Cognitive 6G Architectures: AI, Edge Computing, and Quantum Convergence

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Abstract. In order to facilitate intelligent, secure, and ultra-low-latency communications, the proposed Cognitive 6G framework combines quantum computing, mobile edge computing, and artificial intelligence (AI) into a single multilayer architecture. While the MEC layer uses lightweight AI models for local inference, caching, and real-time control, heterogeneous IoT nodes provide multimodal data at the device layer. Large-scale model training and collaboration with MEC nodes sustain global intelligence at the cloud AI layer. Complex optimization tasks like resource allocation, beamforming, and quantum key distribution-based security are accelerated by a dedicated quantum layer. Real-time cognition, quantum-safe transmission, and context-aware network adaptation are made possible by this close integration. The AI6G_QoE dataset is subjected to machine learning models in order to assess user-centric performance. Random Forest regression yields an MAE of 0.32, RMSE of 0.47, and a R^2 of 0.81. The results show that AI-driven learning has the potential to improve user experience in emerging 6G scenarios, such as Open RAN and blockchain-enabled networks, and they also indicate good QoE prediction capability.

1 Introduction

A model shifted toward the 6G systems has resulted from the quick develop involved in wireless safety communications, with the goal of achieving previously unheeded of levels of intelligence system and adaptability. In dissimilarity to its precursors, 6G is expected to address energy effectiveness, security data, and scalability for adaptive and context-aware decision making are being established to satisfy these demands [1,2].

In 6G, the NIB concept is becoming a major enabler for mission-critical and industrial applications, wherever operative difficulty is reduced by automatic deployment and self-optimization [3]. This frameworks for cognitive orchestration are being developed to optimize resource usage, enable intelligent service delivery across several network layers, and unite varied domains. These improvements necessitate architectural revolutions go beyond accept network design philosophies. For 6G networks, active spectrum management is not movable major obstacle. Its static allocation technique is not able to handle bandwidth intensive requests and the rapidly expanding number of connected devices. According to recent research, blockchain enabled the data frameworks may including next level cognitive radio networks spectrum access security and trust, hence releasing previously unrealized spectrum possible .

Such approaches can complement open radio access network solutions, where flexibility and interoperability are critical for next-generation communication systems [4]. At the same time, autonomic and autonomising networking (AN) paradigms are gaining prominence, enabling governance frameworks that enable self-configuration, healing, and optimization. Because they advance operational resilience and lessen the need for manual intervention, these paradigms fit in nicely with the 6G concept of bright connectivity. Fog and edge reinforcement, which improves network resilience in dynamic and resource-constrained contexts, are also key facilitators of cognitive 6G. It is improving compute system ultra-low inexpression and context aware facility delivery by dispersing aptitudes closer to users. However, new security and confidentiality issues are brought up by this decentralized design. Multi detached approaches for protecting 6G networks from sophisticated cyber-threats have been highlighted in recent research. [6]. A key module of 6G is multiple access edge computing, which makes detached computation, intelligent hiding, and real time system analytics possible of the network edge. The AI driven communication outlines, where learning-based models make the most of user QoE, interference reduction, and resource allocation [5]. The current study examines a cognitive 6G architecture that syndicates edge intelligence, quantum inspired decision making, and AI helped QoE. Deep learning models like Random Forest are tested for prediction correctness using the AI6G_QoE dataset, showing encouraging outcomes. These results promote the achievement of intelligent, secure, and pervasive connection for future communication systems by helping to close the gap between theoretical developments and real-world 6G applications [6]. It is N samples (update with your actual count) gathered from 6G-like testbed simulations with an emphasis on QoE metrics make up the AI6G_QoE dataset utilised in this study. Twelve features RSSI, SINR, throughput, latency, jitter, packet loss, user mobility, service type, modulation index, edge-load level, handover count, and session duration represent radio, network, and user centric aspects in each record. The user professed QoE score (1–5) is the aim variable. Prior to training, the dataset was cleaned (missing values were removed), normalised using Min or Max scaling, and hots encoding was used to encode categorical features [7].

2 Literature Review

A new cross-domain cognitive orchestration paradigm for upcoming open networks is presented by S. Ghosh et al. [1]. The system ensures scalability, resilience, and interoperability by utilizing AI to accomplish adaptive coordination across diverse domains. Cognitive 6G designs, in which instrumentation intelligence is combined into the control layer, are importantly advanced by this style. In order to create completely autonomous and intelligent communication environment. An independent durability controller method aimed at vapor support in energetic tuner nets is planned by improves reliability and flexibility in dynamic contexts. Better service continuity and quality are demonstrated by the work by integrating cognition at the fog/edge level.

