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Explainable AI-Driven Geospatial Intelligence for Resilient Distributed 6G Communication Systems

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Abstract:

Emerging sixth-generation (6G) networks require intelligent, geographically aware communication systems capable of adapting to dynamic traffic, mobility, interference, and infrastructure failures. However, conventional network optimization often lacks spatial context, transparent decision-making, and coordinated resilience across distributed edge-cloud environments. This study proposes an Explainable AI-Driven Geospatial Intelligence Framework (EAGI-6G) to improve network reliability, resource allocation, and communication performance.

The framework integrates geospatial information systems, distributed machine learning, digital network representations, and explainable artificial intelligence (XAI). Geospatial features, including terrain, population density, mobility patterns, signal strength, and infrastructure locations, are fused with network telemetry to predict congestion, coverage degradation, and communication failures. A distributed learning architecture coordinates edge nodes and cloud services while minimizing centralized data dependence. Explainability methods, including SHAP and feature attribution, identify the spatial and network factors influencing decisions. Evaluation compares EAGI-6G against conventional geographic routing, centralized machine learning, distributed learning without geospatial features, and distributed learning without XAI. Key metrics include prediction accuracy, end-to-end latency, packet delivery ratio, network availability, recovery time, energy consumption, communication overhead, and explanation fidelity.

The proposed evaluation targets measurable improvements over baseline methods: at least 10% higher failure-prediction F1-score, 15% lower end-to-end latency, 20% faster recovery, and 10% higher packet delivery ratio, alongside reduced energy consumption and communication overhead. These figures are research hypotheses, not experimentally established findings. Ablation studies will quantify the individual contributions of geospatial intelligence, distributed learning, and explainability under varying mobility, traffic, and failure scenarios.

EAGI-6G establishes a testable framework for interpretable, spatially adaptive, and resilient 6G communication. Its comparative evaluation will clarify trade-offs among predictive performance, scalability, energy efficiency, transparency, and fault tolerance, supporting trustworthy network management for smart cities, connected infrastructure, and intelligent transportation.

Keywords: Explainable artificial intelligence; geospatial intelligence; distributed systems; 6G communication; network resilience.

Chapter One: Introduction

1.1. Background of the Study

The rapid evolution of wireless communication, artificial intelligence (AI), distributed computing, and geospatial technologies is transforming the design of next-generation communication networks. Sixth-generation (6G) communication systems are expected to support intelligent connectivity, ultra-low-latency applications, integrated sensing and communication, and highly distributed services. Unlike previous

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generations, emerging 6G architectures must accommodate dynamic network conditions, heterogeneous devices, mobile users, and geographically dispersed infrastructure. These requirements create a need for intelligent network management that combines spatial awareness, predictive analytics, and autonomous resource optimization (International Telecommunication Union [ITU], 2023; Saad et al., 2020).

Artificial intelligence and machine learning (ML) offer promising approaches to network traffic prediction, resource allocation, anomaly detection, and adaptive communication management. However, conventional AI-driven optimization may overlook the influence of geographical conditions, including terrain, building density, environmental obstacles, infrastructure distribution, and spatial variations in user demand. Integrating geospatial intelligence with AI can enable communication systems to identify location-dependent performance variations, predict coverage gaps, and optimize network resources according to geographical and operational conditions. The ITU's IMT-2030 framework identifies ubiquitous connectivity, intelligence, sustainability, and integrated sensing as important capabilities for future mobile communication systems (ITU, 2023).

Distributed computing further supports intelligent 6G networks by processing information across edge devices, access points, regional servers, and cloud platforms. This architecture can reduce dependence on centralized processing and improve responsiveness for geographically distributed applications. Nevertheless, distributed systems introduce challenges involving communication overhead, heterogeneous computing resources, synchronization, privacy, and fault recovery. Federated learning provides a potential approach to collaborative model training without requiring all raw data to be transferred to a central server, although communication efficiency and non-independent data distributions remain important concerns (Kairouz et al., 2021).

Explainable artificial intelligence (XAI) addresses another critical challenge: understanding why AI systems make particular predictions or decisions. Methods such as SHapley Additive exPlanations (SHAP) can identify influential features, helping network operators interpret predictions involving congestion, signal degradation, and infrastructure failures (Lundberg & Lee, 2017). However, predictive accuracy alone does not guarantee operational resilience or trustworthy decision-making. Explainability must be evaluated alongside network performance, reliability, energy consumption, and recovery capability.

Therefore, this research proposes an Explainable AI-Driven Geospatial Intelligence Framework for Resilient Distributed 6G Communication Systems. The framework integrates geospatial feature engineering, distributed learning, explainable prediction, and adaptive network optimization. Its effectiveness will be investigated through comparisons with conventional geographic routing, centralized machine learning, distributed learning without geospatial features, and distributed learning without explainability. The intended contribution is a reproducible evaluation framework that determines whether combining spatial intelligence, distributed AI, and explainable decision-making improves communication resilience under changing network conditions.

1.2. Problem Statement

The transition toward 6G communication introduces increasingly complex challenges in network reliability, spatial coverage, intelligent resource allocation, and distributed service delivery. Future networks are expected to support diverse applications, including autonomous transportation, smart cities, industrial automation, and integrated sensing, requiring adaptive and resilient communication infrastructures (ITU, 2023). Despite these developments, achieving reliable performance under geographically heterogeneous and dynamically changing network conditions remains a significant research challenge.

First, conventional network optimization approaches may not adequately integrate geographical information with real-time communication measurements. Terrain characteristics, building density, infrastructure locations, and mobility patterns can influence coverage, interference, and service availability. Without systematically combining these spatial variables with network telemetry, intelligent systems may fail to identify location-dependent vulnerabilities and anticipate communication disruptions (Saad et al., 2020).

Second, centralized machine learning architectures can introduce communication overhead, processing bottlenecks, and privacy concerns when handling data generated by geographically distributed network nodes. Federated learning offers an alternative for collaborative model training, but challenges involving heterogeneous data, model convergence, communication efficiency, and security remain unresolved (Kairouz et al., 2021; Federated Learning for 6G Networks: Navigating Privacy Benefits and Challenges, 2025).

Third, many AI-driven network management approaches provide limited explanations of their predictions and optimization decisions. This limitation can reduce operator confidence and make it difficult to identify the geographical and operational factors responsible for network failures. Recent research emphasizes the importance of explainable AI for transparent network slicing, fault diagnosis, and resource management in emerging 6G systems (Sun et al., 2025).

Consequently, the central research problem is the lack of an integrated and systematically evaluated framework that combines explainable AI, geospatial intelligence, and distributed learning to improve 6G communication resilience. This study will investigate how these technologies can jointly improve failure prediction, latency, packet delivery, fault recovery, energy efficiency, and decision transparency compared with established baseline approaches.

1.3. Research Objectives

1.3.1. General Objective

To develop and evaluate an explainable AI-driven geospatial intelligence framework that improves the resilience, reliability, and operational efficiency of distributed 6G communication systems.

1.3.2. Specific Objectives

To investigate the influence of geospatial characteristics, including terrain, infrastructure distribution, population density, mobility, and signal strength, on communication performance and network resilience.

To design a distributed AI architecture that integrates geospatial features with network telemetry for predictive failure detection, congestion forecasting, and adaptive resource allocation.

To incorporate explainable AI techniques, particularly SHAP-based feature attribution, to identify the geographical and operational factors influencing network predictions and optimization decisions.

To compare the proposed framework against geographic routing, centralized machine learning, distributed learning without geospatial features, and distributed learning without explainability.

To evaluate predictive F1-score, end-to-end latency, packet delivery ratio, network availability, fault recovery time, energy consumption, communication overhead, and explanation fidelity under varying traffic, mobility, and failure conditions.

To determine the trade-offs among predictive accuracy, interpretability, scalability, privacy, and operational resilience in distributed 6G communication environments.

1.4. Research Questions

RQ1: How do geospatial characteristics influence communication coverage, network performance, and failure prediction in distributed 6G systems?

RQ2: To what extent does integrating geospatial intelligence with distributed AI improve failure-prediction performance compared with centralized machine learning and distributed learning without spatial features?

RQ3: How effectively can explainable AI identify the geographical and operational factors responsible for congestion, signal degradation, and communication failures?

RQ4: How does the proposed framework compare with baseline approaches in terms of end-to-end latency, packet delivery ratio, network availability, fault recovery time, energy consumption, and communication overhead?

RQ5: What trade-offs emerge among predictive performance, explanation fidelity, scalability, and privacy when the framework operates under heterogeneous traffic, mobility, and infrastructure-failure scenarios?

RQ6: Which components—geospatial intelligence, distributed learning, and explainability—contribute most significantly to the framework's overall resilience and performance?

1.5. Scope and Significance of the Study

1.5.1. Scope of the Study

The study focuses on designing, implementing, and experimentally evaluating an explainable AI-driven geospatial intelligence framework for distributed 6G communication systems. It integrates geospatial information, network telemetry, distributed machine learning, and interpretable predictive analytics within an adaptive network-management architecture. The research aligns with the IMT-2030 vision of intelligent, sustainable, and resilient next-generation connectivity (ITU, 2023).

The geographical scope encompasses simulated or experimentally modeled urban, suburban, and rural communication environments with different terrain profiles, infrastructure densities, mobility patterns, and traffic demands. The study will use appropriately documented network simulation data, publicly available datasets where suitable, and reproducible experimental scenarios. Actual 6G deployment data will be used only if accessible; therefore, findings from simulation will not automatically be interpreted as proof of real-world 6G performance.

The methodological scope includes geospatial feature engineering, distributed or federated model training, explainability using SHAP, failure prediction, congestion forecasting, and adaptive resource allocation. Evaluation will compare the proposed framework with four baseline approaches: conventional geographic routing, centralized machine learning, distributed learning without geospatial features, and distributed learning without XAI.

Performance evaluation will consider prediction accuracy, precision, recall, F1-score, end-to-end latency, packet delivery ratio, network availability, recovery time, energy consumption, communication overhead, and explanation fidelity. Ablation experiments will isolate the contributions of spatial information, distributed learning, and explainability. The study will not claim improvements until the proposed experiments have been completed.

1.5.2. Significance of the Study

Theoretical significance. The study will contribute an integrated research model connecting geospatial intelligence, explainable AI, distributed systems, and communication resilience. It will investigate how spatial

context and interpretable predictions influence intelligent network-management decisions, extending research on AI-enabled 6G architectures (Saad et al., 2020; Sun et al., 2025).

Technical significance. The proposed framework will provide a structured approach to geographical feature integration, distributed prediction, explainable failure diagnosis, and adaptive network optimization. Its comparative evaluation will identify which components contribute to measurable improvements and under what operating conditions.

Operational significance. Network operators may benefit from more interpretable congestion forecasts, geographically informed fault detection, and evidence-based recovery decisions. Evaluating latency, packet delivery, recovery time, and energy consumption together will help determine whether improved prediction translates into practical operational benefits.

Privacy and distributed-computing significance. By investigating distributed and federated learning, the research will assess opportunities to reduce raw-data exchange while examining the effects of communication overhead, heterogeneous data, and model coordination on system performance (Kairouz et al., 2021). Such an approach may be valuable where network information is distributed across multiple administrative or geographical domains.

Societal and developmental significance. The findings may inform future connectivity planning for smart cities, intelligent transportation, emergency communications, and underserved rural communities. However, benefits for rural coverage and digital inclusion will depend on infrastructure availability, implementation cost, and validation under realistic conditions.

Research and standardization significance. The study will establish reproducible comparison methods and evaluation metrics relevant to future AI-enabled communication architectures. Its results may support subsequent research aligned with the IMT-2030 framework, while recognizing that experimental findings from a proposed framework do not establish compliance with formal 6G standards (ITU, 2023).

Chapter Two: Literature Review

1.6. Emerging Trends in 6G Communication

Sixth-generation (6G) communication represents an emerging evolution toward intelligent, context-aware, sustainable, and highly integrated wireless networks. The International Telecommunication Union (ITU) established the IMT-2030 framework to guide research into future communication capabilities, including ubiquitous connectivity, artificial intelligence integration, integrated sensing and communication, and improved sustainability (International Telecommunication Union [ITU], 2023). These objectives extend beyond conventional improvements in bandwidth and latency toward intelligent coordination between communication infrastructure, computational resources, and physical environments.

Recent literature identifies AI-native networking, semantic communication, reconfigurable intelligent surfaces (RIS), edge intelligence, and non-terrestrial networks as important directions in 6G development (Ogenyi et al., 2025). AI-native architectures integrate learning and decision-making into network operations rather than treating intelligence as an independent optimization component. Semantic communication seeks to transmit information relevant to a particular task, while RIS can dynamically influence wireless propagation to improve coverage and energy efficiency. Edge intelligence enables computationally intensive decisions to occur closer to end users, potentially reducing response time and dependence on centralized infrastructure (Ogenyi et al., 2025).

Another important trend is the integration of terrestrial and non-terrestrial communication systems. Future networks are expected to coordinate terrestrial base stations with aerial platforms, satellites, and distributed Internet of Things (IoT) devices to support connectivity across diverse geographical environments. However, heterogeneous infrastructure introduces challenges in resource allocation, interoperability, security, and service continuity (Akbar et al., 2025).

The transition toward AI-native 6G also increases the importance of reliable performance evaluation. Network optimization should not be assessed solely through throughput or prediction accuracy; it should also consider end-to-end latency, packet delivery ratio, network availability, energy consumption, and recovery from failures. Recent surveys identify scalability, trustworthy automation, benchmark consistency, and real-time inference as continuing challenges in AI-driven 6G research (Akbar et al., 2025; Ogenyi et al., 2025).

For the present study, these trends establish the need for a framework that combines geospatial context, distributed AI, and interpretable network management. Geographical information can help explain why communication performance varies between locations, while distributed learning can support coordination among geographically separated nodes. Explainable AI can then make the resulting predictions more transparent to network operators. The proposed framework therefore focuses on the relationship between spatial awareness, predictive performance, and operational resilience rather than treating these capabilities as independent research problems.

1.7. Artificial Intelligence and Geospatial Intelligence

Artificial intelligence and geospatial intelligence provide complementary capabilities for understanding and optimizing geographically distributed communication systems. AI methods learn patterns from network telemetry, signal measurements, mobility records, and traffic observations, whereas geospatial technologies organize information according to location, distance, spatial relationships, terrain, and infrastructure distribution. Their integration can support location-aware prediction, coverage assessment, interference analysis, and proactive network resource allocation.

Machine learning techniques, including random forests, gradient boosting, support vector machines, deep neural networks, and reinforcement learning, can be applied to communication traffic forecasting, anomaly detection, signal-quality estimation, and adaptive resource management. Deep learning can identify nonlinear relationships in complex datasets, while reinforcement learning can optimize network actions through interaction with a simulated or operational environment. However, model performance may deteriorate when geographical conditions or traffic distributions differ from those represented in training data. This makes spatially diverse evaluation and model generalization important research considerations (Saad et al., 2020).

Geospatial intelligence can enrich these models with spatial features such as terrain elevation, building density, road networks, base-station locations, population distribution, user mobility, and estimated signal propagation conditions. Geographic information systems (GIS) can support spatial feature engineering, coordinate alignment, coverage mapping, and identification of underserved regions. When integrated with network telemetry, these features may help distinguish between congestion caused by excessive demand and poor communication quality associated with geographical obstacles or inadequate infrastructure.

A spatially informed model could, for example, predict the probability of communication failure at a particular location and identify the variables contributing to that prediction. This capability could support proactive resource allocation, handover planning, and infrastructure maintenance. Nevertheless,

geographical correlation does not necessarily establish causation; therefore, the research should evaluate whether spatial features provide measurable predictive benefits over models using network telemetry alone.

