frontiers | Frontiers in Communications and Networks

TYPE Perspective
PUBLISHED 08 August 2025
DOI 10.3389/frcmn.2025.1606493

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RECEIVED 05 April 2025
ACCEPTED 21 July 2025
PUBLISHED 08 August 2025

CITATION
Nezami Z, Shah SDA, Hafeez M, Djemame K and Zaidi SAR (2025) From connectivity to autonomy: the dawn of self-evolving communication systems.
Front. Commun. Netw. 6:1606493.
doi: 10.3389/frcmn.2025.1606493

From connectivity to autonomy: the dawn of self-evolving communication systems

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This paper envisions 6G as a self-evolving telecom ecosystem, where AI-native capabilities enables dynamic adaptation, autonomy, and resilience beyond traditional connectivity. We present a conceptual framework integrating reconfigurable infrastructure, adaptive middleware, and intelligent network functions, augmented by multi-agent collaboration to support distributed decision-making and scalable automation. The paper outlines how these components can align with emerging industrial frameworks, ensuring seamless integration within smart manufacturing processes. Rather than offering empirical results, we articulate a forward-looking architecture and discuss its implications for real-time responsiveness, efficiency, and robustness in future networked control systems. Ethical, standardization, and deployment considerations are examined, culminating in a proposed technology stack to guide ongoing research and implementation. By synthesizing current trends in AI and telecom convergence, this work aims to inform the development of intent-aware, resilient, and adaptive communication systems for 6G and beyond.

KEYWORDS

telecommunication network, open-endedness, autonomy, self-evolving, 6G, AI-telecom architecture, agent

1 Introduction

Wireless communication has rapidly evolved from basic 2G connectivity to today's intelligent, data-driven 5G systems. As we move toward the sixth generation (6G), a critical paradigm shift is underway: the emergence of self-evolving communication ecosystems. Unlike traditional adaptive networks that merely react to predefined stimuli, self-evolving systems leverage artificial intelligence (AI) to autonomously perceive, reason, and reconfigure themselves in real time. This marks a structural transformation—enabling communication infrastructures that are scalable, resilient, and context-aware.

Recent research has laid foundational insights into this vision. For example, Self-Evolving Networks (SENs) Chaoub et al. (2022); Qian et al. (2024) have been proposed to manage complexity across integrated terrestrial-aerial-satellite systems through machine learning-driven resource optimization and mobility control Liang et al. (2023). Others Chaoub et al. (2022) have introduced multi-layered self-evolving architectures where knowledge is continuously extracted and reapplied across layers to enhance communication system robustness. Moreover, efforts to create transformative protocol architectures Cai et al. (2022), computing frameworks with evolutionary engines Weyns et al. (2023), and neuro-symbolic AI for secure signal processing Kashikar (2024) underscore a growing consensus: future networks must evolve autonomously in response to unforeseen demands and dynamic environments. Notably, research by Google DeepMind Hughes et al. (2024) underscores the importance of continual innovation and evolution in achieving advanced machine intelligence. However, despite these advancements, key gaps remain. Much of the existing work focuses on architectural concepts or domain-specific applications without fully integrating modular infrastructures, middleware intelligence, and agent-based decision-making in industrial contexts. Furthermore, while simulation results in existing studies demonstrate improved metrics such as signal-to-noise ratio Kashikar (2024) or decision efficiency in IoT Liu et al. (2021); Lu et al. (2023), few address how such frameworks can be practically deployed in real-world, latency-sensitive environments.