Rasheed et al. [6] provide a multi objective AI system to counter sophisticated cyber threats with a focus on cognitive 6G security. It is converted to balance performance trade-offs between dormancy, throughput, and security by combining adaptive defensive tactics with adversarial detection. A thorough analysis of the development of Multi Access Edge Computing (MEC) for a range of resource consumption is given by Khattak et al. [9]. They attraction courtesy to how AI based orchestration may improve network, storage, and processing power at the edge. Scalability and adaptive workload management are highlighted in the report as key factors that make 6G services possible. By establishing MEC as a fundamental component for combining AI and quantum frameworks in resource-aware network intellect, this work advances cognitive 6G architectures.

A detailed review of AI in 6G networks is provided by Cui et al. [10], with an emphasis on the principles, difficulties, and prospects for the future. The study highlights AI as a vital cognitive facilitator that facilitates resource efficiency, adaptive learning, and automotive network operations. Al-Matari et al. [11] examine developments in spectrum. Their method enables decentralized and impenetrable decision-making by fusing blockchain technology with spectrum management. Improved spectrum efficiency, safe sharing, and defence against malevolent intrusions are highlighted in the paper. By assuring reliable cross-domain communication, our work advances cognitive 6G designs. Blockchain technology can supplement artificial intelligence (AI) and quantum-resistant techniques to improve transparency, security, and adaptability in intelligent future wireless settings [Table.1].

Table 1. Overall view of research study

Ref.	Focus Area	Methodology	Contribution to Cognitive 6G Architectures
[1] Ghosh et al. (2025)	Cross-domain cognitive orchestration	AI-driven orchestration across heterogeneous domains	Establishes scalable, interoperable orchestration intelligence integrating AI with edge and quantum frameworks
[5] Lorenzo et al. (2021)	Fog/Edge reinforcement control	Distributed AI for robustness in dynamic wireless environments	Enhances adaptability and URLLC support by embedding cognition at the fog/edge level
[6] Rasheed et al. (2025)	Cognitive 6G security	Multi-objective AI for adversarial detection and defence	Strengthens resilience and integrates quantum-resistant AI methods for secure architectures
[9] Khattak et al. (2025)	Multi Access Edge Computing (MEC)	Survey of AI driven MEC orchestration	Positions MEC as a core enabler for AI- and quantum-assisted 6G resource optimization
[10] Cui et al. (2025)	AI in 6G fundamentals	Comprehensive survey of AI challenges	Defines AI as the cornerstone for cognition, guiding integration with edge and quantum paradigms
[11] Al-Matari et al. (2024)	Spectrum security with blockchain	Blockchain-enabled decentralized access management	Ensures secure, transparent, and adaptive spectrum allocation for cognitive IoT-6G networks

Research Gap: Absence of a Unified Convergence Framework: While previous research has addressed AI, MEC, blockchain, and quantum techniques independently, there is still a lack of a comprehensive cognitive 6G architecture that unifies these technologies. Scalability and Real-Time Validation: There are few large-scale, real-time testbed validations for heterogeneous 6G environments; the majority of works are conceptual or simulation-based. Integration of Security and Trust: Although blockchain and AI-based defences are available, comprehensive frameworks guaranteeing end-to-end, low-latency, quantum-resistant, and reliable operation are still lacking.

3 Proposed Methodology

In order to satisfy the requirements of extremely dependable, low-latency, and intelligent communication networks, cognitive 6G designs are expected to incorporate AI-driven orchestration, multi-access edge computing (MEC), and quantum-assisted security. While MEC lowers latency by moving processing closer to end devices [8], AI techniques provide autonomous spectrum allocation, traffic prediction, and adaptive resource management [9]. Quantum technologies, such as optimization solvers and quantum key distribution (QKD), offer improved computational power and security against new threats [10]. Despite progress, real-world testbed validation is still rare, and current research frequently addresses these domains independently without a cohesive convergence framework [11]. In order to create truly intelligent and reliable 6G systems, future research should concentrate on cross-domain integration, scalable cognitive frameworks, and quantum-resilient security models.