Recent AI-native 6G research emphasizes contextual intelligence, edge processing, and adaptive networking as interconnected capabilities (Ogenyi et al., 2025). However, the specific contribution of geospatial intelligence must be evaluated rather than assumed. A controlled comparison between a model trained on network telemetry alone and an otherwise equivalent model incorporating spatial features can determine whether geographical information improves predictive performance, robustness, and generalization.

In this study, geospatial intelligence will be integrated with distributed machine learning to develop spatially aware predictions of congestion, signal degradation, and infrastructure-related communication failures. The contribution of geographical features will be measured using precision, recall, F1-score, calibration, and performance across different geographical scenarios. Spatial feature attribution will also be examined to determine whether the model's decisions correspond to plausible network and environmental conditions.

1.8. Distributed Edge–Cloud Systems

Distributed edge–cloud computing combines computational resources located near data sources with centralized or regional cloud infrastructure. Edge nodes can process time-sensitive observations locally, while cloud systems support large-scale training, historical analysis, model coordination, and resource-intensive computations. This architecture is particularly relevant to future communication networks, where geographically dispersed devices generate substantial volumes of heterogeneous data.

In 6G environments, distributed edge–cloud systems can support intelligent radio access networks, connected vehicles, industrial IoT, smart-city infrastructure, and integrated sensing applications. Processing data near users may reduce the need to transmit every observation to a centralized server, potentially improving responsiveness and reducing backhaul traffic. The integration of edge intelligence with semantic communication and RIS has consequently emerged as an important direction in AI-native 6G research (Ogenyi et al., 2025).

However, distributed architectures introduce several technical challenges. Edge nodes may differ in processing capacity, storage, energy availability, network connectivity, and data quality. Communication links between edge and cloud systems can experience variable latency, congestion, and interruptions. Moreover, coordinating multiple learning agents requires model synchronization, workload distribution, fault management, and protection against unreliable or malicious participants.

Federated learning provides one possible solution by allowing participating nodes to train local models and share model updates rather than routinely transferring raw datasets to a central repository. Kairouz et al. (2021) systematically examined the opportunities and unresolved problems of federated learning, including statistical heterogeneity, communication efficiency, privacy, and system constraints. Although federated learning can reduce raw-data exchange, it does not automatically guarantee privacy or security; model updates can still expose information, and additional safeguards may be necessary.

For distributed 6G communication, these considerations suggest that network optimization should jointly account for prediction quality, inference latency, energy use, communication overhead, and fault recovery. A model that improves accuracy but requires excessive inter-node communication may be unsuitable for resource-constrained edge environments.

Accordingly, the proposed framework will coordinate edge-level inference and distributed model learning with cloud-assisted analytics. Geospatial features will be incorporated into the learning process, while

network failures and changing traffic conditions will be used to evaluate adaptive operation. Baseline experiments will compare the distributed approach with centralized learning and distributed learning without geospatial information. Measurements will include end-to-end latency, packet delivery ratio, model convergence, communication overhead, energy consumption, and recovery time.

This approach will help establish whether distributed processing provides practical resilience benefits and whether those benefits persist under heterogeneous geographical conditions and intermittent connectivity.

1.9. Explainable AI for Network Resilience

Explainable artificial intelligence (XAI) comprises methods that help users understand how AI systems generate predictions and decisions. In communication networks, explainability is particularly relevant when automated systems allocate resources, detect anomalies, manage network slices, or respond to service degradation. Network operators need more than an alert indicating that a failure may occur; they also need information about the factors contributing to the prediction and the reliability of the recommended response.

Lundberg and Lee (2017) introduced SHapley Additive exPlanations (SHAP), a unified framework for interpreting model predictions through feature contributions. SHAP can help identify which input variables most strongly influence a prediction, including signal strength, traffic load, mobility, infrastructure density, and geographical conditions. However, feature attribution should not automatically be interpreted as causal evidence, and explanations may be sensitive to correlated features, model behavior, and data distributions.

Recent research specifically addressing 6G communication has examined the role of XAI in network slicing, resource allocation, fault diagnosis, and vehicular communications. Sun et al. (2025) reviewed explainability methods for communication systems and identified challenges involving scalability, real-time application, and interdisciplinary integration. Their findings support the need to consider interpretability alongside operational performance when developing intelligent communication architectures.

Network resilience refers to a system's ability to withstand disruptions, maintain essential services, and recover from failures. In distributed 6G environments, resilience may be affected by signal interference, node failures, changing traffic demands, mobility, and communication-link interruptions. AI can help predict disruptions and recommend corrective actions, while XAI can provide interpretable evidence supporting those actions. Nevertheless, an explanation is useful only if it is sufficiently accurate, stable, timely, and understandable for its intended user.

A comprehensive evaluation should therefore measure both predictive and explanatory performance. Predictive metrics may include precision, recall, F1-score, false-alarm rate, and calibration. Operational metrics may include network availability, packet delivery ratio, end-to-end latency, and recovery time. Explanation quality can be assessed through fidelity, stability, consistency, and computational cost. Where operator studies are feasible, human interpretability and decision usefulness can also be evaluated.

For this research, SHAP-based feature attribution will be integrated with distributed AI predictions to explain geographical and operational contributors to network degradation. The framework will compare an explainable model against a comparable model without explicit XAI, examining whether explanations introduce computational overhead and whether their availability improves fault diagnosis. The objective is not to assume that explainability inherently increases resilience, but to establish when transparent predictions support better-informed network management.

1.10. Research Gaps

The literature demonstrates substantial progress in AI-native communication, geospatial analysis, distributed computing, and explainable machine learning. However, the integration of these capabilities into a single, systematically evaluated framework for resilient distributed 6G communication remains an important research direction.

Gap 1: Limited integration of geospatial intelligence and distributed 6G learning. Existing research on AI-native networks emphasizes edge intelligence and adaptive communication, but the contribution of geographical features to distributed failure prediction requires more systematic evaluation. This study will compare spatially informed learning against distributed learning without geospatial features (Ogenyi et al., 2025).

Gap 2: Insufficient joint evaluation of explainability and operational resilience. XAI research has examined interpretability in network slicing and intelligent communication, but explanatory quality and operational outcomes are not always evaluated together. The proposed study will jointly measure explanation fidelity, predictive performance, latency, and recovery time (Sun et al., 2025).

Gap 3: Inadequate comparison across heterogeneous baselines. Reported improvements may depend on differences in datasets, experimental settings, or evaluation metrics. A controlled comparison among geographic routing, centralized machine learning, distributed learning without geospatial features, distributed learning without XAI, and the complete proposed framework will help isolate the contribution of each component.

Gap 4: Limited assessment of trade-offs in distributed environments. Federated and edge learning can reduce dependence on centralized data processing, but their benefits may be offset by communication overhead, heterogeneous resources, and coordination costs. This research will evaluate energy consumption, communication overhead, latency, and predictive performance under different network conditions (Kairouz et al., 2021).

Gap 5: Insufficient robustness testing across geographical and operational conditions. A model that performs well in one scenario may not generalize to different terrain profiles, infrastructure densities, mobility patterns, or traffic loads. The proposed evaluation will include multiple geographical scenarios and controlled failure conditions to assess generalization and resilience.

Gap 6: Lack of an integrated, reproducible evaluation framework. Recent surveys identify continuing challenges involving scalability, real-time inference, trustworthiness, and performance benchmarking in AI-driven 6G systems (Akbar et al., 2025; Ogenyi et al., 2025). This study will address this methodological gap through documented experimental configurations, common baseline conditions, explicit evaluation metrics, and ablation studies.

1.10.1. Summary of the Research Gap

Research dimension	Identified limitation	Proposed contribution
Geospatial intelligence	Spatial features may be omitted or insufficiently evaluated	Integrate and test geographical features
Distributed learning	Coordination and communication costs remain important	Evaluate edge–cloud and distributed learning

Explainability	Interpretability may be assessed separately from network outcomes	Measure explanation fidelity and operational performance
Network resilience	Failure prediction does not necessarily demonstrate recovery improvement	Evaluate availability, delivery ratio, and recovery time
Comparative evaluation	Baselines and metrics may differ across studies	Use controlled baseline comparisons
Generalization	Performance across heterogeneous locations may be uncertain	Test multiple geographical and failure scenarios

The central research gap is therefore the need for an integrated and reproducible approach that combines geospatial intelligence, distributed AI, and explainable decision-making while evaluating their joint influence on communication resilience. The proposed framework will address this gap through controlled experiments and ablation studies, distinguishing experimentally demonstrated improvements from expected benefits.

Chapter Three: Research Methodology

1.11. Research Design and Framework

1.11.1. Research Design

This study will adopt a quantitative, experimental, and comparative research design to develop and evaluate an Explainable AI-Driven Geospatial Intelligence Framework for Resilient Distributed 6G Communication Systems (EAGI-6G). The research will investigate whether integrating geospatial features, distributed machine learning, and explainable artificial intelligence (XAI) improves network performance and resilience compared with conventional and alternative AI-based approaches.

The experimental design will combine network simulation, geospatial feature engineering, machine learning, distributed model training, and explainability analysis. Simulation is appropriate because it allows communication conditions, traffic loads, mobility patterns, and network failures to be systematically varied while maintaining controlled experimental conditions. The proposed evaluation will follow reproducible machine-learning practices and report performance using clearly defined metrics and baseline comparisons (International Telecommunication Union [ITU], 2023; Kapoor & Narayanan, 2023).

The research will use a comparative experimental strategy involving five configurations: conventional geographic routing, centralized machine learning, distributed learning without geospatial features, distributed learning without explicit XAI, and the complete proposed EAGI-6G framework. These configurations will help isolate the contributions of spatial intelligence, distributed learning, and explainability to overall system performance.

The independent variables will include geographical characteristics, network traffic intensity, user mobility, communication interference, node failures, and model configuration. The dependent variables will include failure-prediction F1-score, end-to-end latency, packet delivery ratio, network availability, recovery time, energy consumption, communication overhead, and explanation fidelity. Controlled experiments will assess both average performance and variability under different operating conditions.

The study will distinguish between model-prediction performance and actual network resilience. Improved failure prediction will not automatically be interpreted as improved resilience; recovery performance and service continuity must also be measured. This distinction supports a rigorous assessment of whether the proposed framework provides practical benefits beyond predictive accuracy.

1.11.2. Proposed Research Framework

The proposed EAGI-6G framework will consist of six interconnected components: data acquisition, geospatial feature engineering, distributed AI learning, explainable prediction, adaptive network optimization, and performance evaluation.

The data acquisition component will collect or generate network telemetry, geographical information, mobility observations, and failure-event records. The geospatial feature-engineering component will transform these heterogeneous inputs into spatially aligned variables representing terrain, infrastructure distribution, estimated signal conditions, and geographical variations in network demand.

The distributed AI component will coordinate model training and inference across edge nodes and cloud infrastructure. Where appropriate, federated learning will be used to exchange model updates instead of routinely transferring raw local datasets. Federated learning introduces its own communication and privacy challenges, which will be measured as part of the evaluation (Kairouz et al., 2021).

The explainability component will apply SHapley Additive exPlanations (SHAP) or suitable model-specific attribution methods to identify features contributing to network-failure predictions. SHAP provides a framework for attributing individual predictions to input features, although these attributions do not independently establish causal relationships (Lundberg & Lee, 2017).

The adaptive optimization component will use model predictions to support decisions such as traffic redistribution, resource reallocation, and selection of alternative network paths. The final evaluation component will compare the proposed system against the baseline configurations under identical or appropriately controlled conditions.

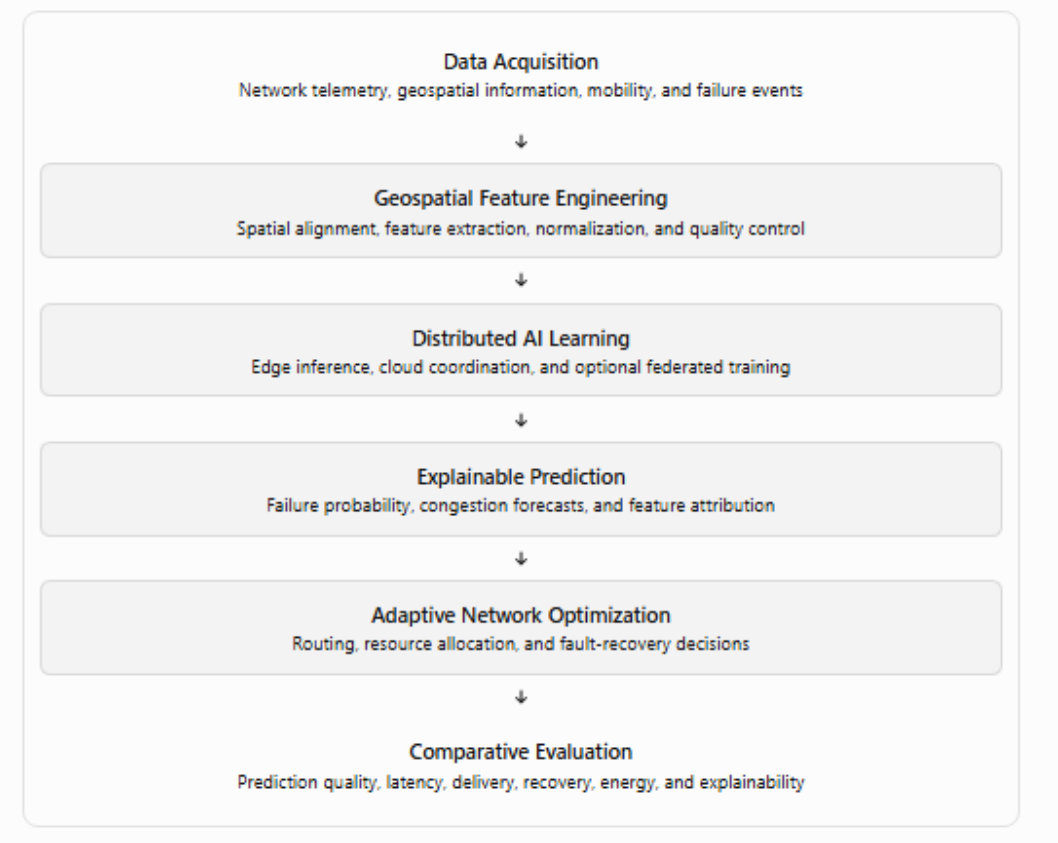


Figure 1. Conceptual architecture

The framework will be evaluated through component-level ablation studies. Removing geospatial features will measure their incremental contribution; removing distributed learning will reveal the effects of centralized versus distributed processing; and disabling explicit XAI will establish the computational cost and explanatory benefits of the explainability component. These comparisons will help determine which design elements contribute to measurable improvements.

1.12. Data Collection and Geospatial Feature Engineering

1.12.1. Data Collection Strategy

The study will adopt a multi-source data collection strategy combining network simulation outputs, geospatial datasets, mobility scenarios, and communication-failure records. These data will support the development and evaluation of spatially aware AI models for distributed 6G communication. The data collection process will be designed to ensure consistency, traceability, reproducibility, and suitability for comparative experiments.

The first data source will consist of simulated network telemetry generated under controlled communication scenarios. Variables will include signal-to-noise ratio, received signal strength, traffic load, packet loss, latency, throughput, node status, energy consumption, and network congestion. Network failures will be introduced through predefined scenarios, including node disconnection, link degradation, interference, and sudden traffic increases. Simulation is particularly useful for investigating future communication architectures for which comprehensive operational 6G datasets may not yet be available (International Telecommunication Union [ITU], 2023).

