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Agentic AI for Service Assurance in Fixed Broadband Networks: A Conceptual Framework for Intelligent NOC Operations

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Abstract*— Fixed broadband operators are increasingly challenged by the growing complexity of fiber access networks, heterogeneous home Wi-Fi environments, rising customer expectations, and the need to improve operational efficiency while maintaining service quality. Conventional service assurance approaches largely rely on rule-based monitoring, fragmented operational support systems, and manual intervention by Network Operations Center (NOC) teams. Although Artificial Intelligence (AI) and Machine Learning (ML) have been applied to fault prediction, anomaly detection, and customer experience analytics, these implementations often operate as isolated solutions with limited autonomy and cross-domain coordination.Recent advances in Agentic Artificial Intelligence (Agentic AI) provide an opportunity to transform service assurance through intelligent agents capable of reasoning, planning, knowledge retrieval, and workflow execution. This paper proposes a conceptual framework for integrating Agentic AI into fixed broadband service assurance processes. The framework combines operational data sources, predictive ML models, Large Language Model (LLM)-based intelligence, multi-agent orchestration, and human-in-the-loop governance to support proactive and explainable operational decision-making.The proposed architecture demonstrates how Agentic AI can enhance key assurance functions, including automated root cause analysis, proactive Quality of Experience (QoE) degradation detection, intelligent incident triage, and NOC copilot assistance. Unlike existing studies that focus on standalone AI applications or mobile network scenarios, this work specifically addresses the operational realities of fixed broadband environments. The findings suggest that Agentic AI can reduce Mean Time to Repair (MTTR), improve customer experience, enhance decision consistency, and increase operational efficiency while maintaining governance and regulatory compliance. The study provides both theoretical insights and practical guidance for telecom operators progressing toward intelligent and autonomous service assurance.

Keywords*— Agentic AI, Fixed Broadband Networks, Service Assurance, FTTH, Network Operations Center, Large Language Models, Telecom AI, Intelligent Operations, Customer Experience, Autonomous Networks.

I. INTRODUCTION

The rapid evolution of fixed broadband services has transformed telecommunications from a connectivity-centric business into an experience-driven digital ecosystem. The widespread deployment of Fiber-to-the-Home (FTTH) infrastructure, increasing adoption of high-speed broadband packages, proliferation of connected devices, and growing dependence on residential Wi-Fi have significantly increased the complexity of service assurance operations. Customers now expect uninterrupted connectivity, consistent throughput, low latency, and rapid issue resolution regardless of whether service impairments originate within the access network, customer premises equipment (CPE), or home Wi-Fi environments.

Traditionally, service assurance in fixed broadband networks has been predominantly reactive. Network Operations Centers (NOCs) rely on threshold-based alarms, fragmented Operational Support Systems (OSS), trouble ticket analysis, and the expertise of experienced engineers to diagnose and resolve incidents. Although these approaches have supported operational continuity for decades, they increasingly struggle to cope with the scale and complexity of modern broadband environments.

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Manual investigations often require engineers to correlate information from multiple systems, resulting in delayed root cause identification, inconsistent decision-making, prolonged restoration times, and increased operational costs.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as promising technologies for addressing these challenges. Existing studies have demonstrated the effectiveness of predictive analytics in anomaly detection, fault prediction, customer churn analysis, and network performance optimization. In their previous work, Mustafa et al. investigated the role of AI-driven analytics in enhancing fixed network performance and operational visibility through predictive and data-driven approaches. However, these applications largely remain domain-specific and advisory in nature, requiring human experts to interpret analytical outputs and translate them into operational actions.

Recent developments in Large Language Models (LLMs) and autonomous AI agents have introduced a new paradigm known as Agentic AI. Unlike traditional AI systems that provide isolated predictions or generate text-based responses, Agentic AI systems are capable of goal-oriented reasoning, planning, knowledge retrieval, tool invocation, and collaborative execution of complex tasks. By combining predictive intelligence with contextual reasoning and workflow orchestration, Agentic AI offers the potential to transform service assurance from a reactive support function into a proactive and adaptive operational capability.

Despite growing interest in autonomous networks and generative AI, existing literature reveals several limitations. First, most telecom AI research focuses on mobile network environments, with comparatively limited attention given to fixed broadband operations. Second, studies investigating LLM applications in telecommunications primarily emphasize conversational assistance and knowledge summarization rather than autonomous operational execution. Third, there remains a lack of conceptual frameworks that integrate predictive ML, LLM reasoning, multi-agent collaboration, and governance mechanisms specifically tailored to fixed broadband service assurance.

To address these gaps, this paper proposes a conceptual framework for applying Agentic AI to intelligent NOC operations in fixed broadband networks. The framework integrates structured operational data, predictive ML capabilities, retrieval-augmented LLM intelligence, agent orchestration mechanisms, and human oversight to support proactive and explainable assurance workflows.

