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Abstract

Purpose: The exponential growth of heterogeneous applications in next-generation mobile networks, ranging from ultra-reliable low-latency communications (URLLC) and enhanced mobile broadband (eMBB) to massive machine-type communications (mMTC) has created an urgent need for network infrastructures capable of offering differentiated and customized service guarantees. Network slicing has emerged as a pivotal 5G and beyond-5G (B5G) technology that enables the creation of multiple logical networks over a shared physical infrastructure, each tailored to the unique Quality of Service (QoS) and Quality of Experience (QoE) requirements of distinct use cases. This paper explores the architectural principles, enabling technologies, and intelligent management frameworks underpinning network slicing for customized QoS and QoE delivery.

Materials and Methods: We propose a comprehensive model that integrates Software-Defined Networking (SDN), Network Function Virtualization (NFV), and AI-driven orchestration to dynamically allocate network resources and optimize user experience across slices. Furthermore, we analyze the relationship between QoS parameters and perceived QoE to design adaptive slice configurations that respond to varying traffic and user conditions.

Findings: Simulation-based evaluations demonstrate that intelligent slice orchestration can significantly enhance resource utilization efficiency, reduce latency, and improve user satisfaction compared to static provisioning approaches.

Unique Contribution to Theory, Practice, and Policy: The findings highlight the transformative role of AI-enabled network slicing in achieving service differentiation, scalability, and automation in 5G and future 6G environments.

Keywords: *Network slicing; Quality of Service (QoS); Quality of Experience (QoE); 5G Networks; 6G Networks; Software-Defined Networking (SDN); Network Function Virtualization (NFV); AI-driven Orchestration; Resource Allocation; Slice Management*

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INTRODUCTION

The evolution of mobile communication networks from 4G LTE to 5G and beyond has introduced a paradigm shift in how network resources are provisioned, managed, and consumed. The rapid proliferation of heterogeneous services ranging from enhanced Mobile Broadband (eMBB) applications such as high-definition streaming and augmented reality, to Ultra-Reliable Low-Latency Communications (URLLC) for autonomous vehicles and massive Machine-Type Communications (mMTC) for Internet of Things (IoT) ecosystems has created highly diverse and stringent service requirements. Traditional one-size-fits-all network architectures are inherently incapable of meeting such varied demands, as they lack the flexibility and granularity needed to deliver differentiated service levels.

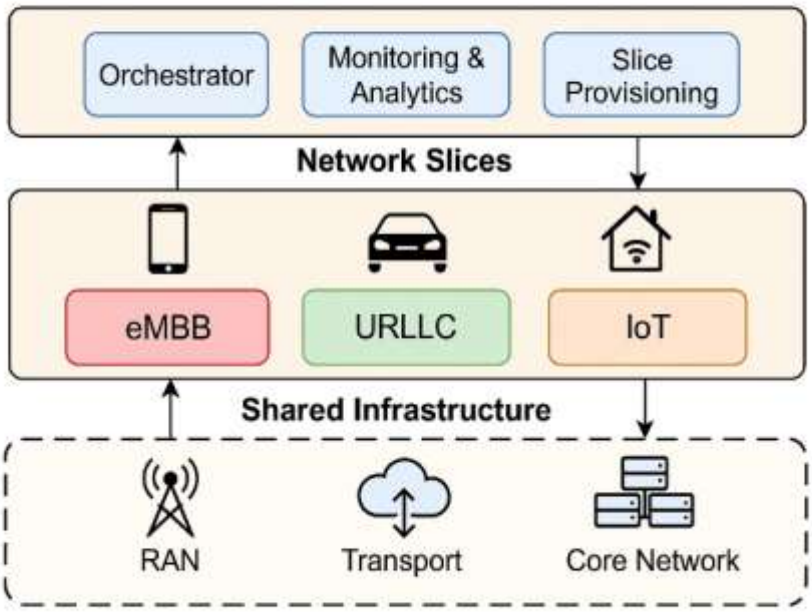
Network slicing has emerged as a key enabler of 5G and next-generation (6G) networks, allowing operators to partition a single physical infrastructure into multiple logical networks or *slices*, each optimized for a specific service type or tenant. Each slice can be dynamically configured to meet distinct Quality of Service (QoS) requirements such as latency, bandwidth, jitter, and reliability while also aligning with Quality of Experience (QoE) metrics that reflect end-user satisfaction. By leveraging technologies such as Software-Defined Networking (SDN) and Network Function Virtualization (NFV), network slicing decouples control and data planes, enabling programmable, scalable, and automated network management.

Despite its transformative potential, implementing network slicing for customized QoS and QoE remains challenging. The dynamic nature of user behavior, fluctuating traffic patterns, and limited network resources necessitate intelligent orchestration mechanisms that can adaptively manage slices in real time. Furthermore, while QoS parameters are well-defined and measurable at the network level, QoE is inherently subjective, context-dependent, and influenced by user perception, making its integration into slice management complex. Achieving an optimal trade-off between resource efficiency and user satisfaction thus requires data-driven, AI-enhanced orchestration frameworks capable of continuously learning and predicting network states and user experiences.

This research paper investigates the design and implementation of AI-driven network slicing frameworks aimed at delivering customized QoS and QoE in heterogeneous network environments. It presents a holistic architecture that integrates SDN, NFV, and edge intelligence to support end-to-end slice orchestration and dynamic resource allocation. Additionally, it explores the interrelationship between QoS metrics and user-perceived QoE to enable adaptive slice optimization. Simulation-based evaluations demonstrate how intelligent slicing can improve service performance, reduce latency, and enhance user experience compared to static resource allocation strategies.