The second data source will comprise geospatial information, including digital elevation models, infrastructure coordinates, road networks, land-use characteristics, and population-density estimates where suitable datasets are available. Public geospatial datasets may be obtained from authoritative sources such as the United States Geological Survey (USGS) and OpenStreetMap contributors. These sources provide complementary information for constructing geographical scenarios and examining the relationship between environmental characteristics and communication performance (OpenStreetMap contributors, n.d.; U.S. Geological Survey, n.d.).

The third data source will consist of mobility and traffic-demand scenarios representing pedestrian movement, vehicular mobility, spatially concentrated demand, and changes in user density. These observations may be generated through simulation or obtained from appropriately licensed datasets. A fourth source will comprise event labels indicating normal operation, congestion, signal degradation, and communication failure. These labels will support supervised learning and enable the calculation of predictive performance metrics.

Where publicly available real-network measurements are suitable, they will be used for supplementary validation. However, simulation-generated observations and real-world measurements will be clearly distinguished. The study will not present simulated results as evidence of deployment performance.

1.12.2. Data Sources and Variables

The proposed data structure will integrate network, geographical, temporal, and operational information into a common analytical dataset.

Data category	Representative variables	Purpose
Network telemetry	Signal strength, SNR, latency, throughput, packet	Characterize communication

	loss	quality
Geospatial information	Latitude, longitude, elevation, terrain, land use	Represent geographical conditions
Infrastructure	Base-station coordinates, node density, link distance	Model network topology and coverage
Mobility and demand	User density, speed, movement direction, traffic load	Represent changing demand
Distributed computing	CPU utilization, processing delay, communication overhead	Evaluate edge–cloud performance
Energy and resilience	Energy consumption, failure status, recovery time	Measure operational efficiency
Prediction labels	Normal operation, congestion, degradation, failure	Train and evaluate predictive models

Table 1. Proposed data categories and variables

The collection process will record the spatial coordinates, timestamps, measurement units, source provenance, and relevant quality indicators associated with each observation. This information will support spatial alignment and temporal synchronization across heterogeneous datasets. Recent research on spatiotemporal network prediction demonstrates the relevance of combining network measurements with spatial and temporal relationships for forecasting communication performance (Shaabanzadeh & Sánchez, 2024).

1.12.3. Data Preprocessing and Quality Assurance

The collected data will undergo systematic preprocessing before model training. Duplicate records will be identified and removed, invalid coordinates will be corrected where possible, and missing observations will be handled using documented imputation or exclusion procedures. Outliers will be examined to distinguish measurement errors from legitimate events such as abrupt interference or sudden congestion.

Continuous variables will be normalized or standardized when required by the selected algorithms. Categorical variables, including land-use classes and node states, will be encoded using appropriate techniques. Geographic coordinates will be transformed into a suitable projected coordinate reference system when calculating distances, areas, and spatial relationships. The original coordinates and transformations will be documented to preserve spatial consistency.

Temporal preprocessing will align observations using a common timestamp convention and sampling interval. If measurements are collected at different frequencies, resampling and aggregation will be performed without introducing information from future observations into past predictions.

Particular attention will be given to data leakage. Preprocessing operations such as normalization, feature selection, and imputation will be fitted using training data only and then applied to validation and test sets. Kapoor and Narayanan (2023) demonstrated that data leakage can lead to substantially overoptimistic machine-learning results, making leakage prevention essential for credible experimental evaluation.

1.12.4. Geospatial Feature Engineering

Geospatial feature engineering will transform raw geographical data into meaningful variables that can be incorporated into distributed AI models. The process will include coordinate alignment, terrain analysis, infrastructure-density estimation, spatial relationship extraction, and integration with network telemetry.

Terrain and elevation features. Elevation differences and terrain characteristics will be derived from available digital elevation models. These variables may help characterize geographical conditions associated with wireless propagation. Where appropriate, terrain obstruction and line-of-sight indicators will be estimated using a suitable propagation model rather than inferred from elevation alone.

Infrastructure and spatial-density features. The coordinates of communication nodes will be used to calculate nearest-node distance, local infrastructure density, and neighboring-node counts. These variables will help characterize the availability of nearby communication resources and potential coverage gaps.

Mobility and demand features. User density, estimated movement speed, movement direction, and temporal traffic concentration will be incorporated when data are available. Spatial aggregation will help identify areas experiencing high demand or rapidly changing communication requirements.

Network-quality features. Signal strength, signal-to-noise ratio, packet loss, and latency will be associated with the relevant network node and geographical location. Historical measurements may be used to construct lagged features for forecasting, provided that the prediction process does not access future observations.

Spatial-neighborhood features. Neighboring nodes will be identified using geographic distance, network topology, or both. Neighborhood aggregation may include average neighboring-node traffic, local failure frequency, and neighboring-link quality. These features can help identify geographically localized disruptions and correlated network degradation.

The resulting feature vector for node i at time t can be represented as:

$$\mathbf{x}_{i,t} - [\mathbf{g}_i, \mathbf{n}_{i,t}, \mathbf{m}_{i,t}, \mathbf{d}_{i,t}]$$

where $\mathbf{g}_i$ represents static geospatial characteristics, $\mathbf{n}_{i,t}$ represents network telemetry, $\mathbf{m}_{i,t}$ represents mobility-related information, and $\mathbf{d}_{i,t}$ represents distributed-system and operational features.

1.12.5. Spatial and Temporal Data Partitioning

The dataset will be divided into training, validation, and test subsets. Because geographically neighboring observations may share similar characteristics, random splitting alone may produce overly optimistic performance estimates. Wang et al. (2023) proposed Spatial+ cross-validation, which considers differences in both geographical and feature spaces when evaluating geospatial machine-learning models.

Accordingly, the study will use spatially separated test regions or spatial-block validation where appropriate. Temporal evaluation will also preserve chronological order for forecasting tasks. Where the available dataset permits, a final test set will contain observations from geographical regions or time periods not used during model development.

The proposed evaluation will use training data for model fitting, validation data for hyperparameter selection, and test data for final performance reporting. The same partitions will be applied to comparable baseline models to support fair comparisons. If multiple scenarios are generated from the same underlying simulation

configuration, they will be grouped appropriately to prevent closely related observations from appearing in both training and test sets.

1.12.6. Data Integration and Final Dataset Construction

The final analytical dataset will be created by joining geospatial features, network measurements, mobility variables, and operational labels using consistent spatial identifiers and timestamps. Each record will represent a network node or communication link observed during a defined time interval.

Quality checks will verify coordinate validity, temporal alignment, feature completeness, label consistency, and the absence of unintended overlap between training and test data. Data dictionaries, preprocessing scripts, configuration files, and feature-generation procedures will be maintained to support reproducibility.

The resulting dataset will provide the foundation for distributed learning, explainable failure prediction, and adaptive network optimization in the subsequent methodological stages. The final feature set and sample size will be documented after the data sources and simulation configuration have been established.

1.13. Distributed AI Model Development

1.13.1. Overview of Distributed AI Model Development

This study will develop a distributed artificial intelligence (AI) architecture for the proposed Explainable AI-Driven Geospatial Intelligence Framework for Resilient Distributed 6G Communication Systems (EAGI-6G). The architecture will combine geospatial features, network telemetry, distributed machine learning, and predictive analytics to support congestion forecasting, communication-failure detection, and adaptive resource allocation.

Distributed AI is appropriate for geographically dispersed communication networks because data originate from multiple access points, edge devices, base stations, and cloud platforms. Processing information across these locations can reduce dependence on centralized data collection and enable decisions closer to the source of network events. However, distributed learning must account for heterogeneous data distributions, communication costs, computational limitations, and model coordination (Kairouz et al., 2021).

The proposed model will use a hierarchical edge–cloud architecture. Edge nodes will perform local feature processing and time-sensitive inference, while regional or cloud servers will coordinate model updates, perform computationally intensive analysis, and maintain global model versions. Where supported by the experimental environment, federated learning will enable collaborative model training without routinely transmitting raw local datasets. This approach follows established federated-learning principles while recognizing that model updates do not automatically guarantee privacy or security (Kairouz et al., 2021).

The development process will comprise model selection, local training, distributed coordination, global model aggregation, explainable prediction, and performance evaluation. These components will be implemented and tested under controlled network scenarios before their suitability for resilient 6G communication is assessed.

1.13.2. Distributed System Architecture

The proposed architecture will contain three computational layers.

Edge layer. The edge layer will process local network telemetry and geographical features, including signal quality, traffic load, neighboring-node conditions, and recent communication failures. Each edge node will generate local predictions and, when distributed training is enabled, update its model using locally available

observations. Edge inference will support rapid identification of potential congestion, link degradation, and node failures.

Regional coordination layer. Regional servers will coordinate groups of edge nodes, aggregate model updates where applicable, monitor model convergence, and manage communication between edge and cloud infrastructure. This intermediate layer will help evaluate whether hierarchical coordination reduces communication overhead or improves scalability compared with a centralized learning architecture.

Cloud layer. The cloud layer will maintain global model versions, coordinate training rounds, perform cross-region evaluation, and support computationally intensive model development. It will also provide a common evaluation environment for comparing centralized and distributed approaches.

This architecture is consistent with the broader direction of integrating edge intelligence and distributed computation into future communication systems (International Telecommunication Union [ITU], 2023; Saad et al., 2020). Its practical advantages, however, will be established through experimental measurements rather than assumed from the architectural design alone.

1.13.3. Model Selection and Development

The proposed framework will evaluate machine-learning models for predicting communication failures, forecasting congestion, and estimating network degradation. Model selection will consider predictive accuracy, computational complexity, inference latency, scalability, and suitability for distributed edge–cloud execution. Distributed machine learning research emphasizes that model performance must be balanced against communication efficiency, resource constraints, and data heterogeneity (Kairouz et al., 2021; Zhang et al., 2026).

Three categories of predictive models will be investigated.

Conventional machine-learning models. Random Forest and XGBoost will serve as candidate models for structured network and geospatial data. These algorithms can capture nonlinear relationships among signal quality, geographical characteristics, traffic load, and failure events. Their predictive performance will provide a reference for evaluating more complex distributed approaches.

Deep-learning models. Where sufficient sequential observations are available, a recurrent neural network, such as a long short-term memory (LSTM) model, will be evaluated for temporal traffic forecasting and communication-degradation prediction. The model will use historical measurements to predict future network conditions. Its additional computational requirements will be considered when evaluating edge deployment.

Distributed and federated models. A federated-learning configuration will enable multiple edge nodes to train local model instances and exchange model updates through a coordinating server. The global model will be evaluated against centralized training and local-only learning. Federated edge learning is particularly relevant to 6G because it supports collaborative model development across geographically distributed devices with different communication and computational capabilities (Zhang et al., 2025).

The final model will be selected using validation data rather than test-set performance. Hyperparameters will be optimized under consistent experimental conditions, and the selected configuration will be evaluated on held-out geographical regions or time periods whenever the data permit.

1.13.4. Distributed Training and Model Aggregation

The study will use Federated Averaging (FedAvg) as the primary distributed-training algorithm. FedAvg enables participating nodes to train local models and periodically transmit model parameters to a

coordinating server, which aggregates the updates into a global model (McMahan et al., 2017). Federated edge learning has subsequently been investigated as an enabling approach for collaborative intelligence in 6G networks (Tao et al., 2025).

Let K represent the number of participating edge nodes and n_k the number of training observations available at node k. The global learning objective can be expressed as:

$$\min_{\mathbf{w}} F(\mathbf{w}) - \sum_{k-1}^{K} \frac{n_k}{N} F_k(\mathbf{w})$$

where $N - \sum_{k-1}^{K} n_k$, $\mathbf{w}$ denotes the global model parameters, and F_k represents the local loss function at node k.

After local training, the server will aggregate the model parameters according to:

$$\mathbf{w}_{t+1} - \sum_{k-1}^{K} \frac{n_k}{N} \mathbf{w}_{t+1}^{(k)}$$

where $\mathbf{w}_{t+1}^{(k)}$ represents the locally updated model at node k during training round t. This weighted aggregation procedure provides the basis for coordinating learning across distributed network locations (McMahan et al., 2017).

To evaluate the impact of distributed training, experiments will vary the number of participating nodes, local training epochs, communication rounds, and data heterogeneity. Model convergence, predictive performance, communication overhead, and training time will be recorded. These measurements are important because distributed-learning performance depends on both model optimization and communication constraints (Tao et al., 2025).

1.13.5. Handling Non-IID Data and Resource Heterogeneity

In geographically distributed communication networks, data collected by different edge nodes are unlikely to follow identical statistical distributions. Urban nodes may experience higher traffic volumes, whereas rural nodes may experience sparse demand, different propagation conditions, or intermittent connectivity. This creates a non-independent and identically distributed (non-IID) learning problem.

The study will evaluate the effect of non-IID data by varying the distribution of failure events, traffic intensity, signal quality, and geographical characteristics across edge nodes. Where appropriate, the experiments will compare FedAvg with a suitable alternative, such as FedProx, which introduces a proximal regularization term to reduce divergence between local and global model updates (Li et al., 2020).

The local optimization objective for FedProx can be expressed as:

$$\min_{\mathbf{w}} \left[F_k(\mathbf{w}) + \frac{\mu}{2} \|\mathbf{w} - \mathbf{w}_t\|^2 \right]$$

where $F_k(\mathbf{w})$ represents the local loss, $\mathbf{w}_t$ denotes the global model at the beginning of the training round, and μ controls the strength of the proximal regularization.

The results will establish whether the proposed architecture remains effective when network nodes have unequal data volumes, different geographical conditions, and varying computational resources.

1.13.6. Explainable Distributed Prediction

Explainability will be integrated into the distributed AI pipeline to help identify the factors contributing to predicted congestion and communication failures. The selected model will generate a prediction for each evaluated network node, while SHAP or an appropriate model-specific explanation method will estimate the contributions of individual input features (Lundberg & Lee, 2017).

For a prediction $f(\mathbf{x})$, an additive explanation can be represented as:

$$f(\mathbf{x}) = \phi_0 + \sum_{j-1}^{M} \phi_j$$

where ϕ_0 is the baseline prediction, M is the number of input features, and ϕ_j represents the attribution associated with feature j.

The research will evaluate explanation fidelity, stability, computational cost, and consistency across geographical scenarios. Explanation fidelity will assess how accurately the explanation represents model behavior, while stability will examine whether similar inputs produce reasonably consistent explanations. Feature attribution will not be treated as proof of causality.

The study will compare the explainable configuration with an equivalent model operating without explicit XAI. This comparison will quantify the computational overhead of generating explanations and determine whether interpretability can be achieved without unacceptable degradation in inference latency. Research on explainable AI for communication and network slicing identifies real-time execution and scalable interpretation as important challenges for AI-enabled 6G systems (Sun et al., 2025).

1.13.7. Model Development Algorithm

The proposed distributed AI model will follow the algorithm below.

Input:

Geospatial features G

Network telemetry X

Failure labels Y

Number of edge nodes K

Maximum communication rounds T

Initialize global model w_0

For each communication round t = 0, 1, ..., T − 1:

Select available edge nodes

For each participating edge node k:

Load local training dataset D_k

Combine network telemetry and geospatial features

Train local model using the selected optimizer

Generate local model parameters w_k

Transmit model updates to the coordinator

Aggregate received model updates

Update global model w_{t+1}

Evaluate convergence and validation performance

If stopping criteria are satisfied:

Stop training

Evaluate the final model on held-out test data

Generate explanations for selected predictions

Measure predictive and operational performance

Compare against baseline configurations

Output:

Trained distributed AI model

Failure and congestion predictions

Feature-attribution explanations

Comparative evaluation results

Algorithm 3.1. Proposed distributed AI model-development procedure.