One promising enabler of this shift is the Open-Radio Access Network (O-RAN)[1], which decouples legacy architectures and introduces AI-native control for dynamic, programmable operations. In parallel, the emergence of Large Language Models (LLMs) enhances network intelligence by supporting automation, optimization, and intent-based reconfiguration Mondal et al. (2023); Bariah et al. (2024). In this paper, we define a self-evolving telecom system as one that not only adapts to real-time stimuli but also continuously refines its internal policies, control logic, and decision mechanisms through learning. This is achieved via closed-loop intelligence pipelines that integrate telemetry, user intent, and environmental signals across network layers. Self-evolving systems can autonomously determine optimization goals, modify operational workflows, and expand functional capabilities (e.g., by onboarding new xApps or decision agents) without human intervention. This evolution spans multiple planes from topology and protocol behavior to resource orchestration and semantic reasoning, enabling telecom infrastructure to co-adapt with changing societal, application-level, and environmental conditions in real time.

By bridging the gap between conceptual innovation and practical deployment, this paper explores how AI–telecom synergy can catalyze the next-generation of intelligent networks, creating a globally interconnected digital ecosystem that continuously learns from network telemetry, user intent, and environmental context; adapts resource allocation, topology, and policies accordingly; and evolves its capabilities through feedback-driven optimization and modular agent collaboration. This dynamic learning-adaptation loop enables telecom systems to autonomously respond to emerging demands, societal needs, and technological shifts in real time. This paper addresses the above gaps by presenting a conceptual and architectural vision of a self-evolving telecom ecosystem. Our key contributions are as follows: (i) A unified technology stack that integrates reconfigurable infrastructure, adaptive middleware, and intelligent network functions to support self-evolving communication systems. (ii) A multi-agent framework for distributed decision-making, enabling real-time autonomy and self-optimization at scale. (iii) A critical discussion of ethical, standardization, and practical implementation challenges for realizing self-evolving communication systems.

2 Autonomous telecom ecosystem: roadmap and vision

The transition from traditional telecom networks to self-evolving ecosystems represents a paradigm shift, unfolding in strategic phases. This evolution transforms networks from static infrastructures into autonomous, adaptive systems capable of real-time decision-making and continuous self-improvement, driving efficiency, inclusivity, and societal progress.

The *first phase: Foundations for Self-Evolving Networks* integrates AI and automation into existing telecom infrastructures, enabling AI-driven resource optimization, fault resolution, and traffic management. These enhancements lay the groundwork for autonomous 6G systems, where AI-powered agents dynamically allocate bandwidth, resolve issues, and optimize operations without human intervention. This automation improves efficiency and expands connectivity to underserved regions, bridging the digital divide.

The *second phase: Context-Aware and Hyper-Adaptive Networks* incorporates Integrated Sensing and Communication (ISAC[2]) and edge computing Lin et al. (2023). ISAC enhances situational awareness, enabling networks to sense and respond to real-time conditions such as adjusting traffic in emergencies or optimizing based on environmental data. Edge computing reduces latency through localized processing, ensuring intelligent, context-aware decision-making. These advancements support hyper-connectivity across use cases such as industrial automation and smart cities, driving economic growth and improving quality of life.

The *final phase: Open-Ended Self-Evolution* introduces continual, autonomous innovation. Inspired by DeepMind's work on open-endedness Hughes et al. (2024), 6G networks evolve by developing novel protocols, adapting to unforeseen scenarios, and implementing self-optimization through continuous feedback. Analogous to self-driving protein laboratories Rapp et al. (2024), these AI-native systems independently refine operational strategies. AI scientists Lu et al. (2024) further exemplify this potential by autonomously generating hypotheses and analyzing results, reinforcing the vision of fully self-evolving telecom systems. These systems draw on the Self-X paradigm Kephart and Chess (2003) — encompassing self-healing, self-optimizing, and self-configuring capabilities—to autonomously adapt, recover, and enhance performance without external input.

