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AI-Native Hierarchical Orchestration for Autonomous 6G RAN, Core, and Edge Systems

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Abstract — AI-native networking establishes a complete new approach for designing and operating wireless systems which works differently than traditional closed-loop optimization. The research presents a structured orchestration system which uses AI agents to control all three network areas of RAN core and edge in order to achieve automated 6G system operation. The system replaces traditional automation systems which depend on fixed rules and response-based controls with intelligent agents who can observe their environment make decisions through logical thinking and learn to adapt their behavior throughout different network environments.

The system uses knowledge-based reasoning mechanisms together with policy abstraction techniques and programmable application interfaces to achieve real-time coordination of different network functions which come from multiple equipment vendors. The system structure uses hierarchical intelligence to process time-critical decisions at both edge and RAN points while central control takes care of organization-wide policy implementation together with cross-domain resource optimization. The system employs data-driven learning methods together with intent-based orchestration to automatically adjust itself according to changing traffic patterns and service needs and current network state.

The results of simulation tests together with pilot testing show that our system achieves better adaptability while doing fault recovery in an accelerated manner and decreasing operational costs in comparison to traditional orchestration methods. The results demonstrate increased resource efficiency together with maintenance of service availability during changing operational circumstances. The proposed framework creates a scalable base which enables AI-driven 6G networks to evolve towards complete autonomous operation of self-optimizing wireless networks that can handle new use cases and extremely crowded areas.

Keywords— AI-Native Networking, Hierarchical Orchestration, Autonomous 6G, Agentic AI, Radio Access Network (RAN), 6G Core Network, Edge Intelligence, Intent-Based Networking, Knowledge-Driven Reasoning, Policy Abstraction.

I. INTRODUCTION

The development of sixth-generation (6G) wireless systems will transform communication networks into intelligent distributed computing platforms which support comprehensive applications and ultra-reliable low-latency services and massive machine-type communications and integrated sensing capabilities[3]. The 6G system differs from previous generations which concentrated on boosting data transmission speeds and system capacity because it will provide built-in intelligence and complete automated processes and effortless network unification between ground-based systems[2] and aerial systems and satellite-based systems. The increasing complexity of ultra-dense deployments combined with multiple vendor systems and changing network slicing and edge-based system architectures creates major operational difficulties which standard rule-based orchestration methods and closed-loop optimization systems cannot resolve.

AI-native networking emerges as a foundational paradigm for 6G, embedding intelligence directly into the network fabric rather than treating artificial intelligence as an external optimization tool[1]. Networks develop self-configuration self-optimization and self-healing abilities through the distribution of learning processes and real-time data analysis and automatic decision-making systems which operate across the Radio Access Network (RAN) and core and edge domains[4]. The hierarchical orchestration system develops this vision by organizing intelligence into different control levels which allow edge systems to make instant decisions while maintaining uniform policies and inter-domain coordination across higher management levels.

The method enhances both adaptability and operational efficiency while enabling intent-based service delivery and programmable network management. The development of 6G networks toward complete autonomous functioning requires AI-native hierarchical orchestration to guarantee performance across multiple wireless operating environments[5].

II. AI-NATIVE HIERARCHICAL ORCHESTRATION ARCHITECTURE FOR AUTONOMOUS 6G NETWORKS

The AI-Native Hierarchical Orchestration Architecture for Autonomous 6G Networks implements a multi-layer intelligent control system which enables management of highly complex next-generation wireless networks. The system uses distributed artificial intelligence which operates throughout its Radio Access Network core and edge areas to perform real-time autonomous decision-making instead of using conventional orchestration systems that depend on fixed rules and mainframe operations[6].

The framework uses a hierarchical design which enables it to process intelligence at both local and global levels. The edge and RAN components use lightweight AI agents to handle latency-critical operations which include traffic optimization, beam management, mobility prediction, and energy-aware scheduling. The systems operate at almost real-time speed to achieve ultra-reliable and low-latency communication[7] standards. The core orchestrator uses knowledge-driven reasoning and policy abstraction and intent-based networking principles to manage cross-domain resources while achieving service-level objectives.