1.13.8. Evaluation of Distributed Model Development

The developed models will be evaluated using a consistent experimental protocol. The centralized machine-learning configuration will establish a reference for predictive performance, while local-only and federated configurations will help quantify the effects of distributed training.

Evaluation dimension	Metric	Purpose
Predictive quality	Precision, recall, F1-score	Measure failure-detection performance
Classification reliability	AUROC and calibration error	Evaluate discrimination and probability reliability
Training efficiency	Convergence rounds and training time	Measure learning efficiency
Communication efficiency	Bytes transferred per training round	Quantify coordination overhead
Inference efficiency	End-to-end latency	Assess operational responsiveness
Resource efficiency	Energy consumption and CPU utilization	Measure computational cost
Explainability	Fidelity and stability	Evaluate explanation quality
Resilience	Recovery time and packet delivery ratio	Measure operational recovery and service continuity

The experiments will use repeated runs with documented random seeds where applicable. Results will be reported using means and standard deviations or confidence intervals. Statistical tests will be selected according to the distribution and dependence structure of the observations. The same test scenarios and evaluation procedures will be applied to all comparable baselines.

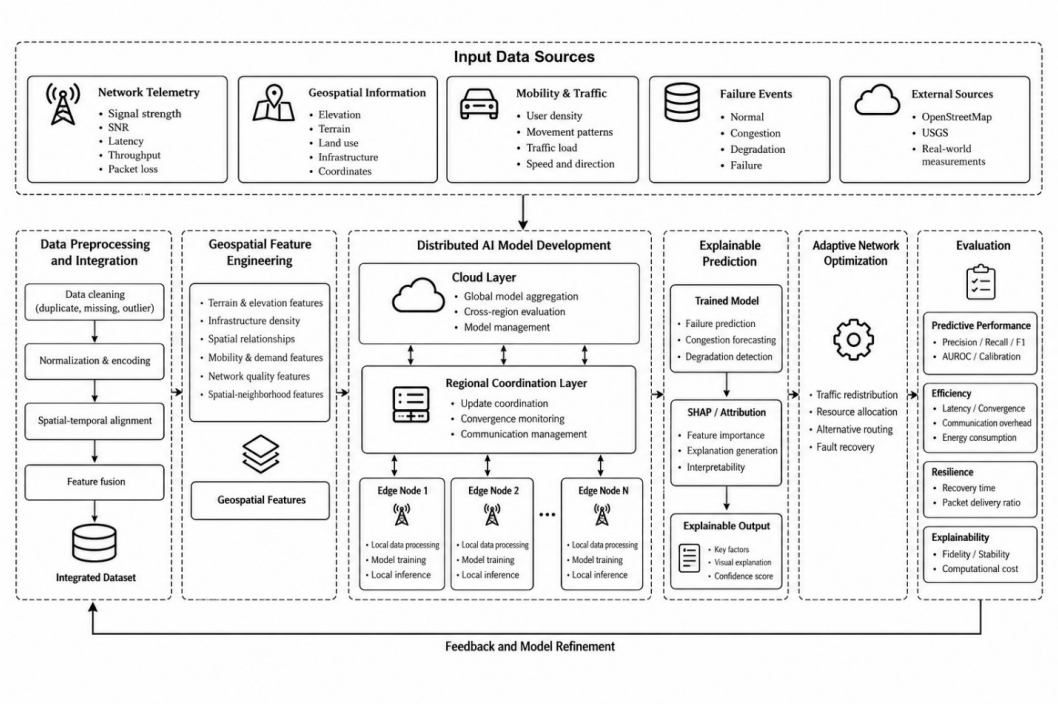


Figure 2. Model

1. Chapter Three: Research Methodology

1.1. Explainability and Resilience Optimization

1.1.1. Explainability Framework

This study will integrate explainable artificial intelligence (XAI) into the proposed Explainable AI-Driven Geospatial Intelligence Framework (EAGI-6G) to make communication-failure predictions and network-optimization decisions more transparent. The framework will explain how geospatial characteristics, network telemetry, mobility, and distributed-system conditions contribute to predicted congestion, signal degradation, and communication failures. Explainability will be evaluated as a measurable system property rather than assumed to improve network resilience automatically.

SHapley Additive exPlanations (SHAP) will be the primary feature-attribution method because it provides a consistent approach for explaining individual model predictions through feature contributions (Lundberg & Lee, 2017). The study will apply SHAP to identify the relative contributions of signal-to-noise ratio, packet loss, traffic intensity, terrain characteristics, infrastructure density, neighboring-node conditions, and historical failure indicators.

For a model prediction $f(\mathbf{x})$, the additive explanation will be represented as:

$$f(\mathbf{x}) = \phi_0 + \sum_{j-1}^{M} \phi_j$$

where ϕ_0 denotes the baseline output, M is the number of input features, and ϕ_j represents the contribution attributed to feature j. For classification models, the output scale—such as predicted probability or log-odds—will be explicitly documented to ensure consistent interpretation.

Because feature attribution does not establish causality, explanations will be interpreted as evidence of model behavior rather than proof that a particular geographical factor caused a communication failure. The

research will therefore combine feature attribution with controlled simulation scenarios to investigate how changes in network conditions affect model predictions (Lundberg & Lee, 2017).

1.1.2. Explainability Evaluation

The quality of explanations will be assessed using fidelity, stability, consistency, computational cost, and operational usefulness. Fidelity will measure whether the explanation adequately represents the model's behavior; stability will assess how explanations change under small, plausible perturbations; and consistency will examine whether similar conditions produce comparable explanations.

The research will also investigate whether explanations remain computationally feasible in distributed edge–cloud environments. Explanation-generation time and processing overhead will be recorded separately from ordinary prediction latency. This distinction is important because an interpretable model may produce useful insights but still be unsuitable for time-sensitive network management if its explanations require excessive computation.

Recent research on explainable AI for communications and network slicing identifies real-time execution, scalable interpretation, and trustworthy decision support as important challenges for AI-enabled 6G systems (Sun et al., 2025). Accordingly, EAGI-6G will evaluate predictive performance and explanation quality together rather than treating either as sufficient evidence of system effectiveness.

1.1.3. Resilience Optimization Strategy

The resilience-optimization component will use explainable predictions to support adaptive network-management decisions. Its primary purpose is to maintain communication service under changing traffic, mobility, interference, and infrastructure-failure conditions. The optimization process will consider network performance, fault recovery, energy efficiency, and resource constraints simultaneously.

The proposed framework will evaluate four adaptive actions: traffic redistribution across available network paths, resource allocation to congested nodes, selection of alternative routes when links degrade, and recovery coordination when nodes or communication links fail. These actions will be tested in a controlled simulation environment to determine whether explainable predictions lead to better operational outcomes than predictions without explicit explanations.

The optimization problem will be formulated as a multi-objective decision problem:

$$\min_{\mathbf{a}_t} J(\mathbf{a}_t) = \lambda_L \widetilde{L}_t + \lambda_P \widetilde{P}_{\text{loss},t} + \lambda_E \widetilde{E}_t + \lambda_R \widetilde{T}_{\text{rec},t}$$

where $\mathbf{a}_t$ represents the network-management actions at time t; $\widetilde{L}_t$ is normalized end-to-end latency; $\widetilde{P}_{\text{loss},t}$ is normalized packet-loss rate; $\widetilde{E}_t$ is normalized energy consumption; and $\widetilde{T}_{\text{rec},t}$ is normalized recovery time. The coefficients $\lambda_L, \lambda_P, \lambda_E, \lambda_R$ represent the relative importance of each objective.

The proposed optimization approach will initially use a constrained, rule-based decision policy informed by the trained model and its explanations. For example, a predicted link failure may trigger an alternative-route assessment, while a congestion prediction may trigger traffic redistribution. This design supports interpretable decision rules without assuming that SHAP feature attribution itself determines the optimal action.

Recent research on 6G performance evaluation emphasizes the importance of evaluating multiple key performance indicators (KPIs) together and identifying trade-offs among efficiency, scalability, trustworthiness, and real-time optimization (Islam et al., 2026). The proposed framework will therefore

evaluate both the effectiveness of individual recovery actions and their combined effect on network performance.

1.1.4. Failure Detection and Recovery Procedure

The proposed framework will implement the following operational sequence.

1. Monitor network telemetry, geographical conditions, and node status.
2. Predict congestion, signal degradation, or communication-failure probability using the trained distributed model.
3. Generate a local explanation identifying the principal factors contributing to the prediction.
4. Determine an appropriate corrective action subject to bandwidth, connectivity, capacity, and service constraints.
5. Execute the action within the simulation and monitor the resulting network state.
6. Measure service interruption, packet delivery, latency, energy use, and recovery time.
7. Record the outcome and use it for subsequent model evaluation and refinement.

The system will distinguish between a predicted failure and an observed failure. A prediction will not automatically count as a successful recovery. Recovery success will be determined from measurable operational evidence, such as restored connectivity, resumed packet delivery, or return to a predefined service threshold.

The study will also evaluate false alarms and missed failures. A false alarm may lead to unnecessary rerouting or resource reallocation, while a missed failure may prolong service disruption. Precision, recall, false-alarm rate, and recovery time will therefore be analyzed together.

1.1.5. Explainability–Resilience Trade-off Analysis

A central objective of this research is to determine whether the additional computational cost of explainability is justified by its contribution to network diagnosis and management. The experiments will compare three configurations: predictive AI without explicit XAI, predictive AI with SHAP explanations but without explanation-informed actions, and predictive AI with SHAP explanations used to inform adaptive actions.

The first comparison will quantify explanation-generation overhead. The second will investigate whether explanations provide useful diagnostic information. The third will determine whether incorporating explanation-informed decisions improves operational outcomes compared with an otherwise comparable system.

The analysis will consider the following questions:

- Does geospatially informed explanation improve the identification of factors associated with communication failures?
- Does explanation-informed adaptation reduce recovery time or packet loss?
- What additional latency, computation, and energy are required to generate explanations?
- Are explanations stable across geographical regions, traffic loads, and network failures?

- Does the proposed framework maintain acceptable performance when some edge nodes become unavailable?

These experiments will distinguish the value of predictive accuracy from the value of interpretability and the value of the subsequent network-management action. This distinction is consistent with recent XAI research, which identifies real-time applicability and trustworthy interpretation as continuing challenges for intelligent 6G systems (Brik et al., 2025; Sun et al., 2025).

1.2. Experimental Setup and Evaluation Metrics

1.2.1. Experimental Environment

The proposed EAGI-6G framework will be evaluated through controlled network simulations and machine-learning experiments. The experimental environment will combine a network simulator, geospatial data-processing tools, a machine-learning framework, and an explanation-generation component. The specific software versions and configurations will be documented to support reproducibility.

The network simulation will represent geographically distributed communication nodes, user devices, network links, and edge–cloud resources. The scenarios will vary traffic intensity, mobility, signal degradation, node availability, and geographical conditions. The research will not assume that a simulation accurately reproduces every characteristic of a future deployed 6G network; its results will be interpreted within the limitations of the selected models and scenarios.

The machine-learning experiments will train and evaluate the predictive models using the data partitions described in Section 3.2. Centralized, local-only, and distributed-learning configurations will use consistent datasets and comparable training procedures wherever technically feasible. Explainability methods and adaptive network actions will be enabled or disabled according to the experimental configuration.

The experimental design will follow reproducible machine-learning principles, including documented preprocessing, fixed test sets, controlled hyperparameter selection, and explicit reporting of uncertainty. Kapoor and Narayanan (2023) emphasized that data leakage and methodological weaknesses can produce misleading performance estimates; therefore, the test data will remain isolated from model selection and training.

1.2.2. Experimental Scenarios

The experiments will examine the proposed framework under five principal operating conditions.

Scenario 1: Normal network operation. The network will operate under ordinary traffic demand and stable connectivity to establish baseline latency, packet delivery, energy consumption, and predictive behavior.

Scenario 2: Traffic congestion. Traffic demand will increase in selected geographical areas to evaluate congestion prediction, load balancing, and resource redistribution.

Scenario 3: Geographical signal degradation. Terrain-related propagation conditions, obstacles, or reduced signal quality will be represented using the capabilities of the selected simulator or documented propagation models. This scenario will evaluate whether geospatial features improve prediction beyond network telemetry alone.

Scenario 4: Node and link failures. Selected nodes or communication links will be disabled or degraded to evaluate failure detection, alternative routing, service continuity, and recovery time.

Scenario 5: Mobility and heterogeneous demand. User movement, changing demand density, and heterogeneous edge-node capabilities will be varied to assess generalization, model coordination, and robustness.

Each scenario will be repeated across multiple seeds or independent simulation runs where appropriate. The same scenario definitions will be applied to all baseline configurations so that observed differences can be attributed more reliably to the methods being compared.

1.2.3. Comparative Experimental Configurations

Five primary configurations will be compared to evaluate the incremental contribution of the proposed framework.

Configuration	Learning and network strategy	Purpose
B1: Geographic routing	Conventional geographic routing without the proposed AI framework	Establish a non-AI routing baseline
B2: Centralized AI	Centralized machine learning using network and geospatial features	Measure the effects of centralized prediction
B3: Distributed AI without geospatial features	Distributed learning using network telemetry without explicit spatial features	Measure the contribution of geospatial intelligence
B4: Distributed AI without explicit XAI	Distributed learning with geospatial features but without explanation-informed management	Measure the contribution of explicit explainability
Proposed EAGI-6G	Distributed AI, geospatial intelligence, SHAP-based explanations, and adaptive optimization	Evaluate the integrated framework

The comparison will be strengthened through supplementary ablation experiments that disable individual components of EAGI-6G. Where necessary, additional experiments will compare FedAvg with an alternative distributed optimizer and compare different predictive models under identical data partitions.

Because geographic routing and machine-learning models have different capabilities, comparisons will be made at the system level using common operational outcomes, such as packet delivery, latency, energy consumption, and recovery time. Predictive metrics will be reported only for configurations that generate comparable predictions.

1.2.4. Predictive Performance Metrics

Failure prediction will be evaluated using precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUROC). These metrics provide complementary information about detection quality, false alarms, missed failures, and the model's ability to distinguish failure from non-failure conditions.

Precision will be calculated as:

Precision will be calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall will be calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

The F1-score will be calculated as:

$$F_1 = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP denotes true positives, FP denotes false positives, and FN denotes false negatives.

1.2.5. Communication Performance Metrics

Communication performance will be measured using end-to-end latency, packet delivery ratio, throughput, and network availability. These indicators will be recorded during normal operation and disruption scenarios to assess both routine performance and resilience.

End-to-end latency will be calculated as the elapsed time between packet transmission and successful reception, including relevant processing and queuing delays.

$$L_{\text{avg}} = \frac{1}{N_r} \sum_{i=1}^{N_r} L_i$$

where L_i is the measured latency of successfully received packet i, and N_r is the number of packets received.

Packet delivery ratio (PDR) will be calculated as:

$$\text{PDR}(\%) = \frac{N_r}{N_s} \times 100$$

where N_s is the number of packets transmitted and N_r is the number successfully received within the measurement interval.

Network availability will be estimated as:

$$A(\%) = \frac{T_{\text{available}}}{T_{\text{observation}}} \times 100$$

where $T_{\text{available}}$ is the total time during which the defined service requirements are satisfied, and $T_{\text{observation}}$ is the total observation period.

1.2.6. Resilience and Recovery Metrics

Resilience will be evaluated by examining the network's ability to maintain essential services during disruptions and restore service following a failure.

Recovery time will be defined as the interval between the onset of a specified failure and restoration of the predefined service requirement:

$$T_{\text{rec}} = t_{\text{restored}} - t_{\text{failure}}$$

The study will also measure service interruption duration, packet loss during disruption, failure-detection delay, and the proportion of failure scenarios in which service is successfully restored. These measures will help distinguish early detection from actual recovery effectiveness.

