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REVIEW ARTICLE

# A Comprehensive Review on Architecture, Channel Intelligence, and Autonomous Optimization of AI-Native Communication Systems for 6G Networks

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## Abstract

The evolution of sixth-generation (6G) wireless communication systems demands a paradigm shift from conventional model-driven architectures to intelligent, data-driven, and autonomous communication frameworks. Traditional communication systems, which rely on predefined models and static optimization strategies, are inadequate for highly dynamic and heterogeneous 6G environments characterized by ultra-high data rates, sub-millisecond latency, and massive connectivity. To address these challenges, this paper presents a comprehensive review and unified framework for AI-native communication systems, where artificial intelligence is deeply embedded into the communication stack as a fundamental design principle. The framework integrates three core components: (i) channel intelligence based on deep learning and Transformer models for accurate estimation and proactive prediction, (ii) distributed learning using federated architectures for scalable and privacy-preserving intelligence, and (iii) reinforcement learning-based autonomous optimization for dynamic resource allocation under multi-objective constraints. A mathematical formulation is developed to model quality of experience, energy efficiency, and constrained optimization using Markov decision processes. The paper further identifies key challenges related to scalability, model generalization, computational complexity, and security, and outlines future research directions including semantic communication and digital twin-enabled optimization. Overall, this work establishes AI-native communication as a foundational paradigm for enabling intelligent, self-optimizing, and fully autonomous 6G wireless networks.

*Keywords:* Sixth-generation (6G), Wireless communication, AI-native networks, Channel intelligence, Deep learning, Transformer models, Autonomous optimization, Semantic communication, Digital twin, Edge intelligence, QoE optimization.

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## 1. Introduction

The evolution of wireless communication systems toward 6G networks represents a paradigm shift from connectivity-centric architectures to intelligence-driven communication

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**Graphical abstract: AI-Native 6G communication paradigm.**

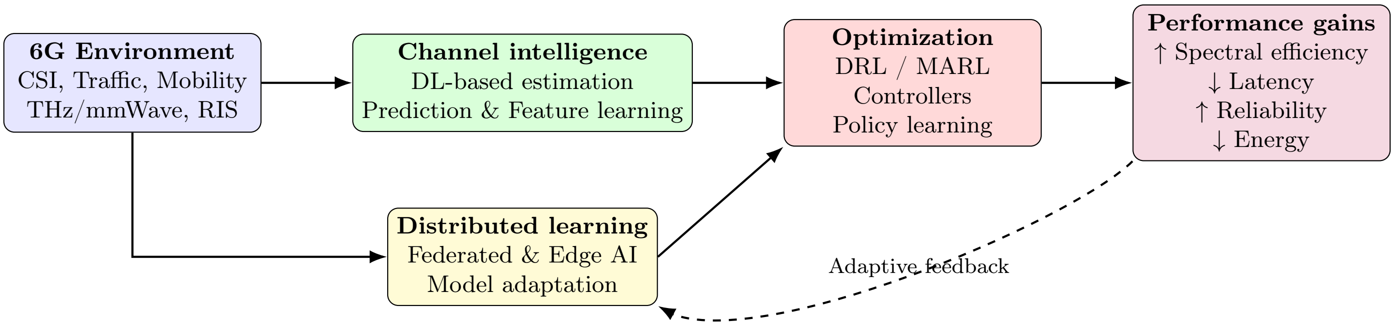


Table 1: System model and channel-state notations.

| Notation | Definition | Meaning |
|---|---|---|
| $\mathcal{N}$ | Set of network nodes | Includes user equipment, edge nodes, base stations, and cloud-assisted entities. |
| $N$ | Number of nodes | Total number of participating nodes or agents. |
| $i$ | Node index | Index of a specific node in $\mathcal{N}$. |
| $t$ | Time index | Discrete time instant used for observation, prediction, and control. |
| $\tau$ | Prediction horizon | Future offset used for proactive channel prediction. |
| $s_i(t)$ | Local state | State observed by node $i$ at time $t$. |
| $S(t)$ | Global state | Aggregated network state across all nodes. |
| $h_i(t)$ | Channel state information | Instantaneous CSI of node $i$. |
| $\hat{h}_i(t)$ | Estimated CSI | AI-estimated channel state at time $t$. |
| $\hat{h}_i(t+\tau)$ | Predicted CSI | Future channel state predicted for proactive optimization. |
| $q_i(t)$ | Queue length | Traffic load or buffer occupancy at node $i$. |
| $e_i(t)$ | Energy state | Available or residual energy of node $i$. |
| $c_i(t)$ | Context information | Mobility, interference, location, and environmental context. |
| $x_i(t)$ | Input feature vector | Features used for AI-driven channel estimation and prediction. |
| $y_i(t)$ | Pilot signal | Received pilot observation at node $i$. |
| $v_i(t)$ | Mobility feature | Speed or movement characteristic of node $i$. |
| $\eta_i(t)$ | Noise/interference statistics | Statistical representation of noise and interference. |

Table 2: AI-driven channel intelligence and learning notations.

| Notation | Definition | Meaning |
|---|---|---|
| $f_\theta(\cdot)$ | Channel estimation model | Deep neural network used for CSI estimation. |
| $g_\phi(\cdot)$ | Temporal prediction model | LSTM/Transformer-based model used for future CSI prediction. |
| $\theta$ | Estimation parameters | Trainable parameters of $f_\theta(\cdot)$. |
| $\phi$ | Prediction parameters | Trainable parameters of $g_\phi(\cdot)$. |
| $\theta_i$ | Local model parameters | Node-specific model parameters updated locally. |
| $\theta^{(r)}$ | Global model | Federated model at communication round $r$. |
| $\theta^{(r+1)}$ | Updated global model | Aggregated model after communication round $r$. |
| $r$ | FL round index | Communication round index in federated learning. |
| $w_i$ | Aggregation weight | Weight assigned to local model $\theta_i$. |
| $\mathcal{L}_{\text{chan}}$ | Channel loss | Mean-squared CSI estimation error. |
| $\mathcal{L}_{\text{est}}$ | Estimation loss | Supervised loss for channel estimation. |
| $\mathcal{L}_{\text{unc}}$ | Uncertainty loss | Loss used to account for probabilistic prediction uncertainty. |
| $\mathcal{L}_i$ | Local loss | Combined local estimation and uncertainty loss. |
| $\mu_i(t)$ | Prediction mean | Expected value of predicted CSI. |
| $\sigma_i^2(t)$ | Prediction variance | Variance of predicted CSI uncertainty. |
| $\sigma_i(t)$ | Uncertainty term | Standard-deviation-based risk term used in reward design. |
| $\mathcal{U}(\cdot)$ | Uncertainty operator | Function estimating prediction mean and variance. |
| $Q, K, V$ | Query, key, value | Transformer self-attention matrices. |
| $d_k$ | Key dimension | Scaling term in attention computation. |
| softmax$(\cdot)$ | Softmax function | Normalization function used in attention. |
| $\mathcal{N}(\mu_i, \sigma_i^2)$ | Gaussian distribution | Probabilistic model of channel prediction uncertainty. |

