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Original Article

AI-Native 6G Network Management

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Abstract:

The evolution toward sixth-generation (6G) wireless systems demands a shift from traditionally engineered networks to AI-native network management, where intelligence is embedded across the entire architectural stack. As 6G targets extreme performance metrics sub-millisecond latency, terabit-level throughput, integrated sensing, and massive device density, legacy management approaches become insufficient (Dang et al., 2020; Zhang et al., 2021). Recent studies argue that embedding machine learning, distributed intelligence, and real-time automation into network control is essential for managing future complexity and enabling autonomous operation (Saad et al., 2020; Chen et al., 2022). AI-native management integrates technologies such as multi-agent reinforcement learning, network digital twins, semantic communication, and intent-based orchestration to create self-optimizing, self-healing, and context-aware networks (Flórez et al., 2023; Mahmood et al., 2024). This paper examines the conceptual foundations, architectural principles, and enabling technologies for AI-native 6G network management. It further analyzes emerging challenges—including data sparsity, model explainability, cross-domain trust, and scalability and outlines open research directions critical for achieving fully autonomous, resilient, and adaptive 6G networks. The findings suggest that AI-native design is not an enhancement but a fundamental requirement for realizing the operational ambitions of next-generation communication systems.

Keywords:

AI-native network management, 6G wireless networks, Network automation, Machine learning in networks, Multi-agent reinforcement learning, Network digital twins, Intent-based orchestration, Semantic communication, Self-optimizing networks.

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1. Introduction

The rapid evolution of mobile communication systems has transformed network management from manual configuration to increasingly automated and data-driven paradigms. With fifth-generation (5G) networks, operators introduced early forms of intelligent automation such as self-organizing networks (SON), AI-assisted orchestration, and closed-loop optimization to address growing network complexity (Zhang et al., 2021). However, the scope and scale of next-generation use cases expected in sixth-generation (6G) systems such as holographic telepresence, immersive extended reality (XR), digital twins, and ultra-massive machine-type communication demand a transformative shift toward AI-native network management, where artificial intelligence becomes a foundational design principle rather than an auxiliary tool (Saad et al., 2020; Chen et al., 2022).

Unlike 5G, which relies heavily on human intervention for configuration, monitoring, and troubleshooting, 6G networks are envisioned as autonomous, self-evolving systems capable of real-time adaptation to dynamic environments and diverse service requirements (Dang et al., 2020). The integration of technologies such as terahertz (THz) communication, reconfigurable intelligent surfaces (RIS), integrated sensing and communication (ISAC), and cell-free massive MIMO further increases the complexity of network operation, making traditional static management models insufficient (Gharaibeh et al., 2023). In this context, AI-native network management embeds distributed intelligence at the edge, in the radio access network (RAN), and across the core network to enable predictive optimization, semantic-level decision-making, and autonomous orchestration (Flórez et al., 2023).

The concept of AI-native reflects a paradigm in which learning algorithms are tightly integrated with network functions, data collection pipelines, and control loops. This includes the adoption of multi-agent reinforcement learning for resource optimization, foundation models for context-aware decision-making, and digital twin frameworks for real-time simulation and prediction (Mahmood et al., 2024). Furthermore, the transition toward intent-based and zero-touch network management introduces new requirements for interpretability, security, and cross-domain trust, as AI models increasingly assume roles historically managed by network engineers (ITU-T, 2023).

This paper contributes to the evolving research landscape by (1) providing a comprehensive overview of the principles and architecture of AI-native 6G network management, (2) examining key enabling technologies such as collaborative AI, semantic communication, and network digital twins, (3) identifying major challenges in scalability, explainability, data governance, and autonomous control, and (4) articulating promising research directions for achieving fully autonomous 6G networks. As global standardization bodies refine the IMT-2030 frameworks and early 6G experimental platforms emerge, AI-native management stands out as a critical pillar for realizing the performance, resilience, and flexibility envisioned for 6G communication systems.

2. Literature Review

2.1. AI in 5G and 5G-Advanced Networks

The implementation of 5G and 5G-Advanced networks marked the first meaningful integration of artificial intelligence into mobile network management. Early efforts focused on enhancing self-organizing networks (SON), where machine learning supported tasks such as anomaly detection, mobility load balancing, and energy-efficient cell operation (Zhang et al., 2019). AI-assisted resource allocation models also gained attention for optimizing spectrum sharing and mitigating interference in dense network deployments (Sun et al., 2020). Additionally, 5G introduced the foundational concept of network slicing, where AI helped predict traffic patterns, allocate resources dynamically, and maintain service-level objectives (Afolabi et al., 2018).