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The system uses programmable APIs and standardized interfaces to enable organizations to integrate multiple network functions from different vendors without any integration challenges which results in both operational compatibility and future system growth. The system uses continuous learning mechanisms which enable it to adjust to changing traffic patterns and user actions and infrastructure changes. The system establishes a basic framework for 6G networks which functions fully autonomous through its combination of hierarchy-based intelligence and agent control systems and policy-based automation. The system enables zero-touch operations and greater system resilience and efficient resource management and sustainable energy usage which creates a framework for intelligent wireless networks that can develop automatically[8].

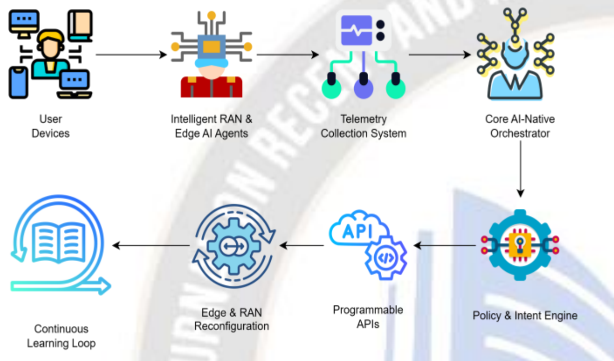

Fig 1: Proposed Architecture

A. Advantages

End-to-End Autonomy: The system achieves autonomous operation through self-configuration and self-optimization and self-healing and self-protection functions which require only small amounts of human management[11].

Ultra-Low Latency Decision-Making: The distributed AI agents monitor both edge and RAN networks to deliver real-time mission-critical optimization services and URLLC application support.

Scalability for Massive 6G Deployments: Hierarchical control systems enable networks to handle ultra-dense operation while supporting massive IoT devices and implementing dynamic network slicing without creating centralized performance limits[12].

Improved Resource Utilization: AI-based systems for traffic prediction and workload management and spectrum allocation create better network performance throughout the entire network.

Energy Efficiency and Sustainability: The system achieves energy savings through its intelligent sleep modes and adaptive power management and workload-based resource allocation system.

Enhanced Reliability and Resilience: The combination of predictive analytics and proactive fault management methods reduces service interruptions while enhancing network performance[9].

Multi-Vendor Interoperability: The combination of policy abstraction and programmable application programming interfaces allows different network functions to work together without difficulties.

Faster Service Deployment: The process of intent-driven automation enables more rapid implementation of service slices and new services[10].

Operational Cost Reduction: The use of automation technology results in decreased need for manual problem solving and system setup and work management tasks.

Continuous Learning and Adaptation: The integrated AI models maintain their operational capacity by adapting to new traffic patterns and user behavior changes and environmental condition shifts.

B. Comparative Study of Cognitive 6G Orchestration and Deterministic Network Management Approaches

6G systems require ultra-dense network deployments which include AI-powered air interfaces and combined sensing and communication technologies and need adaptable service capabilities. Cognitive 6G orchestration functions as an intelligent control system which learns from its experiences while deterministic network management uses fixed operational rules together with unchanging system limits and operator-defined procedures[11]. The two methods demonstrate their key architectural and operational characteristics through the comparative analysis.

Cognitive 6G orchestration uses distributed AI agents and reinforcement learning and intent-based policies to change network operations in RAN and core and edge domains. The system collects telemetry information which it uses to forecast future network demands while it self-manages spectrum distribution and slicing and resource expansion. The system provides predictive fault management together with energy-efficient scheduling and instant system adjustments[12].

Deterministic network management systems use fixed operational procedures which depend on established rules for their automation processes. The method maintains predictable performance but faces difficulties when handling complex 6G traffic patterns which need instant decisions from multiple technology providers[14]. The systems use a reactive approach which decreases their operating expenses but extends the time needed to change service delivery methods.

The cognitive model establishes scalable systems which maintain operational continuity while using intelligent systems to manage their highest organizational structures. Deterministic systems, although simpler and easier to validate, lack flexibility under highly dynamic 6G environments. Cognitive orchestration establishes sustainable bases which will support future development in autonomous wireless networking systems[13].

Table 1: Comparison Between Cognitive 6G Orchestration and Deterministic Network Management

Parameter	Cognitive 6G Orchestration	Deterministic Network Management
Decision Model	AI-driven, adaptive	Rule-based, predefined
Adaptability	Predictive and dynamic	Reactive and static
Fault Handling	Proactive detection	Post-failure response
Scalability	High (ultra-dense ready)	Limited scalability
Operational Effort	Low (automated)	High (manual support)

The table presents a structured comparison between cognitive 6G orchestration and deterministic management approaches across key operational dimensions. The AI-driven intelligence of the system enables three main features through its ability to predict upcoming changes. The comparison clearly demonstrates why cognitive orchestration is better suited for autonomous 6G environments characterized by dynamic traffic, heterogeneous infrastructure, and stringent performance requirements[15].