Table 3: QoE, energy, reinforcement learning, and constrained optimization notations.

| Notation | Definition | Meaning |
|---|---|---|
| $QoE_i(t)$ | Quality of Experience | User-centric communication quality metric. |
| $R_i(t)$ | Achieved data rate | Throughput achieved by node $i$. |
| $D_i(t)$ | End-to-end latency | Communication delay experienced by node $i$. |
| $U_i(t)$ | Reliability metric | Successful transmission probability or reliability level. |
| $\alpha$ | Throughput/QoE weight | Weight associated with rate or QoE contribution. |
| $\beta$ | Delay/energy penalty weight | Weight associated with latency or energy penalty. |
| $\gamma$ | Reliability weight | Used as reliability weight in QoE or discount factor in RL. |
| $B_i(t)$ | Allocated bandwidth | Bandwidth assigned to node $i$. |
| $B_{\text{total}}$ | Total bandwidth | Network-wide bandwidth budget. |
| $P_i(t)$ | Transmission power | Power allocated to node $i$. |
| $P_{\max}$ | Maximum power | Upper bound on transmission power. |
| $N_0$ | Noise spectral density | Thermal noise term used in achievable-rate modeling. |
| $E_i(t)$ | Energy consumption | Total energy consumed by node $i$. |
| $T_i(t)$ | Transmission duration | Time period used for wireless transmission. |
| $E_i^{\text{comp}}(t)$ | Computation energy | Energy consumed by AI inference or training. |
| $\pi$ | Policy | Resource allocation and control policy. |
| $\pi^*$ | Optimal policy | Policy maximizing expected cumulative reward. |
| $\pi_i(t)$ | Beamforming decision | Scheduling or beam-selection decision at node $i$. |
| $\pi_i(a_i\|s_i)$ | Local policy | Probability of selecting action $a_i$ under state $s_i$. |
| $a_i(t)$ | Action | Resource allocation decision of node $i$. |
| $\mathcal{M}$ | MDP | Markov Decision Process for autonomous optimization. |
| $\mathcal{S}$ | State space | Set of possible network states. |
| $\mathcal{A}$ | Action space | Set of possible optimization actions. |
| $\mathcal{P}$ | Transition probability | Probability of state transition. |
| $\mathcal{R}$ | Reward function | RL reward used for policy learning. |
| $r(t)$ | Global reward | Aggregate reward over the network. |
| $r_i(t)$ | Local reward | Reward obtained by node $i$. |
| $R(\pi)$ | Expected reward | Expected cumulative reward under policy $\pi$. |
| $C(\pi)$ | Constraint cost | Energy, delay, or resource cost under policy $\pi$. |
| $C_{\max}$ | Cost limit | Maximum allowable cost in CMDP. |
| $C_k(\pi)$ | Constraint function | Individual QoS/resource constraint indexed by $k$. |
| $C_k^{\max}$ | Constraint threshold | Upper bound for constraint $k$. |
| $\lambda$ | Lagrangian multiplier | Penalty coefficient for constraint handling. |
| $\delta$ | Uncertainty penalty | Risk-aware weight penalizing channel uncertainty. |
| $\Delta_{\text{TD}}$ | TD error | Temporal-difference error for critic update. |
| $V_\omega(s)$ | Value function | Expected long-term reward of state $s$. |
| $\omega$ | Critic parameters | Trainable parameters of the value network. |
| $\eta$ | Learning rate | Step size for gradient-based model updates. |
| $J(\theta)$ | Policy objective | Objective optimized by the actor network. |
| $\mathbb{E}[\cdot]$ | Expectation | Statistical expectation over states, policies, and transitions. |
| $\\|\cdot\\|^2$ | Squared norm | Error magnitude used in loss functions. |
| $\nabla$ | Gradient operator | Used for learning-based parameter updates. |
| $\log_2(\cdot)$ | Base-2 logarithm | Used in achievable-rate expression. |

ecosystems. The vision of 6G encompasses ultra-high data rates in the terabit-per-second range, sub-millisecond latency, ultra-reliable communication, and seamless integration of heterogeneous devices and services [1], [3], [50]. These requirements are driven by emerging applications such as holographic communication, extended reality (XR), autonomous transportation, and large-scale cyber–physical systems, which demand unprecedented levels of performance and reliability [2], [48], [49].

A key challenge in realizing 6G systems lies in the increasing complexity and heterogeneity of wireless environments. Future networks are expected to operate across multiple frequency bands, including sub-6 GHz, millimeter-wave, and terahertz spectra, while supporting ultra-dense deployments and highly dynamic mobility patterns [12], [47]. In addition, technologies such as reconfigurable intelligent surfaces (RIS) and ultra-dense network architectures further complicate channel modeling and resource management [13], [14], [44]. Traditional communication system designs, which rely on simplified mathematical models and static optimization techniques, are insufficient to handle the nonlinear and time-varying characteristics of such envi-

**List of acronyms.**

| Acronym | Expansion |
|---|---|
| DNN | Deep Neural Network |
| RNN | Recurrent Neural Network |
| LSTM | Long Short-Term Memory |
| GRU | Gated Recurrent Unit |
| RL | Reinforcement Learning |
| MARL | Multi-Agent Reinforcement Learning |
| FL | Federated Learning |
| CSI | Channel State Information |
| QoE | Quality of Experience |
| QoS | Quality of Service |
| RIS | Reconfigurable Intelligent Surface |
| mmWave | Millimeter Wave |
| MIMO | Multiple Input Multiple Output |
| UAV | Unmanned Aerial Vehicle |
| URLLC | Ultra-Reliable Low-Latency Communication |
| eMBB | Enhanced Mobile Broadband |
| mMTC | Massive Machine-Type Communication |
| O-RAN | Open Radio Access Network |
| RAN | Radio Access Network |
| NFV | Network Function Virtualization |
| MEC | Multi-access Edge Computing |
| CMDP | Constrained Markov Decision Process |
| MDP | Markov Decision Process |
| CSI-RS | Channel State Information Reference Signal |
| SINR | Signal-to-Interference-plus-Noise Ratio |
| SNR | Signal-to-Noise Ratio |
| BER | Bit Error Rate |
| SE | Spectral Efficiency |
| KPI | Key Performance Indicator |
| FPGA | Field Programmable Gate Array |
| ASIC | Application Specific Integrated Circuit |
| API | Application Programming Interface |
| TCP | Transmission Control Protocol |
| UDP | User Datagram Protocol |
| NOMA | Non-Orthogonal Multiple Access |
| OFDM | Orthogonal Frequency Division Multiplexing |
| CSI Feedback | Channel State Information Feedback |
| DQN | Deep Q-Network |

ronments [26], [27], [53]–[56].