Despite such advancements, several limitations remained. The distributed and heterogeneous nature of 5G infrastructure made real-time coordination challenging, while centralized AI models faced bottlenecks in scalability and data privacy (Bennis et al., 2018). These challenges highlighted the need for more decentralized, context-aware, and autonomous intelligence an orientation that has shaped the 6G vision.

2.2. The Shift Toward AI-Native 6G Management

6G is expected to support unprecedented service requirements, including multisensory extended reality, ultra-reliable low latency communication (URLLC+), and integrated communication–sensing workloads. To meet these demands, researchers emphasize moving from AI-assisted to AI-native architectures, where intelligence is embedded across the RAN, core, and edge layers (Saad et al., 2020; Dang et al., 2020). This shift reflects a move toward networks that can observe, analyze, predict, and act autonomously through closed-loop intelligence.

Key advancements expected in 6G include multi-agent reinforcement learning (MARL) for distributed optimization, federated learning for privacy-preserving model updates, and hierarchical AI spanning device-level and network-level intelligence (Chen et al., 2022). Further, semantic communication, which transmits meaning rather than raw data, is emerging as a promising paradigm for reducing signaling overhead and enhancing context-aware decision-making (Shi et al., 2023).

AI-native designs envision every network function monitoring, configuration, troubleshooting, and security being coordinated by intelligent agents capable of continuous adaptation. This transformation marks a shift toward fully autonomous systems unlike the semi-autonomous models seen in 5G.

Table 1. Summary of Key Themes in the Literature on AI-Native 6G Network Management

Theme	Description	Key Technologies / Concepts	Representative Sources (≤ 2024)
AI in 5G & 5G-Advanced	AI was mainly used for automation assistance in SON, anomaly detection, and resource allocation. Limitations in scalability and data privacy remained.	SON, ML-based optimization, dynamic network slicing	Zhang et al. (2019); Sun et al. (2020); Afolabi et al. (2018); Bennis et al. (2018)
Shift Toward AI-Native 6G	Transition from AI-assisted to AI-native architectures where intelligence is embedded throughout the network fabric. Supports extreme 6G performance requirements.	MARL, federated learning, semantic communication, hierarchical AI	Saad et al. (2020); Dang et al. (2020); Chen et al. (2022); Shi et al. (2023)
Network Digital Twins (NDTs)	NDTs create real-time virtual replicas of networks for predictive optimization and proactive orchestration.	Predictive control, simulation-driven optimization, real-time analytics	Flórez et al. (2023); Mahmood et al. (2024)
Zero-Touch & Intent-Based Management	Zero-touch architectures aim for fully autonomous network operations via closed-loop control, intent translation, and automated assurance.	Intent-based networking, automation frameworks, closed-loop AI	ETSI (2022); ITU-T (2023)
6G Standards & Frameworks	Global bodies define early 6G requirements, emphasizing intelligence, sensing, openness, and autonomy.	IMT-2030, O-RAN architectures, intelligent RAN	ITU-T (2023); O-RAN Alliance (2023)

2.3 Network Digital Twins and Autonomous Orchestration

The concept of the network digital twin (NDT) has become a focal point in pre-6G research due to its role in enabling predictive intelligence. An NDT provides a real-time virtual replica of the physical network environment, enabling simulation, optimization, and anomaly forecasting without disrupting service (Flórez et al., 2023). Researchers argue that NDTs will serve as the foundation for predictive orchestration, where resource allocation, fault management, and traffic engineering occur proactively rather than reactively (Mahmood et al., 2024). Additionally, standards bodies such as ETSI and ITU have proposed zero-touch network and service management (ZSM) frameworks that emphasize complete automation of end-to-end network operations (ETSI, 2022). These frameworks form the stepping stone toward fully autonomous 6G management, integrating intent-based networking, closed-loop control, and distributed AI inference.

