivity, AI and communication, integrated sensing and communication, and massive communication.

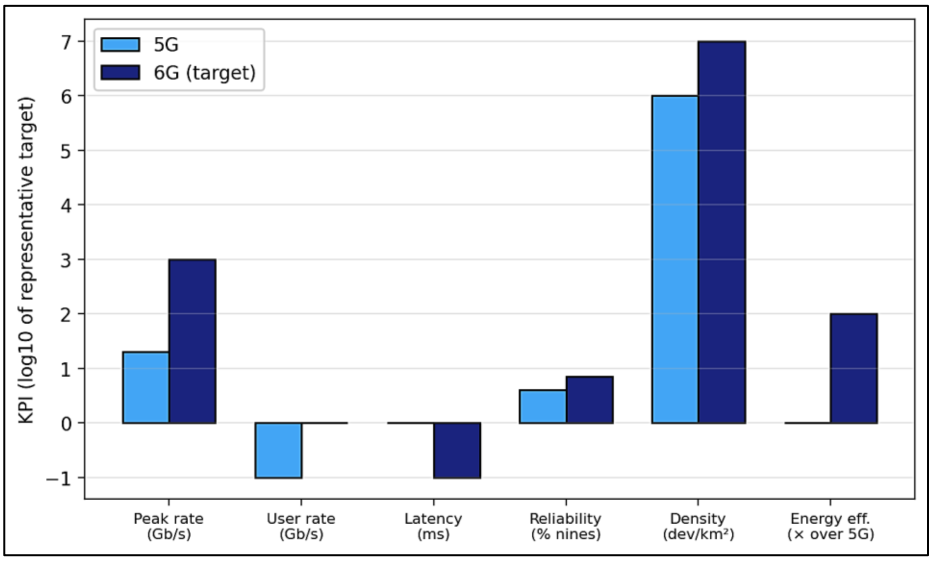
An organising principle of 6G research is AI-native design: machine learning is no longer bolted on top of fixed protocols but used as a primary tool for waveform design, channel estimation, beam management, scheduling, and orchestration [4]. This paper surveys the resulting architecture and the open research problems it raises. Section II reviews the 6G vision and KPIs. Section III analyses spectrum and physical-layer enablers. Section IV examines AI integration across layers. Section V covers Open RAN. Section VI discusses semantic communications. Section VII reviews network digital twins. Section VIII addresses challenges.

II. 6G VISION AND KEY PERFORMANCE INDICATORS

6G targets are deliberately ambitious. Peak data rates of 1 Tb/s and user-experienced rates of 1 Gb/s correspond to roughly two orders of magnitude over comparable 5G targets [1]. Air-interface latency below 0.1 ms enables tactile internet and immersive XR. Connection densities of 10^7 devices per km^2 support massive IoT, while energy efficiency must improve by two orders of magnitude to keep total energy use bounded as traffic grows. Figure 1 summarises representative 5G versus 6G targets on a log-normalised scale.

RESEARCH PUBLICATIONS

Fig. 1. Representative 5G vs. 6G key performance indicators (log-normalised).



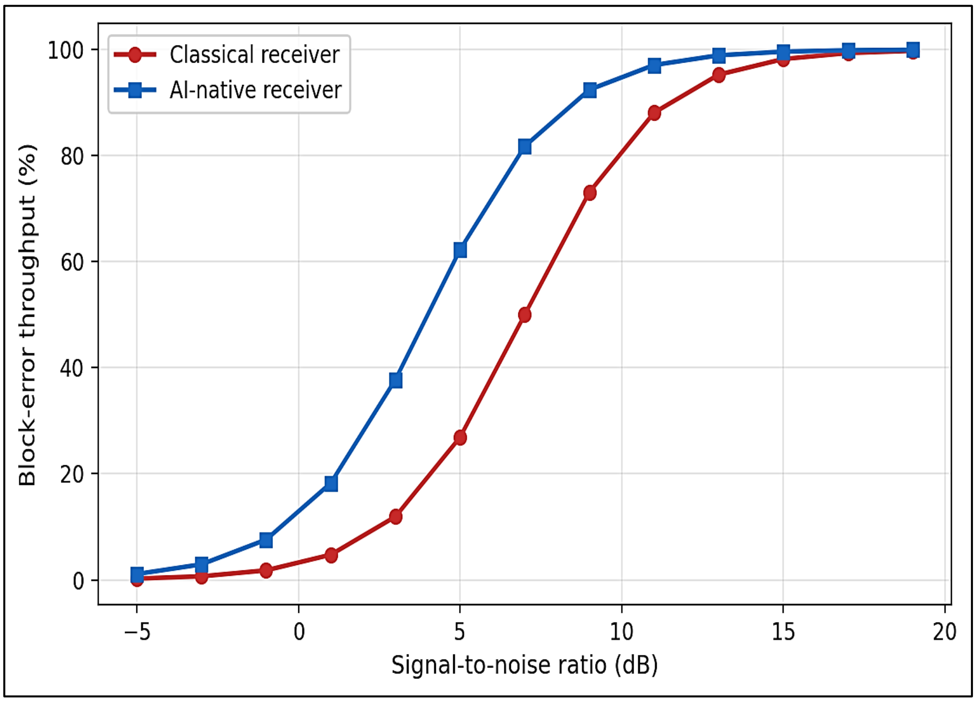
III. SPECTRUM AND PHYSICAL-LAYER ENABLERS