To address these challenges, Artificial Intelligence (AI) has emerged as a key enabler for next-generation wireless communication systems. AI techniques have been successfully applied to various problems, including channel estimation, interference mitigation, traffic prediction, and resource allocation [36]–[38]. However, most existing approaches follow an AI-assisted paradigm, where machine learning models are applied as external tools to optimize specific components of the communication system. Such approaches are inherently limited in their ability to support real-time, scalable, and fully autonomous network operation [4], [5].

In contrast, the concept of *AI-native communication systems* has recently gained significant attention as a fundamental design paradigm for 6G networks. In AI-native systems, intelligence is embedded directly into the communication architecture, enabling joint optimization of physical layer operations, medium access control, and network-level decision-making [9], [10]. This paradigm enables real-time learning, predictive control, and adaptive resource management, transforming wireless networks from reactive systems into proactive and self-evolving entities [6].

A central component of AI-native communication is *channel intelligence*, which leverages deep learning models to capture complex propagation characteristics and predict channel states in dynamic environments [15]. Data-driven channel estimation and prediction techniques enable proactive resource allocation, beam management, and mobility handling, significantly improving spectral efficiency and system reliability. Furthermore, emerging concepts such as semantic communication aim to transmit meaningful information rather than raw data, thereby reducing communication overhead and improving efficiency [31], [33], [34].

Another critical aspect of AI-native communication systems is *autonomous optimization*, which enables dynamic adaptation of network resources with minimal human intervention. Reinforcement learning and multi-agent learning frameworks provide powerful tools for optimizing spectrum allocation, power control, and network slicing under dynamic constraints [21]. These approaches enable continuous learning and adaptation in highly dynamic environments, supporting efficient and scalable network operation.

Despite these advancements, several open challenges remain in the realization of AI-native 6G systems [39], [40]. These include the scalability of distributed learning frameworks, generalization of AI models in non-stationary environments, computational and energy overhead, and the lack of standardized interfaces for integrating AI into communication systems [17], [18], [41] . Additionally, security and privacy concerns associated with distributed AI models, including adversarial attacks and data leakage, pose significant risks to system reliability [30], [32]. While existing literature provides valuable insights into individual aspects of AI in wireless communication, there is a lack of unified frameworks that integrate channel intelligence, distributed learning, and autonomous optimization into a cohesive AI-native architecture.

To address this gap, this paper presents a comprehensive review and unified framework for AI-native communication systems in 6G networks. All the mathematical notations used in this work, their definitions and meanings are given in Tables 1, 2 and 3. The key contributions are as follows:

- A systematic review of AI-native communication paradigms and enabling technologies.
- A unified architectural framework integrating channel intelligence, distributed learning, and autonomous optimization.
- Mathematical insights into AI-driven channel modeling and reinforcement learning-based optimization.
- Identification of key challenges and future research directions for AI-native 6G systems.

## 2. Related work

The role of AI in wireless communication has evolved from task-specific enhancements to a foundational design paradigm for next-generation networks. In the context of 6G, this evolution is characterized by the transition from AI-assisted communication toward fully AI-native systems, where intelligence is embedded across all layers of the communication stack. This section critically reviews the existing literature by categorizing prior work into five key domains: (i) AI-assisted versus AI-native communication, (ii) distributed and edge intelligence, (iii) reinforcement learning-based autonomous optimization, (iv) channel intelligence and intelligent environments, and (v) emerging paradigms including semantic communication and digital twins.

### *2.1. From AI-assisted to AI-native communication*

Early applications of AI in wireless networks focused on improving isolated functionalities such as channel estimation, traffic prediction, and interference mitigation using machine learning models [36], [37], [46]. While these AI-assisted approaches demonstrated measurable performance gains, they were inherently limited by their modular integration and lack of cross-layer coordination.

To overcome these limitations, recent research has introduced the concept of AI-native communication systems, where learning, inference, and optimization are deeply integrated into the communication architecture. The work in [4] highlighted the need for native AI integration in 6G networks to enable real-time adaptation and predictive control . Similarly, AI-native communication principles that unify signal processing and machine learning for end-to-end system optimization [9]. These approaches enable proactive and context-aware communication, marking a significant shift from reactive network management.

### *2.2. Distributed learning and edge intelligence*

Scalable intelligence in 6G networks requires distributed learning frameworks capable of operating across heterogeneous and geographically dispersed devices. Federated learning has emerged as a promising solution, enabling decentralized model training without sharing raw data, thereby preserving privacy and reducing communication overhead [17]. This paradigm is particularly relevant in large-scale wireless systems involving mobile users and IoT devices.

Edge intelligence further enhances system responsiveness by bringing computation and learning closer to data sources. Park *et al.* demonstrated that edge-based AI enables low-latency decision-making and efficient resource utilization in wireless networks [19]. The authors of work [20], [42], [43] emphasized the role of edge intelligence in bridging the gap between cloud computing and real-time inference [52]. Moreover, hierarchical AI frameworks combining user equipment, edge nodes, and cloud infrastructure have been proposed to achieve scalable and coordinated intelligence [16], [18], [51].

### *2.3. Reinforcement learning for autonomous optimization*

Autonomous resource management is a central requirement in AI-native communication systems. The RL provides a principled framework for learning optimal policies through interaction with dynamic environments [21]. Deep reinforcement learning methods, including DQN, DDPG, and PPO, have been widely applied to optimize spectrum allocation, power control, and network scheduling [22]. Multi-agent reinforcement learning extends this capability to distributed environments, enabling cooperative decision-making among multiple network entities [23]. While classical optimization methods such as convex optimization and dynamic programming provide strong theoretical foundations [24], [25], they often lack scalability and adaptability in highly dynamic wireless environments, motivating the adoption of learning-based approaches.

### *2.4. Channel intelligence and intelligent environments*

Accurate channel modeling is essential for reliable communication in 6G systems, particularly in high-frequency bands such as millimeter-wave and terahertz. Traditional statistical models fail to capture the nonlinear and non-stationary characteristics of modern wireless environments. Deep learning-based channel estimation and prediction techniques have shown significant improvements in modeling complex propagation dynamics [11], [15].