2.4. Existing Architectural and Standardization Efforts

Leading global organizations have begun defining early 6G architectural guidelines. The ITU IMT-2030 framework outlines the critical role of AI, integrated sensing, and network automation as foundational capabilities (ITU-T, 2023). Similarly, the O-RAN Alliance emphasizes open, intelligent, and virtualized RAN architectures supported by embedded AI/ML workflows (O-RAN Alliance, 2023). These frameworks serve as the conceptual backbone for AI-native 6G systems. While these initiatives provide direction, they also highlight persistent challenges such as interoperability, data governance, real-time constraints, and trust in autonomous decision-making that must be addressed before widespread adoption.

3. AI-Native 6G Network Management Architecture

The transition to 6G introduces a fundamental redesign of network management, shifting from centralized, rule-based control toward distributed, AI-driven, and autonomous systems. An AI-native architecture embeds intelligence throughout the network fabric including the device, edge, RAN, core, and cloud layers to enable real-time learning, predictive decision-making, and closed-loop automation (Saad et al., 2020; ITU-T, 2023). This section presents a structured architectural overview defining the core principles and key components required to achieve AI-native 6G management.

3.1. Core Architectural Principles

3.1.1. Native and Pervasive Intelligence

Unlike 5G where AI augments network operations, 6G integrates intelligence as a foundational layer. Decisions related to scheduling, routing, slice management, interference mitigation, and energy optimization are delegated to distributed AI agents capable of self-learning and continuous adaptation (Chen et al., 2022).

3.1.2. Autonomy and Self-Evolution

6G management must support autonomous behavior including self-configuration, self-optimization, self-healing, and self-protection. Zero-touch and intent-based frameworks guide automatic execution of high-level operator goals without manual intervention (ETSI, 2022; Mahmood et al., 2024).

3.1.3. Context and Semantic Awareness

Future networks must understand the *meaning* of transmitted information, leveraging semantic communication for efficient control signaling and context-aware decision-making at ultra-low latency (Shi et al., 2023).

3.1.4. Edge-Centric Coordination

To meet sub-millisecond latency constraints, intelligence is pushed closer to the network edge. Edge AI accelerators and distributed learning methods ensure rapid inference for local optimization (Gharaibeh et al., 2023).

3.1.5. Closed-Loop and Intent-Driven Control

Closed-loop orchestration enables continuous monitoring, prediction, and adjustment across network layers. Intent-based networking translates operator goals ("minimize energy," "prioritize URLLC traffic") into machine-executable policies (ITU-T, 2023).

3.2. Architecture Layers

The following subsections describe the main architectural layers that collectively support AI-native 6G network management.

3.2.1. Data Fabric Layer

The data fabric serves as the backbone for real-time sensing, telemetry, and cross-domain data integration. It aggregates data from multiple sources including RAN elements, user devices, RIS surfaces, sensors, and core network components. Effective data management is essential for training AI models, enabling situational awareness, and maintaining accurate network digital twins (Flórez et al., 2023).

Key components include:

- Real-time telemetry and sensing systems
- Unified data lakes and feature stores
- Cross-domain context data integration
- High-speed data pipelines for AI inference and training

3.2.2. AI Fabric Layer

The AI fabric hosts the intelligence required for autonomous operation. It includes distributed AI models running on device, edge, RAN, and cloud environments. Key technologies include multi-agent reinforcement learning, federated learning, and foundation models tailored for 6G tasks (Chen et al., 2022).

Core functions include:

- On-device AI for local decisions
- Edge-based inference and cooperative learning
- Centralized model refinement and optimization
- Collaborative multi-agent coordination
- Domain-specific network foundation models

3.2.3. Control and Orchestration Layer

This layer transforms operator intents into machine-executable actions. It also hosts closed-loop control logic for predictive orchestration and proactive fault prevention (Mahmood et al., 2024).

Key capabilities:

- Intent-based networking (IBN)
- Network slicing lifecycle automation

- Policy-driven and SLA-aware decision-making
- Closed-loop optimization and troubleshooting
- Service orchestration for multi-domain networks

3.2.4. Service and Application Layer

The service layer ensures quality-of-experience (QoE) and end-to-end service performance. It manages vertical applications such as holographic communication, XR, autonomous vehicles, remote surgery, and digital twins (Dang et al., 2020).

