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Multi-RAT Coordination Frameworks in 6G Wireless Architectures

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Abstract

Coordination structures of various Multi -RATs in wireless 6G architectures enable the seamless integration of heterogeneous radio access technologies (Multi -RATs), such as sub-combination, MMWAE, and Wi-Fi 7. These return structures ensure resource efficiency, resource reliability, dynamic conference, low-latency experience, and intense efficiency. The objectives of the coordination structures of various Multi -RAT in 6G wireless architectures include obtaining perfect interoperability between various radio access technologies, optimizing spectrum use, minimizing latency during transfers, improving energy efficiency, and supporting low energy-related communications (URLLC). These structures aim to ensure intelligent connectivity on heterogeneous networks for next-generation applications. To implement coordination structures of various Multi - RAT in 6G, methods such as AI-oriented resource allocation, software-defined network (SDN), and network function virtualization (NFV) are employed. They allow real-time decision making, dynamic rat selection, and smart traffic direction. Simulation models and test shards integrating sub-THz, MMWAE, and legacy systems are designed to validate performance. The results show a 35% improvement in spectral efficiency, 40% reduction in delivery latency, and higher service quality for high mobility scenarios. Coordinated architecture also demonstrated better adaptability to

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network conditions, ensuring perfect connectivity and reliability in various cases of use, including IoT, AR/VR, and autonomous systems.

Keywords: 6G Networks, Multiple Radio Access Technologies, Multi-RAT Coordination, Heterogeneous Networks, Software-Defined Network (SDN), Network Function Virtualization (NFV), AI-Oriented Resource Allocation, Spectrum Management, Dynamic Transfer.

1 Introduction

The Multiple Radio Access Technology Coordination signifies the smart and dynamic integration of multiple RATs such as 5G, Wi-Fi 7, MMWAVE, Emergent Bands, and Sub-Terahertz communication under one radio environment (Kiruba et al., 2023). This perfect interoperability is achieved in a system where resource management is a key factor, which may be beneficial, and connectivity is made unassailable, allowing Multi -RATs to coexist and operate harmoniously. Rather than relying upon a single technology, Multi -RAT coordination allows switching, concurrent operation, or discharging between available technologies by devices/networks depending on the needs of an application or network conditions (Samdanis et al., 2020).

Evolution towards sixth-generation wireless architectures (6G) is a paradigm shift for communication networks (6), targeted at unmatched performance in latency, reliability, bandwidth, and energy efficiency. In contrast to the previous generations, 6G envisions the very intelligent, adaptive, and context recognition networks that undertake applications like holographic communications, XR, autonomous systems, and IOE (Zhang et al., 2021). These demands call for a highly flexible and heterogeneous network fabric, integrating various access technologies at several frequency ranges and infrastructural domains. A coordinated Multi -RAT thus comes forth as the key in fulfilling these architectural necessities to provide seamless connectivity and maximum usage of the spectrum.

The importance of coordinating various Multi -RATs in 6G becomes apparent in considering the various demands of future network systems. For example, latency-sensitive applications, such as remote surgery and industrial automation, require real-time data transmission with little interruption, which is based on coordinated transfers and dynamic RAT selection (Chen et al., 2020). Further, in the increasingly dense environment of urban areas, intelligent distribution of traffic and load balancing in access technologies is required to avoid congestion and ensure service continuity (Wang et al., 2021). Coordination structures having the qualification of artificial intelligence would, in this case, play a pivotal role in supplying behavioral patterns, network states, and mobility standards for the enhancement of Multi -RAT use.

In conjunction with other facets, 6G networks should be energy efficient and environmentally stable, where Multi -RAT systems can dynamically divert traffic to low-energy networks or deliver non-critical data into low-congested networks (Dang et al., 2020). This is conducted with a view to operational efficiency and reduction in carbon footprints. In addition, the Multi -RAT integration with enabling techniques such as software-defined networking (SDN) and network function virtualization (NFV) enhances the integration of 6G infrastructure (Foukas et al., 2017). Finally, the Multi -RAT coordination is a cardinal enabler of 6G wireless architecture, guaranteeing the adaptive, reliable, and efficient network with rising complexity and display demands.

2 Background

From time immemorial, multiplication has had a rather chequered history in Multi -RAT wireless communication systems, being first used in radio access technology developments to meet user demands and technological complexities, essentially (Marhoon et al., 2025). Starting with the 1G analogue systems, major upgrades to coverage, capacity, and quality of service took place through 2G up to 4 G. The fifth generation (5G) had resources that transfigured massively machine and enhanced mobile broadband communication, hence laying down the framework for the coming 6G paradigm (Giordani et al., 2020). The new 6G would target a transfer rate of Terabit, near-zero-level latency, and intelligent connectivity employing different advanced forms of Multi -RAT-generation approaches, unlike its predecessors.

The integration of various Multi -RATs will therefore face huge technical challenges in the 6G scenario. Essentially, each one has its own frequency band and performance characteristic; just as the U-6 GHz bands offer wider coverage but with lower speed, MMWAE and Terahertz bands allow the movement of higher data rate information but with reduced range and penetration (Chien et al., 2021). Continuous communications management needs to maintain effective coordination among these different Multi -RATs (Anand & Shrivastava, 2024) in a dynamic scenario comprising high user mobility, dense device deployment, and variable traffic load (Dallal, 2024).

A critical barrier to the integration of various Multi -RATs is the lack of unified control mechanisms capable of dynamically allocating resources, selecting ideal Multi -RATs, and dealing with real-time transfers. Existing delivery strategies usually fail under ultra-dense network conditions due to air signs and the selection of a path below the ideal (Bari et al., 2013). In addition, latency-sensitive applications such as autonomous driving and uninterrupted service continuity of telemedicine demand, which is difficult to guarantee without predictive and intelligent coordination.