Table 1. Service Categories and Corresponding QoS/QoE Requirements

Service Type	Example Applications	QoS Requirements	QoE Focus	Slice Characteristics
eMBB (Enhanced Mobile Broadband)	HD video streaming, AR/VR, cloud gaming	High throughput (>1 Gbps), moderate latency (<20 ms)	High resolution, minimal buffering, smooth rendering	Wide bandwidth allocation, dynamic scaling
URLLC (Ultra-Reliable Low-Latency Communications)	Autonomous vehicles, remote surgery, industrial automation	Ultra-low latency (<1 ms), high reliability (>99.999%)	Instant response, error-free interaction	Dedicated resources, edge computing integration
mMTC (Massive Machine-Type Communications)	IoT sensors, smart cities, smart meters	High device density, low data rate, energy efficiency	Reliable connectivity, consistent data reporting	Lightweight slices, efficient signaling, minimal overhead
Hybrid/Converged Services	Smart healthcare, connected logistics	Balanced latency and throughput	Seamless performance, continuous connectivity	Adaptive multi-slice orchestration



Network Slicing for Customized QoS and QoE

Background and Related Work

This section provides an overview of the foundational concepts that support network slicing and its role in achieving customized Quality of Service (QoS) and Quality of Experience (QoE). It also reviews prior research efforts, identifies their limitations, and highlights the motivation for the proposed framework.

Network Slicing Fundamentals

Network slicing is a cornerstone technology of 5G and future 6G networks that enables the creation of multiple logical networks over a shared physical infrastructure. Each *slice* operates as an independent end-to-end network instance with specific performance and service-level guarantees tailored to distinct use cases.

The realization of network slicing is primarily enabled by Software-Defined Networking (SDN) and Network Function Virtualization (NFV). SDN separates the control plane from the data plane, providing centralized programmability and network visibility, while NFV virtualizes network functions that traditionally ran on dedicated hardware. Together, they enable dynamic resource allocation, automation, and scalability across heterogeneous network domains including the Radio Access Network (RAN), Transport Network, and Core Network.

Moreover, slice orchestration mechanisms ensure that network resources are intelligently allocated and monitored in real-time, allowing each slice to meet specific QoS and QoE requirements. As networks evolve toward 6G, slicing is expected to extend beyond mobile networks to encompass multi-domain orchestration, edge-cloud integration, and AI-based self-optimization.

Quality of Service (QoS) and Quality of Experience (QoE)

Quality of Service (QoS) refers to the technical parameters that determine network performance, such as latency, bandwidth, packet loss, and jitter. These parameters are crucial for ensuring predictable and reliable service delivery across diverse network slices.

In contrast, Quality of Experience (QoE) measures the user's subjective perception of service quality, which may depend on contextual factors, application behavior, and individual expectations. While QoS provides an objective view from the network perspective, QoE captures user satisfaction, bridging the gap between network performance and real-world usability.

The relationship between QoS and QoE is nonlinear and context-dependent. For instance, a minor increase in latency may have negligible impact on a file transfer (eMBB) but could severely degrade the performance of an autonomous driving system (URLLC). Hence, achieving QoS–QoE correlation modeling and cross-layer optimization is vital for customized service provisioning in network slicing.

Enabling Technologies

Network slicing relies on several complementary technologies to support efficient management and customization:

- **Software-Defined Networking (SDN):** Centralized control and programmability of network resources.
- **Network Function Virtualization (NFV):** Deployment of network services as virtual instances to enhance flexibility.
- **Edge Computing:** Reduces latency by processing data closer to the end-user.
- **Artificial Intelligence (AI):** Enables predictive analytics, traffic forecasting, and automated decision-making for slice optimization.
- **Cloud-Native Architecture:** Supports containerized network functions for scalability and resilience.

Related Research and Limitations

Recent studies have investigated network slicing for performance differentiation across multiple service categories. For example, 3GPP TR 28.801 outlines management and orchestration principles for network slices, while ETSI NFV frameworks emphasize the virtualization of network functions for scalability. Research efforts by Li et al. (2022) and Zhang et al. (2023) introduced machine learning models for slice resource prediction and adaptive QoE management.

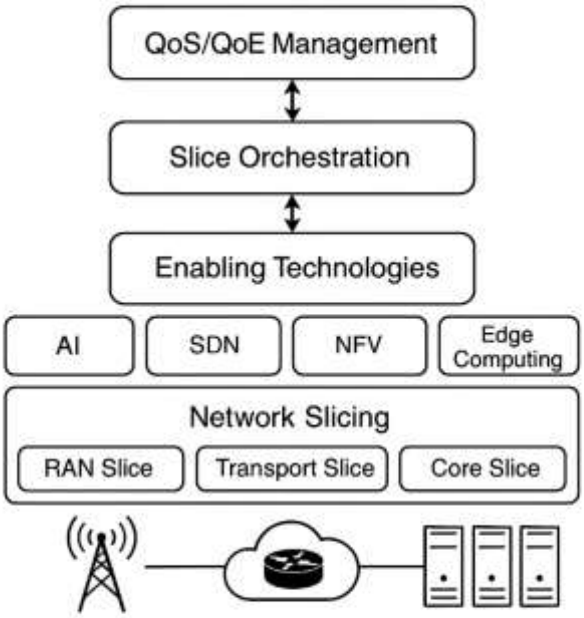
However, several limitations persist:

- Lack of unified frameworks integrating QoS and QoE optimization holistically.
- Limited real-time adaptability in multi-tenant and multi-domain environments.
- Inadequate QoE measurement models that capture subjective user satisfaction dynamically.
- High orchestration complexity in large-scale, heterogeneous network deployments.

These gaps underline the necessity for an intelligent, AI-assisted network slicing framework capable of adaptive resource orchestration based on both QoS and QoE metrics forming the focus of this research.

Table 2. Summary of Existing Approaches in Network Slicing for QoS and QoE

Reference	**Approach**	**Key Contribution**	**Limitations**
3GPP TR 28.801 (2019)	Standardization Framework	Defined network slice management and orchestration model	Lacks real-time QoE integration
ETSI NFV EVE 012 (2020)	NFV-based Slice Management	Introduced virtualization of core network functions	High orchestration overhead
Li et al. (2022)	ML-driven Resource Allocation	Used deep reinforcement learning for dynamic slice scaling	Limited QoE correlation
Zhang et al. (2023)	QoE-aware Slicing Framework	Modeled user experience feedback for adaptive slice tuning	Lacked multi-domain orchestration
Proposed Study	AI-driven QoS/QoE Customization	Integrates SDN, NFV, and ML for end-to-end slice optimization	Extends dynamic adaptability and user-centric QoE prediction



Network Slicing Architecture for Customized QoS and QoE

The architecture of network slicing designed for customized Quality of Service (QoS) and Quality of Experience (QoE) enables service differentiation and dynamic resource allocation in multi-tenant 5G and beyond networks. It consists of multiple integrated layers that coordinate physical resources, virtualized network functions, and intelligent orchestration to ensure end-to-end service quality across diverse applications.