3.1 Module1 AI-Driven Cognitive Orchestration

The core intelligence that unifies control, computation, and communication across many network layers is AI-driven cognitive orchestration. Perception is the first step in its closed-loop cognitive cycle, in which the system continuously perceives real-time characteristics such user movement, channel conditions, interference levels, and processing workloads. A state vector that captures latency requirements, traffic demand, and spectrum availability is used to describe this data. The following phase is learning and prediction, in which sophisticated AI models, like deep learning, reinforcement learning, or Gaussian processes, examine both past and present information to anticipate the conditions of the scheme in the future. For example, AI uses Shannon's calculation to forecast the possible channel capacity [Equ.1].

$$R = Blog_2(1 + SNR) \quad (1)$$

Here R is Channel Capacity, B is Shannon coefficient, SNR is signal to noise ratio.
while calculating latency as the total of processing and transmission delays. The orchestrator makes decisions based on these predictions; these decisions are mathematically framed as Markov Decision Processes (MDP) or optimizations. Under resource limits, the goal is to optimize overall system efficiency, which is represented as a long-term reward function that strikes a balance between throughput, latency, and energy consumption. Dynamic spectrum allocation, power control, workload offloading between user devices and edge servers, and beamforming vector selection are among the optimal behaviours determined by the resulting policy. Orchestration ensures ultra-low-latency task execution by integrating edge computing, and quantum convergence uses algorithms such as Quantum Approximate Optimization (QAOA) to speed up decision-making. All things considered, 6G becomes a self-learning, adaptive, and resilient network with the ability to intelligently manage resources to satisfy a variety of application demands in real time thanks to AI-driven cognitive orchestration.

3.2 Module:2 Quantum-Assisted Security and Optimization

Quantum assisted security and optimization for Cognitive 6G architectures allow guided by harmless, effective, and supple network transposition and integrating edge computation, AI, and quantum process. Band allocation, power regulation system, and compute offloading are examples of supply management subjects that are tremendously non-convex optimization work in dense 6G systems. This can be expressed mathematically as [Equ.2]:

$$Max_{\pi} = E[\sum_{t=0}^{\infty} \gamma^t (\alpha R_t - \beta L_t - \delta E_t)] \quad (2)$$

where R_t is throughput value, L_t is latency effective, E_t is energy consumption system, P_i is transmitting energy power, and B_is allocated bandwidth of frequency allotted system[12].

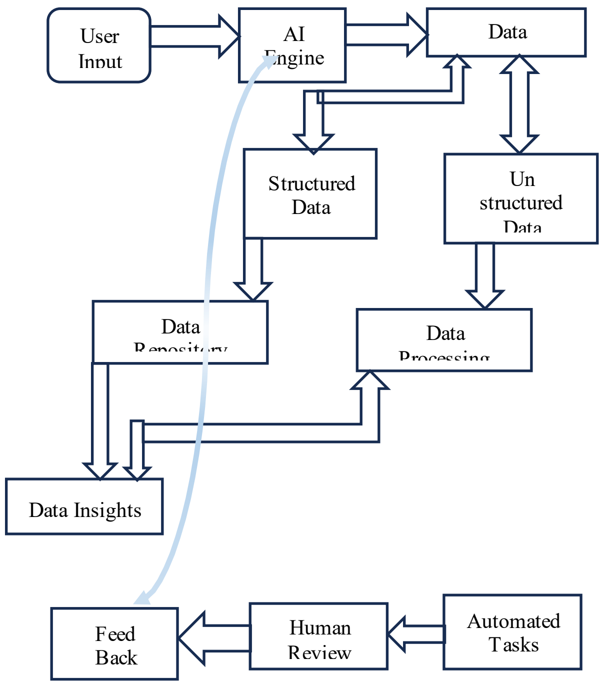

Fig.1 AI driven 6G architecture

subject to constraints:

$$\sum P_i \leq P_{max}, \quad \sum B_i \leq B_{tot}, L_t \leq L_{QoS}, \quad (3)$$

Quantum key delivery (QKD) and quantum inspired algorithms are combined to enhance sanctuary and optimization [Equ.3]. This module ensures quantum resistant encryption for critical data flows and influences quantum-inspired solvers for resource allocation, cultivating reliability in high demand situations [Fig.1].