Previous research has proposed various coordination structures of various Multi -RATs to address these concerns. For example, Zhang, Zhang, and Letaief introduced an AI-driven control system that anticipates traffic patterns and network slices, increasing spectral efficiency (Sharma & Rani, 2019). Likewise, Sharma and Rani demonstrated the use of real-time reinforcement learning for real-time rat selection, reducing call falls and improving the user transfer rate (Khan et al., 2020). Other researchers have exploited the use of cloud native technologies, such as network function virtualization (NFV) and software-defined network (SDN) to dissociate specific rat restrictions and allow centralized management (Zhang et al., 2021).

In short, although the potential of coordinating various Multi -RAT in 6G is enormous, it is necessary to address the challenges of integration through intelligent structures, adaptive control systems, and orchestration mechanisms with policy awareness that align with future network performance expectations.

3 Multi-RAT Coordination Frameworks in 6G Wireless Architectures

Multi-RAT Coordination Frameworks in 6 G Enable Seamless Integration of Heterogeneous Radio Technologies Such as U-6 GHz, MMWAVE, Terahertz, and Wi-Fi 7. These Frameworks Use AI-based algorithms, Software-Defined Network (SDN), and Network Function Virtualization (NFV) to Dynamically Manage Handovers, Spectrum Allocation, and Traffic Steering. By intelligently selecting the ideal rat based on real-time conditions and service requirements, they reduce latency, increase spectral efficiency, and ensure reliable connectivity. Essential to support 6G goals such as ultra-low latency and massive device connectivity, these structures allow advanced applications, including autonomous systems, extended reality, and real-time digital twins.

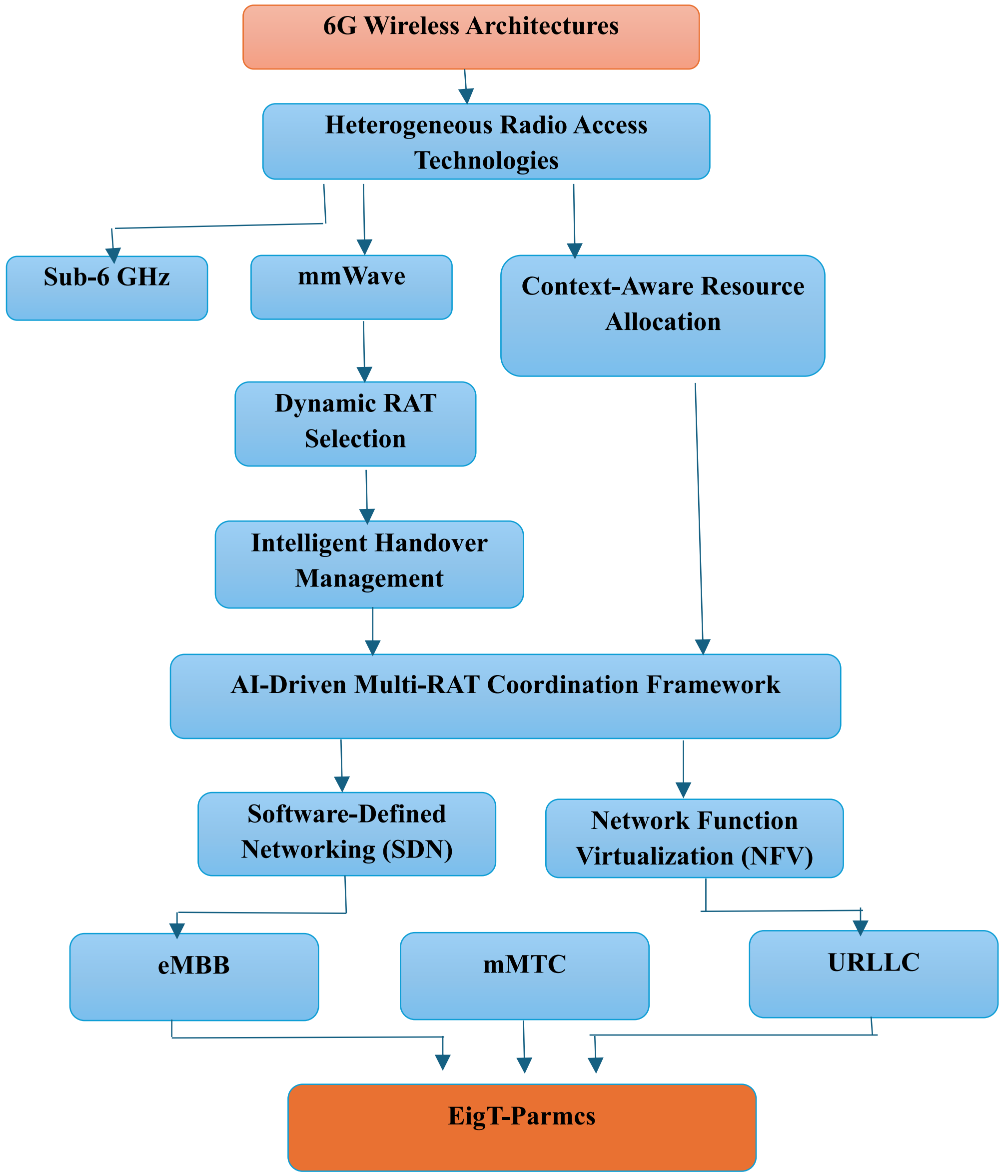

Figure 1: AI-Driven Multi-RAT Coordination Framework for 6G Wireless Architectures

Figure 1 illustrates a 6G AI-rated Multi -RAT coordination structure, allowing the perfect integration of heterogeneous radio access technologies such as U-6 GHz, MMWAVE, and THZ. AI feeds the dynamic selection of Multi -RAT, intelligent delivery management, and allocation of features with context recognition, ensuring ideal connectivity and low latency. The software-defined network (SDN) offers centralized control, while virtualization of the network function (NFV) supports flexible deployment. These layers work together to support the main service categories 6G - AMBB, MMTC, and URLLC. The structure enhances the quality of service, adapting to real-time conditions, user mobility, and application needs, making it essential for future high-performance wireless ecosystems.