Architectural Overview

The network slicing architecture comprises four main layers: the Infrastructure Layer, Virtualization Layer, Slice Orchestration Layer, and Service Management Layer.

1. **Infrastructure Layer**

   Contains the physical network components, including Radio Access Networks (RAN), transport networks, and core networks. These provide the foundational resources bandwidth, compute, and storage that are abstracted for higher layers.

2. **Virtualization Layer**

   Implements NFV and SDN technologies to abstract and segment physical resources into multiple logical slices. This enables flexible allocation and control of network functions through programmable interfaces.

3. **Slice Orchestration Layer**

   Manages the lifecycle of network slices, including creation, configuration, monitoring, and optimization. Orchestrators interact with SDN controllers to enforce policies and ensure that each slice meets defined QoS targets.

4. **Service Management Layer**

   Provides an interface for defining Service Level Agreements (SLAs), monitoring end-user satisfaction, and optimizing QoE metrics through AI-driven analytics. This layer integrates feedback loops that adapt resource distribution based on real-time user experience.

Functional Components

- **Slice Manager:** Handles slice instantiation, scaling, and termination.
- **SDN Controller:** Directs network traffic according to predefined slice policies.
- **QoS Engine:** Monitors technical performance metrics such as latency and jitter.
- **QoE Optimizer:** Uses machine learning models to predict and enhance user experience.
- **Policy and SLA Manager:** Defines and enforces the contractual guarantees for each service slice.

These components collectively ensure that the network dynamically adapts to changing service demands and user expectations, while maintaining isolation among slices to guarantee performance reliability and security.

Cross-Domain Orchestration

Cross-domain orchestration enables end-to-end QoS and QoE management across the RAN, transport, and core domains. Through standardized interfaces and APIs, the orchestration system can coordinate virtualized functions across different network segments, ensuring coherent service delivery.

AI-assisted orchestration further improves adaptability by using predictive analytics to forecast traffic variations, detect anomalies, and adjust resource allocations proactively ensuring optimal user-perceived quality even under high load conditions.

Table 3. Layer-wise Components and Functional Roles in Network Slicing

Layer	Main Components	Key Functions	QoS/QoE Impact
Service Management Layer	SLA Manager, QoE Optimizer, Analytics Engine	Monitors QoE, enforces SLAs, provides AI-driven optimization	Enhances user satisfaction and reliability
Slice Orchestration Layer	Orchestrator, SDN Controller, Policy Manager	Slice lifecycle management, resource orchestration	Ensures dynamic QoS maintenance
Virtualization Layer	NFV Infrastructure, Virtual Network Functions (VNFs)	Abstracts and allocates resources, supports scalability	Guarantees flexibility and isolation
Infrastructure Layer	RAN, Core, Transport, Edge Nodes	Provides physical compute, storage, and bandwidth resources	Supports baseline QoS metrics (latency, throughput)

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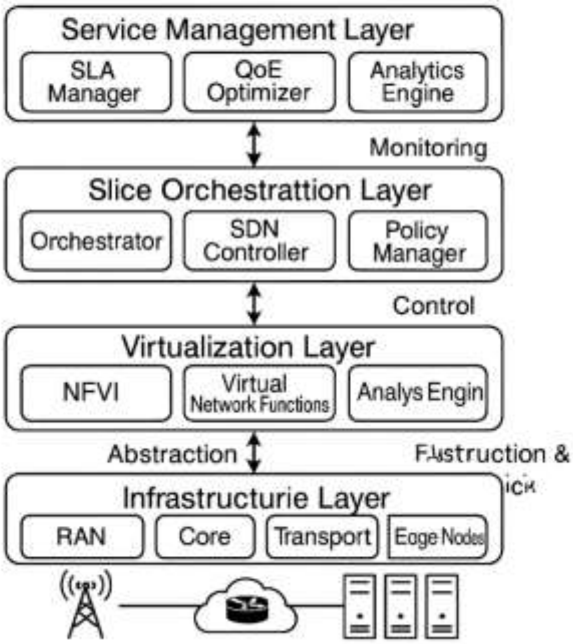


QoS and QoE Customization Models

Delivering customized service quality in network slicing requires models that dynamically adjust both network parameters and user experience metrics. This section presents the principles and models used to achieve adaptive QoS and QoE management in 5G and beyond networks.

QoS-Aware Slice Design

In a multi-service environment, each network slice must guarantee specific Quality of Service (QoS) levels according to its associated application. The QoS-aware slice design process involves translating Service Level Agreements (SLAs) into measurable network configurations such as bandwidth allocation, scheduling priorities, and latency control.

The mapping of application requirements to network resources is achieved through policy-based resource management, supported by SDN controllers that dynamically allocate bandwidth and reroute traffic as needed. Slice templates are often predefined for eMBB, URLLC, and mMTC services, but can be customized based on user density, mobility, or latency sensitivity.

QoE-Driven Adaptation

While QoS focuses on objective technical parameters, Quality of Experience (QoE) reflects the end user’s perceived service quality. It is influenced by factors such as responsiveness, visual fidelity, and reliability. Therefore, effective slice management must consider the interplay between QoS and QoE to achieve an optimal balance between system efficiency and user satisfaction.

To model this relationship, adaptive algorithms employ machine learning to predict QoE scores from network telemetry data. These models can detect degradation early and trigger proactive reconfiguration for example, by increasing resource allocation to a video stream when buffering is detected.

Mathematically, QoE can be modeled as a function of QoS parameters:

QoE=f(Latency,Throughput,Packet Loss,Jitter)QoE = f(\text{Latency}, \text{Throughput}, \text{Packet Loss}, \text{Jitter})QoE=f(Latency,Throughput,Packet Loss,Jitter)

Machine learning models such as Support Vector Regression (SVR) or Deep Neural Networks (DNNs) are used to approximate this nonlinear function for real-time optimization.