Functions include:

- SLA monitoring and assurance
- Cross-layer application adaptation
- Latency- and reliability-aware service tailoring

3.2.5. Security and Trust Layer

In AI-native 6G, security shifts from reactive rule-based methods to predictive and adaptive intelligence. AI-driven threat detection, trust scoring, and real-time anomaly detection are essential for protecting distributed infrastructures (Bennis et al., 2018).

Key components:

- AI-based intrusion detection and mitigation
- Privacy-preserving learning algorithms
- Trust management for devices, models, and agents
- Secure model lifecycle management

3.3. Architectural Summary

An AI-native 6G architecture integrates pervasive intelligence, distributed decision-making, real-time predictive orchestration, and intent-driven control across all network layers. The layered structure supports a seamless flow from raw data to autonomous execution, enabling networks capable of self-evolving, self-optimizing, and delivering the extreme performance targets of the 6G era.

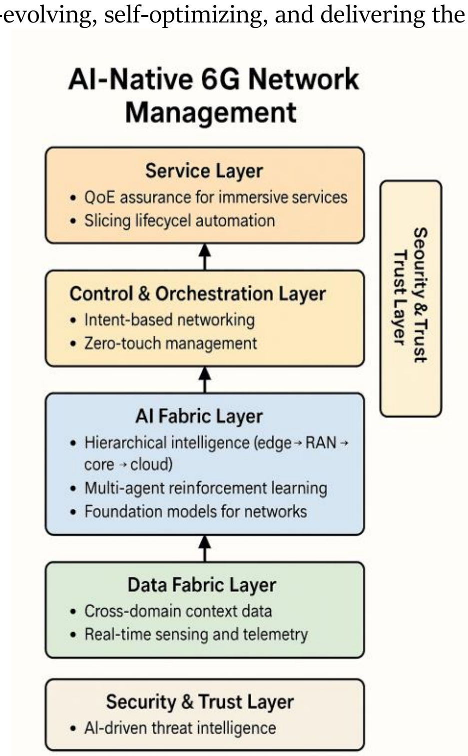

Figure 1. AI-Native 6G Network Management

4. Enabling Technologies for AI-Native 6G Network Management

AI-native 6G network management depends on an ecosystem of advanced computational, sensing, and communication technologies working together to enable autonomy, predictive intelligence, and real-time adaptability. This section reviews the key enabling technologies that form the backbone of AI-driven 6G systems, including distributed learning, network digital twins, semantic communication, and intelligent radio access technologies. These innovations collectively allow the network to perceive, learn, decide, and act with minimal human involvement (Saad et al., 2020; ITU-T, 2023).

4.1. Distributed and Collaborative AI

Distributed AI is foundational for 6G due to the massive scale and geographically diverse nature of future networks. Rather than relying on centralized training and inference, 6G leverages federated learning, swarm intelligence, and multi-agent reinforcement learning (MARL) to coordinate decisions across thousands of nodes and devices (Chen et al., 2022).

4.1.1. Federated Learning

Federated learning enables devices and edge nodes to collaboratively train models without sharing raw data, addressing privacy and bandwidth constraints. This is particularly important for dense networks, vehicular systems, and edge-assisted applications (Shi et al., 2023).

4.1.2. Multi-Agent Reinforcement Learning

MARL supports decentralized optimization for tasks such as power control, scheduling, and beamforming, where individual agents must cooperate to achieve network-wide objectives (Gharaibeh et al., 2023). MARL also enables cell-free massive MIMO and RIS-assisted environments to self-optimize under dynamic conditions.

4.1.3. Swarm Intelligence

Inspired by collective biological behavior, swarm intelligence provides scalable decision-making for ultra-dense network deployments. It allows distributed nodes to negotiate and coordinate actions efficiently without central controllers (Sun et al., 2020).