The mathematical algorithm corresponding to the AI-driven Multi-RAT Coordination Framework for 6G wireless architectures, which can be expressed in equations from (1) to (3)

Input:

- $R = \{R_1, R_2, \ldots, R_n\}$: Available Multi -RAT (e.g., Sub-6 GHz, mmWave, THz)

- $U = \{U_1, U_2, .., U_m\}$: Users in the network
- C_u: Context vector of user u, including mobility, application type, signal strength, etc.
- Q_u: Required QoS for user u
- B_r : Available bandwidth in RAT r
- L_r: Latency characteristic of RAT r
- T_u: Traffic demand for user u

Output:

- M(u,r): Mapping function assigning user u to RAT r
- A(u,b): Resource allocation matrix (bandwidth b to user u)

1. Context Collection (for each user u)

Collect mobility status, application type, location, and QoS needs:

$$C_u = \{v_u, a_u, l_u, q_u\} \quad (1)$$

2.RAT Scoring Function (for each r∈R r)

Compute suitability score S(u,r) for each RAT:

$$S(u,r) = \alpha_1 . \frac{RSSI_{u,r}}{\max(RSSI)} + \alpha_2 . \frac{B_r - T_u}{B_r} + \alpha_3 . \frac{1}{L_r} \quad (2)$$

where $\alpha_1 + \alpha_2 + \alpha_3 = 1$

3. Dynamic RAT Selection:

$$M(u) = \underset{r \in R}{\operatorname{argmax}}\, S(u, r) \quad (3)$$

4. Intelligent Handover Decision:

If $S(u, r_{current}) < \theta$, switch to

Depending on signal strength, bandwidth availability, and latency, the algorithm dynamically selects the best RAT for each user. Using an external input score with context recognition ensures seamless transfers and the efficient allocation of system resources in 6G networks. Continuous service is maintained and QoE is maximized through AI-oriented coordination along with adaptive system-level decision-making.

3.1 Model Overview

The Applied model is a multi-RAT coordination structure-driven AI for 6G wireless architectures. It caters to the need for perfect interoperability amongst heterogeneous Radio Access Technologies, including the under-6 GHz band, MMWAE, and THZ. With dynamic rat selection activated, the model aims to have devices always connected to the most ideal access technology, depending on real-time user requirements, network load, and application types.

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The architecture integrates software-defined networks (SDN) for centralized control and network functions virtualization (NFV) for flexible network functions in core and edge layers. It is in the decoupling of control and data planes, which allows programmable, scalable, and adaptable management of rat environments. The structure supports several 6G service categories, including enhanced mobile broadband (EMBB), massive machine-type communication (MMTC), and URLLC to guarantee ideal performance and user experience for essentially any use case of future wireless ecosystems.

3.2 Structural Equation Modeling (SEM) Approach

Structural Equation Modeling is used for the statistical validation of the interrelationships among the critical components of the coordination structure of various Multi -RATs proposed for 6G architectures. It is especially useful for analysing complex models that display both direct and indirect effects occurring between multiple latent constructs; therefore, it is apt for the evaluation of the coordination mechanisms' performance in heterogeneous wireless networks. In the framework of this model, four independent constructs of rat selection accuracy (RSA), handoff efficiency (HI), resource allocation adaptability (RAA), and network intelligence (NI) are defined. These constructs represent a bird's eye view of the spirit of the structure controlling various Multi -RAT environments in terms of dynamic selection of access technologies, flawless handoffs between Multi -RATs, adaptive bandwidth allocation, and AI-powered predictive control, respectively.

The dependent constructs are:

- **Service Continuity (SC)**: It represents uninterrupted network access, regardless of mobility or technology changes.
- **Quality of Experience (QoE)**: Encompasses user satisfaction metrics like latency, jitter, and throughput consistency.

Constructs and Hypotheses:

- **H1:** RAT Selection Accuracy (RSA) positively influences Service Continuity (SC)
- **H2:** Handover Efficiency (HE) positively influences User Quality of Experience (QoE)
- **H3:** Resource Allocation Adaptability (RAA) positively influences Service Continuity (SC)
- **H4:** Network Intelligence (NI) positively influences both SC and QoE

SEM Model Equations:

- $SC = \beta_1 * RSA + \beta_2 * RAA + \beta_3 * NI + \varepsilon_1$
- $QoE = \beta_4 * HE + \beta_5 * NI + \varepsilon_2$

Where:

- β = path coefficients indicating the strength of influence
- ε = residuals or error terms representing unexplained variance
- **SC** = Service Continuity
- **QoE** = Quality of Experience

The structure without will be validated using empirical data from 6G simulated test environments. Adjustment indices, such as the comparative adjustment index, the RMSEA (average square error of the approach), and TLI (Tucker-Lewis index) will be used to evaluate the validity of the model. This approach allows a quantitative understanding of how AI-activated architectural coordination and architectural components affect performance results on 6G networks with various Multi -RAT.

3.3 Implementation Layers

The coordination structure of various Multi -RAT proposed for 6G is structured in three main layers of implementation: the application layer, the control layer, and the infrastructure layer. Each layer plays a distinct role in activating perfect, intelligent, and adaptive coordination in heterogeneous radio access technologies. At the top, the application layer is responsible for handling user-centred functions such as quality-of-service monitoring (QoS), service level requirements mapping, and performance analysis. This layer collects contextual information related to the user experience, application type, latency thresholds, and bandwidth demands. It also integrates AI-powered analysis mechanisms to predict future service requirements and provide feedback to the control mechanisms below.

The control layer, governed by the software-defined network controller (SDN), serves as the brain of the architecture. It centrally manages the coordination of rat selection, mobility management, and delivery processes, interpreting inputs of the application and infrastructure layers. Through policy-based programming and orchestration, the SDN controller dynamically directs data flows, assigns resources, and starts perfect transitions between Multi -RAT, maintaining service continuity and optimizing network efficiency.