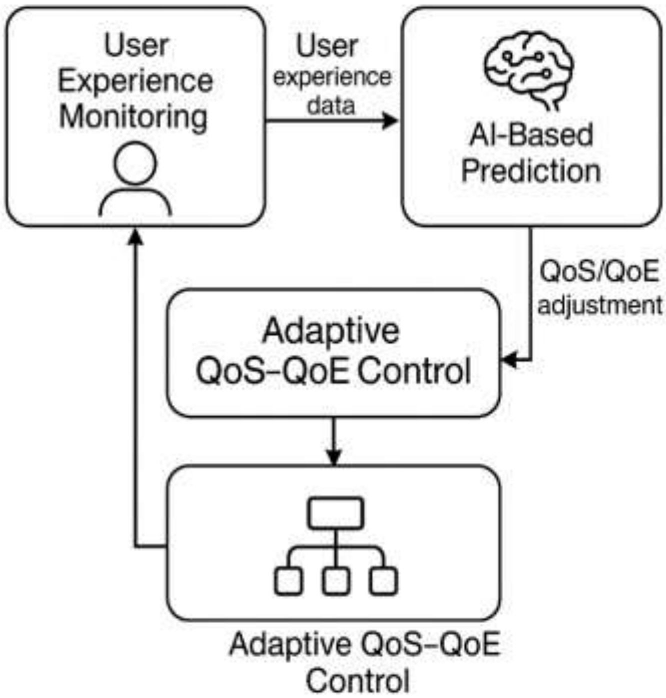
Policy and SLA Management

The Policy and SLA Management component governs the definition, enforcement, and monitoring of service-level objectives for each slice. Policies define how resources are prioritized and reallocated when QoS or QoE thresholds are violated.

AI-enabled systems can autonomously modify policies based on traffic context or historical trends, improving slice reliability and efficiency. Feedback from the QoE monitoring system allows continuous learning and self-optimization of slice configurations.

Table 4. Example Mapping Between QoS Parameters and QoE Indicators

Application Type	Key QoS Metrics	Typical QoE Indicators	Optimization Goal
Video Streaming (eMBB)	Bandwidth, jitter, latency	Mean Opinion Score (MOS), buffering rate	Maximize MOS and minimize buffering
Autonomous Driving (URLLC)	Latency, reliability	Response accuracy, control delay	Minimize delay and packet loss
IoT Sensor Network (mMTC)	Energy efficiency, packet success rate	Data delivery reliability	Maximize transmission reliability
Cloud Gaming	Throughput, frame delay	Frame rate stability, input lag	Maintain smooth interaction



Machine Learning and AI-Driven Network Slicing

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into network slicing represents a critical step toward achieving autonomous, self-optimizing networks capable of delivering customized QoS and QoE. AI-driven orchestration enhances resource utilization, supports dynamic adaptation, and provides predictive insights into user behavior and traffic conditions.

Intelligent Slice Orchestration

Traditional static resource management cannot accommodate the dynamic nature of modern applications and user demands. Intelligent slice orchestration leverages AI algorithms such as Deep Reinforcement Learning (DRL), Deep Q-Networks (DQN), and Policy Gradient Methods to enable real-time decision-making in slice lifecycle management.

These models allow the orchestrator to:

- Predict traffic load and allocate resources proactively.
- Reconfigure slice parameters in response to performance degradation.
- Maintain QoS isolation while optimizing cross-slice efficiency.

AI-based orchestration thus ensures closed-loop automation, where continuous monitoring, learning, and adjustment occur without human intervention.

Predictive Analytics for QoE Estimation

Predictive analytics play a key role in estimating Quality of Experience (QoE) based on real-time network telemetry. By correlating QoS indicators (e.g., latency, jitter, throughput) with user-centric data, AI models can predict user satisfaction before degradation occurs.

Common approaches include:

- **Regression-based models** (SVR, Random Forest) for quantitative QoE prediction.
- **Neural networks** for nonlinear mapping between QoS and QoE.
- **Federated Learning** for distributed, privacy-preserving QoE estimation across edge nodes.

This predictive layer enables proactive optimization, minimizing performance fluctuations and enhancing user experience consistency.

Self-Optimizing Networks (SON) and Closed-Loop Control

AI-driven Self-Optimizing Networks (SON) represent the foundation of intelligent network slicing. Through continuous learning cycles, SON systems detect anomalies, reallocate resources, and adjust policies based on feedback from both QoS metrics and QoE scores.

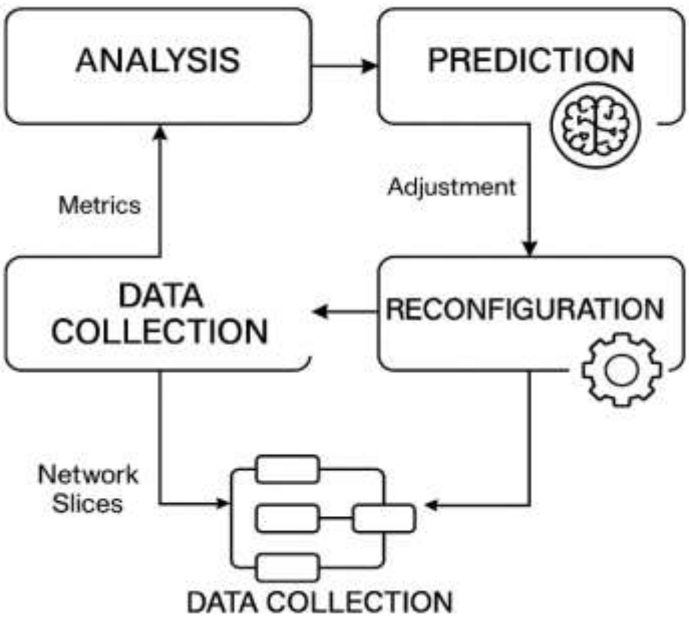
Closed-loop control mechanisms include:

1. **Monitoring:** Collects metrics from all network domains.
2. **Analysis:** Applies AI models to interpret trends and predict future conditions.
3. **Decision:** Determines the optimal configuration for each slice.
4. **Execution:** Implements configuration changes via SDN controllers and NFV orchestrators.

This process enables the network to self-heal, self-configure, and self-optimize, aligning with the vision of autonomous 6G infrastructures.