Reconfigurable intelligent surfaces (RIS) have further transformed the wireless environment by enabling programmable control of signal propagation [13], [14]. These technologies, when integrated with AI-based channel intelligence, enable adaptive beamforming, interference management, and improved spectral efficiency. The combination of data-driven channel modeling and intelligent environments is a key enabler of AI-native communication systems.

### *2.5. Emerging paradigms: Semantic communication and digital twins*

Semantic communication represents a paradigm shift from conventional bit-level transmission to meaning-oriented communication. By transmitting only task-relevant information, semantic communication significantly reduces bandwidth requirements while improving efficiency [33], [34]. Recent studies suggest that semantic communication will play a central role in AI-native 6G systems by aligning communication processes with application-level objectives [7], [8].

Digital twin technology has also gained attention as a powerful tool for network optimization. By creating virtual replicas of physical network components, digital twins enable real-time monitoring, simulation, and optimization of network operations [28], [29]. These models facilitate predictive control and closed-loop optimization, enhancing system reliability and adaptability.

### *2.6. Research gaps and limitations*

Despite significant progress, several challenges remain in the development of AI-native communication systems. First, many AI-based solutions suffer from high computational complexity and energy consumption, limiting their deployment in resource-constrained environments. Second, the generalization of machine learning models in non-stationary and heterogeneous wireless environments remains an open problem. Third, issues related to interoperability, standardization, and cross-layer integration are not fully addressed in existing frameworks. Furthermore, security and privacy concerns, including adversarial attacks and data leakage in distributed learning systems, pose serious risks to network reliability. These limitations highlight the need for unified frameworks that integrate channel intelligence, distributed learning, and autonomous optimization in a scalable and secure manner.

### *2.7. Summary:*

The reviewed literature demonstrates a clear transition toward AI-native communication systems, supported by advancements in deep learning, edge intelligence, and reinforcement learning. However, a comprehensive and unified framework that seamlessly integrates these components remains largely unexplored. This paper addresses this gap by proposing an AI-native architecture that combines channel intelligence, distributed learning, and autonomous optimization for next-generation 6G networks.

## 3. AI-native system model and mathematical formulation

This section presents a unified mathematical framework for AI-native communication systems in 6G networks. The formulation integrates channel intelligence, distributed learning, and autonomous optimization into a cohesive model, enabling real-time adaptation and self-optimization across heterogeneous network environments [34], [35].

### *3.1. System model*

We consider a multi-tier AI-native 6G network consisting of user equipment, edge nodes, base stations, and cloud intelligence. Let the network be represented as a set of nodes by (1).

$$\mathcal{N} = \{1, 2, \dots, N\} \tag{1}$$

In (1), each node $i \in \mathcal{N}$ observes a local state $s_i(t)$ at time $t$, defined as (2).

$$s_i(t) = \{h_i(t), q_i(t), e_i(t), c_i(t)\} \tag{2}$$

The global network state is given by (3).

$$S(t) = \bigcup_{i \in \mathcal{N}} s_i(t) \tag{3}$$

### *3.2. AI-driven channel intelligence model*

Traditional channel models are insufficient for dynamic environments. We define a data-driven channel estimation model is written as (4).

$$\hat{h}_i(t) = f_\theta(x_i(t)) \tag{4}$$

The estimation error is minimized as (5) and to enable proactive adaptation, channel prediction is modeled as (6).

$$\mathcal{L}_{\text{chan}} = \mathbb{E}\left[\|h_i(t) - \hat{h}_i(t)\|^2\right] \tag{5}$$

$$\hat{h}_i(t + \tau) = g_\phi(h_i(t), h_i(t-1), \dots) \tag{6}$$

### *3.3. Quality of Experience (QoE) model*

The QoE is defined as (7), which is a function of throughput, latency, and reliability.

$$QoE_i(t) = \alpha \cdot R_i(t) - \beta \cdot D_i(t) + \gamma \cdot U_i(t) \tag{7}$$

The achievable rate is given by (8).

$$R_i(t) = B_i(t) \log_2\left(1 + \frac{P_i(t)h_i(t)}{N_0}\right) \tag{8}$$

### *3.4. Energy consumption model*

Energy efficiency is critical in 6G systems. The energy consumption of node $i$ is modeled as (9).

$$E_i(t) = P_i(t) \cdot T_i(t) + E_i^{\text{comp}}(t) \tag{9}$$

In (9), $P_i(t)$ is the transmission power, $T_i(t)$ is the transmission duration and $E_i^{\text{comp}}(t)$ is the computation energy (AI inference/training).

### *3.5. Multi-objective optimization problem*

The objective is to jointly maximize QoE while minimizing energy consumption, given by (10) and which is subject to (11)-(13). This forms a constrained optimization problem under dynamic network conditions.

$$\max_{\pi} \; \mathbb{E}\left[\sum_t \sum_{i \in \mathcal{N}} (\alpha QoE_i(t) - \beta E_i(t))\right] \tag{10}$$

$$P_i(t) \leq P_{\max}, \quad \forall i, t \tag{11}$$

$$D_i(t) \leq D_{\max}, \tag{12}$$

$$B_i(t) \leq B_{\text{total}} \tag{13}$$

### *3.6. Reinforcement learning formulation*

The problem is modeled as a Markov Decision Process (MDP) and which is given by (14).

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}) \tag{14}$$

The reward function ($\mathcal{R}$) is defined as (15).

$$r(t) = \sum_i (\alpha QoE_i(t) - \beta E_i(t)) \tag{15}$$

The optimal policy $\pi^*$ is obtained by (16).