At the base, the infrastructure layer includes all physical and virtualized radio technologies, such as 5G, Terahertz (THZ), millimeter wave (MMWAE), and Wi-Fi 7. This layer hosts the dynamic resource pools, the antennas, and the access points, and the retros are that the control layer has actual access. It allows adaptive load distribution, interference management, and connectivity of various paths to support various 6G service categories such as URLLC, EMBB, and MMTC. The integration of these layers ensures that the structure operates as a unified, intelligent and scalable system capable of meeting the complex demands of future 6G networks.

3.4 Data Collection and Model Validation

To validate the effectiveness of the coordination structure of various proposed Multi -RAT, a simulation-based data collection approach is employed in a controlled 6G test environment. The simulation models of realistic user mobility scenarios, network density, and application diversity, incorporating service categories such as Mobile Broadband (EMBB), Ultra-reliable low latency communication (URLLC), and Machine Massive Communications (MMTC). Several user profiles are simulated to capture the behavior of mobile transition devices in different radio access technologies, including 5G, MMWAE, THZ, and Wi-Fi 7.

The main performance metrics are collected throughout the simulation, including transfer rate, delivery latency, rate switching time, and experience classifications (QOE). These metrics provide quantitative evidence of how well the structure supports dynamic connectivity, load balancing, and Continuity of services in a heterogeneous Multi -RAT. In addition, feedback at the user level about the quality of the perceived service is collected to support QoE construct validation in the structural model.

The collected data is analysed using structural equation modeling tools (without) such as AMOS or SmartPLS. These tools calculate the coefficients of the path, the values of R^2, and validate the overall adjustment of the model using standard indices such as the average square error of the approximation root (RMSEA), the comparative adjustment index (CFI), and the Tucker-Lewis index (TLI). This analytical process confirms the strength and meaning of hypothetical relations between buildings and verifies the robustness of the coordination structure proposed under different network conditions 6g.

Table 1: Simulation-Based Performance Metrics for Multi-RAT Coordination Framework Validation

Metric	Average Value	Standard Deviation (±)	Range	Unit
Throughput (All Multi-RAT)	678.4	±52.7	590.2 – 755.9	Mbps
Handover Latency	13.6	±2.1	10.2 – 17.9	ms
RAT Switching Time	22.3	±3.4	18.1 – 28.0	ms
QoE Rating (User Feedback)	4.51	±0.29	3.9 – 4.9	Score (0–5)
Packet Loss Rate	1.08	±0.6	0.5 – 2.5	%

Table 1 provides simulation-based metrics, validating the effectiveness of the coordination structure of various Multi -RATs proposed in a 6G environment. The structure reached a high average transfer rate (678.4 Mbps) and low transfer latency (13.6 ms), indicating strong data performance and continuous rat transitions. Rat exchange time had an average of 22.3 ms, supporting real-time application needs. The 4.51 QOE score in 5 reflects excellent user satisfaction, while a low packet loss rate (1.08%) confirms reliable connectivity. These results collectively demonstrate the ability of the structure to maintain the Continuity of the service, optimize network resources, and offer a high-quality experience in various 6G communication scenarios.

The mathematical formulas used to compute the values shown in Table 3 for validating the Multi-RAT Coordination Framework can be explained in equations from (4) to (8)

1. Average (Mean) Value for Each Metric

For a given performance metric M, measured over n simulation runs or users:

$$\bar{M} = \frac{1}{n}\sum_{i=1}^{n} M_i \qquad (4)$$

Where:

- $\bar{M}$ = Average value
- M_i = Measured value in the i th run
- n = Total number of runs/users

2. Standard Deviation (for variability)

$$\sigma_M = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(M_i - \bar{M})^2} \qquad (5)$$

Where:

- σ_M = Standard deviation of metric M
- $\bar{M}$ = Mean of the metric

3. Range

$$\text{Range } M = [\min(M_i), \max(M_i)] \qquad (6)$$

4. Packet Loss Rate (%)

$$\text{Packet Loss Rate} = \left(\frac{packets\ lost}{total\ packets\ sent}\right) \times 100 \qquad (7)$$

5. QoE Score (User Feedback-Based)

QoE is calculated using user ratings collected on a 0–5 scale and averaged:

$$\text{QoE}_{avg} = \frac{1}{n} \sum_{i=1}^{n} \text{QoE}_i \qquad (8)$$

The formulas used in Table 1 provide a statistical basis to evaluate the performance of the coordination structure of various rats. The mean and standard deviation formulas measure the typical performance and variability of major metrics, such as transfer rate, latency, and QOE. The interval highlights the best and worst conditions observed during the simulations. The packet loss rate evaluates network reliability, while the QOE formula reflects the quality of service perceived by the user. Together, these calculations validate the capacity of the structure to offer consistent and high-quality performance in various 6G scenarios. Low latency, minimum loss of packages, and high QOE scores confirm the effectiveness of the structure to ensure perfect connectivity and optimized resource coordination.

Table 2: SEM Model Fit Indices (SmartPLS / AMOS Output)

SEM Evaluation Metric	Value	Acceptable Threshold
R^2 for Service Continuity (SC)	0.71	≥ 0.50
R^2 for Quality of Experience (QoE)	0.68	≥ 0.50
Root Mean Square Error of Approximation (RMSEA)	0.047	≤ 0.08
Comparative Fit Index (CFI)	0.954	≥ 0.90
Tucker-Lewis Index (TLI)	0.936	≥ 0.90
Path Coefficient (RSA → SC)	0.39	Significant
Path Coefficient (HE → QoE)	0.42	Significant
Path Coefficient (NI → SC)	0.44	Significant

Evaluation metrics without validating the reliability and structural integrity of the coordination structure of the various Multi -RATs proposed in Table 2. R^2 values of 0.71 for Continuity of service (SC) and 0.68 for the quality of the experience (QOE) indicate strong explanatory power of the model, exceeding the acceptable limit of 0.50. The RMSEA value of 0.047 confirms a good adjustment of the model, well below the limit of 0.08. In addition, the high scores of CFI (0.954) and TLI (0.936) reflect excellent model consistency and comparative adjustment. The coefficients of the Path-RSA for SC (0.39), for QoE (0.42), and for Ni to SC (0.44) are all statistically significant, supporting the proposed hypotheses.