Achieving headline rates requires aggressive use of new spectrum. The sub-terahertz region (100-300 GHz) and selected terahertz windows are central to the 6G plan, offering tens of gigahertz of contiguous bandwidth at the cost of severe path loss and atmospheric absorption [5]. Dense small cells, ultra-massive MIMO with thousands of antenna elements, and beamforming with narrow pencil beams compensate. Cell-free massive MIMO [6] replaces the cellular abstraction with user-centric coordination across distributed access points. Reconfigurable intelligent surfaces (RIS) [7], [8], built from sub-wavelength tunable elements, allow programmable control of the wireless propagation environment, turning passive walls into active beamformers that can extend coverage and reduce energy.

IV. AI ACROSS NETWORK LAYERS

AI is being integrated across all layers of the 6G stack. At the physical layer, end-to-end learned communication systems, in which encoder, channel, and decoder are trained jointly, have demonstrated robustness to non-linear channels and reduced pilot overhead [9]. Channel estimation with deep learning leverages spatio-temporal correlations beyond the reach of classical estimators. AI-driven beam management exploits site-specific patterns to reduce sweep overhead. At the MAC layer, reinforcement learning is widely studied for scheduling and power control [10]. At the network layer, AI-based mobility management, slicing, and orchestration use telemetry to optimise resource allocation. Figure 2 illustrates the typical block-error throughput improvement of an AI-native receiver over a classical receiver as a function of SNR.

Fig. 2. Block-error throughput vs. SNR: classical receiver vs. AI-native receiver.



V. OPEN RAN AND AI-RAN

Open RAN disaggregates the previously monolithic radio access network into open, multi-vendor components defined by the O-RAN Alliance specifications [11]. The RAN Intelligent Controller (RIC), in both near-real-time and non-real-time variants, provides a standardised home for ML applications (xApps and rApps) that observe RAN telemetry and adjust radio parameters. AI-RAN, a recent industrial coalition, extends this thinking by repurposing GPU-based RAN platforms to host both ML inference and traditional radio processing on the same accelerator [12]. The combination promises substantial energy and capacity gains, contingent on solving real-time constraints, latency budgets, and multi-vendor integration challenges.

VI. SEMANTIC COMMUNICATIONS

Classical Shannon-theoretic communication treats source bits as opaque symbols. Semantic communications, revisited by Strinati and Barbarossa [13] and others, transmits the meaning of a message rather than its raw representation, with a learned encoder selecting features relevant to the receiver's task. For text, image, and video, semantic compression can reduce bandwidth by order-of-magnitude factors when both endpoints share a learned representation. Open challenges include robust performance under distribution shift, joint design of source and channel coding, and standardisation of representation interfaces between vendors [14].

VII. NETWORK DIGITAL TWINS

A network digital twin is a synchronised software model of the deployed network used for monitoring, what-if analysis, and closed-loop optimisation. Twin models combine ray tracing, stochastic geometry, traffic generators, and learned components, and are increasingly mandatory for managing the complexity of dense, multi-band 6G deployments [15]. Twins also provide a controlled environment in which reinforcement-learning policies can be trained safely before live deployment.

Table 1. AI Use Cases Across the 6G Network Stack

Layer	AI use case	References
Physical layer	End-to-end learned transceiver	[9]
Physical layer	Deep channel estimation	[16]
MAC layer	RL-based scheduling and power control	[10]
Network layer	AI-driven mobility and slicing	[17]
RIC (Open RAN)	xApp/rApp ML control loops	[11]
End-to-end	Network digital twin	[15]

VIII. CHALLENGES AND OPEN PROBLEMS

Several issues must be resolved before 6G can deliver its promised benefits. AI explainability is required for regulatory acceptance and operational trust, and current deep models offer limited interpretability. Energy efficiency targets are aggressive: even with hardware advances, AI inference cost in the RAN must be tightly bounded. Spectrum sharing between communication and integrated sensing applications is technically and politically difficult. Security, particularly against adversarial inputs into learned receivers and against ML supply-chain compromise, requires new defence techniques [18]. Cross-vendor interoperability of ML models, standardisation of telemetry, and reproducibility of ML-based RAN performance claims are active problems [19]. Finally, sustainable deployment, including embodied carbon of dense small-cell infrastructure, deserves more attention than it has received in standardisation discussions.