Accordingly, this study seeks to answer the following research question:

How can Agentic AI be integrated into fixed broadband service assurance processes to enhance operational efficiency, improve customer experience, and support intelligent NOC decision-making?

The contributions of this paper are threefold:

- It proposes one of the first conceptual Agentic AI frameworks specifically designed for fixed broadband service assurance and intelligent NOC operations.
- It integrates predictive ML, LLM-based reasoning, and multi-agent orchestration into a unified architecture that reflects the operational realities of fixed broadband environments.
- It provides practical guidance through representative use cases, illustrating how telecom operators can progressively adopt Agentic AI while maintaining explainability, governance, and human oversight.

The remainder of this paper is organized as follows. Section II reviews related work on AI-driven service assurance and identifies key research gaps. Section III outlines the research methodology and development approach. Section IV presents the proposed Agentic AI framework. Section V discusses practical use cases and expected business impacts. Section VI examines implementation challenges and future research directions. Finally, Section VII concludes the paper.

II. RELATED WORK AND RESEARCH GAP

A. AI in Fixed Broadband Service Assurance

Service assurance has evolved from traditional fault management toward a customer-centric discipline encompassing network performance, service quality, and Quality of Experience (QoE). In fixed broadband environments, assurance activities extend beyond the operator-controlled access infrastructure to include residential Wi-Fi conditions, customer premises equipment (CPE), and end-user behavior. Consequently, operators increasingly depend on diverse data sources, including network KPIs, alarm systems, trouble tickets, CRM records, and customer experience platforms.

Recent research has demonstrated the value of Artificial Intelligence (AI) and Machine Learning (ML) in addressing several assurance challenges. Common applications include anomaly detection, fault prediction, traffic forecasting, churn analysis, and QoE assessment. These techniques enable operators to identify abnormal patterns, prioritize interventions, and improve operational visibility. Furthermore, predictive models have supported preventive maintenance initiatives and more efficient resource utilization.

In their previous study, Mustafa et al. investigated the application of AI-driven analytics for optimizing fixed network performance through operational intelligence and predictive insights. The findings highlighted the role of AI in enhancing performance monitoring and supporting data-driven decision-making in modern telecom environments. However, the study primarily focused on predictive and analytical capabilities without exploring autonomous execution or intelligent orchestration mechanisms.

Similarly, emerging research on customer-centric broadband analytics has emphasized the importance of integrating customer experience indicators into operational decision-making. These efforts demonstrate that service assurance should move beyond infrastructure-centric metrics toward proactive experience management. Nevertheless, existing approaches often stop at generating recommendations, leaving the translation of analytical outputs into operational actions largely dependent on human expertise.

Collectively, these studies confirm the growing importance of AI within fixed broadband operations while also exposing the limitations of current implementations.

B. Generative AI and Agentic AI in Telecommunications

The emergence of Large Language Models (LLMs) has expanded the scope of AI applications beyond statistical prediction. LLMs possess advanced capabilities in natural language understanding, summarization, contextual reasoning, and conversational interaction. Early telecom applications have explored their use for:

- Knowledge retrieval from operational documents;
- Troubleshooting assistance;
- Ticket summarization;
- Customer support chatbots;
- Engineering copilots.

These applications improve accessibility to organizational knowledge and reduce the time required to interpret operational information.

However, most existing implementations position LLMs as passive advisory tools. They typically generate responses based on user prompts but lack the capability to autonomously pursue objectives, invoke external tools, or coordinate complex workflows.

Recent developments in Agentic AI seek to address these limitations. Agentic AI refers to systems composed of intelligent agents capable of perceiving their environment, reasoning about goals, selecting appropriate tools, executing tasks, and collaborating with other agents to achieve desired outcomes. Unlike conventional automation, Agentic AI introduces adaptive decision-making and goal-oriented behavior.

Within the broader AI community, researchers have investigated concepts such as:

- Reasoning and acting frameworks;
- Retrieval-augmented generation (RAG);
- Multi-agent collaboration;
- Memory-enhanced agents;
- Planning mechanisms.

These advances provide a foundation for the next generation of intelligent operational systems.

Despite this progress, their application within telecommunications remains at an early stage. Existing studies predominantly focus on conceptual discussions of autonomous networks or exploratory demonstrations of generative AI capabilities. Practical frameworks illustrating how Agentic AI can support service assurance processes in fixed broadband environments remain scarce.

C. Research Gap Analysis

The review of contemporary literature reveals three major gaps that motivate this study.

1) Gap 1: Limited Focus on Fixed Broadband Operations

Much of the telecom AI literature concentrates on mobile and radio access network scenarios, particularly within the context of 5G and autonomous mobile networks. By comparison, fixed broadband environments present distinct operational characteristics, including:

- Dependence on FTTH infrastructure;
- Variability introduced by residential Wi-Fi;
- Heterogeneous CPE ecosystems;
- Customer-driven service experience factors.