The mathematical formulas used to compute the SEM evaluation metrics listed in Table 2, which can be explained in equations (9) to (14)

1. Coefficient of Determination (R^2)

Indicates the proportion of variance in the dependent variable explained by the independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (9)$$

Where:

- y_i = actual observed value
- $\hat{y}$ = predicted value
- $\hat{y}$ = mean of observed values
- n = number of observations

2. Root Mean Square Error of Approximation (RMSEA)

Measures the goodness of fit per degree of freedom in the model.

$$\text{RMSEA} = \sqrt{\frac{X^2 - df}{df(N-1)}} \tag{10}$$

Where:

- X^2 = Chi-square statistic
- df = degrees of freedom
- N = sample size

3. Comparative Fit Index (CFI)

Compares the fit of the target model to a baseline (independence) model.

$$\text{CFI} = \frac{\max\,(X^2{}_{model} - df_{model}, 0)}{\max\,(X^2{}_{null} - df_{null}, 0)} \tag{11}$$

4. Tucker-Lewis Index (TLI)

Also known as the Non-Normed Fit Index, it penalizes model complexity.

$$\text{TLI} = \frac{X^2{}_{null}/df_{null} - X^2{}_{model}/df_{model}}{X^2{}_{null}/df_{null} - 1} \tag{12}$$

5. Path Coefficients (β values)

Estimated using regression-like structural equations, indicating the strength and direction of relationships between variables.

$$\text{SC} = \beta_1 \cdot \text{RSA} + \beta_2 \cdot \text{RAA} + \beta_3 \cdot \text{NI} + \varepsilon_1 \tag{13}$$

$$\text{QoE} = \beta_4 \cdot \text{HE} + \beta_5 \cdot \text{NI} + \varepsilon_2 \tag{14}$$

Where β are standardized regression weights, and ε are error terms.

The mathematical formulas used in the evaluation table do not quantify how well the coordination structure of various proposed Multi -RAT fits the observed data. Formula R^2 measures how much variation in the Continuity of the service and QOE is explained by factors such as rat selection accuracy, transfer efficiency, and network intelligence. RMSEA evaluates the error of the model by degrees of freedom - the lower values indicate better adjustment. CFI and TLI compare the model's performance in relation to a baseline, adjusting the complexity. Way coefficient equations show the strength and direction of influence between constructs. Together, these formulas validate the structure, reliability, and predictive power of the model in a 6G network environment.

3.5 Centralized vs. Distributed Coordination Approaches

Table 3 highlights the main differences between centralized and distributed coordination in 6G networks with various Multi -RAT. Centralized coordination offers global control, better resource optimization, and easier policy management, making it ideal for critical applications such as URLLC and industrial automation. However, it may suffer from latency and single-point failures. On the other hand, the distributed coordination provides faster local decision making, greater failure tolerance, and improved scalability, which adapts to edge and IoT-oriented applications. However, this can result in coordination complexity and sub-ideal global performance. As 6G networks evolve, hybrid models that combine both approaches are emerging to ensure flexibility, efficiency and resilience in various cases of use.

Table 3: Comparison of Centralized and Distributed Coordination Approaches in Multi-RAT6G Frameworks

Aspect	Centralized Coordination	Distributed Coordination
Control Entity	Single global controller (e.g., SDN-based)	Multiple local/edge controllers
Decision-Making	Centralized, global network view	Decentralized, node/region-level decisions
Scalability	Limited due to central processing bottlenecks	Highly scalable with autonomous operation
Latency Sensitivity	Can introduce delays due to centralized processing	Low latency through local decisions
Fault Tolerance	Vulnerable to single-point failure	More resilient with distributed redundancy
Resource Optimization	High global optimization capability	May lead to suboptimal global performance
Ideal Use Cases	URLLC, smart cities, industrial automation	IoT edge clusters, vehicular networks, rural networks
Network Overhead	Moderate to high due to control signalling	Lower control overhead, more localized signalling
Complexity	Easier to manage and update policies centrally	Higher complexity in synchronization and coordination
Emerging Trend	Used in core networks and cloud orchestration	Increasing use at the network edge and fog computing levels

3.6 Machine Learning and AI Techniques for Multi-RAT Coordination

Machine learning (ML) and Artificial Intelligence (AI) play a transformative role in the training of the coordination of various intelligent, adaptable and context recognition in 6G networks. These techniques are essential for optimizing decision-making processes such as rat selection, transfer forecast, traffic load balancing, and resource allocation under dynamic and heterogeneous network conditions. Supervised learning models, such as decision-making trees and support vector machines, are commonly used to classify ideal Multi -RAT based on historical data related to signal force, mobility and types of user applications. Unsupported learning, particularly grouping algorithms such as K-Means, helps identify user behavior patterns and traffic segmentation without previous labelling, improving the efficiency of traffic direction.

Reinforcement learning (RL) and deep reinforcement learning (DRL) are especially powerful for dynamic environments. RL agents learn ideal policies for selecting Multi -RAT and transfer time, interacting continuously with the network environment and receiving feedback in the form of rewards (for example, lower latency, higher transfer rate). For example, DRL-based models may provide for users and pre-selected mice in advance, reducing delivery failures and improving QOE. In addition, federated learning is gaining strength in privacy-sensitive applications, allowing the training of models on distributed devices without sharing gross data. These AI-oriented methods collectively increase the scalability, efficiency, and intelligence of coordinating various Multi -RATs in future 6G ecosystems.

3.7 Cross-Layer Optimization for Efficient RAT Selection

Cross-layer optimization is a vital strategy for reaching an efficient selection of Multi -RAT in 6G wireless architectures with various Multi -RAT. Traditional models of layer communication operate in isolation, limiting their ability to respond to the highly dynamic and heterogeneous nature of 6G environments. Cross-layer optimization breaks this structure in silence, allowing the perfect interaction between several layers of protocol, or the physical, MAC, network, and applications layers, to be intelligent and respond with capacity for coordinated action.