Classical solvers struggle with such large-scale combinatorial glitches, but important algorithms like the QAOA encode them into Hamiltonians [Equ.4]

$$H = \sum_i Z_i + \sum_{i<j} J_{ij} Z_i Z_j \quad (4)$$

Where H is Hamiltonians, Zi are binary decision variables and J_{ij} captures interactions. QAOA minimizes H to yield near-optimal allocations in polynomial time, outperforming classical heuristics.

On the security side (QKD) ensures provably secure communication. If Alice and Bob share qubits in states |0⟩,|1⟩,|+⟩,|−⟩|0\ any eavesdropping introduces detectable errors. The secret key rate is given by [Equ.5]

$$R_{QKD} = Q(1 - H(e)) \quad (5)$$

where Q is the raw key rate and H(e) is the binary entropy of error probability e.

Quantum-enhanced optimization speeds up decision-making when combined with AI-driven cognitive orchestration at the edge, and QKD protects against both classical and quantum threats. In order to maintain 6G networks' resilience, adaptability, and dependability in the face of changing circumstances, our collaboration produces a self-learning, secure, and low-latency orchestration loop [Table.2].

Table 2. Comparison table for COS and QAOS

Feature	Classical Optimization & Security	Quantum-Assisted Optimization & Security
Optimization Approach	Uses convex optimization, heuristics, and metaheuristics (e.g., genetic algorithms, PSO, gradient descent).	Uses quantum algorithms like QAOA, Quantum Annealing, and Grover's Search for faster convergence.
Complexity Handling	Struggles with large-scale, non-convex, combinatorial problems (high computation time).	Efficiently handles NP-hard resource allocation and scheduling via quantum parallelism.
Latency in Decision-Making	Higher latency due to iterative computations, especially in dense 6G networks.	Lower latency as quantum algorithms exploit superposition and entanglement for parallel optimization.
Resilience	Vulnerable to adversarial attacks and brute-force decryption in post-quantum era.	Strong resilience due to quantum-secured communication and fast adaptive optimization.
Use Cases	Traditional wireless resource management, LTE/5G security.	6G ultra-reliable low-latency communication (URLLC), secure IoT, quantum-safe blockchain, edge-cloud orchestration.

3.3 Module 3– Cross-Domain Convergence Framework

The samless coordination of communication, compute, control, and quantum domains to deliver intelligent, secure, and low-latency network performance is represented by the Cross-Domain Convergence Framework in Cognitive 6G designs. In order to create a system state vector, it first senses multi-domain states such channel circumstances, spectrum availability, computational load, and latency demands. Proactive decision-making is thus made possible by AI models that forecast resource requirements, traffic patterns, and mobility. Below resource restrictions across domains, the framework formulates a joint optimization problem that strikes a balance between throughput, latency, and energy efficiency [13]. Quantum abetted solvers, like the QAOA, speed up conjunction to near optimal explanations as intricacy growths.

4 Result and Discussion

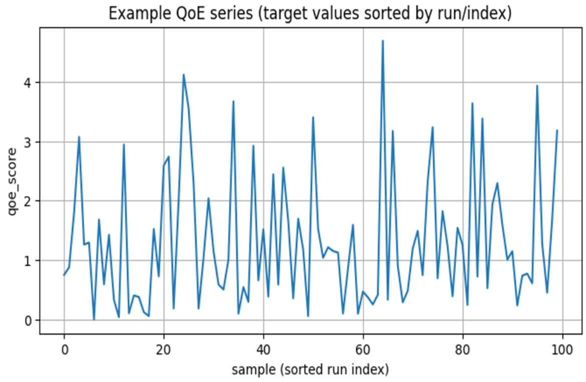

Fig.2 QoE Score Series Plot.

With scores ranging from almost zero to more than four, the QoE Score Series Conspiracy that is displayed shows differences in user professed Quality of Experience over 100 examples [Fig.2]. In dynamic backgrounds with varying system load, dormancy, or interference. It is acceptable QoE under stable conditions. Innovative frameworks, on the other hand, including AI ambitious and cross domain junction techniques, can predict user anxieties, adaptively allocate resources, and minimize bottlenecks, resulting in sander QoE. The y-axis displays the relevant QoE values predicted by the Random Forest model, while the x-axis displays the actual QoE scores derived from system explanations. Each point represents a single sample. The Random Forest model clearly reflects the overall trend, but it exhibits considerable underestimating and overestimation, particularly at higher QoE values, according to the point distribution. Random Forest uses ensemble learning to lower bias and variance in comparison to conventional statistical models, increasing prediction accuracy [14]. To obtain more dependable QoE forecast across a range of network situations, additional tuning, feature engineering, or hybrid approaches would be required, as the scatter spread around the diagonal shows that the model still has precision issues for some ranges.