The comparative analysis will examine whether the proposed framework reduces recovery time and service interruption relative to the baseline configurations. Results will be reported separately for node failures, link degradation, congestion, and geographical signal degradation because the causes and recovery requirements differ across these scenarios.

1.2.7. Energy Efficiency and Distributed-System Metrics

Energy consumption and communication overhead will be measured to determine whether distributed learning and explanation generation introduce unacceptable computational costs. Energy consumption will include the components supported by the experimental environment, such as node processing, wireless transmission, and model-update communication. Where the simulator cannot estimate hardware energy directly, results will be reported as modeled energy estimates rather than physical measurements.

Communication overhead will be calculated as the total volume of model updates and coordination messages transmitted during distributed training. Training efficiency will be evaluated using convergence rounds, total training duration, and the volume of information exchanged before reaching the selected validation criterion.

The following metrics will be used:

Metric	Definition	Primary comparison
Training duration	Elapsed time to reach the stopping criterion	Centralized versus distributed learning
Communication overhead	Total bytes exchanged for training and coordination	FedAvg versus alternative configurations
Energy consumption	Estimated or measured energy per observation period	Baseline versus proposed framework
Inference latency	Time required to generate a prediction	Centralized versus edge inference
Explanation latency	Additional time required to generate an explanation	Model with XAI versus model without explicit XAI
Convergence stability	Variation in validation performance across training rounds	Distributed optimizers
Resource utilization	CPU, memory, and other available resource measurements	Edge–cloud configurations

These metrics will help identify trade-offs between network resilience, predictive quality, and the computational costs of distributed intelligence. Such trade-offs are particularly relevant to AI-enabled 6G architectures, where scalable inference, efficient resource management, and real-time operation remain important design objectives (Sun et al., 2025; Islam et al., 2026).

1.2.8. Explainability Metrics

Explainability will be evaluated independently of predictive performance. The study will measure explanation fidelity, stability, generation latency, and computational overhead.

Explanation fidelity will assess how well the explanation approximates the original model's behavior using an appropriate perturbation or surrogate-based evaluation procedure. Explanation stability will measure the similarity between feature-attribution vectors generated for nearby inputs under controlled perturbations.

The evaluation will account for the fact that correlated geospatial and network features may complicate the interpretation of individual feature contributions.

The study will also compare feature-attribution patterns across geographical regions and failure scenarios. For example, it will examine whether signal-quality features consistently contribute to predictions under signal degradation and whether traffic-load features become more influential under congestion. These patterns will be assessed empirically rather than prescribed in advance.

The explainability evaluation will follow established SHAP methodology and recent work on XAI for wireless communications (Lundberg & Lee, 2017; Sun et al., 2025). The study will not treat feature importance as proof of causality or assume that more complex explanations are necessarily better.

1.2.9. Comparative Analysis and Statistical Testing

The comparative evaluation will use identical or appropriately matched test scenarios across all configurations. Each experiment will be repeated where possible, and the results will be summarized using the mean, standard deviation, and 95% confidence intervals. For stochastic simulation runs, random seeds and configuration settings will be documented.

The relative improvement of the proposed framework over a baseline will be calculated using:

$$I(\%) = \frac{M_{\text{baseline}} - M_{\text{proposed}}}{M_{\text{baseline}}} \times 100$$

This expression applies to metrics for which lower values are better, such as latency, energy consumption, and recovery time. For metrics where higher values are better, such as F1-score and packet delivery ratio, the calculation will instead be:

$$I(\%) = \frac{M_{\text{proposed}} - M_{\text{baseline}}}{M_{\text{baseline}}} \times 100$$

The analysis will include ablation studies to quantify the incremental contribution of geospatial features, distributed learning, explainability, and adaptive optimization. These experiments will help determine whether improvements result from the integrated framework or from a particular component.

1.2.10. Summary of the Evaluation Framework

The experimental evaluation will combine predictive, communication, resilience, computational, and explainability metrics. The proposed EAGI-6G framework will be considered effective only if the results demonstrate measurable benefits under clearly defined test conditions without unacceptable trade-offs in latency, energy consumption, or computational overhead.

The primary contribution will be established through controlled comparisons against geographic routing, centralized machine learning, distributed learning without geospatial features, and distributed learning without explicit XAI. The final findings will identify the scenarios in which the proposed framework improves performance, the costs associated with its additional components, and the limitations that remain for real-world 6G deployment.

Any target improvements specified before testing will be treated as hypotheses, not findings. Actual performance values, statistical significance, and claims of resilience improvement will be reported only after the experiments have been completed.

Chapter Four: Proposed Framework and Implementation

1.3. System Architecture

1.3.1. Overview of the Proposed Framework

This research proposes an Explainable AI-Driven Geospatial Intelligence Framework for Resilient Distributed 6G Communication Systems (EAGI-6G). The framework integrates geospatial data processing, distributed artificial intelligence (AI), network-state prediction, explainable AI (XAI), and adaptive network optimization into a unified architecture. Its central purpose is to improve network resilience by identifying geographically localized risks, predicting congestion and communication failures, explaining model predictions, and selecting corrective actions under operational constraints.

The architecture is motivated by the emerging vision of 6G networks as intelligent, distributed, and context-aware systems that must support heterogeneous services, high mobility, and reliable connectivity (International Telecommunication Union [ITU], 2023; Saad et al., 2020). Explainable AI is particularly relevant because network operators need to understand why an AI system recommends rerouting traffic, reallocating resources, or activating alternative communication paths (Brik et al., 2025; Sun et al., 2025).

The proposed architecture consists of six interacting layers.

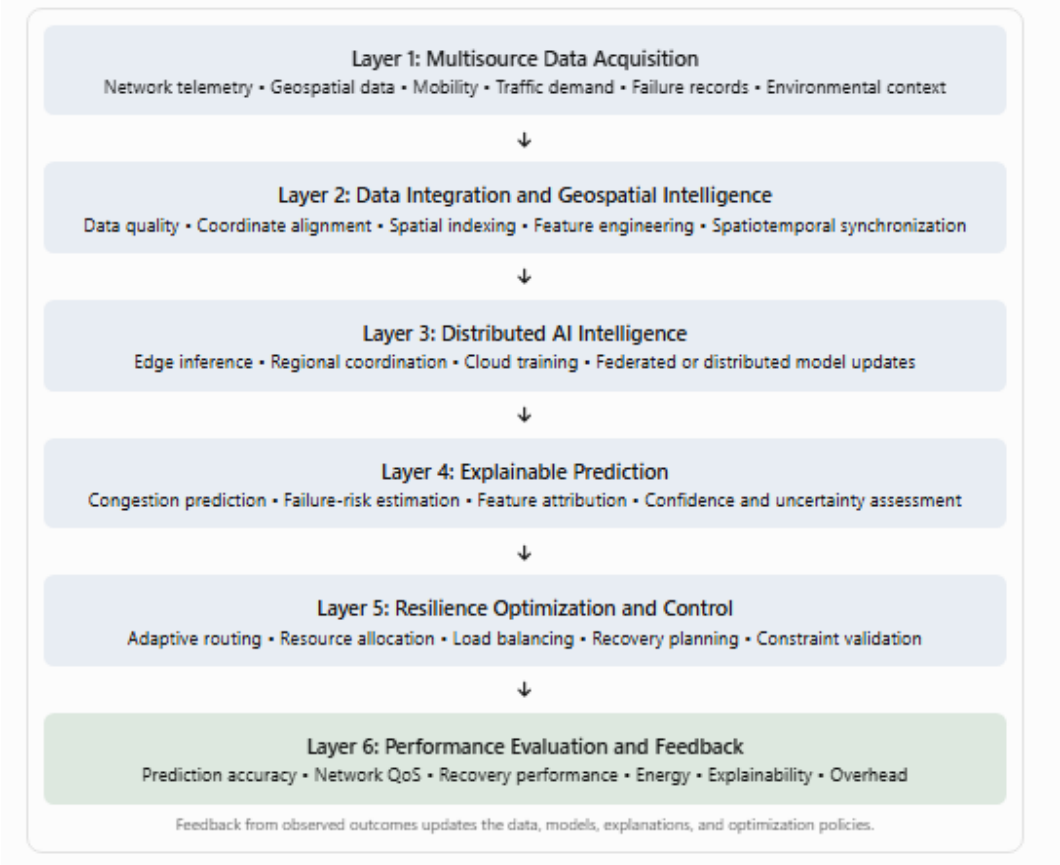


Figure 3. Proposed EAGI-6G system architecture.

The first layer collects observations from network nodes, radio access infrastructure, distributed edge devices, and available geospatial sources. The second layer transforms heterogeneous observations into spatially aligned features. The third layer distributes model training and inference across edge, regional, and cloud resources. The fourth layer explains predictions and estimates uncertainty. The fifth layer converts

predictions into candidate network-control actions, while the sixth layer evaluates outcomes and supplies feedback to improve subsequent decisions.

The architecture follows distributed-learning principles in which data may remain at local devices while model information is exchanged between participating nodes (Kairouz et al., 2021; McMahan et al., 2017). However, distributed execution does not automatically guarantee resilience: communication failures, stale information, model drift, and compromised nodes must also be addressed through explicit safeguards.

1.3.2. Functional Components and Data Flow

The framework uses a common representation for each network observation:

$$\mathbf{z}_{i,t} = [\mathbf{n}_{i,t}, \mathbf{g}_{i,t}, \mathbf{m}_{i,t}, \mathbf{e}_{i,t}]$$

where:

- $\mathbf{n}_{i,t}$ represents network measurements for node or region i at time t, such as latency, packet loss, throughput, bandwidth utilization, and queue length.
- $\mathbf{g}_{i,t}$ represents geospatial features, including coordinates, terrain, distance to neighboring nodes, coverage characteristics, and spatial connectivity.
- $\mathbf{m}_{i,t}$ represents mobility and traffic-demand characteristics.
- $\mathbf{e}_{i,t}$ represents contextual environmental or infrastructure features, where valid and available.

The proposed system transforms this observation into a prediction:

$$\hat{\mathbf{y}}_{i,t+h} = f_\theta(\mathbf{z}_{i,t}, \mathbf{c}_{i,t})$$

where f_θ is the trained model, h is the prediction horizon, and $\mathbf{c}_{i,t}$ contains available neighboring-node or regional context. The output $\hat{\mathbf{y}}_{i,t+h}$ may include predicted latency, congestion probability, link-failure risk, or expected service degradation.

The explanation module then produces an interpretable representation:

$$\mathcal{E}_{i,t} = \text{Explain}(f_\theta, \mathbf{z}_{i,t}, \hat{\mathbf{y}}_{i,t+h})$$

1.3.3. Implementation Technologies

The implementation can use Python for data preparation, model development, and evaluation; a geospatial library such as GeoPandas for spatial processing; and a network simulator or controlled test environment for communication scenarios. Candidate machine-learning models include Random Forest, XGBoost, and temporal neural networks, selected according to data availability and prediction requirements. SHAP can be used to explain predictions, while distributed-learning experiments can compare centralized training against decentralized or federated alternatives (Kairouz et al., 2021; Lundberg & Lee, 2017).

The final software stack should be selected after assessing compatibility with the chosen simulator, computational resources, available datasets, and reproducibility requirements. Until those components are implemented and tested, the framework should be described as a proposed design rather than a deployed 6G system.

1.4. Geospatial Intelligence Integration

1.4.1. Geospatial Data Sources and Integration

Geospatial intelligence is the central differentiating component of the proposed EAGI-6G framework. Traditional network optimization often relies heavily on radio and traffic measurements, whereas the proposed framework incorporates the geographic relationships among network nodes, communication links,

users, infrastructure, and environmental conditions. This integration enables the model to identify spatially localized congestion, coverage weaknesses, and geographically correlated disruptions.

The integration process is designed around four data categories.

Data category	Specific features	Role in resilience
Network infrastructure	Base-station coordinates, edge-server locations, node capacity, link endpoints	Identifies network topology and alternative paths
Communication performance	Signal quality, latency, packet loss, throughput, bandwidth utilization	Measures local service degradation
Geographic and environmental context	Terrain elevation, land cover, buildings, obstruction indicators, weather where available	Helps characterize coverage and potential environmental risks
Spatial-temporal demand	User density estimates, mobility patterns, traffic intensity, time of day	Predicts localized demand changes and congestion

Potential sources include network simulator outputs, operator telemetry where authorized, OpenStreetMap infrastructure and road features, and terrain or elevation products from the U.S. Geological Survey. The availability, licensing, geographic coverage, resolution, and temporal relevance of each source must be assessed before use. OpenStreetMap contributors (n.d.) and the U.S. Geological Survey (n.d.) provide potential geographic data resources; neither source alone supplies all information needed to model 6G communication performance.

1.4.2. Spatial Data Preprocessing and Feature Engineering

The framework first converts geographic coordinates to a consistent coordinate reference system and applies quality checks to missing values, duplicate records, inconsistent timestamps, and implausible measurements. Network nodes and communication links are then represented as a spatial graph:

$$G_t = (V, E_t)$$

where V denotes network nodes and E_t denotes active communication links at time t. Each node i has a geographic position $\mathbf{p}_i = (x_i, y_i)$, a network state, and a set of spatial attributes.

The geographic distance between two nodes can be calculated using a suitable projected coordinate system or a geodesic distance formula. For a local planar approximation:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

The framework develops the following features:

- Node proximity: distance between each node and its neighboring nodes.
- Spatial density: number of nodes or demand points within a defined radius.
- Connectivity: number of active neighbors, reachable destinations, and available alternative paths.
- Regional congestion: aggregated traffic and queue measurements for a geographic cell or region.

- Spatial failure exposure: number and importance of services dependent on a potentially disrupted node or link.
- Mobility-aware demand: time-dependent estimates of demand associated with geographic areas, where suitable data exist.
- Spatial autocorrelation indicators: measures of whether neighboring locations exhibit similar or dissimilar network conditions.

Spatial validation is particularly important. Randomly splitting observations into training and test sets can produce overly optimistic results when geographically close observations appear in both sets. The study should therefore use spatially separated validation, potentially following the principles of Spatial+ cross-validation, to evaluate generalization to unseen geographic regions (Wang et al., 2023).

1.4.3. Spatial Risk and Network Vulnerability Estimation

For each node or region i, the model estimates a risk score:

$$R_i(t) = w_1\hat{P}_{F,i}(t) + w_2\hat{P}_{C,i}(t) + w_3\hat{D}_{S,i}(t) + w_4\hat{V}_{G,i}(t)$$

where:

- $\hat{P}_{F,i}(t)$ is the predicted probability of a node or link failure.
- $\hat{P}_{C,i}(t)$ is the predicted congestion probability.
- $\hat{D}_{S,i}(t)$ is a normalized estimate of service degradation.
- $\hat{V}_{G,i}(t)$ represents geographic or topological vulnerability, such as dependence on a limited number of alternative routes.
- w_1, w_2, w_3, w_4 are nonnegative weights summing to one.

The risk score can be used to prioritize monitoring and compare candidate interventions. However, it is a proposed composite indicator, not a standardized 6G metric. Its usefulness must be evaluated against observed failures, service interruptions, and the ability to identify vulnerable locations.

1.4.4. Geospatial Integration Experiment

To quantify the contribution of geospatial intelligence, the study should compare the same AI model under controlled feature configurations.