To ensure responsible autonomy, future networks must embed semantic knowledge representation and human oversight mechanisms. Semantic models allow systems to interpret contextual signals, prioritize critical services, and make decisions that align with societal values. Human-in-the-loop governance will

1 O-RAN Alliance, available at: https://www.o-ran.org/, accessed November 2024

2 ISAC, by Robert Baldemair, available at: https://www.ericsson.com/en/blog/2024/6/integrated-sensing-and-communication, accessed July 2025

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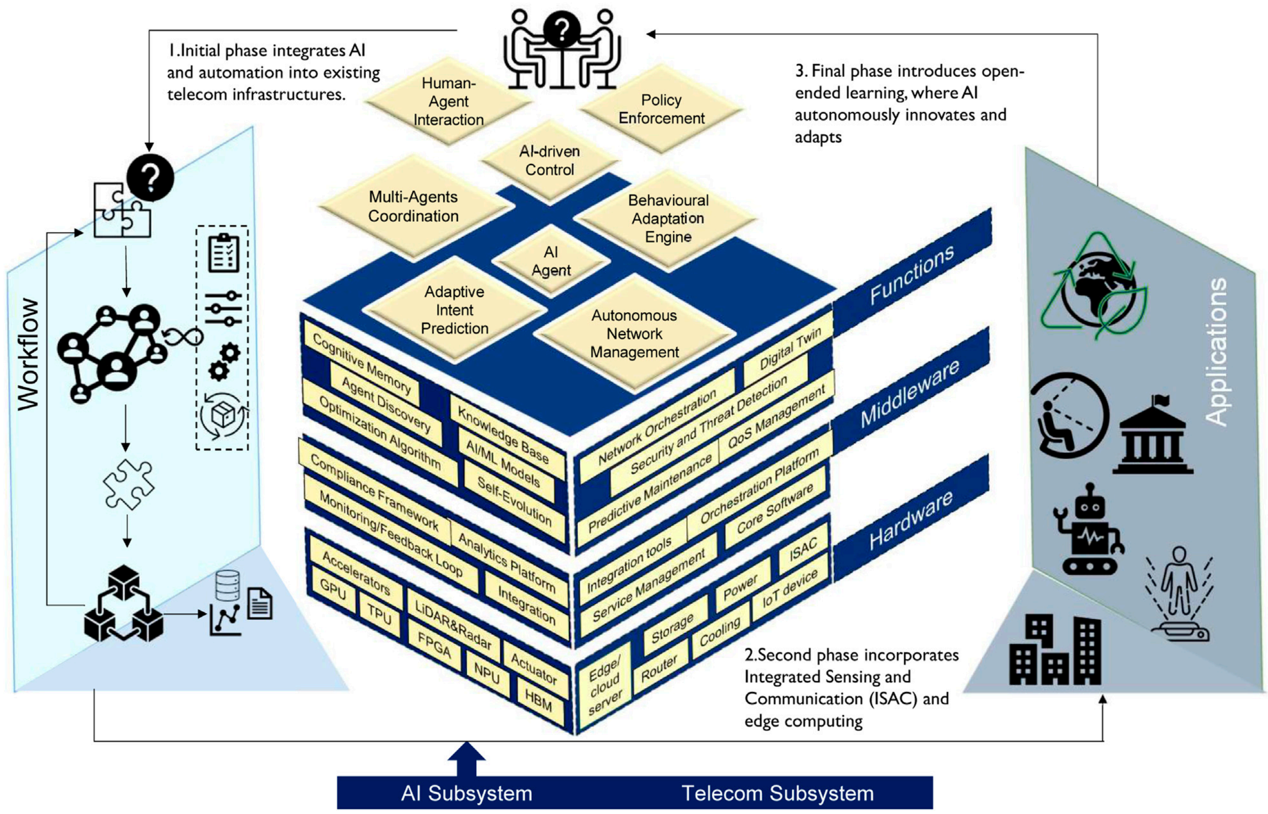

FIGURE 1
Architecture of AI-6G/ORAN for self-evolving communication systems.

remain vital, not as a bottleneck, but as a layer of ethical reasoning and feedback integration. By fusing real-time network telemetry with socio-technical context Nezami et al. (2025), these systems will dynamically adapt across environments. This includes balancing external constraints—such as environmental conditions (e.g., energy availability, weather-induced disruptions, carbon footprint), economic factors (e.g., deployment costs, resource pricing, and access equity), and social dimensions (e.g., digital inclusion, accessibility, cultural norms, and usage patterns) — with internal performance goals, creating telecom ecosystems that are efficient, inclusive, and sustainable.