IX. STANDARDISATION TIMELINE AND VENDOR LANDSCAPE

The 6G research roadmap is now reflected in concrete standardisation activity. 3GPP Release 19, in progress at the time of writing, advances AI/ML for the NR air interface, including channel-state-information feedback compression, beam management, and mobility prediction [19]. Release 20 is expected to add native support for AI-driven scheduling and energy-efficiency optimisations. ITU-R completed the IMT-2030 framework recommendation in late 2023 [3], setting the formal target for 6G capabilities. The actual 6G specification work in 3GPP is anticipated to begin in earnest with Release 21 in 2027-28, with a first commercial deployment window in the early 2030s, broadly tracking the ten-year cadence between mobile generations.

On the vendor side, the landscape is unusually crowded by historical standards. Nokia, Ericsson, Samsung, Huawei, and ZTE remain the principal radio infrastructure suppliers, but Open RAN has admitted a wider field including Mavenir, Rakuten Symphony, and Parallel Wireless. AI-RAN, formed in 2024, includes Nvidia, T-Mobile, Microsoft, and several incumbents, and proposes to repurpose GPU platforms for joint RAN processing and inference [12]. The European Smart Networks and Services Joint Undertaking [20] funds the principal European 6G research consortium. Geopolitical considerations have produced parallel regional ecosystems, with Chinese, North American, European, and South Korean stakeholders running partly overlapping research programmes that nevertheless aim at the same ITU-R targets.

Spectrum allocation is on a parallel timeline. WRC-23 in late 2023 began the discussion of harmonised sub-terahertz allocations, with WRC-27 expected to make initial allocations and WRC-31 to formalise the bands used by commercial 6G. Progress is faster than for many previous generations because the technical case for sub-terahertz operation is well documented, but national-security and incumbent-service considerations remain contested in several jurisdictions. Reconfigurable intelligent surface deployment also raises spectrum-policy questions because RIS is a passive radiative element whose regulatory classification has no exact precedent in existing radio law.

Several questions remain unresolved at the standards level. The form in which trained ML models are exchanged across vendor boundaries is not yet specified. Reproducibility of ML-based RAN performance claims is largely informal. The interaction between AI-RAN and the Open RAN security framework is an active area of work. Energy-efficiency reporting, which is now a hard requirement under European telecommunications regulation, will probably drive standardisation of measurement protocols across the industry. The 6G specification process is therefore as much about institutional and regulatory coordination as it is about new physical-layer technology, and those who treat it as a purely technical exercise tend to underestimate how long it will take.

A note of caution is warranted on the headline KPIs. Each previous generation of mobile networks promised peak rates and latency targets that were rarely delivered to the median user, and 6G is unlikely to be different. The terabit-per-second peak is a property of a few favourable cells with line-of-sight to the user; everyday user-experienced rates will land at a lower order of magnitude. Sub-millisecond latency requires the radio access path, the core network, and the application server all to cooperate, and most of today's latency budget is spent in software rather than over the air. AI-native receivers and reconfigurable intelligent surfaces are technically real, but their gains depend on tight integration with the surrounding stack. None of this is an argument against the 6G programme. It is, rather, an argument for setting expectations honestly. The most useful framing for non-specialists is that 6G will deliver, in median deployments, capabilities that 5G-Advanced approached but did not generalise: ubiquitous gigabit, predictable low latency for time-critical applications, integrated sensing for spatial awareness, and substantially better energy efficiency per delivered bit. These improvements are valuable in their own right, and they make 6G worth pursuing even if the headline numbers are met only in flagship deployments. The discipline of comparing what is promised with what is later measured remains a useful corrective for everyone in the field.

X. CONCLUSION

6G represents a deliberate redesign of mobile networks around artificial intelligence as a first-class architectural element. Sub-terahertz spectrum, ultra-massive MIMO, reconfigurable intelligent surfaces, AI-RAN, semantic communications, and network digital twins together form a coherent vision of an AI-native communication system. Realising the vision will require sustained collaboration across telecom standards bodies, ML researchers, and operators, and demands disciplined attention to explainability, energy use, and security. If executed well, 6G will not merely increase data rates but transform the network into a programmable, intelligent, and sensing-aware substrate for the digital economy.