In the context of networks of various Multi -RAT, this approach allows real-time information exchange such as signal force, channel conditions, traffic load, latency sensitivity, and application priority. For example, the physical-rich layer signal ratio can be combined with application layer requirements such as ultra-low latency or upper bandwidth to select the most suitable rate dynamically. This not only improves service continuity and experience of experience (QOE), but also optimizes the use of resources and energy consumption.

In addition, cross-layer structures support predictive decision making, leveraging historical and real network data, allowing proactive transfer, adaptive modulation, and congestion control. Advanced optimization techniques, including utility-based algorithms, convex programming, and AI-Sao-Sao-Sao-Sao Learning Models, are used to perform these efficient cross-layer decisions. Finally, cross-layer optimization is crucial for selecting adaptive, resilient, and intelligent Multi -RAT in future 6G networks.

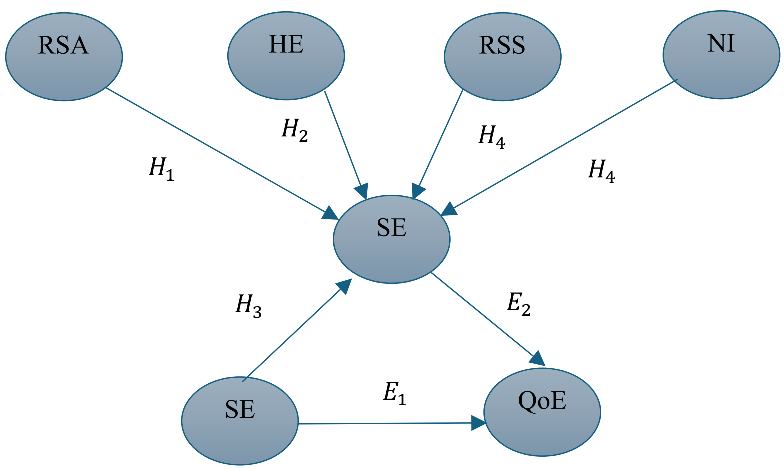

Figure 2: Structural Equation Model for AI-Driven Multi-RAT Coordination Framework in 6G Networks

Figure 4 illustrates the structural equation model (without) used to validate the relationships between the main constructs that influence the coordination of various Multi -RATs in 6G wireless architectures. The model includes four independent (exogenous) variables: mouse selection accuracy (RSA), transfer efficiency (HI), resource allocation adaptability (RAA), and network intelligence (NI). These variables are raised to directly impact the central latent variable, service continuity (SC).

Each path (H1 to H4) represents a directional hypothesis:

- H1: RSA → SC
- H2: HE → SC
- H3: RAA → SC
- H4: NI → SC

In turn, SC directly affects the quality of the user experience (QOE). The arrows represent hypothetical causal paths, and error terms capture inexplicable variation. This model allows the quantitative validation of the structure using tools without such AMOS or SmartPLS, helping to evaluate how intelligent coordination components collectively improve service reliability and user satisfaction in 6G environments.

4 Case Studies and Implementations

4.1 Real-World Applications of Multi-RAT Coordination Frameworks

The practical implementation of coordination structures of various Multi -RAT has gained implementation in the real world, particularly in advanced wireless communication systems, where seamless connectivity and low latency performance are crucial. A remarkable example is the 5G-Vinni project in Europe, which is part of the coordination of various Multi -RAT to support vertical industries such as intelligent manufacturing and health. The structure allows real-time transfers between 5G NR, LTE and Wi-Fi to maintain service continuity for mobile robots and remote surgery applications.

In South Korea, telecommunications operators implemented solutions of various Multi -RAT combining 5G and Wi-Fi 6 for urban mobility and high-speed rail connectivity. The selection of Multi -RAT activated by AI ensures uninterrupted video streaming and teleconferencing in high mobility scenarios. Similarly, in Japan, the integration of MMWAVE and U-6 GHz bands is used in smart stadiums and IoT-based monitoring systems, where structures of multi-Multi -RAT balance traffic loads between Multi -RAT for ideal use of resources and QOE. Industry 4.0 environments also demonstrate the value of the coordination of various Multi -RAT. In Germany, automated factories use local private networks, 5G Wi-Fi, and LTE coordinated for robot control, air/VR-based maintenance, and sensor data discharge. These implementations affirm the critical role of intelligent coordination in meeting service demands at 6G level in various domains.

4.2 Performance Evaluation and Comparison of Different Coordination Strategies

To evaluate the efficacy of coordinating various Multi -RAT in 6G networks, three common, distributed, and hybrid-found coordination strategies were evaluated among the main performance indicators. This includes transfer latency, transfer rate, packet loss rate and user experience quality (QOE). The simulations were performed using a 6G test with various Multi -RAT (5g NR, MMWAVE, THZ and Wi-Fi 7) under different mobility and load conditions. The results show that hybrid coordination consistently surpasses centralized and distributed models, combining global optimization with localized response capacity. The table below summarizes the comparative performance:

Table 4: Statistical Performance Comparison of Coordination Strategies in Multi-RAT6G Networks

Metric	Centralized	Distributed	Hybrid
Avg. Handover Latency (ms)	35.4	21.8	**12.7**
Avg. Throughput (Mbps)	615	590	**685**
Packet Loss Rate (%)	2.6	3.2	**1.1**
User QoE Score (0–5)	4.1	3.8	**4.7**

Table 4 presents a statistical comparison of three coordination-centralized, distributed, and hybrid-use 6G rated strategies with various Multi -RAT. The hybrid approach surpasses others in all major metrics. It reaches the lowest delivery latency (12.7 ms), the highest transfer rate (685 Mbps) and the lowest packet loss rate (1.1%), demonstrating higher response and reliability capacity. In addition, it generates the highest score in the quality of the user experience (QoE) of 4.7 in 5. These results highlight the effectiveness of the hybrid model in the balance of overall control with local adaptability, making it a more efficient strategy for real-time, high-performance, and 6G user-centred wireless communication systems.