Multimodal LLMs serve as key enablers of this human-centric autonomy. They interpret high-level goals expressed through natural input including speech, gestures, or visual context, and ground these into semantically aligned, machine-readable instructions. Acting as reasoning engines within human-in-the-loop frameworks, multimodal LLMs support real-time, intent-driven reconfiguration of networks. This paradigm is powered by recent advances in generative AI and reinforcement learning from human feedback (RLHF) Qin et al. (2025), allowing tight coupling between user expectations and system response. This shift toward intent-consistent, multimodal interaction marks a critical inflection point in telecommunications—enabling adaptive services in mobility, healthcare, and immersive computing, while making intelligent systems more accessible and intuitive for all.

3 Key enablers of self-evolving communication systems

AI and telecom technologies are deeply intertwined, each serving as both an enabler and a beneficiary of the other. Telecom infrastructure supports AI's distributed computing, connectivity, and real-time data exchange. In return, AI transforms static networks into intelligent systems that learn from data, adapt to context, and improve autonomously over time. This synergy fosters scalability, autonomy, and continuous optimization, driving innovations that redefine industries and enhance global connectivity. This paper presents a conceptual architecture grounded in recent research across AI and telecom, outlining a pathway toward autonomous, self-evolving 6G systems.

The multi-layered architecture of autonomous telecom networks, shown in Figure 1, illustrates how AI and telecom components interact across each layer. At the base, the Hardware Layer provides a reconfigurable infrastructure that supports seamless data transmission. The Middleware Layer introduces programmability and scalability, allowing networks to adapt based on context. The Functions Layer includes modular AI and telecom operations that learn from past interactions and optimize decision-making. At the top, AI agents collaborate using distributed policies and shared memory to refine network behavior continuously. This combination of sensing, reasoning, learning, and adaptation defines the self-evolving nature of next-generation telecom systems.

3.1 Hardware layer: reconfigurable and versatile infrastructure

The Hardware Layer forms the foundation of self-evolving telecom ecosystems by providing reconfigurable infrastructure that adapts to future communication demands. It integrates traditional telecom components with AI-driven hardware to enable seamless data transmission, real-time responsiveness, and scalable computing. This adaptability supports networks that can evolve with technology and user needs, enabling both Human-to-Machine (H2M) and Machine-to-Machine (M2M) communication.

Telecom components at this layer include essential devices such as routers, edge servers, and IoT nodes that dynamically allocate resources based on real-time data. IoT sensors provide environmental and contextual information, allowing the network to adapt its behavior. ISAC enhances this layer by enabling devices to sense their surroundings while communicating. This dual capability supports situational awareness, energy-efficient transmissions, and adaptive M2M coordination, which are critical in dense or safety-sensitive environments. **AI components** such as High Bandwidth Memory (HBM), AI accelerators, Neural Processing Units (NPUs), and Field-Programmable Gate Arrays (FPGAs) deliver the computational capacity required for data processing and learning at the edge. These components enable machine learning models to process local data, update policies, and optimize performance without relying on centralized infrastructure. Their configurability ensures that the hardware evolves to support increasingly autonomous and context-aware systems.

The hardware layer also enables H2M interactions through reconfigurable platforms like the RAN Intelligent Controller (RIC) Balasubramanian et al. (2021), which leverages machine learning and NLP models to provide personalized user experiences. Physical-layer AI agents utilize hardware capabilities to perform real-time optimization of power control, frequency allocation, and beamforming. These agents reduce interference, manage spectrum resources, and adapt to channel dynamics, supporting high-quality communication even in complex or congested scenarios. This layer demonstrates how AI and telecom subsystems jointly support sensing, learning, and adaptive behavior.