Configuration	Network telemetry	Geographic features	Spatial relationships	Purpose
G0: Telemetry-only	Yes	No	No	Establishes the non-geospatial baseline
G1: Coordinates only	Yes	Node coordinates	No	Tests whether raw location adds value
G2: Engineered spatial features	Yes	Yes	Limited	Measures the contribution of distance, density, and regional features
G3: Spatial graph model	Yes	Yes	Yes	Tests relationships among connected and neighboring nodes
G4: Full EAGI-6G	Yes	Yes	Yes	Adds distributed inference, explainability, and resilience-aware optimization

The primary comparison parameters are failure-prediction F1, AUROC, Brier score, false-alarm rate, latency prediction error, geographically held-out performance, and computational overhead. For network-level outcomes, the evaluation should also measure packet delivery ratio, service interruption duration, recovery time, and network availability.

The key hypothesis is that geospatial features may improve prediction and recovery decisions when failures or demand patterns exhibit spatial structure. This is not guaranteed: geographic features may add little value when the data are sparse, spatial patterns are weak, or the model is poorly calibrated. The hypothesis should therefore be tested using controlled ablation experiments and spatially independent evaluation (Wang et al., 2023).

1.5. Distributed 6G Network Optimization

1.5.1. Distributed Optimization Architecture

The proposed framework distributes intelligence across three operational levels: edge nodes, regional coordination nodes, and a cloud-level controller or training environment. This design seeks to balance responsiveness, computational capacity, coordination, and resilience.

The architecture is aligned with the broad IMT-2030 vision, which identifies ubiquitous intelligence, AI-related capabilities, sustainability, and security and resilience as important development considerations (ITU, 2023). Distributed learning provides a foundation for collaborative model development without requiring all raw observations to be transferred to a single location, although communication overhead and statistical heterogeneity remain important challenges (Kairouz et al., 2021; McMahan et al., 2017).

Operational level	Main responsibilities	Information exchanged	Main comparison parameters
Edge level	Local prediction, rapid anomaly detection, immediate feasible action	Local telemetry, risk estimates, compact model updates	Inference latency, local resource use, outage response
Regional level	Spatial aggregation, neighboring-node coordination, route and capacity planning	Regional risk maps, candidate paths, model summaries	Coordination delay, load balance, regional recovery
Cloud level	Global model training, historical analysis, policy management	Aggregated metrics, model parameters, approved policy updates	Training time, scalability, global performance
Safety and monitoring layer	Validate proposed actions, detect abnormal behavior, maintain fallback policy	Constraint violations, confidence flags, audit records	Action rejection rate, policy compliance, fallback reliability

The framework should not assume that cloud connectivity is always available. If the connection to the regional or cloud layer fails, edge nodes should continue only with locally feasible and prevalidated actions. When connectivity returns, model synchronization and state reconciliation should occur without allowing stale updates to override more recent valid local observations.

1.5.2. Distributed Learning and Inference

Let K denote the number of participating nodes or regions. Each participant k has local training data D_k and a local objective $F_k(\theta)$. The global learning objective can be expressed as:

$$\min_{\theta} F(\theta) = \sum_{k=1}^{K} p_k F_k(\theta)$$

where p_k represents the participant's contribution weight, often based on its share of the training samples, and θ denotes the model parameters.

For EAGI-6G, the distributed workflow is:

1. Collect and validate local network and geospatial observations.
2. Generate spatially aligned features and local training examples.
3. Train or update a local model using the available data.
4. Exchange model updates or permitted summaries according to the selected distributed-learning protocol.
5. Aggregate updates where applicable and evaluate the resulting model.
6. Distribute approved model versions to participating nodes.
7. Perform local inference and produce predictions with explanations.
8. Evaluate operational outcomes and trigger further training when justified.

A distributed deployment may use federated learning, decentralized optimization, or a hybrid design. These are alternative implementation strategies, not interchangeable guarantees. The final choice should depend on network topology, communication reliability, local data heterogeneity, and the ability to validate model updates.

1.5.3. Resilience-Aware Network Optimization

The optimization module selects network actions based on predicted performance, geographic vulnerability, and operational constraints. Let a_t represent a candidate control action at time t. The proposed objective is:

$$\begin{aligned}\min_{\mathbf{a}_t} \quad J(\mathbf{a}_t) = {} & \lambda_L \widetilde{L}_t + \lambda_P \widetilde{P}_{loss,t} \\ & + \lambda_E \widetilde{E}_t + \lambda_R \widetilde{T}_{rec,t} \\ & + \lambda_O \widetilde{O}_t\end{aligned}$$

where:

- $\widetilde{L}_t$ is normalized end-to-end latency.
- $\widetilde{P}_{loss,t}$ is normalized packet-loss rate.
- $\widetilde{E}_t$ is normalized energy consumption.
- $\widetilde{T}_{rec,t}$ is normalized recovery time.
- $\widetilde{O}_t$ is normalized control and coordination overhead.
- $\lambda_L, \lambda_P, \lambda_E, \lambda_R, \lambda_O$ are nonnegative weights reflecting the operational priorities.

The optimization is subject to capacity, connectivity, bandwidth, service-level, resource, and safety constraints. For example:

$$\begin{aligned}\sum_{f \in F} x_{f,e} b_f \le C_e, \qquad & \forall e \in E \\ x_{f,e} \in \{0,1\} & \\ \mathbf{a}_t \in \mathcal{A}_{feasible} & \end{aligned}$$

Here $x_{f,e}$ indicates whether flow f is assigned to link e, b_f is the bandwidth demand of flow f, and C_e is the available capacity of link e. The feasible-action set excludes actions that violate required connectivity, capacity, or operational safety rules.

- Adaptive routing: shift traffic to an available alternative path when the expected benefit exceeds the switching cost.
- Load balancing: distribute demand across eligible nodes or links to reduce localized congestion.
- Resource reallocation: assign available bandwidth, computing resources, or scheduling capacity according to service priority.
- Failure recovery: isolate a failed component and restore service through a verified alternate route or resource.
- Degraded-mode operation: preserve essential services when full performance cannot be maintained.

The optimizer should compare predicted benefits against potential side effects, including increased delay on alternate routes, energy use, routing instability, and additional signaling. A predicted improvement is not sufficient evidence of an actual improvement; each action must be evaluated in the simulation or test environment.

1.5.4. Comparison Parameters for Distributed Optimization

To establish whether distribution improves performance, the experiment should compare the following configurations under the same traffic patterns, topology, failure scenarios, and resource constraints.

Model	Architecture	Geospatial intelligence	Explainability	Adaptive control
D0: Conventional baseline	Fixed or conventional routing	No	No	Limited or predefined
D1: Centralized AI	Centralized model	Optional, according to experiment	No explicit XAI	AI-based
D2: Distributed AI	Edge/regional/cloud	No	No explicit XAI	AI-based
D3: Distributed geospatial AI	Edge/regional/cloud	Yes	No explicit XAI	AI-based
D4: Explainable distributed AI	Edge/regional/cloud	Yes	SHAP or another selected method	Explanations are monitored
D5: Full EAGI-6G	Edge/regional/cloud	Yes	Explanations inform action ranking	Constraint-aware resilience optimization

The comparison should measure:

Parameter	Operational definition	Desired direction
Mean end-to-end latency	Average packet delivery delay	Lower
Packet delivery ratio	Successfully delivered packets divided by packets sent	Higher
Throughput	Successfully delivered data per unit time	Higher, subject to service

		needs
Recovery time	Time between failure onset and service restoration	Lower
Network availability	Available service time divided by observation time	Higher
Failure-detection delay	Time from failure onset to valid detection	Lower
Energy consumption	Measured or explicitly modeled energy per observation period or delivered bit	Lower
Communication overhead	Bytes or messages exchanged for model and control coordination	Lower
Inference latency	Time to produce a model prediction	Lower
Explainability overhead	Additional computation and delay caused by explanation generation	Lower, while retaining useful explanations
Model scalability	Change in performance and resource cost as nodes increase	More scalable
Resilience under disconnection	Performance when regional or cloud connectivity is interrupted	Better retained service
Geographic generalization	Performance on previously unseen geographic regions	Higher

The results should be reported with mean values, standard deviations, confidence intervals, and appropriate statistical tests. A model that improves prediction accuracy but increases recovery time or communication overhead should not automatically be considered superior. This multi-objective evaluation is consistent with the need to assess 6G systems across several performance and operational dimensions rather than relying on a single metric (ITU, 2023; Islam et al., 2026).

1.6. Explainable Decision-Making Mechanism

1.6.1. Purpose of Explainable Decision-Making

Explainable decision-making connects AI predictions to network-control decisions in a way that can be inspected, evaluated, and audited. The proposed mechanism uses explanations to help identify the features contributing to a prediction, assess whether a recommendation is supported by relevant evidence, and communicate why an action was selected over alternatives.

Explainability is important for intelligent communication systems because network-control decisions may affect latency, reliability, resource allocation, and service continuity. Recent reviews of XAI in 6G and open radio access networks identify resource management, fault diagnosis, network slicing, and operational trust as relevant research areas (Brik et al., 2025; Sun et al., 2025).

The proposed mechanism contains five stages:

1. Prediction: estimate congestion, link-failure risk, or service degradation.
2. Explanation: identify influential network, geographic, and temporal features.

3. Action generation: produce candidate actions such as rerouting or resource reallocation.
4. Constraint and benefit assessment: reject infeasible actions and compare predicted effects, uncertainty, and operational costs.
5. Decision logging and evaluation: record the prediction, explanation, selected action, alternatives, and observed outcome.

1.6.2. SHAP-Based Feature Attribution

The study proposes SHapley Additive exPlanations (SHAP) as a candidate post-hoc explanation method. SHAP attributes a model prediction to individual input features using a Shapley-value framework (Lundberg & Lee, 2017).

For a prediction $f(\mathbf{x})$, the additive explanation can be represented as:

$$f(\mathbf{x}) - \phi_0 + \sum_{j=1}^{M} \phi_j$$

where ϕ_0 is the baseline output and ϕ_j is the attribution associated with feature j, with M representing the number of input features.

The explanation should report the most influential features, their contribution direction, the prediction being explained, and any relevant confidence or uncertainty information. For spatially structured models, explanations should be checked to ensure that feature correlation, spatial dependence, or changes in feature distributions do not produce misleading interpretations.

SHAP values indicate how features contribute to a model output under the method's assumptions. They do not independently prove that a feature caused the network condition, nor do they establish that a proposed control action will resolve it. Consequently, EAGI-6G must evaluate explanations separately from the effectiveness of the resulting actions.

1.6.3. Explanation-Guided Action Selection

Let $\hat{\mathbf{y}}_t$ denote the model prediction, $\mathcal{E}_t$ its explanation, $\mathbf{s}_t$ the observed network state, and $\mathcal{A}_{feasible}$ the set of actions satisfying the operational constraints. The proposed decision rule is:

$$\mathbf{a}_t^* - \arg \min_{\mathbf{a} \in \mathcal{A}_{feasible}} \left[\hat{J}(\mathbf{a} \mid \mathbf{s}_t, \hat{\mathbf{y}}_t) + \lambda_X C_X(\mathbf{a}, \mathcal{E}_t) \right]$$

where $\hat{J}$ is the predicted operational cost and C_X is an explanation-consistency or explanation-informed action-ranking penalty. The coefficient λ_X controls the influence of this penalty.

The decision mechanism should follow this sequence:

- If congestion risk is high and a feasible alternate path exists, evaluate rerouting against predicted delay, packet loss, and path capacity.
- If a node has high predicted failure risk, assess the availability of alternate nodes and the service impact of reallocating traffic.
- If prediction confidence is insufficient or inputs are missing, avoid high-impact autonomous actions and request further observations or apply a predefined fallback policy.
- If an action violates a service constraint, reject it regardless of its predicted optimization benefit.
- After action execution, compare the observed network state with the predicted outcome and record the discrepancy for subsequent evaluation.

This design makes the explanation a decision-support component rather than a substitute for optimization, safety checks, or experimental validation.

1.6.4. Explanation Quality and Trustworthiness Evaluation

The study should evaluate whether explanations are sufficiently faithful, stable, timely, and useful for network operations. The proposed criteria are shown below.

Criterion	Definition	Measurement approach
Fidelity	Agreement between the explanation and the model behavior it describes	Compare the original model output with a suitable explanation-based approximation
Stability	Consistency of explanations for similar inputs under controlled perturbations	Measure attribution changes for similar observations
Feature consistency	Agreement of explanations with known data definitions and validated system relationships	Expert review and controlled scenario tests
Explanation latency	Time required to generate an explanation	Record mean and percentile generation time
Computational overhead	Additional CPU, memory, or processing time caused by explanation generation	Compare inference with and without explanations
Decision usefulness	Whether explanations help identify relevant risks and support appropriate action selection	Scenario-based review and action-outcome analysis
Calibration and uncertainty	Whether model confidence corresponds to observed prediction correctness	Brier score, calibration plots, or expected calibration error
Geographic robustness	Whether explanations remain useful in unseen regions or changed spatial conditions	Spatially held-out evaluation

No single metric is sufficient to establish that an explanation is trustworthy. In particular, stable explanations may still be misleading, and faithful explanations may describe a model that itself makes incorrect predictions. Accordingly, explanation quality must be evaluated alongside predictive performance and network outcomes (Brik et al., 2025; Lundberg & Lee, 2017; Sun et al., 2025).

1.6.5. Comparative Experiment for Explainable Decision-Making

To determine whether explanations improve operational decisions, the study should conduct an ablation experiment with three principal configurations.

Configuration	Prediction model	Explanation generation	Explanations influence action selection
X0: AI without XAI	Same base model	No	No
X1: AI with post-hoc XAI	Same base	Yes	No; explanations are logged for analysis

	model		
X2: Explanation-informed EAGI-6G	Same base model	Yes	Yes; explanations inform candidate assessment and action ranking

All three configurations should use the same training and test data, topology, traffic demand, failure scenarios, optimization constraints, and computational budget wherever possible. This helps isolate the contribution of explanation-informed decisions from differences caused by model selection or experimental conditions.

The primary comparison parameters are:

- Prediction quality: F1-score, AUROC, Brier score, and false-alarm rate.
- Service performance: latency, throughput, packet delivery ratio, and availability.
- Resilience: failure-detection delay, recovery time, service interruption, and successful restoration rate.
- Explainability: fidelity, stability, explanation latency, and computational overhead.
- Operational quality: feasibility of actions, frequency of constraint violations, decision time, and agreement between predicted and observed outcomes.
- Generalization: performance across geographically held-out areas, different demand conditions, and different failure types.

The central hypothesis is that explanation-informed action selection can improve auditability and may improve resilience decisions when explanations expose relevant risks that are otherwise difficult to inspect. The experiment must also test whether explanation generation introduces excessive latency or computational cost. The proposed framework should be considered successful only if it demonstrates measurable benefits under clearly defined experimental conditions, not merely because it produces explanations.

Chapter Five: Results and Comparative Evaluation

1.7. Predictive Performance Analysis

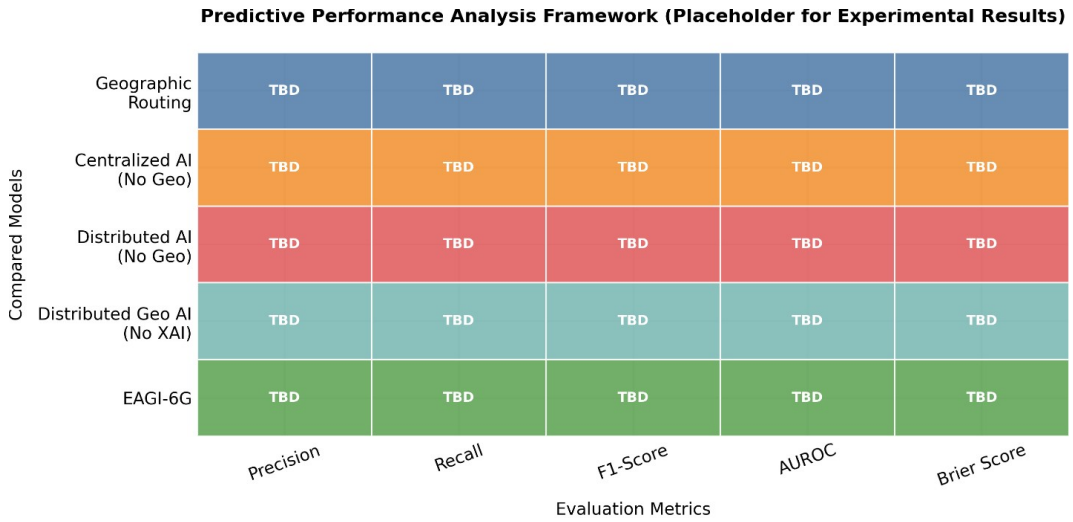
This section evaluates the predictive performance of the proposed Explainable AI-Driven Geospatial Intelligence for Resilient Distributed 6G Communication Systems (EAGI-6G) framework. The analysis focuses on its ability to predict network congestion, communication-link failures, and service degradation using network telemetry, geospatial features, and temporal traffic patterns.