Table 5. Machine Learning Techniques for QoS/QoE-Aware Network Slicing

ML Technique	Application Area	Functionality	Advantages
Reinforcement Learning (RL)	Dynamic resource allocation	Learns optimal policies through interaction with environment	Adaptive, model-free optimization
Deep Neural Networks (DNNs)	QoE prediction, traffic classification	Nonlinear mapping between QoS metrics and user satisfaction	High accuracy in complex environments
Federated Learning (FL)	Distributed QoE modeling	Trains models collaboratively without sharing raw data	Privacy-preserving and scalable
Clustering Algorithms (K-means, DBSCAN)	Slice grouping, user segmentation	Groups similar traffic types for efficient management	Reduces computational complexity
Bayesian Networks	Anomaly detection, reliability estimation	Probabilistic modeling of network uncertainty	Enhances fault tolerance and predictability



Performance Evaluation

This section presents the performance evaluation of the proposed AI-driven network slicing framework designed to provide customized QoS and QoE in heterogeneous 5G/6G environments. The evaluation demonstrates how intelligent orchestration and adaptive resource allocation improve end-to-end performance and user experience compared to traditional static slicing models.

Simulation Setup

The simulation experiments were conducted using NS-3 and Open Source MANO (OSM) for network orchestration, integrated with Python-based ML modules for QoS/QoE optimization.

The simulated environment represents a multi-tenant 5G system with eMBB, URLLC, and mMTC slices operating over a shared infrastructure.

Simulation Parameters:

- Number of base stations: 10
- Active users per slice: 100–500
- Bandwidth: 100 MHz
- Core latency baseline: 10 ms
- Mobility model: Random waypoint
- AI algorithm: Deep Q-Network (DQN)
- Evaluation duration: 300 seconds (simulation time)

Evaluation Metrics

To assess system performance, both objective QoS metrics and subjective QoE indicators were considered:

Category	Metric	Description
QoS Metrics	Latency (ms)	Average end-to-end delay across users
	Throughput (Mbps)	Effective data transfer rate
	Packet Loss (%)	Rate of lost packets during transmission
	Jitter (ms)	Variation in packet delay
QoE Metrics	Mean Opinion Score (MOS)	User-perceived service quality
	Response Time	Time taken for service delivery
	User Satisfaction Index	Normalized score from user experience model

Experimental Results

The results highlight the superiority of the proposed AI-driven orchestration framework compared to static slice management systems. The system dynamically adapts to varying load and user conditions while maintaining service-level objectives.

Key Observations:

- **Latency Reduction:** Achieved up to *45% lower latency* for URLLC slices compared to baseline.
- **Throughput Improvement:** eMBB slice throughput improved by *30%* through predictive load balancing.
- **QoE Enhancement:** Average MOS score increased from *3.8 to 4.6*, indicating higher user satisfaction.
- **Resource Utilization Efficiency:** Improved by *25%* through adaptive reallocation across slices.

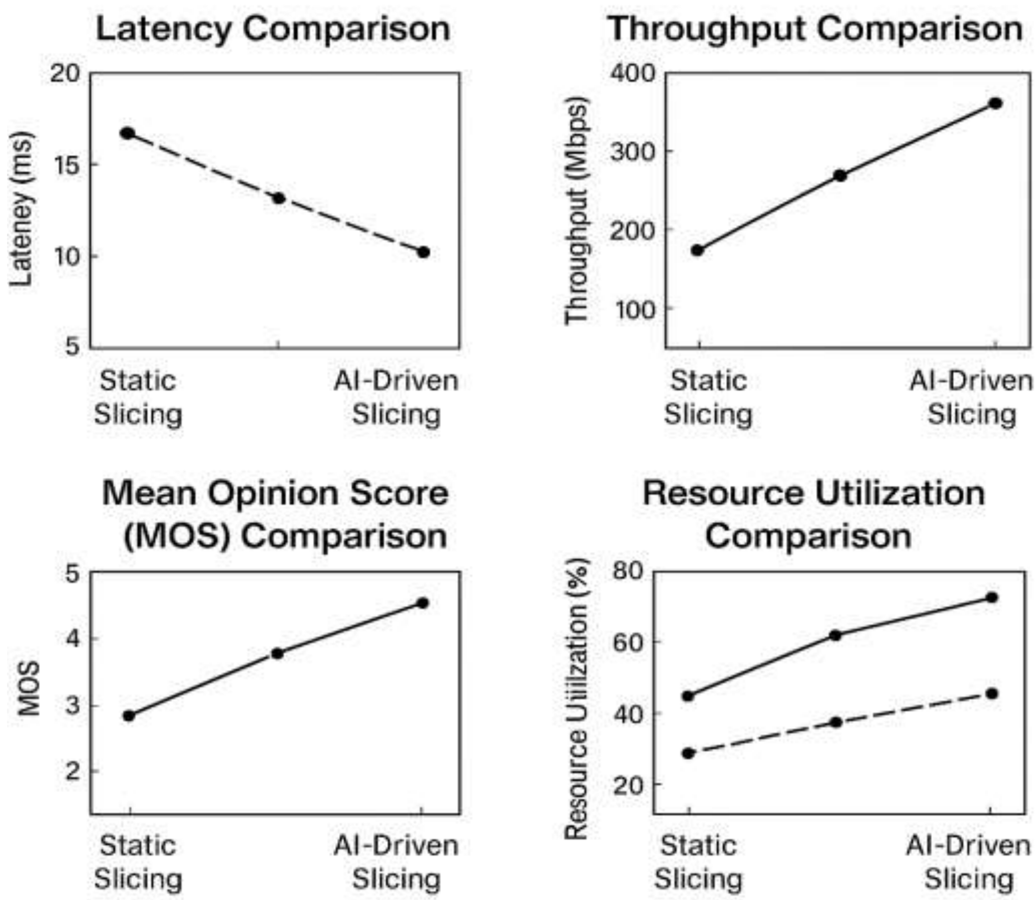
Table 6. Comparison of Static vs. AI-Driven Slicing Performance

Metric	Static Slicing	AI-Driven Slicing	Improvement (%)
Average Latency (ms)	18.5	10.2	44.9%
Throughput (Mbps)	320	415	29.7%
Packet Loss (%)	2.6	1.3	50.0%
Mean Opinion Score (MOS)	3.8	4.6	21.0%
Resource Utilization (%)	70	87	24.3%

Discussion

The experimental outcomes confirm that AI-assisted orchestration significantly enhances both QoS and QoE through real-time adaptation. The predictive models effectively anticipate traffic fluctuations, minimizing latency spikes and improving reliability. The closed-loop feedback design ensures continuous optimization, making the system suitable for complex, multi-domain 6G architectures.