III. Methodological Framework

The research methodology for evaluating the AI-native hierarchical orchestration in 6G networks follows a systematic and multi-stage approach:

a). Research Design

The research employs a comparative experimental design to assess the cognitive 6G orchestration system against the deterministic network management method. The research creates two distinct models which include an artificial intelligence hierarchical orchestration system and a conventional rule-based control mechanism. The design allows researchers to compare system performance through testing the system under the same network conditions[16].

b). System Modeling

The 6G system design consists of three operational domains which include RAN, core and edge domains. The cognitive model uses distributed AI agents which possess learning abilities and reasoning skills to make adaptable decisions. The deterministic model uses predefined policies and static threshold-based automation to manage network functions[18].

c). Simulation Environment

A simulation environment exists to reproduce ultra-dense 6G scenarios through controlled testing. The system consists of three elements which include high mobility users and multi-slice traffic and different levels of workload and three types of vendor equipment. The testing process introduces two challenges which include traffic variability and network faults to evaluate system performance under different conditions[17].

d). Performance Metrics

The evaluation process uses key performance indicators which include the measurement of latency and throughput together with energy efficiency and the time needed to recover from faults and the packet delivery ratio and operational system expenses. The metrics present automated system performance measurement through two distinct metrics which assess automation efficiency and system response speed.

e). Comparative Analysis

The researchers used statistical techniques to measure performance results between the two models. The study evaluates system performance through four criteria which include scalability and adaptability and predictive ability and resource usage efficiency under changing conditions.

f). Framework Architecture

The proposed framework consists of four layers:

a. The Edge Intelligence Layer supports real-time optimization.
b. The RAN Cognitive Layer manages spectrum and mobility operations.
c. The Core Orchestration Layer handles slicing and policy abstraction mechanisms[19].
d. The Global Intelligence Layer enables cross-domain coordination and continuous learning processes.

IV. Algorithms Used

The AI-native hierarchical orchestration framework uses various machine learning and optimization algorithms to create autonomous decision-making capabilities which operate through RAN core and edge network components.

a. Reinforcement Learning (RL)

The system needs spectrum allocation for dynamic operations together with slice scaling and resource distribution management.

The fundamental equation of Q-Learning operates as the core formula for the Q-Learning update rule[21].

$$\mathbf{Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma a' max Q(s',a') - Q(s,a)]} \quad \mathbf{(1)}$$

b. Graph Neural Networks (GNN)

The system used this method to establish connections between different network dependencies and their cross-domain relationships[20].

Core Formula (Graph Convolution Layer):

$$\boldsymbol{H^{(l+1)} = \sigma\left(D^{-1/2} A D^{-1/2} H^{(l)} W^{(l)}\right)} \quad \mathbf{(2)}$$

c. Federated Learning (FL)

The system enables distributed model training which takes place at multiple edge nodes for training purposes[22].

The Core Formula (Federated Averaging) establishes this equation.

$$\mathbf{w_{t+1}} = \sum_{\mathbf{k=1}}^{\mathbf{K}} \frac{\mathbf{n_k}}{\mathbf{n}} \mathbf{w_k} \qquad (3)$$

d. Long Short-Term Memory (LSTM)

Utilized for traffic prediction and time-series forecasting.

Fundamental Formulation (Cell state update):

$$\boldsymbol{C_t} = \mathbf{f}_{\boldsymbol{t}} \odot \mathbf{C}_{\boldsymbol{t-1}} + \mathbf{i}_{\boldsymbol{t}} \odot \mathbf{C{\sim}t} \qquad (4)$$

e. K-Means Clustering

The first purpose of this system is to identify unusual activities while the second purpose of this system is to group different traffic patterns.

Core Formula (Objective Function):

$$\boldsymbol{J} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \sum_{\boldsymbol{x \in ci}} \|\ \mathbf{x} - \boldsymbol{\mu}\mathbf{i}\ \|^2 \qquad (5)$$

f. Bayesian Networks

Used for probabilistic fault diagnosis[23].