3.2 Middle-ware layer: enabling programmable and adaptive networks

The Middleware Layer bridges the underlying hardware with intelligent AI-driven systems, enabling programmability, scalability, and continuous adaptation across network services. This layer empowers telecom systems to evolve beyond rigid architectures by supporting dynamic reconfiguration and AI-enabled decision-making, forming a core part of the self-evolving framework.

AI components at this layer include service orchestration modules that manage the deployment, lifecycle, and scaling of AI models across distributed environments. Core AI software layer facilitate real-time decision-making using streaming data, while integration frameworks handle data preprocessing, transformation, and harmonization. AI analytics platforms support predictive and real-time insights, enabling continuous adaptation of network behavior. Edge AI capabilities reduce latency and improve responsiveness by processing data closer to the source. Interoperability mechanisms ensure seamless communication between diverse modules, while security and privacy frameworks enforce compliance and resilience. Performance monitoring loops feed operational feedback into the system, allowing agents to adjust behavior based on evolving patterns and outcomes.

Telecom components such as Software-Defined Networking (SDN) and Network Function Virtualization (NFV) provide the control and abstraction needed to reconfigure and manage network functions dynamically. Modular platforms like xApps and rApps allow targeted optimization tasks, including fault detection, quality assurance, and resource tuning. Telemetry pipelines gather real-time metrics, feeding them to orchestration platforms such as MANO Lee and Kim (2021) and Kubernetes, which coordinate containerized services. The integration of APIs and observability tools enables robust, adaptive, and policy-compliant system behavior that evolves with network demands and operational context.

3.3 Functions and operations: the autonomy core of intelligent networks

The Functions and Operations layer forms the cognitive core of next-generation telecom systems. It enables networks to continuously learn, adapt, and optimize operations in real time, transforming them into self-evolving ecosystems capable of intelligent decision-making and autonomous innovation.

AI components in this layer include Federated Learning, Transfer Learning, and Reinforcement Learning, each supporting different aspects of adaptive behavior. Federated Learning enables the system to learn from distributed data while preserving privacy. Transfer Learning accelerates adaptation across heterogeneous domains, and Reinforcement Learning drives self-optimization through feedback loops. Together, they form the basis for Self-X capabilities that define self-evolving networks. The Self-Evolving Framework builds on these foundations by incorporating open-endedness, where AI agents generate novel strategies in response to unforeseen challenges. Optimization techniques, including evolutionary algorithms, support efficient resource allocation and policy refinement. Cognitive Memory stores prior decisions and contextual patterns to inform future actions, while Retrieval-Augmented Generation (RAG) modules provide real-time access to evolving domain knowledge. Visualization and reporting tools offer interpretable insights into the network's decision-making process, enhancing transparency and oversight.

Telecom components include intelligent Network Orchestration systems that automate traffic routing, resource provisioning, and anomaly resolution. Quality of Service (QoS) management modules prioritize latency-sensitive tasks, while predictive maintenance and anomaly detection ensure proactive fault handling. Security modules monitor for intrusions and policy violations, enabling resilience against evolving threats. Digital Twins simulate operational states, allowing safe testing of new configurations before deployment and supporting adaptive planning.

3.4 Multi-agent collaborative telecom system

The multi-agent system is central to autonomous network management, where distributed AI agents coordinate to optimize operations across the telecom infrastructure. Built on lower-layer modules and powered by AI models, orchestration tools, and optimization algorithms, these agents enable decentralized intelligence and responsiveness.