These characteristics require dedicated service assurance approaches that cannot be directly inferred from mobile network studies.

2) Gap 2: Fragmented Intelligence Capabilities

Current research typically addresses individual AI functions in isolation.

Examples include:

- Predictive models for fault detection;
- QoE analytics;
- Conversational assistants;
- Knowledge retrieval systems.

Although valuable, these technologies often operate independently and fail to provide an integrated operational workflow capable of progressing from detection to recommendation and execution.

Consequently, operators continue to rely heavily on manual coordination among teams and systems.

3) Gap 3: Lack of Agentic AI Frameworks for Service Assurance

Existing studies investigating LLMs in telecommunications primarily emphasize human assistance rather than operational autonomy. Similarly, autonomous network initiatives focus on closed-loop automation but often overlook reasoning, planning, and explainability requirements.

There remains a lack of frameworks that simultaneously integrate:

- Predictive ML capabilities;
- LLM-based contextual reasoning;
- Multi-agent collaboration;
- Workflow execution mechanisms;
- Human oversight and governance.

This gap is particularly evident within fixed broadband service assurance, where operational decisions directly affect customer experience and regulatory obligations.

TABLE I
RESEARCH GAP MATRIX

Research Area	Existing Focus	Strengths	Identified Limitation	Contribution of This Study
AI for Telecom Operations	Fault prediction and anomaly detection	Improved visibility and early warnings	Limited operational execution	Integrates predictive intelligence into assurance workflows
Customer Experience Analytics	QoE monitoring and churn analysis	Customer-centric insights	Weak linkage to remediation actions	Connects experience analytics with agent-driven responses
Generative AI in Telecom	Summarization and conversational support	Enhanced knowledge accessibility	Primarily advisory in nature	Extends LLMs toward reasoning and action
Autonomous Networks	Closed-loop automation	Reduced manual intervention	Limited contextual reasoning and explainability	Incorporates planning and governance mechanisms
Multi-Agent AI	Collaborative problem solving	Distributed intelligence	Minimal telecom assurance applications	Tailors' agent collaboration to fixed broadband NOC operations

The gaps identified above indicate that the foundational technologies required for intelligent assurance already exist but remain fragmented. Fixed broadband operators require a practical framework capable of integrating predictive analytics, contextual reasoning, autonomous coordination, and human oversight within existing OSS/BSS ecosystems.

Accordingly, this study adopts a design-oriented perspective to develop a conceptual Agentic AI framework that addresses these dficiencies and provides a practical roadmap for intelligent NOC operations in fixed broadband environments.
The following section outlines the research methodology employed to develop the proposed framework.

III. RESEARCH METHODOLOGY

This study adopts a Design Science Research (DSR) approach to develop a conceptual framework for applying Agentic AI to fixed broadband service assurance. DSR is widely used in information systems research to create and evaluate innovative artifacts intended to address practical problems through rigorous and systematic design.
The selection of DSR is appropriate for this study for three reasons. First, the research aims to propose a novel artifact in the form of an architectural framework rather than empirically test an existing theory. Second, the study addresses a real-world operational challenge encountered by fixed broadband operators. Third, the framework is intended to provide practical utility while contributing to the emerging body of knowledge on Agentic AI in telecommunications.
The framework development process consisted of four stages:

A. Problem Identification

A review of current service assurance practices and recent literature was conducted to identify limitations associated with traditional fixed broadband operations. Key challenges included fragmented OSS/BSS environments, reactive troubleshooting, dependence on expert knowledge, and limited integration between existing AI capabilities and operational workflows.

B. Knowledge Synthesis

Relevant literature relating to predictive machine learning, Large Language Models (LLMs), retrieval-augmented generation (RAG), multi-agent systems, and autonomous networking initiatives was synthesized. Insights derived from prior studies were complemented by practical knowledge from fixed broadband operations, including NOC practices, customer experience management, incident handling, and SLA monitoring.

C. Artifact Design

Based on the identified requirements, a multi-layer Agentic AI framework was developed. The proposed artifact integrates predictive analytics, contextual reasoning, agent orchestration, and governance mechanisms to support intelligent service assurance processes within existing telecom ecosystems.
The findings were synthesized into a conceptual framework illustrating relationships between AI technologies and customer experience outcomes.

D. Demonstration Through Use Cases

Although the framework is conceptual and does not rely on proprietary datasets, its applicability is demonstrated using representative fixed broadband service assurance scenarios commonly encountered by telecom operators. These use cases illustrate how Agentic AI capabilities may enhance operational decision-making and support progressive movement toward autonomous assurance.
Figure 1 presents the proposed framework derived through this design-oriented process.