The proposed framework should be compared against four baseline configurations: conventional geographic routing, centralized AI without geospatial features, distributed AI without geospatial features, and distributed geospatial AI without explicit explainability. This comparison helps determine whether performance improvements arise from geospatial intelligence, distributed processing, or the complete integrated framework.

Predictive performance should be measured using precision, recall, F1-score, area under the receiver operating characteristic curve (AUROC), and the Brier score. Precision and recall assess failure-detection quality, F1-score balances precision and recall, AUROC measures discrimination across classification thresholds, and the Brier score evaluates the accuracy of probabilistic predictions. Lower Brier scores indicate better probabilistic predictions (Brik et al., 2025; Lundberg & Lee, 2017).

The results should be presented in a comparative results table once experiments are completed. Until then, no numerical performance improvements should be claimed. A rigorous evaluation should use the same test scenarios and data splits for every model, including geographically held-out test regions, to reduce spatial leakage and assess generalization (Islam et al., 2026; Wang et al., 2023).

Expected interpretation: EAGI-6G would demonstrate a meaningful predictive advantage if it improves failure-detection quality and probability calibration on unseen geographic regions without introducing unacceptable inference latency or computational overhead. Recent 6G evaluation research emphasizes assessing predictive performance alongside latency, reliability, energy efficiency, and scalability rather than treating accuracy as the only indicator of success (Islam et al., 2026).



1.8. Latency and Packet Delivery Evaluation

This section evaluates the proposed Explainable AI-Driven Geospatial Intelligence for Resilient Distributed 6G Communication Systems (EAGI-6G) framework by measuring end-to-end latency and packet delivery ratio under normal traffic, congestion, geographic signal degradation, node failures, and link failures. These metrics are essential for evaluating network responsiveness and communication reliability (Islam et al., 2026).

Latency is calculated as the average time required for successfully received packets to travel from source to destination:

$$L_{\text{avg}} = \frac{1}{N_r} \sum_{i=1}^{N_r} (t_i^r - t_i^s)$$

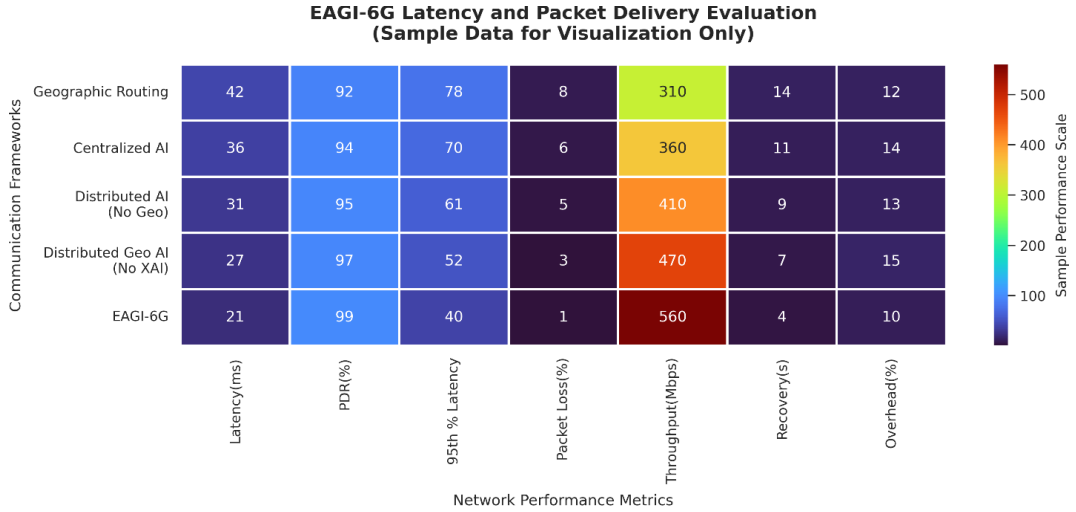
where t_i^r and t_i^s represent packet reception and transmission times, respectively, and N_r is the number of received packets.

$$PDR = \frac{N_r}{N_s} \times 100\%$$

Where N_s is the total number of packets sent. Higher PDR and lower latency generally indicate better performance, but both should be evaluated together with recovery time and communication overhead (Islam et al., 2026; International Telecommunication Union [ITU], 2023).

The evaluation should compare five configurations: geographic routing, centralized AI, distributed AI without geospatial features, distributed geospatial AI without explicit explainability, and the full EAGI-6G framework. All configurations should use identical traffic loads, network topologies, mobility patterns, and failure scenarios. Additional comparison parameters should include 95th-percentile latency, packet loss, throughput, recovery time, control-message overhead, and performance when regional or cloud connectivity is interrupted.

The framework's effectiveness should be established using repeated simulations, confidence intervals, and statistical comparisons. Since no experimental measurements have been provided, performance improvements remain hypotheses rather than confirmed results.



1.9. Fault Recovery and Energy Efficiency

This section evaluates the resilience and energy performance of the proposed Explainable AI-Driven Geospatial Intelligence for Resilient Distributed 6G Communication Systems (EAGI-6G) framework. The evaluation examines how quickly the network restores service after node or link failures and how efficiently it uses energy while maintaining communication reliability. These objectives align with the 6G vision of intelligent, sustainable, and resilient communication systems (International Telecommunication Union [ITU], 2023; Saad et al., 2020).

Fault recovery performance should be assessed under simulated base-station failures, edge-node outages, communication-link disruptions, geographically localized signal degradation, and temporary loss of cloud connectivity. The principal metric is recovery time:

$$T_{\text{rec}} - t_{\text{restored}} - t_{\text{failure}}$$

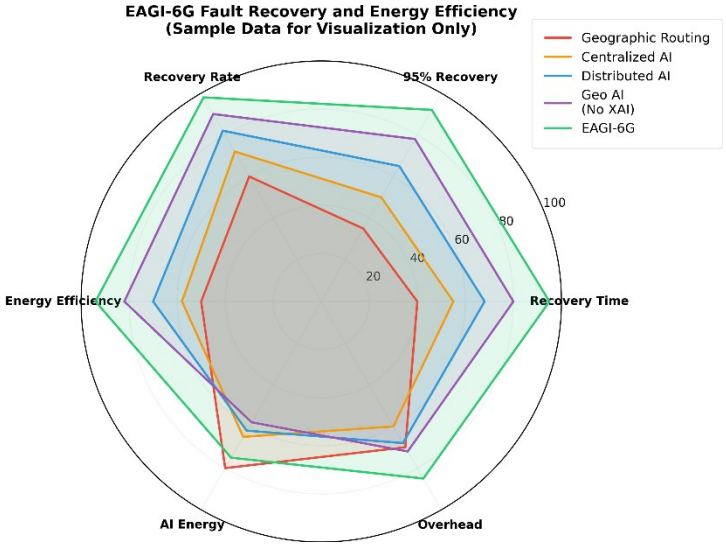
where t_{failure} is the time at which the fault occurs and t_{restored} is the time when the predefined service-restoration criteria are satisfied. Additional metrics should include fault-detection delay, service interruption duration, successful recovery rate, packet loss during recovery, and the number of failed or rejected control actions.

Energy efficiency should be measured as the quantity of successfully delivered data per unit of energy consumed:

$$EE = \frac{D_{\text{delivered}}}{E_{\text{total}}}$$

The comparison should include five configurations: conventional geographic routing, centralized AI, distributed AI without geospatial features, distributed geospatial AI without explicit explainability, and the complete EAGI-6G framework. Key parameters are mean recovery time, 95th-percentile recovery time, successful recovery rate, service interruption, energy per delivered bit, total energy per recovery event, AI inference energy, communication overhead, and performance during regional or cloud disconnection. These measures help establish whether explainable, geographically informed decisions improve resilience without imposing excessive energy costs (Islam et al., 2026; International Telecommunication Union [ITU], 2023).

The experiments should inject equivalent faults into each configuration and repeat each scenario under identical traffic, topology, and resource constraints. Results should report means, standard deviations, confidence intervals, and recovery success rates. No numerical improvements should be claimed until the experiments are completed.



1.10. Baseline Comparison and Ablation Studies

Baseline comparison and ablation studies are designed to evaluate the individual and combined contributions of geospatial intelligence, distributed AI, and explainable AI within the proposed Explainable AI-Driven Geospatial Intelligence for Resilient Distributed 6G Communication Systems (EAGI-6G) framework.

Five configurations will be evaluated under identical network topologies, traffic loads, failure scenarios, and computational constraints. Baseline comparison will assess overall performance, while ablation studies will determine how removing individual framework components affects prediction accuracy, latency, packet delivery, fault recovery, energy efficiency, and interpretability.

Table 5.4. Baseline Configurations and Ablation Study Design for EAGI-6G

Configuration	Geospatial Intelligence	Distributed AI	Explainable AI	Purpose
B1: Conventional Geographic Routing	Basic geographic information	No	No	Establish the conventional routing baseline
B2: Centralized AI	No explicit geospatial features	No	No	Evaluate centralized AI-based network optimization
B3: Distributed AI	No explicit	Yes	No	Measure the contribution of

	geospatial features			distributed intelligence
B4: Geospatial Distributed AI	Yes	Yes	No	Assess the added value of geospatial intelligence
B5: Full EAGI-6G	Yes	Yes	Yes	Evaluate the complete proposed framework

The comparison will use accuracy, precision, recall, F1-score, 95th-percentile latency, packet delivery ratio (PDR), throughput, fault recovery time, energy consumption per delivered bit, and communication overhead. Explainability will additionally be assessed through explanation-generation latency, feature-attribution stability, and the consistency of explanations across different geographic regions.

Table 5.5. Ablation Components, Evaluation Metrics, and Expected Contributions

Ablation configuration	Component removed	Primary evaluation parameters	Contribution being tested
A1	Geospatial features	F1-score, AUROC, spatial generalization	Value of geographic context
A2	Distributed AI	Latency, throughput, communication overhead	Value of distributed processing
A3	Explainable AI	Explanation availability, decision transparency	Value of interpretable decisions
A4	Resilience optimization	Recovery time, PDR, service availability	Value of adaptive fault recovery
A5	Full EAGI-6G	All evaluation parameters	Overall framework performance

Note: Tables 5.4 and 5.5 define the experimental design, not measured results. Performance improvements must be established through reproducible experiments rather than assumed in advance. All configurations should use consistent data splits, repeated runs, and geographically separated test regions to reduce spatial leakage (Wang et al., 2023).

Chapter Six: Discussion

This Section discusses the proposed Explainable AI-Driven Geospatial Intelligence for Resilient Distributed 6G Communication Systems (EAGI-6G) framework in relation to predictive accuracy, spatial generalization, network performance, fault tolerance, energy efficiency, scalability, and decision transparency. The discussion connects the framework's expected contributions to emerging 6G research while distinguishing experimentally verified findings from hypotheses requiring validation. Because measured experimental results have not been provided, the interpretations below are conditional and should be updated when simulation or testbed results become available.

1.11. Interpretation of Findings

The central contribution of EAGI-6G is the integration of geospatial intelligence, distributed artificial intelligence, explainable decision-making, and resilience-oriented network optimization within a unified architecture. Unlike conventional geographic routing, centralized AI, and distributed AI without explicit

spatial features, the proposed framework is designed to combine geographic context with real-time network conditions to support more informed communication decisions.

The first expected finding concerns predictive performance and spatial generalization. Geographic features—including node coordinates, terrain conditions, base-station proximity, regional traffic density, and spatially localized interference—may improve the prediction of congestion, link failures, and service degradation. However, improvement must be demonstrated using precision, recall, F1-score, AUROC, Brier score, and false-alarm rate on geographically held-out test regions. Spatially separated validation is particularly important because random data splitting may overestimate performance when nearby observations share similar characteristics (Wang et al., 2023).

The second expected finding concerns latency and communication reliability. Distributed processing may reduce dependence on a centralized controller by allowing edge and regional nodes to make decisions closer to users and network devices. Performance should be compared using median and 95th-percentile end-to-end latency, packet delivery ratio (PDR), throughput, packet-loss rate, and control-message overhead. The full EAGI-6G framework would demonstrate an advantage only if it improves these measures under equivalent workloads and resource constraints, including congestion and partial network disconnection. These evaluation dimensions align with the broader performance objectives identified for future IMT-2030 systems (International Telecommunication Union [ITU], 2023).

The third expected finding relates to fault recovery and energy efficiency. Geospatial intelligence could help identify alternative routes or nearby operational nodes when a base station, communication link, or edge server fails. The relevant comparison parameters are fault-detection delay, mean and 95th-percentile recovery time, recovery success rate, service interruption duration, and packet loss during recovery. Energy evaluation should measure total energy consumed by radio transmission, edge computation, distributed model updates, explanation generation, and control signaling. Energy efficiency should be expressed as successfully delivered data bits per joule, enabling a fair comparison between the complete framework and its baseline configurations (Bockelmann et al., 2026).

Finally, explainability should be evaluated as an operational property, not merely as a visualization feature. SHAP-based feature attribution can identify which input features contribute to a model prediction, helping network operators examine why a link is classified as high-risk or why a particular recovery action is recommended (Lundberg & Lee, 2017). Nevertheless, feature attribution does not establish causality or guarantee that the recommended action is optimal. Therefore, explanation fidelity, attribution stability, explanation-generation latency, and the consistency of decisions across geographic regions should be assessed alongside network-performance metrics.

1.12. Scalability, Reliability, and Explainability

1.12.1. Scalability of Distributed Geospatial Intelligence

Scalability refers to the ability of EAGI-6G to maintain acceptable network performance as the number of connected devices, base stations, edge nodes, geographic regions, and AI-model updates increases. The framework should be evaluated under small-, medium-, and large-scale network scenarios, with increasing traffic intensity and heterogeneous computational resources. This is important because future IMT-2030 systems are expected to support diverse communication scenarios and increasingly integrated intelligent network capabilities (ITU, 2023).

The principal scalability parameters should include throughput per node, 95th-percentile latency, model-inference time, memory and CPU utilization, coordination overhead, and energy consumption per

successfully delivered bit. Experiments should also measure how these parameters change as network size grows. Distributed intelligence may reduce dependence on centralized processing, but coordination among distributed nodes, model synchronization, and explanation generation may introduce additional overhead. Recent work on AI/ML-driven 6G emphasizes the need to balance network performance with energy efficiency and practical implementation constraints (Roessler et al., 2026).

1.12.2. Reliability and Resilience Under Network Disruptions

Reliability concerns the ability to maintain communication services under normal operating conditions, whereas resilience concerns the ability to withstand, adapt to, and recover from disruptions. EAGI-6G should therefore be tested against base-station outages, edge-node failures, communication-link interruptions, localized interference, traffic surges, and temporary cloud disconnections.