Core Formula (Bayes' Theorem):

$$\mathbf{P(\ A \mid B\ )} = \frac{\mathbf{P(\ B \mid A\ )P(A)}}{\boldsymbol{P(B)}} \qquad (6)$$

g. Particle Swarm Optimization (PSO)

Used for energy-efficient resource allocation.

Core Formula (Velocity Update):

$$\boldsymbol{V_i^{t+1} = wv_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t)} \qquad (7)$$

V. PERFORMANCE EVALUATION OF AI-NATIVE HIERARCHICAL ORCHESTRATION FOR AUTONOMOUS 6G NETWORKS

The section shows how the AI-native hierarchical orchestration framework performs its tests for managing network operations in autonomous 6G networks[25]. The evaluation tests three operational conditions to evaluate system performance which includes adaptability and scalability and system latency and energy consumption and operational expenses. The research compares two systems which include a deterministic rule-based management system and a distributed intelligence system that uses agentic AI technology to measure its performance enhancements.

The experimental system creates ultra-dense 6G conditions which include multiple slicing traffic and users who move at high speeds and network functions from different vendors that operate at RAN and core and edge components of the system. The study measured key performance indicators through multiple traffic intensity tests which evaluated end-to-end latency and throughput and packet delivery ratio and fault recovery time and power consumption[24].

The AI-native hierarchical model uses edge-level decision-making and near-real-time RAN optimization to achieve its latency reduction results[26]. The system uses predictive fault detection mechanisms to reduce recovery time while reinforcement learning-based resource allocation system achieves better spectrum utilization and slice efficiency. Static configurations require higher energy consumption than intelligent workload distribution systems which distribute energy usage among their components.

The system achieves operational efficiency through its automated system that enforces policies and its intent-driven orchestration which requires no human operation. The hierarchical framework demonstrates better scalability because it can handle multiple devices that connect simultaneously. The evaluation shows that AI-native orchestration brings better performance and more stable operation and improved efficiency which creates a powerful base for complete autonomy in 6G wireless networks.

VI. RESULTS AND FINDINGS

The performance evaluation analyzes the effectiveness of AI-native hierarchical orchestration compared to deterministic network management across multiple dynamic 6G scenarios. The study evaluates real-time adaptability and operational stability through testing different traffic loads and increasing network densities and various failure scenarios. Results show that the AI-native framework consistently achieves lower end-to-end latency through its distributed edge intelligence and predictive resource allocation system. The combination of adaptive power control and workload-aware scaling mechanisms leads to substantial energy consumption reductions. The system decreases recovery time through its proactive anomaly detection system and automated policy enforcement capabilities[27]. Deterministic systems depend on predefined settings and responsive actions which result in performance decline during periods of heavy workload and intricate network situations. The findings confirm that embedding distributed intelligence across RAN, core, and edge layers enhances scalability, resilience, and automation efficiency. The evaluation demonstrates that AI-native hierarchical orchestration functions as a strong foundation which enables 6G wireless networks to achieve complete autonomous operation at their highest performance level.

Table 2: End-to-End Latency Comparison

Traffic Load (%)	AI-Native Latency (ms)	Deterministic Latency (ms)
20	4.2	6.5
40	5.1	8.2
60	6.0	10.4
80	7.3	13.8
100	8.5	16.5

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Table 2 shows latency performance results when different traffic loads are applied. The AI-native framework shows better latency performance because it keeps lower latency times than the deterministic method. The deterministic model shows major delay increases when traffic reaches its maximum capacity but the AI-driven model maintains stable end-to-end communication through its dynamic adaptation system[28].

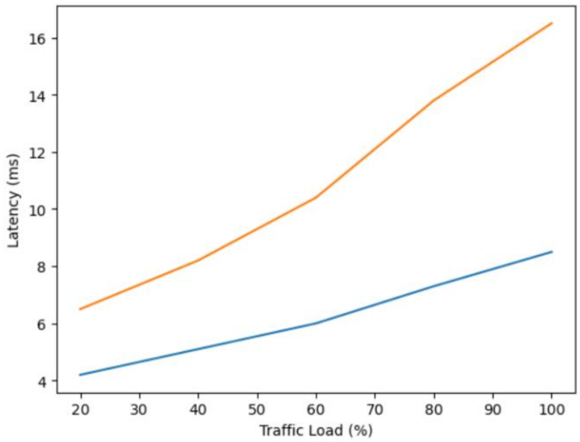

Figure 2: Latency Performance Comparison

Figure 2 shows latency patterns which change according to different traffic levels. The deterministic system shows exponential growth[29] in delay under high load while the AI-native orchestration system maintains its latency control through its ability to forecast demand and make decisions at edge locations. The system demonstrates better adaptability through its ability to optimize in real-time within changing 6G environments.