IV. PROPOSED AGENTIC AI FRAMEWORK FOR INTELLIGENT NOC OPERATIONS

A. Framework Overview

The proposed framework aims to transform service assurance from a reactive and alarm-driven function into a proactive, intelligence-enabled capability. Unlike traditional approaches that depend heavily on manual correlation and static workflows, the framework enables AI agents to collaborate across operational domains, synthesize evidence, generate recommendations, and support workflow execution under human supervision.
The architecture comprises five interconnected layers:

- Data Layer;
- Machine Learning Layer;
- LLM Intelligence Layer;
- Agent Orchestration Layer; and

- Human Governance Layer.

Together, these layers establish an operational intelligence ecosystem capable of supporting both advisory and semi-autonomous assurance activities.

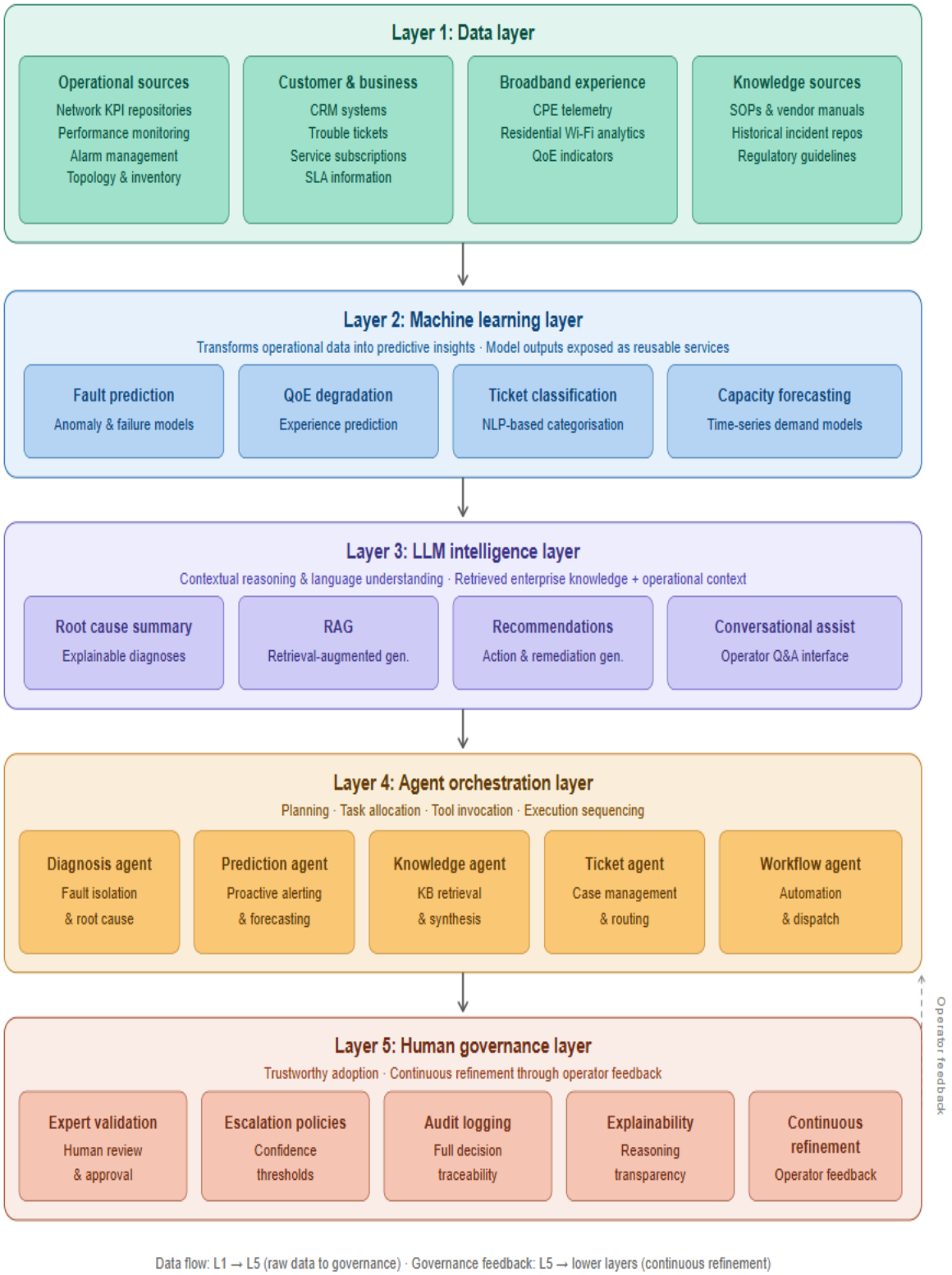

Fig. 1 Agentic AI Framework for Intelligent Fixed Broadband Service Assurance

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B. Data Layer

Effective service assurance requires an integrated view of operational and customer contexts. However, telecom environments are frequently characterized by fragmented data silos.

The Data Layer addresses this challenge by consolidating information originating from multiple domains.