Table 2. Enabling Technologies for AI-Native 6G Network Management

Enabling Technology	Description / Role in 6G	Key Technical Features	Representative Sources (≤ 2024)
Distributed & Collaborative AI	Supports autonomous decision-making across edge, RAN, and core through decentralized learning.	Federated learning, Multi-agent RL, Swarm intelligence	Chen et al. (2022); Gharaibeh et al. (2023); Sun et al. (2020)
Network Digital Twins (NDTs)	Provide real-time virtual replicas for predictive optimization and risk-free testing.	Real-time synchronization, Predictive simulation, Proactive orchestration	Flórez et al. (2023); Mahmood et al. (2024)
Semantic & Goal-Oriented Communication	Transmits meaning or task-level intent instead of raw data to reduce signaling overhead.	Semantic encoding, Goal-oriented networking, Knowledge graphs	Shi et al. (2023)
Intelligent RAN & THz Management	Uses AI to optimize RIS, massive MIMO, beamforming, and THz links in dense or dynamic environments.	RIS control, THz beam alignment, Distributed RAN intelligence	Dang et al. (2020); Gharaibeh et al. (2023)
Zero-Touch & Intent-Based Networking	Enables fully autonomous lifecycle management and closed-loop orchestration.	Intent translation, Policy automation, Explainable AI	ETSI (2022); ITU-T (2023

4.2. Network Digital Twins (NDTs)

Network digital twins are among the most transformative technologies for 6G, providing real-time virtual replicas of network states. NDTs continuously synchronize with the physical network to support predictive maintenance, resource scheduling, anomaly forecasting, and energy optimization (Flórez et al., 2023).

An NDT-enabled 6G network offers three core benefits:

1. Predictive Optimization: Simulations run on the twin can test resource allocation or routing decisions before applying them to the live network (Mahmood et al., 2024).

2. Risk-Free Testing: Optimization strategies and AI policies can be validated inside the twin to avoid disruptions or performance degradation.
3. Real-Time Adaptation: The twin acts as a continuously updated context engine that feeds insights to AI agents in the control layer.

NDTs are expected to be integrated with intent-based orchestration and closed-loop automation, forming the brain of autonomous 6G networks.

4.3. Semantic and Goal-Oriented Communication

Semantic communication shifts the focus from transmitting raw data to transmitting *meaning*. This approach significantly reduces bandwidth consumption, improves energy efficiency, and enables more context-rich decision-making in AI-native environments (Shi et al., 2023).

4.3.1. Semantic Encoding

Instead of encoding bits, semantic encoders represent knowledge, intent, or task-specific meaning. This improves communication efficiency for control signals, digital twin synchronization, and distributed learning.

4.3.2. Goal-Oriented Networking

Goal-oriented networking allows nodes to exchange only task-relevant information e.g., “detect anomaly” or “maintain beam alignment” rather than full data sets. This supports ultra-low latency use cases such as tactile Internet applications.

4.3.3. Knowledge Graph–Driven Control

Knowledge graphs can be used to represent context and relationships, enabling AI agents to make more informed decisions with minimal signaling overhead.

4.4. Intelligent RAN and THz Management

The radio access network (RAN) in 6G is expected to operate in challenging environments including THz bands, ultra-dense deployments, and RIS-enhanced propagation. AI plays a critical role in enabling efficient RAN operation (Dang et al., 2020).

4.4.1. Reconfigurable Intelligent Surfaces (RIS)

AI models dynamically adjust RIS elements to shape wireless channels, improve coverage, and enhance energy efficiency (Gharaibeh et al., 2023).

4.4.2. Cell-Free Massive MIMO

Distributed AI agents collaboratively manage beamforming, interference mitigation, and user association in shared-RAN topologies.

4.4.3. THz Communication

THz frequencies introduce challenges such as high path loss, beam alignment difficulties, and blockages. AI-driven prediction and reinforcement learning improve beam tracking and mobility support.

4.5. Zero-Touch and Intent-Based Networking

Zero-touch networks (ZTN) and intent-based networking (IBN) form the operational backbone of AI-native 6G. These frameworks allow networks to interpret high-level objectives and autonomously translate them into actionable policies (ETSI, 2022; ITU-T, 2023).

4.5.1. Autonomous Lifecycle Management

AI automates service provisioning, slicing, monitoring, and fault recovery minimizing operational complexity.

4.5.2. Closed-Loop Orchestration

Continuous sensing, prediction, and adjustment enable real-time optimization without human intervention.

4.5.3. Explainable AI and Trust

Intent-driven systems require AI models that are auditable, trustworthy, and interpretable, ensuring safe automation of critical services.

4.6. Summary

The enabling technologies discussed distributed AI, NDTs, semantic communication, intelligent RAN, and zero-touch management form the cornerstone of AI-native 6G networks. Together, they support the autonomous, self-evolving, and context-aware operation required to meet the extreme performance and service demands of future wireless systems.