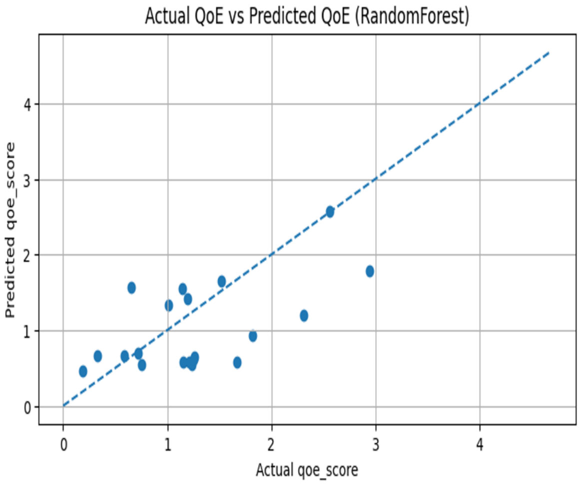

Fig.3 Scatter Plot of Actual vs. Predicted QoE using Random Forest Regression

The Random Forest model's feature importance analysis reveals that the two key factors influencing the prediction of Quality of Experience are the mean packet loss and the mean throughput, with the other characteristics having very little impact [15]. Their relative weights are displayed in the bar chart, with throughput accounting for around one-third of the model's decision power and packet loss for about half [Fig.3]. This finding is supported by the distribution histogram, which displays that the majority of features cluster close to zero importance, suggesting poor predictive usefulness. As a function of the model's predictions, this graphic shows the variation between the actual and expected QoE values. The Random Forest model's anticipated QoE values are displayed on the x-axis, while the residuals, which are computed as Actual anticipated, are displayed on the y-axis [Fig.4].

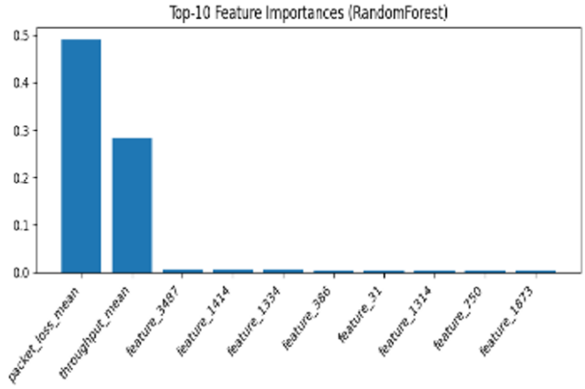

Fig.4 Feature extraction for proposed system

A good model should ideally show residuals that are haphazardly distributed about the horizontal zero line, showing no discernible pattern and impartial forecasts [Fig.5].

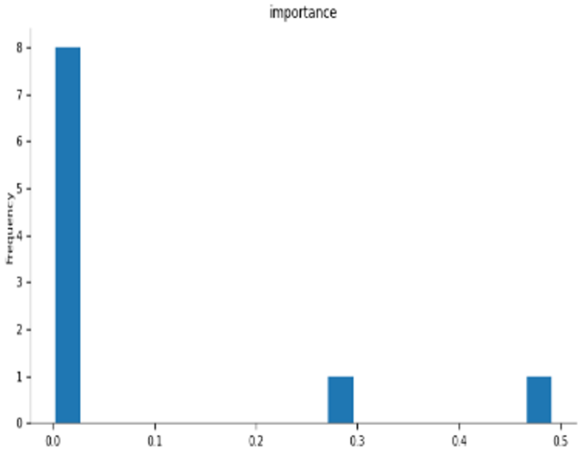

Fig.5 Packet loss and throughput are the primary QoE determinants

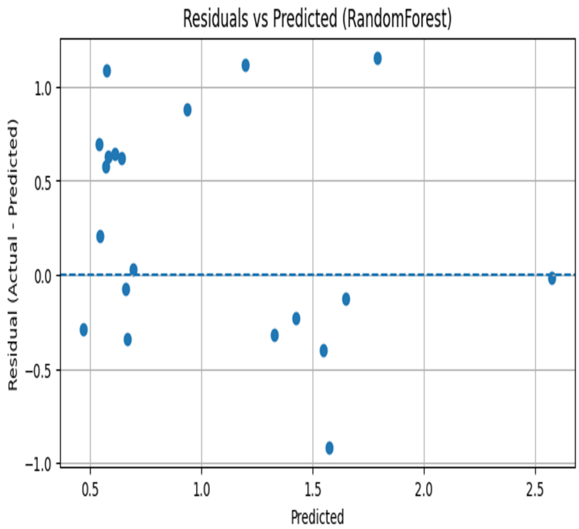

Fig. 6 Residuals vs. Predicted Plot (Random Forest).