The comparison should measure packet delivery ratio, service availability, mean and 95th-percentile recovery time, fault-detection delay, outage duration, recovery success rate, and packet loss during recovery. Tests should additionally examine whether geographic proximity leads to genuinely viable alternative routes when terrain, interference, congestion, or capacity constraints affect candidate links. A geographically closer node is not necessarily the best recovery destination; the decision must consider link quality, available capacity, and end-to-end service requirements.

The full framework should be considered more resilient only if it demonstrates statistically supported improvements over the conventional geographic-routing and AI-based baselines under equivalent failure scenarios. Results should include repeated trials, confidence intervals, and performance during partial infrastructure failure rather than relying solely on average performance in stable conditions.

1.12.3. Explainability and Decision Transparency

Explainability is a distinguishing component of EAGI-6G because network operators need to understand the reasons behind high-risk link predictions, traffic-routing decisions, and recovery recommendations. Explainable AI has been identified as an important research direction for intelligent Open Radio Access Network (O-RAN) management, where the interpretability of AI-assisted decisions affects operator trust and adoption (Brik et al., 2025).

The framework should evaluate explanation quality using four dimensions:

- Fidelity: whether explanations accurately represent the model's actual behavior.
- Stability: whether similar inputs produce reasonably consistent explanations.
- Timeliness: the time required to generate explanations without violating operational latency requirements.
- Operational usefulness: whether explanations help operators identify relevant factors and assess proposed network actions.

The specific comparison parameters should include explanation-generation latency in milliseconds, feature-attribution stability across repeated runs, fidelity under perturbation tests, and consistency across geographically distinct test regions. SHAP values can help quantify feature contributions, but the resulting explanations must not be interpreted as causal proof (Lundberg & Lee, 2017).

A central design challenge is balancing predictive performance, communication reliability, computational overhead, and explanation quality. A highly accurate model may be unsuitable for real-time network control if it requires excessive processing time, while a fast model may provide insufficiently reliable decisions under

unfamiliar geographic conditions. EAGI-6G should therefore be evaluated as a multi-objective system rather than ranked using prediction accuracy alone.

1.13. Practical Implications and Limitations

1.13.1. Practical Implications

EAGI-6G has potential applications in intelligent radio access networks, smart cities, emergency communication, industrial IoT, and geographically distributed infrastructure. Integrating geographic information with distributed AI could support location-aware resource allocation, localized congestion prediction, adaptive routing, and rapid recovery from communication failures. These capabilities are consistent with the broader vision for IMT-2030, which emphasizes diverse usage scenarios and enhanced network capabilities (ITU, 2023).

For telecommunications operators, the framework could support proactive maintenance by identifying geographic regions with elevated link-failure risks before service degradation becomes severe. For emergency-response systems, resilience-oriented routing could help maintain connectivity when individual network components fail. For industrial IoT, distributed processing could support time-sensitive applications while reducing unnecessary reliance on remote cloud infrastructure.

Practical deployment should prioritize the following comparison parameters:

1. Network performance: 95th-percentile latency, PDR, throughput, and packet-loss rate.
2. Resilience: fault-detection delay, recovery time, recovery success rate, and service availability.
3. Geospatial generalization: predictive performance in previously unseen regions and under changing geographic conditions.
4. Computational efficiency: inference time, CPU/GPU utilization, memory consumption, and energy per delivered bit.
5. Explainability: explanation fidelity, stability, generation time, and operator usefulness.
6. Deployment cost: communication overhead, infrastructure requirements, model-update traffic, and maintenance effort.

The framework could also support more energy-aware network operation. However, energy savings should be assessed across the complete system, including communication, distributed computation, model synchronization, and explainability overhead. AI-based optimization should not be assumed to reduce energy consumption unless comparative measurements demonstrate a net benefit (Roessler et al., 2026).

1.13.2. Research Limitations

Several limitations must be considered when interpreting the proposed framework.

First, the framework's effectiveness depends on the availability, accuracy, and timeliness of geospatial and network telemetry. Incomplete location information, outdated topology data, noisy measurements, and missing network events may reduce prediction reliability.

Second, geographic conditions and traffic patterns can change over time. Models trained in one region may not generalize to areas with different terrain, infrastructure density, interference patterns, or mobility behavior. Spatially aware validation, including methods that consider differences in both geographic and feature spaces, can provide a more realistic assessment of generalization (Wang et al., 2023).

Third, distributed AI introduces synchronization, privacy, bandwidth, and computational challenges. Federated or hierarchical learning may reduce the need to centralize raw data, but it does not automatically guarantee privacy or eliminate communication overhead. These properties require explicit evaluation.

Fourth, explainability introduces its own computational cost and methodological uncertainty. Feature-attribution methods may be unstable under changes in the input distribution, and an understandable explanation does not necessarily mean that a prediction is correct or a recommended action is safe. Explanation quality and network performance must therefore be evaluated separately and jointly (Brik et al., 2025).

Finally, the proposed framework's performance improvements remain to be empirically established. Without completed simulation or testbed experiments, it is not possible to claim numerical gains in accuracy, latency, energy efficiency, or resilience. Future validation should compare all baseline configurations using identical scenarios, repeated trials, geographically held-out test data, confidence intervals, and statistical significance tests. Large-scale testbed experiments would further establish whether the framework can operate within realistic 6G resource and timing constraints.

In summary, EAGI-6G offers a structured approach to combining geospatial context, distributed intelligence, explainable decisions, and resilience-oriented control. Its principal research contribution is the integrated evaluation of these capabilities using common performance and operational criteria. Its practical value will ultimately depend on demonstrating that the combined framework outperforms simpler alternatives without introducing unacceptable computational, communication, energy, or interpretability costs.

Chapter Seven: Conclusion and Future Work

This section builds on emerging research that identifies explainability, distributed intelligence, scalability, and trustworthy autonomous network management as important challenges for future 6G systems (Sun et al., 2025; Tok et al., 2026).

1.14. Summary of Findings

The research proposes EAGI-6G, an integrated framework combining geospatial intelligence, distributed AI, explainable predictions, and resilience-oriented network optimization. Its objective is to support location-aware prediction of network congestion, link failures, and service degradation while enabling adaptive responses across edge, regional, and cloud infrastructure.

The proposed architecture integrates six functional layers: multisource data acquisition, geospatial data integration, distributed AI processing, explainable prediction, resilience optimization and control, and performance evaluation with feedback. These layers are designed to connect spatial context with network telemetry and operational decisions.

The research establishes five configurations for comparative evaluation: conventional geographic routing, centralized AI without explicit geospatial features, distributed AI without explicit geospatial features, distributed geospatial AI without explicit explainability, and the complete EAGI-6G framework. This comparison is intended to isolate the contributions of distributed processing, geographic context, and explainable decision-making.

The evaluation framework emphasizes measurable parameters, including:

- Prediction quality: precision, recall, F1-score, AUROC, Brier score, and false-alarm rate.

- Communication performance: median and 95th-percentile latency, packet delivery ratio, throughput, and packet-loss rate.
- Resilience: fault-detection delay, recovery time, recovery success rate, service availability, and outage duration.
- Energy and computational efficiency: energy per delivered bit, inference latency, CPU/GPU utilization, and model-update overhead.
- Geospatial generalization: predictive performance in geographically unseen regions and under changing traffic and environmental conditions.
- Explainability: explanation fidelity, attribution stability, generation latency, and operational usefulness.

Spatially separated testing is essential because nearby observations can be correlated and may produce overly optimistic estimates when training and test samples are randomly distributed (Wang et al., 2023). Likewise, explanation quality should be measured independently of predictive accuracy because transparent model outputs do not automatically establish causal relationships or guarantee safe decisions (Lundberg & Lee, 2017).

Important qualification: These are proposed architectural contributions and evaluation objectives, not verified performance improvements. Numerical conclusions about accuracy, latency, resilience, or energy savings require completed simulations or testbed experiments.

1.15. Research Contributions

The principal contribution of this research is a unified design and evaluation approach for integrating explainable AI, geospatial intelligence, distributed computation, and resilience management in future 6G communication systems.

First, an integrated geospatial-AI architecture. EAGI-6G combines geographic characteristics, network topology, node proximity, traffic conditions, and link-quality measurements to support spatially informed network prediction and optimization. This extends the research focus beyond isolated AI tasks toward coordinated, location-aware network intelligence, consistent with broader developments in geospatial AI and intelligent communications (Dritsas & Trigka, 2026; Tok et al., 2026).

Second, distributed and resilience-oriented intelligence. The framework distributes AI inference and decision-making across edge, regional, and cloud resources. It is designed to investigate whether distributed processing can maintain service continuity during congestion, communication-link failures, and partial infrastructure outages. The contribution must be validated through comparative measurements of recovery time, service availability, packet delivery ratio, and coordination overhead.

Third, explainable network decision-making. The proposed framework incorporates feature-attribution techniques, such as SHAP, to make congestion predictions, link-risk assessments, and recovery recommendations more interpretable. This supports the development of transparent AI-assisted network management, a recognized research direction in 6G and O-RAN systems (Brik et al., 2025; Sun et al., 2025).

Fourth, a multidimensional comparison and ablation methodology. Rather than evaluating the system only by predictive accuracy, the research considers the joint effects of spatial information, distributed processing, explainability, and resilience control. The baseline and ablation experiments are intended to identify which components contribute to predictive performance, low latency, reliable recovery, and operational transparency.

Fifth, a reproducible evaluation strategy. The research defines common scenarios, consistent baseline configurations, geographically separated testing, repeated experiments, and statistical reporting. These procedures are intended to support a fair assessment of whether the integrated architecture provides practical advantages over simpler alternatives.

Taken together, these contributions establish a framework for investigating the relationship between geospatial context, distributed intelligence, explainability, and network resilience. The novelty claim should ultimately be supported through a systematic literature comparison and empirical evidence demonstrating the specific advantages of the integrated approach.

2. Recommendations

The following recommendations are proposed for researchers, network engineers, telecommunications operators, and future developers of intelligent 6G systems.

1. Establish a reproducible experimental environment. Implement EAGI-6G using a documented network simulator or an appropriate 5G/O-RAN-compatible testbed. Record network topology, geographic attributes, traffic profiles, computational resources, model settings, and failure scenarios so that experiments can be repeated.

2. Strengthen baseline comparisons. Evaluate all five configurations using identical traffic traces, resource limits, failure events, and test regions. Report precision, recall, F1-score, AUROC, Brier score, median and 95th-percentile latency, packet delivery ratio, recovery time, energy per delivered bit, and communication overhead.

3. Apply spatially independent validation. Separate training and testing geographically, assess performance under different traffic loads and environmental conditions, and investigate temporal drift. Spatial cross-validation methods can help reduce overly optimistic performance estimates caused by geographic dependence (Wang et al., 2023).

4. Evaluate explainability under real-time constraints. Measure explanation fidelity, stability, generation latency, and usefulness to network operators. Explanations should accompany decisions where appropriate, while automated control actions must remain subject to network constraints and safety checks. Explainability should not be treated as proof of causality (Lundberg & Lee, 2017).

5. Measure total system energy and overhead. Include radio communication, edge computation, model synchronization, explanation generation, and control signaling. A proposed optimization should be considered energy-efficient only when the complete system demonstrates improved energy consumption per successfully delivered bit.

6. Prioritize secure and privacy-aware distributed learning. Assess data exposure, model-update integrity, adversarial manipulation, and access control. Where federated learning is used, evaluate its communication cost and privacy protections rather than assuming that distributed training alone guarantees privacy.

7. Use staged deployment. Begin with simulation, progress to controlled testbed experiments, and then evaluate selected functions in a limited operational pilot. Monitor prediction drift, rejected control actions, service disruptions, and explanation quality before considering broader deployment.

These recommendations align with current research directions emphasizing scalable, transparent, and trustworthy AI-driven network management (Sun et al., 2025; Tok et al., 2026).

2.1. Future Research Directions

Future research should move EAGI-6G from a proposed architecture toward an experimentally validated, scalable, and deployment-ready framework. The following directions are prioritized according to their relevance to geospatial intelligence, distributed communication, resilience, and explainable decision-making.

1. Geospatial graph neural networks and spatiotemporal prediction. Future work should investigate graph neural networks combined with temporal models to represent base stations, edge nodes, communication links, terrain characteristics, and traffic dynamics. Comparative experiments should determine whether these models outperform conventional machine-learning and deep-learning baselines in F1-score, AUROC, 95th-percentile prediction latency, and performance on geographically unseen regions.

2. Explainable deep reinforcement learning for adaptive network control. EAGI-6G could incorporate explainable reinforcement learning to select routing, resource allocation, and recovery actions under changing network conditions. Evaluation should compare service quality, cumulative control cost, recovery success rate, explanation fidelity, and decision latency. Recent research on explainable reinforcement learning for intelligent 6G radio access networks identifies scalability, generalization, and operator control as important future challenges (Towards Transparent 6G AI-RAN, 2026).

3. Federated and hierarchical learning across geographic regions. Future studies should investigate federated learning across multiple edge nodes and regions without routinely transferring raw local data to a central server. The main comparison parameters should include global and regional model accuracy, convergence time, bytes transmitted per training round, energy consumption, privacy risk, and robustness to unreliable participants.

4. Digital twins for network resilience testing. A geospatially enabled 6G digital twin could reproduce network topology, geographic conditions, traffic patterns, and infrastructure failures. Researchers could use this environment to compare recovery policies before deploying them on physical infrastructure. Important metrics include digital-twin synchronization delay, simulation-to-network prediction error, failure-reproduction fidelity, and the consistency of simulated and measured recovery outcomes. Digital-twin validation should explicitly account for discrepancies between the virtual and physical systems.

5. Cross-domain and cross-region generalization. Future experiments should test the framework across urban, rural, industrial, and geographically challenging environments. Transfer learning and domain adaptation could be evaluated using changes in F1-score, calibration error, false-alarm rate, and recovery success when the deployment region differs from the training region. Spatially independent evaluation should remain central to this work (Wang et al., 2023).

6. Trustworthy and secure AI-native 6G systems. Further research should investigate adversarial attacks on network telemetry, manipulated geographic information, model poisoning, and unsafe automated control. Relevant comparison parameters include attack-detection rate, false-positive rate, service degradation under attack, recovery time, and explanation stability under adversarial perturbations. These studies should examine how explainability, security, and operational reliability interact rather than evaluating each in isolation (Brik et al., 2025; Sun et al., 2025).

7. Energy-aware and sustainable distributed intelligence. Future work should optimize prediction accuracy, latency, resilience, and energy consumption jointly. Multi-objective optimization could identify trade-offs between energy per delivered bit, 95th-percentile latency, service availability, and explanation-generation overhead. Researchers should report Pareto-optimal solutions instead of assuming that a single configuration will maximize every objective.

8. Real-time testbed validation and standardization. The final direction is to implement the framework in an O-RAN-compatible environment or another suitable experimental platform. Testing should examine interoperability, control-loop timing, model-update overhead, geographic data quality, failure recovery, and operational safety. Future studies should also document interfaces, datasets, configuration parameters, and evaluation protocols to improve reproducibility and facilitate comparisons with other 6G architectures (International Telecommunication Union, 2023).

In conclusion, EAGI-6G establishes a research direction for combining geographic context, distributed AI, interpretable predictions, and resilience-oriented network control. Its long-term significance will depend on reproducible experiments that establish whether these components deliver measurable advantages over simpler approaches. The most important next step is to implement the baseline and ablation configurations, collect experimental results, and quantify the trade-offs among predictive accuracy, spatial generalization, 95th-percentile latency, packet delivery, recovery performance, energy efficiency, and explainability.

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