Each agent autonomously handles specialized tasks such as adaptive intent prediction, resource scheduling, and anomaly detection. By working collectively, agents make real-time, data-driven decisions that enhance performance, reduce latency, and minimize human intervention. The system evolves through a Behavioral Adaptation Engine, which enables agents to continuously refine their actions based on feedback and environmental conditions. This supports the self-evolving nature of the network, allowing agents to adapt to unforeseen scenarios and optimize over time. Collaboration between agents is facilitated by a Behavioral Adaptation Engine, enabling continuous evolution of agent actions in response to changing network conditions. AI actions are guided by policy enforcement, ensuring compliance with regulatory, operational, and ethical standards. To maintain oversight and accountability, human-agent interaction modules allow for real-time intervention or guidance, particularly in high-stakes scenarios. This human-in-the-loop approach preserves transparency and trust, enabling the system to achieve autonomy without sacrificing control or alignment with societal goals.

3.5 Applications

Self-evolving communication systems are poised to revolutionize various sectors by enabling intelligent, autonomous network management. In governance and smart cities, these systems autonomously manage urban resources such as traffic flow, energy distribution, and water supply, promoting sustainability and contributing to UN's Sustainable Development Goals (SDGs) United Nations (2015). Real-time analytics and closed-loop feedback mechanisms enable adaptive policy-making, improve public service responsiveness, and facilitate digital democracy, where citizens can participate in real-time voting, deliberation, and decentralized decision-making processes through secure, transparent, and AI-moderated platforms.

Beyond governance, self-evolving networks are critical for immersive and collaborative environments. Technologies such as augmented reality (AR), virtual reality (VR), mixed reality (MR), and holography will benefit from ultra-reliable, low-latency communication, enabling high-quality remote collaboration in design, training, education, and entertainment. In healthcare, these systems support remote robotic surgeries, continuous patient monitoring, and AI-assisted diagnostics, all of which rely on fault-tolerant, real-time connectivity. Transportation networks will benefit from enhanced autonomous vehicle coordination, vehicle-to-everything (V2X) communication, and traffic prediction. In energy systems, dynamic grid management is enabled through edge-based sensing and predictive analytics for resilient power distribution.

Autonomous systems, including self-driving vehicle, drones, industrial robots, delivery bots, and social robots—will increasingly operate as agents in these networks. Enabled by real-time coordination and adaptive reasoning, such agents can navigate unstructured environments, perform distributed tasks, and even collaborate with humans in shared workspaces or public spaces. This is particularly important for applications in manufacturing, logistics, agriculture, and elder care, where autonomy, safety, and coordination are mission-critical.

4 Discussion

Self-evolving communication systems represent the next frontier of telecom networks, where AI transcends connectivity, addressing societal and technological challenges through autonomy. This section explores their ethical implications, future research directions, standardization needs, and required technological components.

4.1 Ethical considerations and challenges

Integrating AI into telecom networks introduces transformative potential alongside significant ethical challenges. Central concerns include *bias and fairness*, as large models like LLMs may amplify societal or geographic biases present in training data. Feedback loops involving synthetic or skewed data can worsen digital inequality by unintentionally favoring certain regions or demographics in resource allocation and service quality. To mitigate these risks, fairness-aware modeling, robust bias detection, and equity-centric resource policies must be embedded into the system.

Privacy and data protection are also critical, given the volume of real-time personal and contextual data collected across network layers. Ensuring compliance with data protection frameworks such as the GDPR European Union (2016) and CCPA State of California (2018) requires rigorous anonymization, encryption, and access control mechanisms.

Accountability and transparency become complex when autonomous systems mismanage resources or behave unexpectedly. Explainable AI (XAI) Brik et al. (2024) plays a key role in clarifying system decisions and attributing responsibility. In high-risk domains such as healthcare and transportation, oversight bodies such as the AI Safety Institute[3] are essential for reviewing model behavior and ensuring safe deployment. These shifts may also disrupt job markets, requiring parallel investment in upskilling and workforce transition.

Security threats intensify as systems become more autonomous. Vulnerabilities include adversarial attacks, unauthorized surveillance, and compromised agents. To address this, multi-agent systems must be resilient to adversarial behavior such as

3 AI Safety Institute, available at https://www.aisi.gov.uk/

falsified telemetry injection or misreporting. Zero-Trust Foundation Models (ZTFMs) Li et al. (2025) introduce continuous verification, least-privilege access, and behavioral analytics throughout the agent lifecycle.