Operational systems contribute infrastructure-related indicators, including network KPIs, alarms, utilization statistics, and topology relationships. Customer-facing platforms provide contextual information such as subscription profiles, complaint histories, and SLA commitments. Broadband-specific sources enrich this perspective through Wi-Fi telemetry, CPE diagnostics, and QoE measurements that reflect subscribers' perceived experiences.

Knowledge repositories further enhance decision support by capturing organizational expertise embedded within troubleshooting guides, operational procedures, and historical incidents.

By establishing a unified assurance knowledge base, the framework enables downstream intelligence components to reason using both technical evidence and customer context.

C. Machine Learning Layer

The Machine Learning Layer provides predictive capabilities that enable assurance activities to shift from reactive responses toward proactive intervention.

Rather than replacing human expertise, these models function as decision-support mechanisms that identify emerging risks and prioritize attention.

1) *Fault Prediction:*Predictive models analyze historical KPI trends and incident patterns to estimate the probability of future failures.

Potential outputs include:

- Likelihood of service degradation;
- Severity estimation;
- Identification of vulnerable service clusters.

2) *QoE Degradation Prediction:*Customer complaints are often preceded by measurable declines in service quality.

By analyzing indicators such as throughput fluctuations, latency patterns, Wi-Fi stability, and historical customer interactions, predictive models can identify subscribers at elevated risk of dissatisfaction before complaints are formally raised.

3) *Ticket Classification:*Natural language processing techniques assist in automating ticket interpretation.

Applications include:

- Categorization of incidents;
- Duplicate detection;
- Urgency assessment;
- Routing recommendations.

These capabilities accelerate triage processes and improve prioritization consistency.

D. Capacity Forecasting

Forecasting models support proactive planning by identifying future congestion risks based on historical utilization trends and demand growth patterns.

The resulting insights assist operators in prioritizing capacity investments and preventive interventions.

Collectively, the Machine Learning Layer transforms raw operational data into actionable intelligence that can be leveraged by higher-level reasoning agents.

The following section introduces the LLM Intelligence and Agent Orchestration components, which distinguish the proposed framework from conventional predictive assurance approaches.

II. LLM INTELLIGENCE, AGENT ORCHESTRATION, AND PRACTICAL USE CASES

A. LLM Intelligence Layer

While predictive machine learning models provide early warning signals and probability-based insights, they often lack the ability to interpret operational contexts, explain findings, and communicate recommendations in a form readily understood by engineers and service teams.

The LLM Intelligence Layer addresses these limitations by introducing reasoning and language capabilities into service assurance workflows.

Unlike conventional chatbot implementations, the proposed LLM component functions as an operational intelligence engine embedded within NOC processes. It complements predictive analytics by transforming fragmented operational evidence into actionable insights.

The LLM Intelligence Layer supports four primary functions:

1) Root Cause Summarization

Service investigations typically require engineers to review multiple sources of information, including alarm dashboards, KPI reports, historical incidents, and troubleshooting notes. The LLM can consolidate these inputs and generate concise summaries that highlight:

- Probable causes of degradation;
- Affected customer segments;
- Evidence supporting the assessment;
- Recommended next actions.

This capability reduces cognitive effort and accelerates knowledge transfer across teams.

2) Retrieval-Augmented Generation (RAG)

General-purpose LLMs may produce inaccurate recommendations when operating without organizational context. Retrieval-Augmented Generation (RAG) addresses this limitation by grounding responses using enterprise knowledge repositories.

Relevant knowledge sources include:

- Standard operating procedures;
- Vendor troubleshooting manuals;
- Escalation matrices;
- Regulatory guidelines;
- Historical resolution records.

By retrieving and incorporating relevant documents into the reasoning process, the LLM produces responses that are more accurate, explainable, and aligned with organizational practices.

3) Recommendation Generation

Based on predictive outputs and retrieved knowledge, the LLM can propose context-aware actions. Illustrative recommendations include:

- Initiating predefined troubleshooting procedures;
- Recommending Wi-Fi optimization activities;
- Suggesting escalation to specialized teams;
- Proposing preventive interventions.

Importantly, these recommendations remain subject to governance controls and human validation according to the level of operational impact.

4) Conversational Assistance

The LLM enables natural language interaction with assurance systems.

Examples of operational queries include:

- Which regions experienced the highest concentration of repeat incidents this week?
- Summarize the probable causes of FTTH complaints associated with this cluster.
- What troubleshooting steps should be attempted before escalation?

Such capabilities democratize access to operational intelligence and reduce reliance on manual report generation.

B. Agent Orchestration Layer

The distinguishing characteristic of Agentic AI lies in its ability to transform intelligence into coordinated action.Traditional automation relies on predefined workflows executed under known conditions. In contrast, Agentic AI employs specialized agents capable of pursuing objectives, invoking tools, and collaborating dynamically according to operational needs.

The proposed framework incorporates five specialized agents.