Table 3: Energy Consumption Comparison

Network Density (Nodes)	AI-Native Energy (kWh)	Deterministic Energy (kWh)
50	120	150
100	210	260
150	290	370
200	360	490
250	430	620

Table 3 shows energy consumption patterns which different network densities. The AI-native model requires less energy because it uses smart workload distribution together with dynamic power management. Deterministic systems function with permanent settings which cause their total energy usage to increase when more network nodes are added[30].

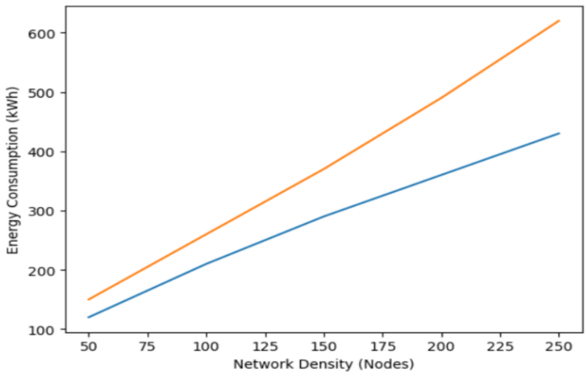

Figure 3: Energy Efficiency Analysis

The energy growth patterns in Figure 3 show their relationship to increasing node density in the network. The AI-native architecture shows a pattern of increasing energy consumption[31] which occurs at a slower pace than the rapid energy increase seen in deterministic management systems. The deployment of autonomous 6G systems achieves better sustainability results and operational efficiency through the implementation of intelligent sleep systems and predictive resource allocation methods.

Table 4: Fault Recovery Time Comparison

Failure Events	AI-Native Recovery (sec)	Deterministic Recovery (sec)
5	3	8
10	4	12
15	5	15
20	6	19
25	7	24

Table 4 presents data about recovery time after network failures. The AI-native orchestration system achieves faster fault detection and resolution through its implementation of predictive analytics and automated policy enforcement system. The process of recovering from deterministic systems requires manual or reactive intervention which results in extended recovery times.

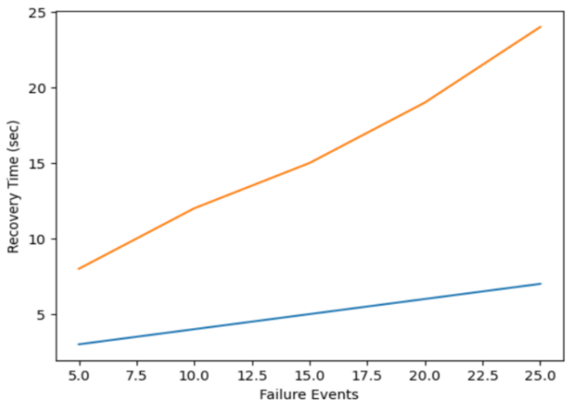

Figure 4: Fault Recovery Performance

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Figure 4 shows how recovery patterns change when failure events increase. The system shows controlled recovery time with AI-driven orchestration[32] while its recovery time increases rapidly with deterministic management. The system demonstrates improved reliability through additional resilience and active fault detection capabilities in AI-native 6G networks.

VII. Challenges and Limitations

The introduction of AI-native hierarchical orchestration for autonomous 6G networks creates multiple technical and operational difficulties even though it shows multiple beneficial results. The main restriction occurs because distributed AI agents must be installed throughout RAN and core and edge environments which creates excessive computational demands in ultra-dense and resource-limited conditions. The system needs strong processing abilities to perform both real-time learning and inference which results in higher equipment expenses and energy requirements. The continuous training and validation systems must operate because model drift and data bias affect decision accuracy in the changing 6G environment[33]. The process of achieving interoperability among different vendor systems remains difficult because of diverse system interfaces and proprietary system designs and missing complete AI orchestration standards. The use of federated or distributed learning introduces security and privacy challenges because adversarial attacks and data poisoning and model inversion threats can lead to system failures. The current system fails to provide proper explainability and transparency for AI decision-making, which makes it harder to meet regulatory requirements and gain operator confidence. The need to synchronize across terrestrial and aerial and satellite-integrated networks creates additional difficulties for coordination between different operational domains. Mission-critical applications require highly dependable and predictable control systems which create problems with AI decision models that use probabilistic methods. The absence of developed 6G standards together with the lack of extensive real-world deployment data creates validation challenges for 6G systems which need additional research and standardization work and industry partnerships to achieve practical deployment[34].