5. Research Challenges in AI-Native 6G Network Management

Although AI-native 6G networks promise unprecedented levels of autonomy, adaptability, and efficiency, several critical research challenges must be resolved before large-scale deployment becomes feasible. These challenges span data availability, model scalability, trustworthiness, resource constraints, and cross-domain governance. Addressing these issues is essential to ensure that AI-driven management systems are reliable, secure, and aligned with operator and user expectations (Saad et al., 2020; ITU-T, 2023).

5.1. Data Scarcity, Quality, and Distribution

AI-native systems rely heavily on large volumes of high-quality, real-time data. However, wireless networks generate highly heterogeneous data ranging from radio measurements to mobility logs which may be noisy, incomplete, or inconsistent across domains (Chen et al., 2022).

Key limitations include:

- Sparse or imbalanced datasets for rare events such as outages or security breaches.
- Limited availability of labeled data, making supervised learning difficult.
- Non-iid data distributions across devices, which complicate federated learning.
- Privacy constraints, reducing the ability to centralize datasets.

These issues hinder the training of accurate and generalizable AI models, motivating research into self-supervised learning, synthetic data generation through digital twins, and privacy-preserving AI.

5.2. Scalability of Distributed AI Models

6G networks are expected to support billions of devices and dense deployment scenarios. Scaling multi-agent reinforcement learning, federated learning, and distributed inference across such massive environments is non-trivial (Gharaibeh et al., 2023). Major challenges include:

- Communication overhead during model synchronization.
- Convergence instability in multi-agent systems experiencing dynamic conditions.
- Computational constraints at the device and edge levels.
- Model drift due to continuous online learning.

Achieving reliable distributed intelligence requires lightweight model architectures, hierarchical coordination, and efficient learning paradigms that adapt to real-time changes.

5.3. Explainability and Trust in AI-Driven Systems

As AI agents assume greater autonomy controlling slicing, mobility, beamforming, security, and fault management stakeholders must trust that decisions are safe, fair, and interpretable. Traditional deep learning models often operate as black boxes, posing risks when applied to mission-critical applications such as autonomous vehicles, remote surgery, or industrial automation (Bennis et al., 2018).

Key concerns include:

- Lack of interpretability in AI-generated decisions.
- Bias propagation from data-driven models.
- Difficulty auditing autonomous actions in real-time.

- Uncertainty quantification for safety-critical tasks.

Explainable AI (XAI), causal inference models, and trustworthy AI frameworks are essential to address these concerns in 6G systems.

5.4. Real-Time Constraints and Extreme Performance Requirements

6G applications such as holographic communication, tactile Internet, and integrated sensing/communication demand ultra-low latency (≤ 1 ms), ultra-high reliability (> 99.9999%), and extreme data rates (Tbps). Meeting these requirements while performing real-time AI inference and decision-making is a major challenge (Dang et al., 2020).

Issues include:

- AI inference delays at edge or device levels.
- High overhead of distributed model updates.
- Dynamic spectrum changes in THz frequencies.
- Frequent topology changes in cell-free massive MIMO and RIS-assisted networks.

Future research must optimize model compression, on-device AI acceleration, and hybrid edge-cloud inference architectures.

5.5. Security, Privacy, and Cross-Domain Trust

AI-native 6G networks are susceptible to a wide range of cyber threats including adversarial attacks, data poisoning, and model inversion that can compromise system performance and safety (ITU-T, 2023).

Major challenges include:

- Attack surfaces expand as intelligence is embedded across distributed nodes.
- Adversarial manipulation of AI models, leading to incorrect decisions.
- Privacy breaches during distributed learning.
- Cross-domain trust issues among operators, cloud providers, and heterogeneous devices.

Robust security frameworks are needed, integrating AI-based threat detection, federated trust scoring, privacy-preserving learning, and secure model lifecycle management.

5.6 Integration Complexity and Interoperability

AI-native management requires seamless integration across multiple layers—data fabric, AI fabric, orchestration, and RAN—which are often developed by different vendors. This leads to interoperability challenges and fragmented architectural designs (ETSI, 2022).

Common issues include:

- Vendor-specific interfaces limiting end-to-end intelligence.
- Inconsistent data formats across domains.
- Lack of standardized AI pipelines for model training and deployment.
- Complex orchestration for multi-operator or multi-cloud environments.