Beyond the technical and standardisation work, 6G will probably be judged ultimately on whether the gains it delivers reach beyond the headline metrics. The case for 6G is strongest where it underwrites new categories of applications that were not feasible at 5G performance, including high-fidelity remote operation of physical systems, ambient pervasive sensing for healthcare and the built environment, and distributed AI workloads that depend on the edge. The case is weakest where 6G is sold as a faster pipe for existing applications. The next several years will surface which of these framings holds up under deployment, and operators that have made expensive infrastructure bets are watching the question closely. Our reading of the evidence is that the technical foundations are sound and the ITU-R 2030 timeline is realistic, but the commercial case for 6G will be made by application developers and end users rather than by the standards process itself. That outcome would be unusual for a generation of mobile network technology, but it is not unprecedented, and it would mark a healthy shift in how connectivity is treated in the digital economy.

REFERENCES

[1] W. Saad, M. Bennis, and M. Chen, “A vision of 6G wireless systems: Applications, trends, technologies, and open research problems,” *IEEE Network*, vol. 34, no. 3, pp. 134–142, 2020.

[2] H. Tataria, M. Shafi, A. F. Molisch, M. Dohler, H. Sjöland, and F. Tufvesson, “6G wireless systems: Vision, requirements, challenges, insights, and opportunities,” *Proceedings of the IEEE*, vol. 109, no. 7, pp. 1166–1199, 2021.

[3] ITU-R, “Framework and overall objectives of the future development of IMT for 2030 and beyond,” Recommendation ITU-R M.2160-0, Nov. 2023.

[4] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y.-J. A. Zhang, “The roadmap to 6G: AI empowered wireless networks,” *IEEE Communications Magazine*, vol. 57, no. 8, pp. 84–90, 2019.

[5] T. S. Rappaport, Y. Xing, O. Kanhere, S. Ju, A. Madanayake, S. Mandal *et al*., “Wireless communications and applications above 100 GHz: Opportunities and challenges for 6G and beyond,” *IEEE Access*, vol. 7, pp. 78729–78757, 2019.

[6] H. Q. Ngo, A. Ashikhmin, H. Yang, E. G. Larsson, and T. L. Marzetta, “Cell-free massive MIMO versus small cells,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 3, pp. 1834–1850, 2017.

[7] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, “Intelligent reflecting surface aided wireless communications: A tutorial,” *IEEE Transactions on Communications*, vol. 69, no. 5, pp. 3313–3351, 2021.

[8] M. Di Renzo, A. Zappone, M. Debbah, M.-S. Alouini, C. Yuen, J. de Rosny, and S. Tretyakov, “Smart radio environments empowered by reconfigurable intelligent surfaces,” *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 11, pp. 2450–2525, 2020.

[9] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Transactions on Cognitive Communications and Networking*, vol. 3, no. 4, pp. 563–575, 2017.

[10] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang, and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3133–3174, 2019.

[11] M. Polese, L. Bonati, S. D'Oro, S. Basagni, and T. Melodia, "Understanding O-RAN: Architecture, interfaces, algorithms, security, and research challenges," *IEEE Communications Surveys & Tutorials*, vol. 25, no. 2, pp. 1376–1411, 2023.

[12] AI-RAN Alliance, "AI-RAN whitepaper: Bringing AI and RAN together for transformative innovation," Industry White Paper, 2024.

[13] E. C. Strinati and S. Barbarossa, "6G networks: Beyond Shannon towards semantic and goal-oriented communications," *Computer Networks*, vol. 190, 2021.

[14] Z. Qin, X. Tao, J. Lu, W. Tong, and G. Y. Li, "Semantic communications: Principles and challenges," *arXiv preprint* arXiv:2201.01389, 2022.

[15] L. U. Khan, W. Saad, D. Niyato, Z. Han, and C. S. Hong, "Digital twin-empowered intelligent communications and networking: Recent advances and future trends," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 2, pp. 850–885, 2022.

[16] H. Ye, G. Y. Li, and B.-H. F. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Communications Letters*, vol. 7, no. 1, pp. 114–117, 2018.

[17] S. Wijethilaka and M. Liyanage, "Survey on network slicing for Internet of Things realization in 5G networks," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 957–994, 2021.

[18] I. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and harnessing adversarial examples," in *Proceedings of the International Conference on Learning Representations (ICLR)*, 2015.

[19] 3GPP, "Study on artificial intelligence (AI)/machine learning (ML) for NR air interface," 3GPP TR 38.843, Release 18, 2024.

[20] European Commission, "Smart networks and services Joint Undertaking (SNS JU) strategic research and innovation agenda," SNS JU, 2024.