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_t \gamma^t r(t)\right] \tag{16}$$

### *3.7. Constrained Markov Decision Process (CMDP)*

To enforce QoS constraints, we extend the formulation to a CMDP as (17).

$$\max_{\pi} \; \mathbb{E}[R(\pi)] \quad \text{s.t.} \quad \mathbb{E}[C(\pi)] \leq C_{\max} \tag{17}$$

Using Lagrangian relaxation (18):

$$\mathcal{L} = \mathbb{E}[R(\pi)] - \lambda\left(\mathbb{E}[C(\pi)] - C_{\max}\right) \tag{18}$$

Table 4: Comparative analysis of key research directions in AI-native 6G communication systems.

| Research category | Adaptability | Scalability | Autonomy | Key characteristics and limitations |
|---|---|---|---|---|
| AI-assisted communication | Medium | Medium | Low | Applies machine learning to isolated tasks such as channel estimation and traffic prediction. Limited cross-layer integration and lacks real-time autonomous decision-making [36] ,[37], [46]. |
| AI-native communication | High | High | High | Embeds intelligence across the communication stack enabling end-to-end learning, predictive control, and self-optimization. Challenges include high complexity and standardization issues [4], [9], [10]. |
| Distributed & edge intelligence | High | High | Medium | Enables decentralized learning using federated learning and edge AI. Reduces latency and preserves privacy but introduces coordination and communication overhead [17], [19], [20]. |
| Reinforcement learning-based optimization | Very high | Medium | High | Supports dynamic resource allocation and adaptive policy learning. Effective in non-linear environments but requires large training data and may suffer from convergence issues [22]. |
| Channel intelligence (DL-based) | High | Medium | Medium | Utilizes deep learning for channel estimation and prediction in complex environments. Improves accuracy but depends on data availability and model generalization [11], [15]. |
| Intelligent environments (RIS-enabled) | High | Medium | Medium | Enhances channel controllability through programmable environments. Improves signal propagation but requires hardware integration and optimization complexity [13], [14]. |
| Semantic communication | Very High | High | High | Focuses on transmitting meaningful information instead of raw bits, significantly reducing bandwidth usage. Still in early stages with challenges in standardization [33], [34], [7]. |
| Digital twin-based networks | High | High | High | Enables real-time simulation and predictive optimization using virtual replicas of physical systems. Computationally intensive and requires accurate modeling [28], [29]. |

### *3.8. Discussion*

The proposed mathematical framework integrates AI-driven channel intelligence, multi-objective optimization, and reinforcement learning into a unified model. Unlike conventional approaches, this formulation enables real-time adaptation, predictive control, and autonomous optimization in dynamic 6G environments. The combination of QoE-aware optimization and energy-efficient learning makes the framework suitable for next-generation intelligent communication systems.

## 4. Channel intelligence framework in AI-native 6G networks

Channel intelligence is a cornerstone of AI-native communication systems, enabling accurate estimation, prediction, and adaptation of wireless channels in highly dynamic environments. Unlike conventional model-based approaches, AI-driven channel intelligence leverages data-driven learning to capture complex propagation characteristics, particularly in high-frequency bands such as millimeter-wave and terahertz communication.

### *4.1. Architecture of channel intelligence engine*

The channel intelligence framework operates across multiple layers of the AI-native architecture, integrating user equipment, edge nodes, and cloud intelligence. The system follows a hierarchical structure:

- UE layer: Collects raw measurements including pilot signals, CSI, and mobility data.
- Edge layer: Performs real-time inference and local model adaptation.
- Cloud layer: Conducts global model training and aggregation.

Let the input feature vector at node $i$ be (19).

$$x_i(t) = \{y_i(t), h_i(t-1), v_i(t), \eta_i(t)\} \quad (19)$$

The objective is to learn a mapping, the following equation 20.

$$\hat{h}_i(t) = f_\theta(x_i(t)) \quad (20)$$

### *4.2. Deep learning-based channel estimation*

Channel estimation is formulated as a supervised learning problem. Given training samples $\{x_i(t), h_i(t)\}$, the model minimizes by using (21).

$$\mathcal{L}_{\text{est}} = \frac{1}{N}\sum_{i=1}^{N} \|h_i(t) - \hat{h}_i(t)\|^2 \quad (21)$$

CNNs are particularly effective for extracting spatial features from CSI matrices, while fully connected layers capture nonlinear relationships.

### *4.3. Temporal channel prediction using transformer models*

To enable proactive network optimization, channel prediction is required. We employ a Transformer-based temporal model (22). The attention mechanism is defined as (23) and this allows the model to capture long-range temporal dependencies in channel variations.

$$\hat{h}_i(t+\tau) = g_\phi\left(h_i(t), h_i(t-1), \ldots, h_i(t-k)\right) \tag{22}$$

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{23}$$

### *4.4. Uncertainty-aware channel prediction*

Due to stochastic channel variations, uncertainty estimation is critical. We model prediction uncertainty as (24).

$$\hat{h}_i(t+\tau) \sim \mathcal{N}(\mu_i(t), \sigma_i^2(t)) \tag{24}$$

The loss function incorporates uncertainty is given by (25), which improves robustness in dynamic environments.

$$\mathcal{L}_{\text{unc}} = \sum_i \left( \frac{\|h_i - \mu_i\|^2}{\sigma_i^2} + \log \sigma_i^2 \right) \tag{25}$$

### *4.5. Edge-assisted distributed learning*

To reduce latency and communication overhead, learning is distributed across edge nodes. Each node updates local parameters $\theta_i$ and shares them with the cloud (26).

$$\theta^{(t+1)} = \sum_{i=1}^{N} w_i \theta_i^{(t)} \tag{26}$$

This federated learning approach ensures scalability and privacy preservation.

### *4.6. Algorithm: AI-based channel intelligence*

This subsection presents the operational workflow of the proposed AI-native channel intelligence framework. The Algorithm 1 integrates deep learning-based channel estimation, Transformer-based temporal prediction, uncertainty-aware modeling, and federated learning for distributed optimization. The objective is to continuously learn and predict channel states while adapting to dynamic network conditions in real time. At each time step, individual network nodes (UE/edge) collect local observations and perform channel estimation using a trained deep neural network. Temporal prediction is then carried out using sequence learning models to forecast future channel states. To ensure robustness, uncertainty estimation is incorporated into the prediction process. The learning process follows a federated paradigm, where local model updates are periodically aggregated at the cloud to form a global model, which is redistributed to all nodes.

The proposed algorithm enables continuous learning and adaptation of channel intelligence models in a distributed manner. By integrating estimation, prediction, and uncertainty modeling within a federated learning framework, the system achieves scalability, privacy preservation, and robustness. Furthermore, the predicted channel states and associated uncertainty are utilized by the reinforcement learning-based optimization module (Section 3) to enable proactive and risk-aware decision-making in dynamic 6G environments.