Standardization efforts such as IMT-2030 and O-RAN are addressing these concerns, but unresolved gaps remain.

5.7. Summary

The major challenges facing AI-native 6G management data, scalability, trust, performance, security, and interoperability highlight the need for new AI paradigms, robust standardization, and stronger cross-disciplinary collaboration. Solving these challenges is critical to realizing the vision of fully autonomous and resilient 6G networks.

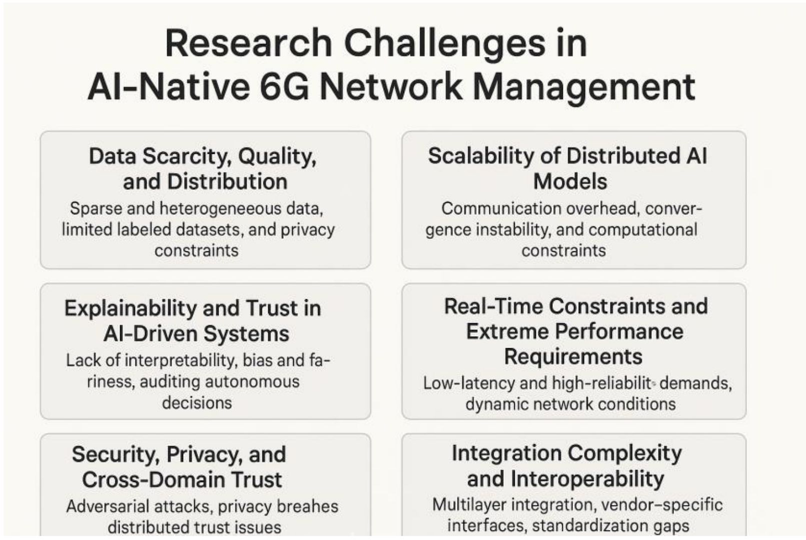

Figure 2. Research Challenges in AI-Native 6G Network Management

6. Open Research Directions for AI-Native 6G Network Management

The evolution toward AI-native 6G presents not only technical challenges but also significant opportunities for innovation across learning paradigms, network design, model governance, and cross-layer optimization. As global research continues to mature, several open research directions have emerged that will shape the development of autonomous 6G systems. These directions focus on enhancing intelligence, resilience, trust, and efficiency across the network (Saad et al., 2020; ITU-T, 2023).

6.1. Development of Network Foundation Models

Foundation models (FMs) have transformed natural language processing and vision tasks, and similar architectures are expected to play a major role in 6G. A network foundation model (N-FM) would learn generalized representations of wireless environments, traffic patterns, user behavior, and RAN dynamics (Mahmood et al., 2024).

Key research questions include:

- How can FMs be specialized for wireless environments with high variability?
- What types of multimodal data—RAN, sensing, mobility, environmental—should they ingest?
- How can FMs support real-time inference with minimal resource overhead?

N-FMs could serve as the “brain” of autonomous networks, enabling predictive optimization and intent translation.

6.2. Autonomous Multi-Agent Coordination

Future 6G networks will involve interactions among thousands of distributed agents including RIS panels, edge nodes, user devices, UAVs, and base stations. Ensuring seamless multi-agent coordination is critical for tasks such as beamforming, handover, spectrum sharing, and load balancing (Gharaibeh et al., 2023).

Key research needs:

- Scalable MARL models that converge reliably in dynamic environments.
- Coordination mechanisms that balance global optimization with local autonomy.
- Incentive mechanisms to align agent objectives and prevent instability.

This area is essential for achieving cell-free massive MIMO and autonomous RAN operation.

6.3. Generative AI for Network Automation and Troubleshooting

Generative AI (GenAI) offers new opportunities for autonomous troubleshooting, synthetic data generation, and policy generation. In 6G, GenAI can:

- Generate synthetic datasets to train AI agents when real data is limited.
- Simulate network behaviors inside digital twins.
- Translate operator intents into actionable policies.
- Predict potential failures or anomalies before they occur (Flórez et al., 2023).

Open research questions:

- How can GenAI's outputs be validated for reliability in mission-critical environments?
- How can GenAI be combined with causal reasoning for better interpretability?
- What safety constraints must guide GenAI-driven orchestration actions?