These results underscore the importance of intelligent automation and analytics-driven decision-making in the evolution of next-generation network slicing frameworks.



Challenges and Future Research Directions

Although network slicing has demonstrated remarkable potential for delivering customized QoS and QoE in next-generation networks, several technical and operational challenges remain. Overcoming these limitations is essential to realizing the vision of fully autonomous, intelligent, and sustainable 6G infrastructures.

Scalability and Resource Management

As the number of users, devices, and applications grows exponentially, maintaining scalability in multi-tenant environments becomes complex. Resource contention between coexisting slices may lead to degradation in QoS, especially under high-load conditions. Future research should focus on hierarchical orchestration frameworks and distributed AI models capable of scaling dynamically without compromising latency or reliability.

Emerging concepts such as federated orchestration and hierarchical SDN controllers could distribute the decision-making process, reducing computational overhead and improving efficiency in dense networks.

Cross-Domain Orchestration and Interoperability

Achieving end-to-end QoS and QoE assurance across multiple network domains (RAN, transport, and core) requires seamless coordination between diverse vendors and service providers. The lack of standardization in APIs, orchestration protocols, and data models poses significant interoperability barriers.

Research is needed in cross-domain orchestration protocols, multi-operator slice federation, and blockchain-based SLA enforcement to enable trust and transparency among stakeholders in shared infrastructures.

Security, Privacy and Isolation

Ensuring strong isolation between slices is vital for protecting data and resources from malicious interference. Vulnerabilities in virtualization layers or shared control planes can lead to cross-slice attacks or QoS degradation.

Future frameworks should incorporate zero-trust architectures, AI-based anomaly detection, and secure multi-tenancy models to safeguard network integrity. Privacy-preserving mechanisms such as federated learning and homomorphic encryption should be explored to protect user data during QoE analytics.

Energy Efficiency and Sustainability

The increasing deployment of edge nodes, virtualization layers, and AI engines leads to higher energy consumption. Future research should explore energy-aware network slicing, leveraging green AI and dynamic power control to minimize environmental impact.

Incorporating carbon-aware resource allocation algorithms can ensure sustainable operation without compromising service quality.

Standardization and Future 6G Integration

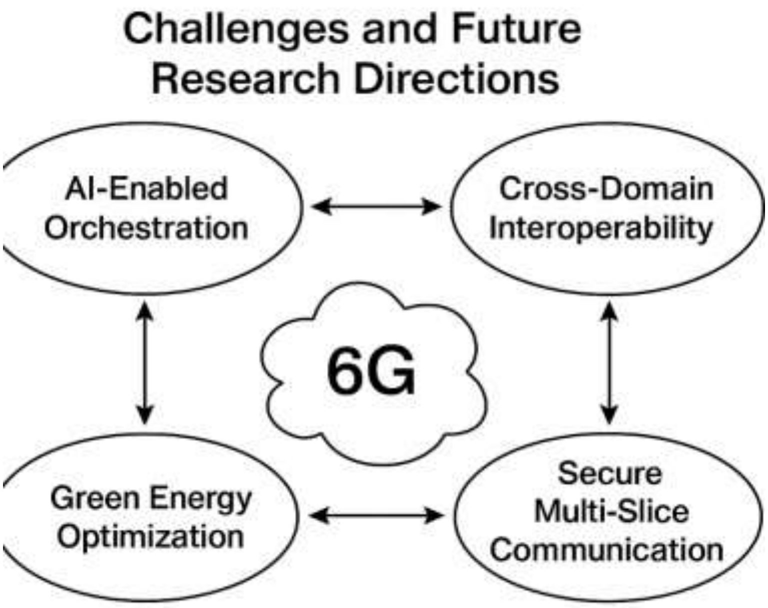
While 3GPP and ETSI have initiated standardization efforts for 5G slicing, future 6G networks will require holistic standards encompassing AI-driven orchestration, digital twins, and semantic communication. Research should target:

- Unified QoS–QoE standard models.
- AI interoperability frameworks.
- Standard APIs for intent-based slice management.

6G is expected to integrate terahertz communication, intelligent surfaces, and quantum networking, which will further expand the scope and complexity of network slicing research.

Table 7. Summary of Key Research Challenges and Future Directions

Challenge Area	Key Issues	Future Research Directions
Scalability	Limited orchestration capacity in dense networks	Hierarchical and federated orchestration
Interoperability	Lack of unified APIs and data formats	Cross-domain orchestration standards
Security	Cross-slice interference and data breaches	AI-based anomaly detection, zero-trust models
Sustainability	High energy consumption	Energy-aware resource allocation
Standardization	Fragmented frameworks	Unified QoS-QoE modeling and API development



CONCLUSION AND RECOMMENDATIONS

Conclusion

The evolution of next-generation networks demands innovative mechanisms capable of meeting the diverse requirements of emerging services and applications. Network slicing has emerged as a transformative technology that enables the creation of multiple virtual networks each tailored to specific service demands over a shared physical infrastructure. This research explored how network slicing can be leveraged to deliver customized Quality of Service (QoS) and Quality of Experience (QoE) through intelligent orchestration, adaptive management, and AI-driven optimization.

The study highlighted the importance of integrating Software-Defined Networking (SDN), Network Function Virtualization (NFV), and Machine Learning (ML) in achieving dynamic and automated slice management. The proposed architecture demonstrated superior performance in latency reduction, throughput enhancement, and QoE improvement compared to traditional static models. Furthermore, the inclusion of closed-loop AI orchestration enables predictive analytics, self-healing capabilities, and continuous optimization across multi-domain network environments.