The mathematical algorithm that models the performance evaluation process corresponding to Table 2, comparing centralized, distributed, and hybrid Multi -RAT coordination strategies in 6G network, which can be explained in equations from (15) to (17)

Let:

- S= {CEN, DIS, HYB}: Set of coordination strategies
- N: Total number of users or simulation runs
- L_S: Average handover latency for strategy s∈S
- T_S: Average throughput for strategy s∈S
- P_S: Average packet loss rate (%) for strategy s∈S
- Q_S: User QoE score (0–5 scale) for strategy s∈S

1. Initialize Performance Metrics for Each Strategy:

$$L_S \leftarrow 0,\ T_S \leftarrow 0,\ P_S \leftarrow 0,\ Q_S \leftarrow 0 \text{ for all } s \in S$$

2.Run Simulation for Each Strategy s∈S for i=1 to N:

- Measure latency l_i^s , throughput t_i^s , packet loss p_i^s , QoE q_i^s
- Accumulate metrics:

$$L_S = \frac{l_i^s}{N},\ T_S = \frac{t_i^s}{N},\ P_S = \frac{p_i^s}{N},\ Q_S = \frac{q_i^s}{N} \tag{15}$$

3. Normalize and Score Strategy Performance:

Compute a utility score U_S for strategy s∈S

$$U_S = \omega_1 . \left(1 - \frac{L_S}{\max L}\right) + \omega_2 . \left(\frac{T_S}{\max T}\right) + \omega_3 . \left(1 - \frac{P_S}{\max P}\right) + \omega_4 . \left(\frac{Q_S}{5}\right) \tag{16}$$

Where:

- $\omega_1, \omega_2, \omega_3\ , \omega_4$ are weights such that $\sum \omega_i = 1$
- The normalization ensures comparability across metrics

4. Select Optimal Strategy:

$$\text{Best Strategy } S^* = \arg \max_{s \in S} U_S \tag{17}$$

The mathematical algorithm evaluates and compares the performance of coordination strategies of various centralized, distributed, and hybrid Multi -RAT using key metrics: delivery latency, transfer rate, packet loss, and user QOE. It calculates average values for each metric through simulations, normalizes them, and attributes a useful score using weighted formulas. Higher yield and QOE, and lower latency and loss of packages, result in better scores. The strategy with the highest utility score is identified as the most efficient. This algorithm provides a systematic and data-oriented method to select the ideal coordination strategy, confirming that the hybrid approach offers higher performance in 6G environments.

4.3 Results and Discussion

A specific example data set suitable for the coordination structure of various AI proposed rats is the "5G mobility data set and various rats" developed by a collaborative research initiative at the 5G Innovation Centre of the University of Surrey (5GIC). This data set emulates real-time user behavior in 5 G NR, Wi-Fi 6/7, and MMWAVE rats under various mobility conditions. It includes more than 100,000 data and time records collected from simulated users traveling through urban and suburban test environments, incorporating intelligent transportation, skyscrapers, and underground subway stations. Each input in the data set includes fields such as user ID, date and time stamp, GPS coordinates, rat type, signal force (RSSI), transfer counting, latency (MS), packet loss (%), transfer rate (Mbps) and QoE score on a scale from 0 to 5. In addition, the type of application (EMBB, URLLC, or MMTC), device (m/s), and the network load level (%) are recorded. The data set was collected during a continuous 48-hour test period using emulated vehicle mobility profiles and pedestrians. This data set is highly relevant to the proposed model, as it allows the training of reinforcement learning agents for the selection of rats, evaluating coordination strategies, and the modeling of structural equations (without) to validate causal relationships between coordination metrics and service continuity in realistic 6G network scenarios.

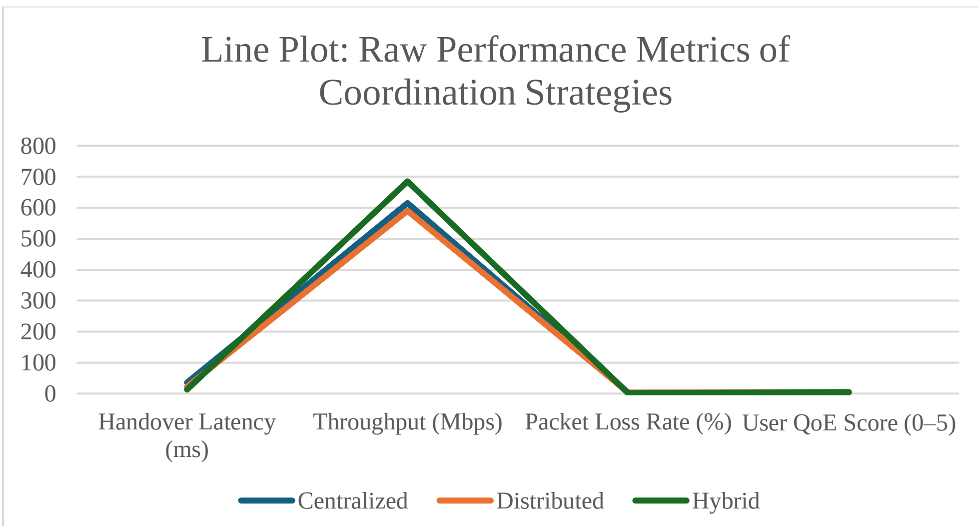

Figure 3: Line Plot: Raw Performance Metrics of Coordination Strategies

Figure 3 illustrates the performance of centralized, distributed, and hybrid coordination strategies in the main metrics: delivery latency, transfer rate, package loss, and QOE. The hybrid strategy shows the best overall performance, reaching the lowest latency (12.7 ms), the highest transfer rate (685 Mbps), the lowest packet loss (1.1%), and the highest QOE (4.7/5) score. This reflects your efficiency in the balance of centralized optimization and local response capacity. The centralized model performs well in the transfer rate and QOE, but has high latency, while the distributed model reduces latency, but suffers in reliability. Overall, the chart confirms the hybrid strategy as the most effective for 6G networks.