**Algorithm 1** AI-native channel intelligence framework.

**Input:** Initial model parameters $\theta$, prediction horizon $\tau$, learning rate $\eta$
**Initialize:** Global model $\theta^{(0)}$
**for** each global communication round $r = 1, 2, \ldots$ **do**
  Distribute global model $\theta^{(r)}$ to all nodes
  **for** each node $i \in \mathcal{N}$ **in parallel do**
    Initialize local model:

$$\theta_i \leftarrow \theta^{(r)}$$

    **for** each time step $t$ **do**
      Collect input features:

$$x_i(t) = \{y_i(t), h_i(t-1), v_i(t), \eta_i(t)\}$$

      **Channel estimation**

$$\hat{h}_i(t) = f_{\theta_i}(x_i(t))$$

      **Temporal prediction**

$$\hat{h}_i(t+\tau) = g_\phi(h_i(t), h_i(t-1), \ldots)$$

      **Uncertainty modeling**

$$(\mu_i(t), \sigma_i^2(t)) = \mathcal{U}\left(\hat{h}_i(t+\tau)\right)$$

      **Loss Computation**

$$\mathcal{L}_i = \mathcal{L}_{\text{est}} + \lambda \mathcal{L}_{\text{unc}}$$

      Update local parameters:

$$\theta_i \leftarrow \theta_i - \eta \nabla \mathcal{L}_i$$

    **end for**
    Transmit updated parameters $\theta_i$ to cloud server
  **end for**
  **Federated aggregation**

$$\theta^{(r+1)} = \sum_{i \in \mathcal{N}} w_i \theta_i$$

**end for**
**Output:** Predicted channel states $\hat{h}_i(t+\tau)$ with uncertainty estimates $(\mu_i, \sigma_i^2)$

### *4.7. Integration with autonomous optimization*

The predicted channel $\hat{h}_i(t+\tau)$ is used by the reinforcement learning agent to make proactive decisions:

- Beamforming optimization
- Spectrum allocation
- Handover management

Figure. 1 illustrates the proposed AI-driven channel intelligence framework, which integrates deep learning-based channel estimation, Transformer-based temporal prediction, uncertainty modeling, and federated learning to enable proactive and adaptive communication in 6G networks.

At the input stage, heterogeneous data sources including pilot signals, historical channel state information (CSI), user mobility patterns, and interference statistics are collected at the user equipment and edge nodes. These inputs are processed through a feature learning module, typically implemented using convolutional or deep neural networks, to extract high-dimensional representations that capture spatial correlations and nonlinear channel characteristics. This learned representation is then utilized by the channel estimation module to generate an accurate estimate of the instantaneous channel state.

To enable predictive and proactive network control, the framework incorporates a temporal prediction module based on Transformer architectures. By leveraging self-attention mechanisms, the model captures long-range temporal dependencies in channel variations and generates future channel estimates $\hat{h}(t+\tau)$. This capability is particularly critical in high-mobility and high-frequency communication scenarios, where rapid channel fluctuations can significantly degrade system performance if not anticipated in advance.

Given the inherent stochasticity of wireless channels, the framework further integrates an uncertainty modeling component that quantifies prediction confidence through probabilistic representations, typically expressed in terms of mean and variance $(\mu, \sigma^2)$. This allows the system to account for prediction reliability and incorporate risk-aware decision-making in subsequent optimization stages. To ensure scalability and low-latency operation, the proposed framework adopts a federated learning paradigm, where model training is distributed across edge nodes and coordinated by a cloud-level aggregator. Local models are updated using device-specific data and periodically aggregated to form a global model, thereby preserving data privacy while enabling collaborative learning across the network. The predicted channel information, along with its associated uncertainty, is then forwarded to the autonomous optimization module, where reinforcement learning agents utilize this knowledge to perform proactive resource allocation, beamforming, and handover decisions. By integrating estimation, prediction, and learning within a unified framework, the proposed channel intelligence system enables a transition from reactive communication strategies to anticipatory and self-optimizing 6G network operation.

### 4.8. Discussion

The proposed channel intelligence framework combines deep learning, Transformer-based prediction, and distributed learning to address the challenges of dynamic 6G environments. Compared to traditional approaches, it enables higher estimation accuracy, proactive adaptation, and reduced latency, making it a critical component of AI-native communication systems.

## 5. Autonomous optimization framework in AI-native 6G networks

Autonomous optimization is a fundamental capability of AI-native communication systems, enabling dynamic and self-adaptive resource management in complex and time-varying wireless environments [45]. Unlike traditional optimization approaches that rely on predefined models and static policies, AI-native systems leverage reinforcement learning to continuously learn optimal strategies through interaction with the environment. This section presents a unified RL-based framework for proactive and energy-efficient optimization in 6G networks.

### 5.1. Framework overview

The proposed autonomous optimization framework operates on top of the channel intelligence module described in Section 4. Predicted channel states $\hat{h}_i(t+\tau)$ and associated uncertainty metrics $(\mu_i, \sigma_i^2)$ are used as inputs to the RL agent, enabling proactive decision-making.

Each network node (or agent) observes a state as given by (27) and it and selects an action as expressed by (28).

$$s_i(t) = \{\hat{h}_i(t), q_i(t), e_i(t), \sigma_i(t)\} \tag{27}$$

$$a_i(t) = \{P_i(t), B_i(t), \pi_i(t)\} \tag{28}$$

### 5.2. Reward design and objective function

The reward function is defined as (29) based on the QoE-energy trade-off introduced in Section 3:

$$r_i(t) = \alpha \cdot QoE_i(t) - \beta \cdot E_i(t) - \delta \cdot \sigma_i(t) \tag{29}$$

The inclusion of uncertainty ensures robust decision-making under imperfect predictions.

### 5.3. Multi-Agent Reinforcement Learning (MARL)

In large-scale 6G networks, centralized optimization is infeasible due to scalability constraints. Therefore, we adopt MARL framework, where each node acts as an independent agent while coordinating with others. The joint objective is written as (30). Agents learn policies $\pi_i(a_i|s_i)$ that maximize cumulative rewards while ensuring network-wide efficiency.

$$\max_{\pi} \mathbb{E}\left[\sum_t \sum_{i\in\mathcal{N}} r_i(t)\right] \tag{30}$$

### 5.4. Constrained Markov Decision Process (CMDP)

To enforce QoS constraints, the optimization is modeled as a CMDP (31):

$$\max_{\pi} \mathbb{E}[R(\pi)] \quad \text{s.t.} \quad \mathbb{E}[C_k(\pi)] \le C_k^{\max} \tag{31}$$

In (31), the constraints are:

- Latency constraint: $D_i(t) \le D_{\max}$
- Power constraint: $P_i(t) \le P_{\max}$
- Bandwidth constraint: $\sum_i B_i(t) \le B_{\text{total}}$

Using Lagrangian relaxation (32):

$$\mathcal{L} = \mathbb{E}[R(\pi)] - \sum_k \lambda_k(\mathbb{E}[C_k(\pi)] - C_k^{\max}) \tag{32}$$