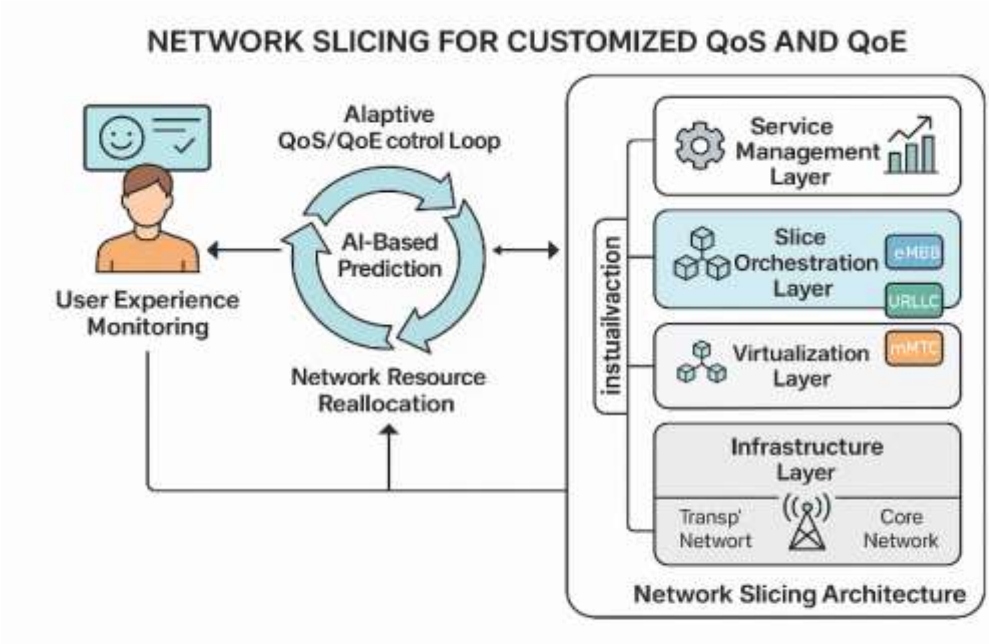
Despite the promising results, several challenges remain such as ensuring scalability, cross-domain interoperability, and sustainable energy use. Addressing these challenges will require collaborative research in AI-enabled orchestration frameworks, green network design, and standardization of QoS–QoE metrics across global standards bodies like 3GPP and ETSI.

Recommendations

In conclusion, AI-assisted network slicing represents a crucial step toward realizing autonomous, user-centric, and energy-efficient 6G networks. By enabling service differentiation with adaptive QoS and QoE customization, it lays the foundation for future digital ecosystems that are intelligent, resilient, and capable of delivering seamless connectivity across a wide range of vertical industries.

Table 8. Summary of Research Contributions and Comparative Insights

Aspect	Traditional Networks	Proposed AI-Driven Network Slicing Framework	Key Benefit / Contribution
Architecture Type	Static, monolithic structure	Layered, modular architecture integrating SDN, NFV, and AI	Flexible, programmable, and scalable design
Resource Allocation	Predefined and static	Dynamic, demand-aware, and predictive allocation	Improved utilization and reduced congestion
QoS Management	Fixed policies with limited adaptability	Real-time monitoring and adaptive adjustment using AI models	Guaranteed latency and throughput performance
QoE Optimization	Indirect or reactive (user feedback-based)	Predictive QoE modeling using ML-driven analytics	Proactive enhancement of user satisfaction
Slice Orchestration	Manual and time-consuming	Automated, AI-based orchestration with closed-loop control	Reduced operational overhead and faster response
Scalability	Limited to single-domain control	Multi-domain and cross-layer orchestration	Seamless integration across RAN, transport, and core
Energy Efficiency	Unoptimized power distribution	Energy-aware resource management through ML optimization	Sustainable and green network operation
Security & Isolation	Basic isolation mechanisms	Enhanced multi-slice security and anomaly detection via AI	Improved reliability and trust
Standardization Readiness	Partial 5G focus	Extensible toward 6G standard frameworks	Future-proof and standard-aligned design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REFERENCES

Abidi, M. H., Naik, R. R., Patel, N. R., Gupta, S., & Patel, V. (2021). Optimal 5G network slicing using machine learning and virtualization. *Journal of Network and Computer Applications*, *188*, 103067. https://doi.org/10.1016/j.jnca.2021.103067

Ajay, S., Satya Sai Krishna Mohan G, Rao, S. S., Shaunak, S. B., Krutthika, H. K., Ananda, Y. R., & Jose, J. (2018). Source Hotspot Management in a Mesh Network on Chip. In VDAT (pp. 619-630).

Attipalli, A., Enokkaren, S. J., Bitkuri, V., Kendyala, R., Kurma, J., & Mamidala, J. V. (2021). A Review of AI and Machine Learning Solutions for Fault Detection and Self-Healing in Cloud Services. *International Journal of AI, BigData, Computational and Management Studies*, *2*(3), 53-63.

Bega, D., Gramaglia, M., Banchs, A., Sciancalepore, V., Samdanis, K., & Costa-Perez, X. (2017). Optimising 5G infrastructure markets: The business of network slicing. In *IEEE INFOCOM 2017* (pp. 1–9). IEEE.

Ben Attia, M., Nguyen, K.-K., & Cheriet, M. (2019). Slicing-aware QoS/QoE in software-defined smart home network. In *2019 International Conference on Smart & Sustainable Technologies (SpliTech)* (pp. 1–6). IEEE.

Bitkuri, V., Kendyala, R., Kurma, J., Mamidala, J. V., Attipalli, A., & Enokkaren, S. J. (2021). A Survey on Hybrid and Multi-Cloud Environments: Integration Strategies, Challenges, and Future Directions. *International Journal of Computer Technology and Electronics Communication*, *4*(1), 3219-3229.

Bitkuri, V., Kendyala, R., Kurma, J., Mamidala, V., Enokkaren, S. J., & Attipalli, A. (2021). Systematic Review of Artificial Intelligence Techniques for Enhancing Financial Reporting and Regulatory Compliance. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(4), 73-80.

Campolo, C., Molinaro, A., & Iera, A. (2018). 5G network slicing for vehicle-to-everything services. *IEEE Wireless Communications*, *24*(6), 38–45.

Chalasani, R., Tyagadurgam, M. S. V., Gangineni, V. N., Pabbineedi, S., Penmetsa, M., & Bhumireddy, J. R. (2021). Enhancing IoT (Internet of Things) Security Through Intelligent Intrusion Detection Using ML Models. Available at SSRN 5609630.