At the middleware layer, agent communication is secured through verifiable interaction protocols, sandboxed execution environments, and anomaly detection pipelines. Byzantine agents can be identified through *cross-agent consistency checks*, trajectory deviation analysis, and challenge-response mechanisms. Approaches like checker agents, dual-memory systems, and adversarial suppression networks Xiong et al. (2025) further enhance reliability. These mechanisms shift trust from static assumptions to dynamic, data-driven trust calibration, enabling robust and secure coordination even in semi-trusted or adversarial telecom environments.

4.2 Research directions

The transition toward autonomous, self-evolving telecom systems demands interdisciplinary collaboration across AI, telecommunications, and systems engineering. Future research should focus on developing real-time AI models that support continual learning and adaptation in dynamic environments. Techniques such as reinforcement learning, hybrid neuro-symbolic systems, and structured reasoning frameworks Mirzadeh et al. (2024); Wadhwa (2024) are key enablers of intelligent decision-making in uncertain network conditions.

Multi-agent systems remain a critical area, particularly for decentralized coordination and intent-driven networking, where users express high-level goals instead of low-level instructions Vallinder and Hughes (2024). These agents can collectively learn, reason, and act to optimize performance, while human-in-the-loop mechanisms ensure oversight and alignment with operator intent. Multimodal LLMs will play an increasingly important role in refining human-machine interaction by enabling agents to understand and respond to a combination of text, audio, video, and sensor inputs. This fosters more intuitive interfaces for network operators and end users, improving explainability, customization, and accessibility.

Emerging areas such as quantum AI Marr (2024) provide opportunities for ultra-secure communication, advanced optimization, and interplanetary data exchange. Integration of ISAC capabilities will further enhance environmental awareness. Edge computing, federated learning, and scalable cloud infrastructures remain essential to support privacy-preserving, low-latency decision-making across distributed network nodes. Finally, sustainability should guide all technical innovation. Energy-efficient AI models and green network design will be necessary to ensure long-term viability. Progress will depend on close coordination between technical, ethical, and regulatory communities to align innovation with public values.

4.3 Standardization efforts

The development of Autonomous Networks requires a forward-thinking approach to standardization, as current frameworks are insufficient for supporting dynamic, AI-driven ecosystems in future communication systems. While organizations such as ITU, IEEE, and 3GPP have laid foundational work, more progress is needed to address the complexities of self-evolving systems. The ITU-T Focus Group on AI for Autonomous Networks (FG AINN) International Telecommunication Union (2024) has identified key architectural shifts, but further work is needed to support quantum-enhanced AI, decentralized coordination, and secure collaboration among heterogeneous AI agents. Similarly, IEEE's "CertifAIEd" IEEE (2025) offers a baseline for trustworthy AI, but must evolve to cover open-ended learning, algorithmic accountability, and adaptive governance as these systems begin to self-learn and self-adapt in real time.

The AI-RAN Alliance AI-RAN (2025) focuses on AI-driven radio access optimization, yet new standards must incorporate ultra-low latency, real-time spectrum management, and secure beamforming, which are critical for ISAC-enabled applications such as holographic telepresence and immersive extended reality (XR). Enhancing interoperability across AI models and communication layers is also vital. This includes defining universal communication protocols and verifiable interfaces for agent collaboration, anomaly detection, and human-in-the-loop interventions when necessary. Standardization should additionally prioritize equity, creating affordable, modular frameworks for deploying self-evolving systems in resource-constrained environments. Privacy-preserving mechanisms, adaptive trust calibration, and resilient architectures will be essential for building inclusive, safe, and globally interoperable autonomous networks.