VIII. Conclusion

The design and management of wireless networks need complete changes for their optimization through the upcoming evolution to 6G technology. The next-generation systems require orchestration mechanisms which can handle their extreme scaling needs together with their ultra-low latency demands and their ability to operate across multiple domains and their changing service requirements. The study presented a hierarchical orchestration architecture which operates with AI technology to distribute intelligence throughout RAN and core and edge systems for autonomous 6G operations. The framework uses reinforcement learning together with knowledge-driven reasoning and intent-based policies and programmable APIs to create a system which allows adaptive decision-making and cross-domain coordination and continuous optimization.

The proposed method delivers better performance results through reduced end-to-end latency and improved energy efficiency and faster fault recovery and decreased operational costs when compared to deterministic management systems. The system uses its hierarchical design to process urgent decision-making at local locations while controlling international rule compliance and extended time performance through central management. The 6G infrastructures achieve their growth potential and their capacity to withstand challenges through the system which combines distributed independence with centralized operation.

The research confirms AI-native orchestration creates an effective pathway toward achieving fully autonomous wireless networks despite the existing challenges of interoperability and AI explainability and computational complexity. The self-configuring self-optimizing and self-healing features of the proposed architecture create an intelligent and sustainable framework which supports future digital ecosystems and ultra-dense connectivity and emerging applications for the 6G era[35].

IX. FutureWork

Future work on AI-native hierarchical orchestration for autonomous 6G networks should focus on enhancing scalability, intelligence maturity, and real-world deployment readiness. The development of advanced multi-agent reinforcement learning models should be pursued because they enable cooperative decision-making across RAN core edge and satellite domains. Autonomous systems will gain more trust from users through explainable AI techniques which enhance transparency and help meet regulatory requirements. Research should also explore lightweight AI models optimized for resource-constrained edge devices to reduce computational overhead and energy consumption. Digital twin networks provide a promising area because they enable real-time simulation which supports predictive validation and proactive optimization before policy enforcement. Standardization needs to be improved to achieve better interoperability between different vendor systems and diverse infrastructure elements. Security research needs to focus on developing methods which protect distributed learning systems from adversarial attacks and model poisoning and privacy violations. The future research should investigate large-scale field experiments which will test 6G systems in authentic scenarios that combine terrestrial and aerial and non-terrestrial networks. Intent-driven service marketplaces combined with AI-powered economic models create new possibilities for dynamic spectrum and resource trading. Continuous model adaptation strategies together with lifelong learning mechanisms should be created to handle changing traffic patterns and new application needs. The development of these technologies will enable the creation of fully autonomous systems which operate with resilience and sustainabilty within 6G wireless networks.

REFERENCES

[1] W. Wu *et al.*, "AI-Native Network Slicing for 6G Networks," *IEEE Wireless Communications*, vol. 29, no. 1, pp. 96–103, 2022. https://doi.org/10.1109/MWC.001.2100338

[2] Bhaskara Raju Rallabandi. (2023). NATIVE OBSERVABILITY FOR PRIVATE 5G: A REFERENCE ARCHITECTURE ON COMBINATION OF NWDAF, SMO, AND EDGE ANALYTICS. American Journal of AI Cyber Computing Management, 3(1),24-28. https://doi.org/10.64751/ajaccm.2023.v3.n1.pp24-28

[3] T. Taleb *et al.*, "Towards Zero-Touch Network and Service Management," *IEEE Communications Magazine*, 2023.

[4] K. Cherladine and B. R. Rallabandi, "Agentic-AI xApps: O-RAN multi-agent control for enterprise policy, scheduling, and spectrum," International Journal of Digital Information Management, vol. 2, no. 4, pp. 54–58, 2023, doi: 10.64751/ijdim.2023.v2.n4.pp54-58.