6.4 Human–AI Collaboration and Governance Frameworks

Even as 6G networks become autonomous, human oversight remains vital. Research must explore how operators interact with AI systems to maintain transparency, safety, and accountability (ITU-T, 2023).

Key questions include:

- What governance structures ensure ethical and explainable AI-driven decisions?
- How can intent-based systems provide meaningful feedback to human operators?
- What human-in-the-loop mechanisms are necessary during emergencies?

Developing robust governance frameworks will prevent over-reliance on opaque decision-making processes.

6.5. Resource-Aware and Green AI

Sustainability is a major requirement for 6G. AI models used for orchestration and optimization must be resource-efficient both in computation and energy consumption (Dang et al., 2020).

Important research directions:

- **Green AI models** optimized for low-power edge devices.
- Carbon-aware scheduling of AI workloads.
- New training methods reducing data and compute requirements.
- Joint optimization of communication and computation resources.

This research area aligns with global goals for climate-conscious network design.

6.6. Quantum-Assisted Optimization for 6G

Quantum computing and quantum-inspired algorithms offer promising solutions for complex optimization tasks such as spectral efficiency maximization, beam steering, and resource scheduling.

Key research topics include:

- Quantum-inspired reinforcement learning.
- Hybrid quantum–classical optimization for large-scale RAN planning.
- Quantum-safe security methods for distributed AI (Bennis et al., 2018).

Although still in early stages, quantum-assisted AI could significantly enhance 6G orchestration capabilities.

6.7. Cross-Layer and Cross-Domain Optimization

AI-native networks must break traditional isolation between the physical, MAC, network, and application layers. Research must address:

- Joint optimization across radio, transport, and application layers.
- Coordinated sensing–communication–computation strategies.
- Techniques enabling seamless interoperability across operators and cloud domains (ETSI, 2022).

Cross-layer learning and integrated resource orchestration will be essential for meeting extreme 6G performance requirements.

6.8 Summary

The open research directions outlined network foundation models, multi-agent collaboration, generative AI, governance, green AI, quantum-assisted optimization, and cross-layer orchestration represent the pathways toward achieving the vision of a fully autonomous, intelligent, and trustworthy 6G ecosystem. Continued research across these domains will be essential to unlock the transformative potential of AI-native 6G networks.

7. Conclusion

The transition to 6G marks a defining moment in the evolution of mobile communication systems, shifting from AI-assisted methodologies to AI-native network management, where intelligence is embedded across every layer of the architecture. This paradigm enables networks that can perceive, learn, adapt, and make autonomous decisions in real time, supporting next-generation applications such as holographic telepresence, immersive XR, intelligent robotics, autonomous transportation, and large-scale digital twins. As demonstrated throughout this paper, AI-native 6G management relies on an interconnected ecosystem of technologies including distributed AI, network digital twins, semantic communication, intelligent RAN operation, and zero-touch orchestration to deliver the performance, scalability, and resilience required for future services (Saad et al., 2020; ITU-T, 2023).

Despite these advancements, significant challenges remain before AI-native 6G systems can be realized in practice. Issues concerning data scarcity, distributed scalability, model trustworthiness, real-time constraints, security vulnerabilities, and multi-vendor interoperability must be addressed through coordinated research and standardization efforts. These challenges underscore the need for robust, trustworthy, and explainable AI models capable of integrating seamlessly with physical, virtualized, and cloud-native network infrastructures (Chen et al., 2022; Mahmood et al., 2024). Furthermore, human–AI collaboration and governance mechanisms will be essential to ensure safe and transparent operation of autonomous systems, particularly for mission-critical applications.

Looking forward, promising research directions including network foundation models, multi-agent coordination, generative AI for orchestration, green AI, quantum-assisted optimization, and cross-layer learning provide pathways toward achieving fully autonomous, self-evolving 6G networks (Gharaibeh et al., 2023). The convergence of these innovations will define the next era of wireless intelligence, enabling networks that are not simply managed by AI but fundamentally driven by AI at their core.

Ultimately, AI-native 6G network management represents a transformative shift in how communication systems are designed, optimized, and operated. Continued interdisciplinary research, industry collaboration, and rigorous standardization will be essential to realize the full potential of AI-native 6G networks and unlock new possibilities for global connectivity, automation, and digital innovation.

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