4.4 Technology stack development

The realization of autonomous 6G networks hinges on a unified technology stack that integrates advanced AI models including deep learning, reinforcement learning, and multi-agent systems, with programmable infrastructures for adaptive learning, real-time optimization, self-configuration, and autonomous decision-making. Frameworks such as TensorFlow, PyTorch, and ONNX ONNX (2025) support the development and deployment of AI systems. At the infrastructure level, platforms such as Google Anthos Google Cloud (2025), AWS Greengrass Amazon Web Services (2025), and Microsoft Azure IoT Microsoft (2025) enable seamless integration across edge and cloud environments. Communication technologies including 5G network slicing, massive MIMO, SDN, and AI-enabled orchestration frameworks such, are further strengthened by testbeds such as Aerial RAN CoLab Over-the-Air, laying the foundation for scalable and responsive telecom systems.

To validate these concepts, we implemented a dynamic orchestration framework Shah et al. (2025) in which the Near Real-Time RIC (NRT-RIC) is extended with a telemetry-driven monitoring xApp and an AI-powered orchestrator. This orchestrator, using a Soft Actor-Critic (SAC) reinforcement learning algorithm, dynamically allocates GPU resources between latency-sensitive RAN functions and generative AI workloads. The system achieved 99% satisfaction for RAN service-level agreements while simultaneously running LLM inference. This experiment demonstrates the feasibility of modular AI-agent integration and intelligent infrastructure sharing within telecom domains, supporting the architecture introduced in this work.

Security across the autonomous 6G stack is addressed through layered defenses that span software, AI, and physical domains. At the system level, techniques such as blockchain-based authentication, AI-enabled intrusion detection (e.g., IBM QRadar Chakrabarty et al. (2021)), and zero-trust policies ensure verifiable interactions and access control. Federated learning frameworks such as NVIDIA FLARE Roth et al. (2022) allow distributed AI models to be trained on private data while maintaining privacy and regulatory compliance.

At the physical layer, secure full-duplex ISAC methods—including dual-functional radar and communication (DFRC) Bazzi and Chafii (2024) beamforming and artificial noise injection—help protect sensing and communication jointly. These methods dynamically steer sensing beams and obscure communication signals to enhance secrecy, optimize power use, and defend against eavesdropping. Generative AI-based secure sensing further protects against unauthorized inference. For instance, recent advances using diffusion models Wang et al. (2025) apply signal masking to pilots, ensuring that only authorized nodes can reconstruct accurate channel state information. Collectively, these developments provide the foundation for secure, privacy-preserving, and continuously adapting 6G systems.

5 Conclusion

This paper presents a modular architecture for autonomous 6G networks, emphasizing self-evolution through the integration of AI agents, programmable infrastructure, and adaptive network layers. By combining technologies such as reinforcement learning, federated learning, and SDN/NFV with ISAC and RAN orchestration, we showed how networks can operate and optimize with minimal human intervention. We discussed ethical and security implications, the need for interdisciplinary research, and emerging standardization efforts. A proof-of-concept implementation demonstrated real-time orchestration using AI in shared infrastructure, highlighting the feasibility of our approach. As telecom systems evolve, embedding intelligence across all layers will enable resilient, adaptive, and secure networks—marking a shift from reactive connectivity to proactive, intelligent automation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZN: Writing – original draft, Writing – review and editing. SS: Writing – review and editing. MH: Writing – review and editing, Conceptualization. KD: Conceptualization, Writing – review and editing. SZ: Writing – review and editing, Funding acquisition, Conceptualization, Project administration.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was funded by the Engineering and Physical Sciences Research Council (EPSRC) – UK Research and Innovation (UKRI) via the Technology Missions Fund (EP/Y037421/1) under the project Communications Hub for Empowering Distributed Cloud Computing Applications and Research (CHEDDAR). Additionally, this research was supported by the UKRI Funding Service under Award UKRI851: Strategic Decision-Making and Cooperation among AI Agents: Exploring Safety and Governance in Telecom.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

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