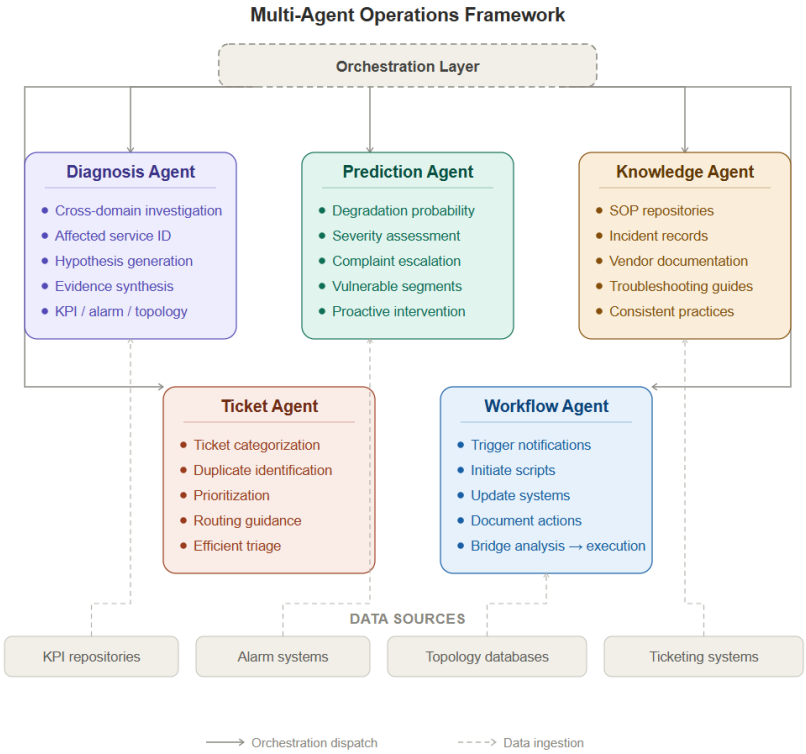

Fig. 2Multi-agent framework

C. Practical Use Cases

To demonstrate operational applicability, four representative use cases commonly encountered in fixed broadband environments are presented.

1) Automated Root Cause Analysis

In traditional NOC environments, engineers manually correlate alarms, performance reports, and historical incidents to identify probable causes of degradation. Under the proposed framework, the Diagnosis Agent coordinates with the Prediction and Knowledge Agents to investigate incidents automatically.

For example, multiple complaints affecting subscribers connected to the same aggregation node may be linked to congestion patterns observed during peak periods. Historical incidents retrieved by the Knowledge Agent may reveal that similar events were previously resolved through load redistribution.

Expected benefits include:

- Faster diagnosis;
- Improved consistency;
- Reduced dependence on individual expertise.

2) Proactive QoE Degradation Detection

Customer complaints often represent a lagging indicator of service quality deterioration.The Prediction Agent continuously evaluates signals such as:

- Declining throughput;
- Increased latency;
- Unstable wi-fi performance;
- Recurring contact patterns.

Subscribers exhibiting elevated degradation risk can be identified before complaints are received.Potential interventions include proactive troubleshooting recommendations and targeted customer communications.

Expected outcomes include:

- Lower complaint volumes;
- Improved customer satisfaction;
- Reduced repeat contacts.

3) Intelligent Incident Triage

Ticket management remains a labor-intensive activity within many broadband operations. The Ticket Agent can streamline this process by:

- Automatically categorizing incidents;
- Detecting duplicate reports;
- Estimating severity levels;
- Recommending escalation priorities.

For instance, multiple complaints associated with a common fiber cluster can be consolidated into a single major incident investigation. Expected benefits include:

- Reduced triage effort;
- Accelerated response initiation;
- Improved prioritization accuracy.

4) NOC Copilot for Engineers

Modern NOCs operate within information-rich environments where engineers frequently navigate multiple systems and documents. The proposed LLM-enabled copilot provides conversational assistance that supports operational decision-making.

Engineers may request:

- Summarize incidents affecting Region A during the past 24 hours.
- Have similar Wi-Fi degradation patterns been observed previously?
- What are the recommended next troubleshooting steps?

The copilot synthesizes operational evidence and retrieved knowledge into concise, explainable responses.

Expected benefits include:

- Increased productivity;
- Faster onboarding of new engineers;
- Reduced cognitive burden;
- Improved knowledge accessibility.

TABLE II

TRADITIONAL VERSUS AGENTIC AI-ENABLED SERVICE ASSURANCE

Dimension	Traditional Assurance	Agentic AI-Enabled Assurance
Operational Approach	Reactive	Proactive and adaptive
Root Cause Analysis	Manual investigation	Automated evidence synthesis
Incident Triage	Human-driven	AI-assisted prioritization
Knowledge Access	Document search	RAG-enabled retrieval
Decision Support	Experience dependent	Context-aware recommendations
Customer Engagement	Reactive communication	Proactive interactions
Learning Capability	Limited organizational learning	Continuous refinement through feedback
Workforce Dependency	High reliance on experts	Expert augmentation
MTTR	Relatively prolonged	Potentially reduced
Explainability	Procedural	Evidence-based and transparent

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The use cases and comparative analysis demonstrate that Agentic AI has the potential to augment human expertise, improve operational responsiveness, and enhance customer-centric service assurance. Rather than replacing engineers, the framework positions AI agents as collaborative partners capable of supporting intelligent NOC operations within fixed broadband environments.