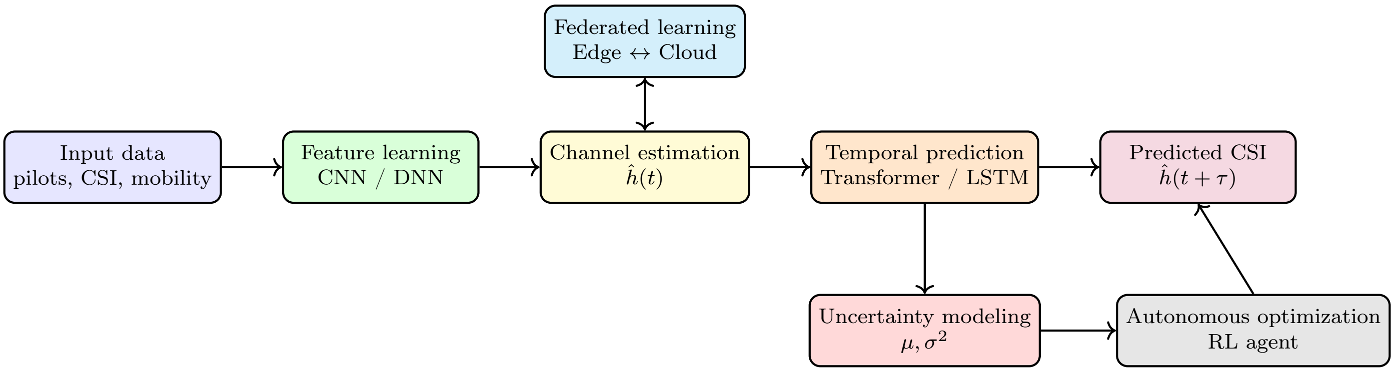


Figure 1: AI-driven channel intelligence framework for proactive 6G communication systems.

**Algorithm 2** AI-native autonomous optimization framework.

Initialize policy $\pi_\theta$ and value function $V_\omega$ each episode each time step $t$ Observe state $s_i(t)$ including predicted channel $\hat{h}_i(t)$ Select action $a_i(t) \sim \pi_\theta(s_i(t))$ Execute action and observe reward $r_i(t)$ and next state Store transition $(s_i, a_i, r_i, s_i')$ Update critic using TD-error:

$$\delta = r + \gamma V_\omega(s') - V_\omega(s)$$

Update actor using policy gradient Apply constraint penalties via Lagrangian multipliers Output optimal policy $\pi^*$

### 5.5. Policy optimization

The optimal policy is obtained using deep reinforcement learning:

$$\pi^* = \arg\max_\pi \mathbb{E}\left[\sum_t \gamma^t r(t)\right] \tag{33}$$

Actor-critic methods are particularly effective:

$$\theta \leftarrow \theta + \eta \nabla_\theta J(\theta) \tag{34}$$
$$\omega \leftarrow \omega - \eta \nabla_\omega \mathcal{L}(\omega) \tag{35}$$

### 5.6. Algorithm: Autonomous optimization

The proposed autonomous optimization framework enables real-time, adaptive, and scalable resource management in AI-native 6G networks. By integrating channel prediction and uncertainty-aware learning into the RL decision-making process, the system achieves proactive optimization rather than reactive control. The use of MARL further enhances scalability in ultra-dense networks, while CMDP ensures compliance with QoS constraints. Algorithm 2 shows a framework for AI-native autonomous optimization.

Compared to conventional optimization approaches, the proposed framework provides superior adaptability, robustness, and efficiency, making it a key enabler of fully autonomous and self-optimizing 6G communication systems.

## 6. Performance evaluation and comparative analysis

This section presents a comparative evaluation of the proposed AI-native communication framework against existing approaches across key performance dimensions. As this work is primarily a review and framework-oriented study, the evaluation is conducted through qualitative synthesis of reported results in the literature, supported by theoretical insights derived from the proposed architecture. The objective is to provide a consistent and meaningful comparison of different communication paradigms under realistic 6G scenarios.

### 6.1. Evaluation metrics

To ensure a structured and technically meaningful comparison, the following performance metrics are considered:

- Spectral Efficiency (SE): Effective utilization of available spectrum under dynamic channel conditions.
- Latency (D): End-to-end communication delay, critical for ultra-reliable low-latency communication (URLLC).
- Energy Efficiency (EE): Trade-off between communication performance and energy consumption.
- QoE: Composite metric defined in Section 3, incorporating throughput, delay, and reliability.
- Adaptability: Ability to respond to dynamic channel variations and traffic conditions.
- Scalability: Capability to maintain performance in large-scale distributed environments.

### 6.2. Comparative analysis

Table 5 presents a qualitative comparison of different communication paradigms across key performance metrics. The proposed AI-native framework demonstrates consistent advantages due to its integrated design, combining channel intelligence, distributed learning, and reinforcement learning-based optimization.

### 6.3. Impact of channel intelligence

Channel intelligence plays a pivotal role in enhancing system performance by enabling proactive adaptation to dynamic wireless environments. Unlike conventional estimation techniques, AI-driven channel prediction allows

Table 5: Comparative performance analysis of AI-native communication framework with existing approaches.

| Approach | SE | Latency | EE | Adaptability | Scalability |
|---|---|---|---|---|---|
| Traditional optimization | Medium | High | Low | Low | Medium |
| AI-Assisted systems | Medium-high | Medium | Medium | Medium | Medium |
| RL-based optimization | High | Medium | Medium-high | High | Medium |
| Edge intelligence systems | High | Low | Medium-high | High | High |
| AI-native framework | Very high | Low | High | Very high | Very high |

the system to anticipate channel variations and adjust transmission strategies accordingly.

Key benefits include:

- Improved beamforming accuracy through predictive channel modeling
- Reduction in feedback overhead due to forward channel estimation
- Enhanced link reliability in high-mobility and high-frequency scenarios

The integration of deep learning and Transformer-based models enables the capture of both spatial and temporal channel dependencies, thereby improving spectral efficiency and system robustness.

### *6.4. QoE-energy trade-off analysis*

The proposed framework explicitly addresses the trade-off between quality of experience (QoE) and energy efficiency through a multi-objective optimization formulation. By incorporating energy-aware reward functions within the reinforcement learning framework, the system achieves a balanced trade-off between performance and resource utilization. The adaptive nature of reinforcement learning enables dynamic adjustment of transmission parameters based on real-time network conditions, ensuring efficient energy usage while maintaining high QoE levels.