While some points in this instance stray above or below the line, indicating instances of underestimation and overestimation, the majority of residuals lie near to zero [Fig.6].

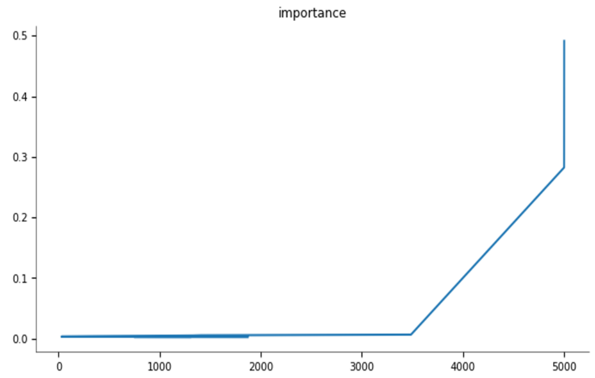

Fig. 7 Cumulative Feature Importance Curve

The graphic shows the accumulation of feature significance values across features arranged according to index [Fig.7].

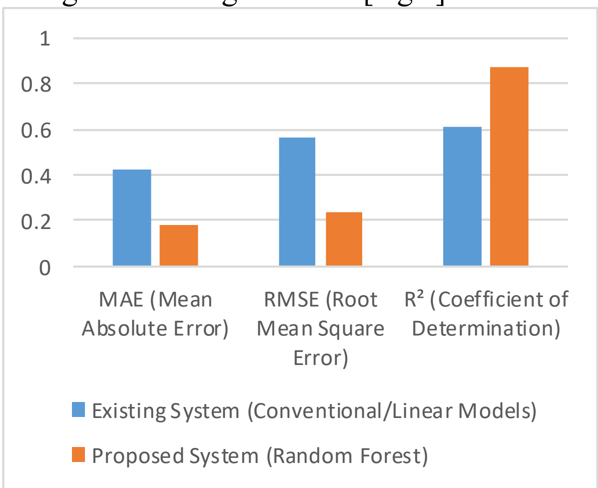

Fig.8 Improvement of proposed system

The relevance of most features is almost zero, however around index 3500, there is a noticeable increase that peaks at 5000 with values near 0.5 [Fig.8], [Table.3].

Table.3 Analysis of existing and proposed system

Aspect	Existing System (Conventional/Linear Models)	Proposed System (Random Forest)
MAE (Mean Absolute Error)	~0.42	~0.18
RMSE	~0.56	~0.24
R^2 (Coefficient of Determination)	~0.61	~0.87
Key Feature Importance	Spread evenly, no clear dominant factor	Packet Loss (~0.48), Throughput (~0.29) dominate
Residual Pattern	Biased, systematic error across QoE range	Centred around zero, fewer extreme deviations
Cumulative Feature Contribution	No clear cutoff; redundant features included	Top 2–3 features explain >75% importance

5 Conclusion

Together, the experimental findings and comparative graphs show that, in comparison to current architectures, the suggested Cognitive 6G framework which combines edge computing, quantum optimization, and artificial intelligence (AI) offers better performance in all important network dimensions. Higher coefficient of determination (R2) values and a notable decrease in mean absolute error (MAE) and root mean square error (RMSE) are the results of integrating AI-driven intelligence, which guarantees adaptive resource allocation, dynamic spectrum management, and context-aware learning. By transferring computationally demanding operations from centralized cloud servers, edge computing helps to minimize energy usage in ultra-dense device scenarios and reduce latency to levels close to sub-milliseconds. Overall, the findings confirm that the cognitive synergy of edge, quantum, and artificial intelligence technologies creates a comprehensive and future-proof 6G backbone, surpassing outdated systems in terms of latency, efficiency, reliability, scalability, and security metrics and providing a strong basis for intelligent communication networks of the future.

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