III.CHALLENGES AND FUTURE RESEARCH DIRECTIONS

While Agentic AI offers considerable promise for transforming fixed broadband service assurance, several technical, organizational, and regulatory challenges must be addressed to enable practical adoption. Recognizing these considerations is essential to ensuring that proposed frameworks remain both implementable and trustworthy.

A. Implementation Challenges

1) Data Quality and Integration

The effectiveness of Agentic AI is fundamentally dependent on the quality of underlying operational data. However, fixed broadband environments often contain fragmented OSS/BSS ecosystems, inconsistent KPI definitions, duplicate records, and incomplete customer information. Poor data quality may adversely affect predictive models, reduce confidence in recommendations, and undermine user trust.

Operators should therefore establish:

- Standardized data definitions;
- Data validation mechanisms;
- Enterprise data governance practices; and
- API-driven integration frameworks.

Data readiness should be viewed as a prerequisite rather than an afterthought in Agentic AI initiatives.

2) Explainability and Trust

Service assurance decisions can directly influence customer experience, operational expenditure, and regulatory reporting. Consequently, engineers and managers must understand why recommendations are generated.

Black-box decision-making may hinder adoption and raise concerns regarding accountability.

Agentic AI systems should therefore provide:

- supporting evidence for recommendations;
- confidence indicators;
- references to retrieved knowledge sources; and
- concise reasoning summaries.

Transparent outputs enhance both operational trust and regulatory defensibility.

3) Privacy, Security, and Compliance

Service assurance processes routinely involve sensitive operational and customer information. The introduction of LLMs and autonomous agents increases exposure to risks related to:

- Unauthorized access;
- Data leakage;
- Prompt manipulation;
- Misuse of organizational knowledge.

To mitigate these concerns, operators should implement:

- Role-based access controls;
- Data anonymization practices;
- Secure retrieval mechanisms;
- Audit logging; and
- Cybersecurity monitoring.

Furthermore, Agentic AI deployments must comply with applicable privacy regulations and telecommunications reporting obligations.

4) Organizational Readiness

Successful implementation extends beyond technology adoption. Organizational culture, workforce capabilities, and process maturity significantly influence outcomes.Operational teams may initially perceive Agentic AI as a replacement rather than an augmentation capability. Resistance to change can therefore become a barrier to adoption.

To address this challenge, operators should prioritize:

- Workforce training and AI literacy initiatives;
- Pilot deployments demonstrating measurable value;
- Cross-functional collaboration; and
- Progressive introduction of autonomy.

Positioning Agentic AI as an enabler of human expertise is likely to improve acceptance.

B. Future Research Directions

Although the proposed framework provides a practical roadmap, several opportunities exist to advance the field further.

1) *Telecom-Specific LLMs*: Future research should investigate the development of domain-adapted language models trained using telecom standards, troubleshooting procedures, vendor manuals, and historical incident records. Such specialization may improve technical reasoning and reduce hallucination risks.
2) *Digital Twins for Assurance:*The integration of Agentic AI with digital twin environments could enable agents to simulate mitigation strategies before deployment within production networks. This capability would facilitate safer experimentation and more informed decision-making.
3) *Reinforcement Learning for Closed-Loop Assurance*: Reinforcement learning techniques may support the optimization of escalation policies, preventive interventions, and resource allocation decisions through continuous feedback mechanisms.However, safeguards and simulation environments will be necessary before applying such approaches to live operational systems.
4) *Standardization and Governance Frameworks:*Industry bodies such as TM Forum, ETSI, and ITU-T may play a pivotal role in defining standards governing:
   - Agent interoperability;
   - Explainability requirements;
   - Confidence reporting mechanisms;
   - Assurance maturity models; and
   - Responsible ai practices.

Standardization efforts will accelerate industry-wide adoption and interoperability.

IV. CONCLUSION

This paper proposed a conceptual framework for applying Agentic AI to service assurance in fixed broadband networks. Motivated by the limitations of traditional assurance approaches and the fragmented nature of existing AI applications, the study explored how predictive machine learning, LLM-based reasoning, agent orchestration, and human oversight can be integrated to support intelligent NOC operations.

The review of contemporary literature highlighted a notable gap in current research. While AI applications in telecommunications continue to expand, most studies focus on isolated use cases or mobile network environments. Practical frameworks tailored to fixed broadband operations and capable of bridging predictive intelligence with operational execution remain limited.