### *6.5. Scalability and distributed learning performance*

The integration of federated learning significantly enhances the scalability of the proposed AI-native framework. Compared to centralized learning approaches, the distributed architecture offers several advantages:

- Reduced communication overhead through localized model updates
- Parallel training across distributed nodes, improving efficiency
- Preservation of data privacy by avoiding raw data transmission

### *6.6. Analytical insights and system-level observations*

The superior performance of the proposed AI-native framework can be attributed to its architectural integration. Unlike traditional and AI-assisted systems that optimize individual components independently, the proposed framework enables cross-layer intelligence, where channel prediction, uncertainty estimation, and resource optimization are jointly considered.

Specifically:

- Spectral efficiency improvements arise from predictive channel modeling and adaptive beamforming.
- Latency reduction is enabled by edge-assisted inference and decentralized decision-making.
- Energy efficiency is improved through reinforcement learning-based adaptive control strategies.
- System robustness is enhanced through uncertainty-aware modeling and risk-sensitive optimization.

These observations are consistent with established trends in deep learning-based channel estimation, reinforcement learning-based resource allocation, and edge intelligence frameworks reported in the literature.

### *6.7. Discussion and evaluation remarks*

The comparison presented in Table 5 is based on a qualitative synthesis of reported results and theoretical analysis, rather than a uniform experimental benchmark. Therefore, the performance levels (e.g., “High”, “Very High”) should be interpreted as relative indicators of capability rather than absolute quantitative measures. Despite this, the proposed AI-native framework consistently demonstrates advantages across multiple dimensions due to its unified integration of predictive channel intelligence, distributed learning, and autonomous optimization. A comprehensive empirical validation using standardized datasets and real-world deployments remains an important direction for future work. Overall, the proposed framework represents a significant advancement toward intelligent, adaptive, and autonomous 6G communication systems.

## 7. Open challenges and future research directions

Despite significant advancements in AI-native communication systems, several critical challenges remain in realizing fully autonomous, scalable, and reliable 6G networks. This section outlines key open research problems and highlights promising directions for future investigation.

### *7.1. Scalability of distributed intelligence*

One of the primary challenges in AI-native 6G systems is the scalability of distributed learning frameworks. While federated learning and edge intelligence enable decentralized model training, large-scale deployments introduce issues such as communication overhead, model divergence, and synchronization delays. Efficient aggregation strategies, adaptive communication protocols, and hierarchical learning architectures are required to ensure scalability in ultra-dense networks.

### 7.2. Generalization in non-stationary environments

Wireless communication environments are inherently dynamic, characterized by time-varying channels, mobility, and interference patterns. Machine learning models trained under specific conditions often fail to generalize across diverse scenarios. Developing robust and adaptive learning models that can generalize across heterogeneous environments remains a major research challenge. Techniques such as meta-learning, continual learning, and domain adaptation are promising directions to address this issue.

### 7.3. Computational complexity and energy overhead

The integration of deep learning and reinforcement learning introduces significant computational and energy overhead, particularly for resource-constrained devices. Real-time inference requirements further exacerbate this challenge. Future research should focus on lightweight model architectures, model compression techniques, and hardware-aware optimization to enable efficient deployment of AI models in edge devices.

### 7.4. Standardization and interoperability

The lack of standardized frameworks for integrating AI into communication systems poses a significant barrier to large-scale deployment. Current approaches are often vendor-specific and lack interoperability across different network components. Developing standardized interfaces, protocols, and architectural guidelines for AI-native communication systems is essential for enabling seamless integration and widespread adoption.

### 7.5. Security, privacy, and trust

The adoption of AI-native architectures introduces new security and privacy challenges. Distributed learning frameworks are vulnerable to adversarial attacks, data poisoning, and model inversion attacks. Ensuring secure and trustworthy AI models requires the development of robust defense mechanisms, including secure aggregation, differential privacy, and adversarial training techniques. Additionally, explainable AI methods are needed to enhance transparency and trust in autonomous decision-making systems.

### 7.6. Integration of semantic communication

Semantic communication represents a paradigm shift from traditional bit-level transmission to meaning-oriented communication. However, several challenges remain in its practical implementation, including semantic representation learning, task-specific optimization, and compatibility with existing communication protocols. Future research should focus on developing unified semantic frameworks that can be seamlessly integrated into AI-native architectures.

### 7.7. Digital twin-enabled network optimization

Digital twin technology offers significant potential for real-time simulation and predictive optimization of network behavior. However, constructing accurate and scalable digital twins for large-scale 6G networks remains challenging due to the complexity of modeling dynamic environments and heterogeneous components.

### 7.8. Towards self-evolving autonomous networks

The ultimate vision of AI-native communication systems is to enable fully self-evolving networks capable of autonomous learning, adaptation, and optimization. Achieving this vision requires the integration of multiple AI paradigms, including reinforcement learning, distributed intelligence, and self-supervised learning. Future research should focus on developing unified frameworks that enable continuous learning and adaptation without human intervention. The realization of AI-native 6G networks requires addressing challenges related to scalability, generalization, efficiency, standardization, and security. Advances in lightweight AI models, robust learning techniques, semantic communication, and digital twin technologies will play a critical role in enabling fully autonomous and intelligent communication systems. The proposed framework in this paper provides a foundation for exploring these directions and guiding future research toward practical implementation.

## 8. Conclusion

This paper presented a comprehensive review and unified framework for AI-native communication systems in 6G networks, addressing the growing need for intelligent, adaptive, and autonomous wireless communication architectures. Unlike conventional approaches that treat artificial intelligence as an auxiliary optimization tool, the proposed AI-native paradigm embeds intelligence directly into the communication stack, enabling real-time learning, predictive channel intelligence, and autonomous resource management. The study systematically integrated three core components-channel intelligence, distributed learning, and reinforcement learning-based autonomous optimization-into a cohesive framework. The channel intelligence module leverages deep learning and Transformer-based models to achieve accurate channel estimation and proactive prediction, while uncertainty-aware modeling enhances robustness under dynamic conditions. The distributed learning framework, based on federated learning, ensures scalability and privacy preservation across edge-enabled environments. Furthermore, the reinforcement learning-driven optimization module enables adaptive and proactive decision-making, effectively balancing QoE and energy efficiency under dynamic network constraints.

## Declarations and ethical statements

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## CRediT authorship contribution statement

**Mehdi Gheisari**: Conceptualization, Investigation, Writing – review & editing. **Jafar A. Alzubi**: Conceptualization, Validation, Editing & Data collection. **Zahra Shirmohammadi**: Conceptualization, Validation & Data collection. **Seyed Danial Naghavi Sadat**: Data curation & Visualization. **Sahar Valizadeh**: Data curation & Visualization. **Roghayeh Rezaei**: Data curation & Visualization. **Sara Abou Chakra**: Conceptualization, Investigation, Editing & Validation.

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