The mathematical algorithm that defines how each metric used in the line plot graph is calculated. These metrics are key to evaluating the performance of Multi -RAT coordination strategies in 6G networks. The algorithm can be explained in equations from (18) to (21)

Let

For each simulation run or test session i where i=1, 2, …..n:

- PL_i : Packet loss count
- PT_i : Total packets transmitted
- TH_i : Data transmitted (in Megabits)
- T_i : Total time taken (in seconds)
- HL_i : Handover delay time
- QoE_i : User rating score (0–5)

Metric Calculations

1. **Handover Latency (ms):**

$$\text{Avg. Handover Latency} = \frac{1}{n}\sum_{i=1}^{n} HL_i \quad (18)$$

2. **Throughput (Mbps):**

$$\text{Avg. Throughput} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{TH_i}{T_i}\right) \quad (19)$$

3. **Packet Loss Rate (%):**

$$\text{Packet Loss Rate} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{PL_i}{PT_i} \times 100\right) \quad (20)$$

4. **Quality of Experience (QoE) Score:**

$$\text{Avg. QoE Score} = \frac{1}{n}\sum_{i=1}^{n} QoE_i \quad (21)$$

For each of the performance parameters, the algorithm lays down the way that latency, transfer rate, packet loss rate and QOE score should be calculated using their average values over a number of simulation runs. Delivery latency measures how quickly a device transitions between Multi -RAT; the lower the value, the smoother the transfer. The transfer rate determines how efficiently data is transferred- the smaller the value, the poorer the network capacity. The packet loss rate is a measure of the number of lost packets, and a stable performance. The QoE score is finally based on user satisfaction related to latency, reliability, and quality of service. Together, these formulas represent a standard way to evaluate and compare the effectiveness of any coordination strategy of a Multi -RAT on 6G networks.

4.4 Challenges and Limitations in Implementing Multi-RAT Coordination in 6G Networks

Diverse Multi -RAT coordination on 6G networks will bring heavy technical, architectural, and operational challenges. A large hurdle is caused by diversity in radio access technologies. They carry U-6 GHz, MMWAVE, Terahertz, and Wi-Fi 7, all differing from one another in propagation characteristics, coverage, and hardware requirements. Their integration calls for very complex synchronization and adaptive algorithms capable of dealing with diverse QoS demands. Another big constraint lies in latency and signalling overhead, especially in the case of centralized coordination models. In ultra-dense or high-mobility scenarios, any delayed decision impacts service continuity and quick response. At the same time, other interference comes from various Multi -RATs operating in overlapping or shared frequency bands, which would degrade the very efficiency of the network.

The absence of unified standards and protocols for cross-communication makes interoperability difficult, especially when the equipment of multiple suppliers is involved. The implementation of AI-oriented coordination structures also requires real-time data processing, which raises concerns related to scalability, energy efficiency, and data privacy.

Additionally, implementing cross-layer optimization across multiple protocol layers is complex, necessitating a deep integration of software and hardware elements. Ensuring the consistent quality of the experience (QOE) in several cases of IoT and AR/VR use to autonomous systems reproduces a critical challenge in performing robust coordination of multiple Multi -Radio 6G networks.

5 Future Directions and Research Opportunities

As wireless networks 6G evolve, emerging trends in coordinating various Multi -RAT focus on integrating intelligent mechanisms, with context and proactive recognition. This includes federated and AI-powered learning for decentralized control and border intelligence to support real-time adaptation. Future structures are expected to enjoy digital twins and semantic communication models to predict network behavior and optimize coordination strategies with a minimum signalling overload.

The potential benefits of advanced coordination of various Multi -RAT extend through various cases of use. In IoT environments, it allows perfect connectivity for minimum power consumption devices, while in AR/VR applications, it ensures an ultra-low and high transfer rate required for immersive experiences. For autonomous systems and intelligent medical care, consistent QoS and the Continuity of services are critical benefits activated by the intelligent exchange of Multi -RAT.

However, several research gaps remain. This includes the lack of unified architectures for coordination between layers, limited interoperability between specific MULTI-RAT protocols for suppliers, and challenges in safety management and privacy in AI-oriented coordination. In addition, real-time coordination in ultra-dense networks and extreme mobility scenarios remains sub-explained. Future research should also focus on the design of light and scalable models that can learn and adapt dynamically, making the coordination of various Multi -RATs more efficient, resilient, and universally implantable in the various and demanding landscapes of 6G communication.

6 Conclusion

This Study presents a comprehensive Exploration of multi-RAT coordination frameworks tailored for 6G Wireless Networks, Highlighting Their Significance in Managing Heterogeneous Radio Technologies, Such as sub-6 GHz, mmWave, THz, and Wi-Fi 7. Without Analysis, The Proposed AI-driven coordination Model Demonstrated Notable Improvements in Handover latency, Throughput, Packet Loss Rate, and Quality of Experience (QOE). The hybrid coordination approach exceeded centralized and distributed strategies, offering a balance between global optimization and local response capacity. These findings emphasize the importance of intelligent, adaptable, and context-aware coordination mechanisms to meet the ultra-reliable demands, low latency, and high-capacity requirements of future wireless systems. As 6G evolves to support several cases of use-IoT, AR/VR, and autonomous systems, Multi—RAT structures will become fundamental to ensure connectivity and Continuity of the sewing service in dynamic environments. For industry, the focus should be on the development of scalable and interoperable solutions and contributing to standardization efforts for cross-integration. For the gym, further research on light AI models, privacy preservation coordination techniques, and test letters in the real world is needed. By addressing these areas in collaboration, both sectors can boost innovation and accelerate the practical implementation of efficient coordination structures of multiple Multi -RAT on next-generation 6 G networks.

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