To address this gap, this study introduced a five-layer architecture comprising a Data Layer, Machine Learning Layer, LLM Intelligence Layer, Agent Orchestration Layer, and Human Governance Layer. The framework was further illustrated through practical use cases involving automated root cause analysis, proactive QoE degradation detection, intelligent incident triage, and NOC copilot assistance.

The findings suggest that Agentic AI has the potential to improve operational efficiency, enhance decision consistency, reduce Mean Time to Repair (MTTR), and strengthen customer experience outcomes while preserving transparency and human accountability. Rather than replacing operational teams, Agentic AI should be viewed as a collaborative capability that augments human expertise and supports progressive movement toward intelligent assurance.

As fixed broadband operators continue their journey toward autonomous operations, Agentic AI represents a promising direction for future service assurance strategies.

The framework presented in this paper offers both a theoretical contribution to emerging telecom AI literature and a practical roadmap for operators seeking to modernize assurance practices within increasingly complex broadband environments.

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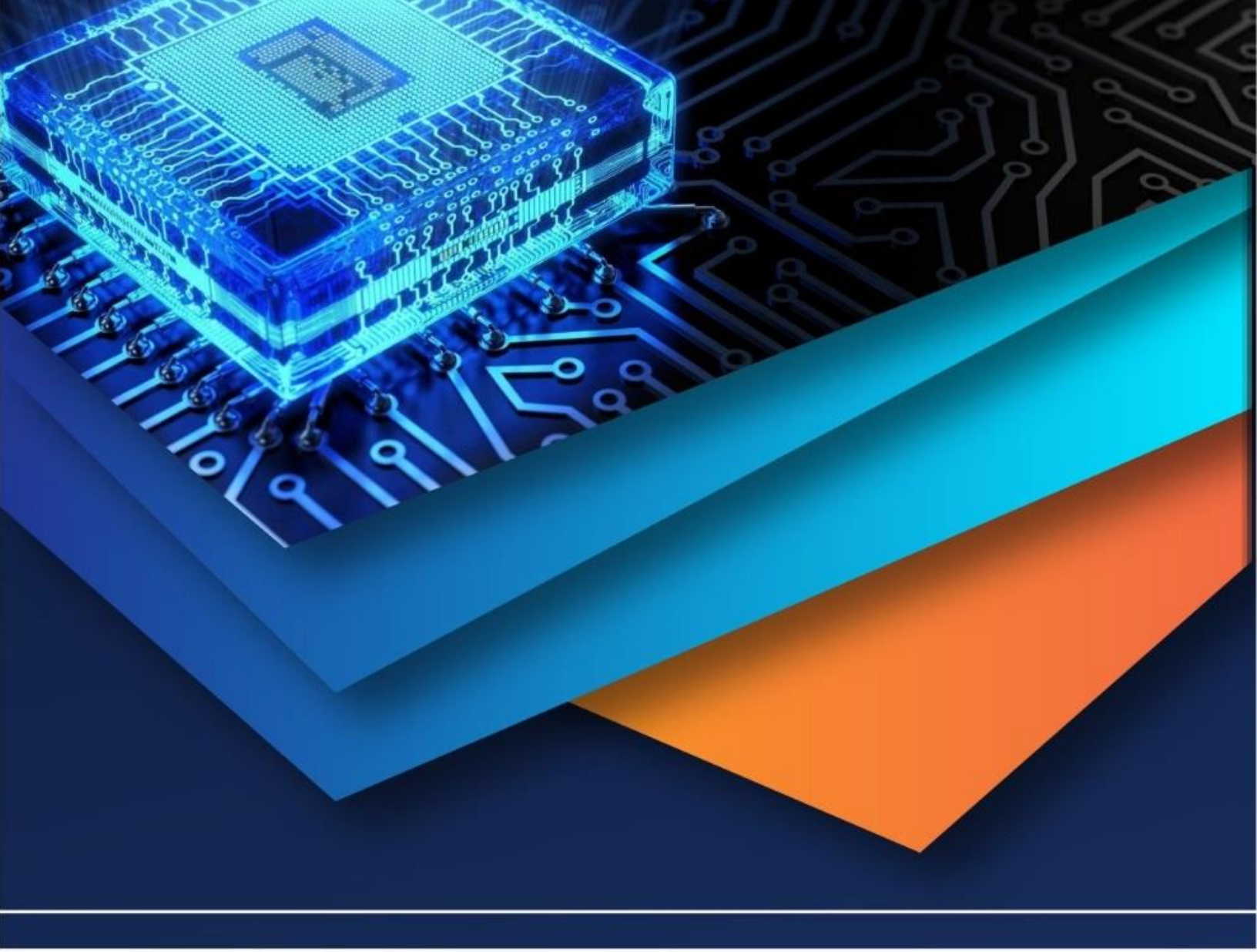

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