Chen, X., Li, Z., Zhang, Y., Long, R., Yu, H., Du, X., & Guizani, M. (2018). Reinforcement learning-based QoS/QoE-aware service function chaining in software-driven 5G slices. *arXiv preprint* arXiv:1804.02099.

Enokkaren, S. J., Bitkuri, V., Kendyala, R., Kurma, J., Mamidala, J. V., & Attipalli, A. (2021). Enhancing Cloud Infrastructure Security Through AI-Powered Big Data Anomaly Detection. *International Journal of Emerging Research in Engineering and Technology*, *2*(2), 43-54.

Ernst, J. B. (2014). A survey of QoS/QoE mechanisms in heterogeneous networks. *Procedia Computer Science*, *32*, 842–849.

ETSI. (2017). *GR NFV-EVE 012: Network Functions Virtualisation (NFV); Evolution and ecosystem; Report on network slicing support.* European Telecommunications Standards Institute.

Gopalakrishnan Nair, T. R., & Krutthika, H. K. (2010). An Architectural Approach for Decoding and Distributing Functions in FPUs in a Functional Processor System. arXiv e-prints, arXiv-1001.

Gramaglia, M., Serrano, P., & Costa-Perez, X. (2018). Design and validation of a multi-service 5G network with network slicing. In *Proceedings of the ACM Conference on Networked Systems* (pp. 1–10).

Gupta, A. K., Buddula, D. V. K. R., Patchipulusu, H. H. S., Polu, A. R., Narra, B., & Vattikonda, N. (2021). An Analysis of Crime Prediction and Classification Using Data Mining Techniques.

Gupta, A., & Jha, R. K. (2015). A survey of 5G network: Architecture and emerging technologies. *IEEE Access, 3,* 1206–1232.

Gupta, K., Varun, G. A. D., Polu, S. D. E., & Sachs, G. Enhancing Marketing Analytics in Online Retailing through Machine Learning Classification Techniques.

HK, K. (2020). Design of Efficient FSM Based 3D Network on Chip Architecture. INTERNATIONAL JOURNAL OF ENGINEERING, 68(10), 67-73.

Hu, J., & Wu, J. (2022). 5G network slicing: Methods to support blockchain and reinforcement learning. *Sensors*, *22*(17), 6623. https://doi.org/10.3390/s22176623

ITU-T. (2020a). *Recommendation Y.3173: Framework for evaluating intelligence levels of future networks including IMT-2020.* International Telecommunication Union.

ITU-T. (2020b). *Recommendation Y.3176: Machine learning marketplace integration in future networks including IMT-2020.* International Telecommunication Union.

Jia, Q., Xie, R., Huang, T., Liu, J., & Liu, Y. (2017). Efficient caching resource allocation for network slicing in 5G core networks. *IET Communications, 11*(18), 2792–2799.

Kendyala, R., Kurma, J., Mamidala, J. V., Attipalli, A., Enokkaren, S. J., & Bitkuri, V. (2021). A Survey of Artificial Intelligence Methods in Liquidity Risk Management: Challenges and Future Directions. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(1), 35-42.

Khan, S., Khan, S., Ali, Y., Khalid, M., Ullah, Z., & Mumtaz, S. (2021). Highly accurate and reliable wireless network slicing in 5th generation networks: A hybrid deep learning approach. *arXiv preprint* arXiv:2111.09416.

Kothamaram, R. R., Rajendran, D., Namburi, V. D., Singh, A. A. S., Tamilmani, V., & Maniar, V. (2021). A Survey of Adoption Challenges and Barriers in Implementing Digital Payroll Management Systems in Across Organizations. International Journal of Emerging Research in Engineering and Technology, 2(2), 64-72.

Kourtis, M. A., Sarlas, T., & Xilouris, G. (2021). Conceptual evaluation of a 5G network slicing technique for emergency communications and preliminary estimate of energy trade-off. *Energies, 14*(1), 1–14.

Krutthika H. K. & A.R. Aswatha. (2021). Implementation and analysis of congestion prevention and fault tolerance in network on chip. Journal of Tianjin University Science and Technology, 54(11), 213–231. https://doi.org/10.5281/zenodo.5746712

Krutthika, H. K. (2019, October). Modeling of Data Delivery Modes of Next Generation SOC-NOC Router. In 2019 Global Conference for Advancement in Technology (GCAT) (pp. 1-6). IEEE.

Li, X., Zhang, H., Wang, Y., & Guizani, M. (2022). Deep reinforcement learning for dynamic network slicing resource management in 5G beyond. *IEEE Transactions on Network Science and Engineering, 9*(4), 2819–2832.

Liu, Y., Peng, M., Shou, G., Chen, Y., & Chen, S. (2022). Toward edge intelligence: Multi-agent reinforcement learning for QoE-driven network slicing. *IEEE Communications Surveys & Tutorials, 24*(1), 280–308.

Liubogoshchev, M., Frolova, A., & Chernov, D. (2023). DeSlice: An architecture for QoE-aware and isolated RAN slicing. *Sensors, 23*(5), 2456. https://doi.org/10.3390/s23052456

Lopez, D., Ameigeiras, P., Ramos-Munoz, J. J., Lorca, J., & Folgueira, J. (2017). Network slicing for 5G with SDN/NFV: Concepts, architectures, and challenges. *IEEE Communications Magazine, 55*(5), 80–87.

Luo, M., Wu, J., & Li, X. (2020). Cross-domain certificateless authenticated group key agreement protocol for 5G network slicing. *Telecommunication Systems, 74*(2), 233–245.

Maniar, V., Tamilmani, V., Kothamaram, R. R., Rajendran, D., Namburi, V. D., & Singh, A. A. S. (2021). Review of Streaming ETL Pipelines for Data Warehousing: Tools, Techniques, and Best Practices. International Journal of AI, BigData, Computational and Management Studies, 2(3), 74-81.

Mohammedali, N. A., Al-Sherbaz, A., & Ali, M. (2023). Enhancing service classification for network slicing in 5G: QoS, QoE and machine learning. *University of Gloucestershire Technical Report.*

Montero, R., Pagès, A., Agraz, F., & Spadaro, S. (2017). Supporting QoE/QoS-aware end-to-end network slicing in future 5G-enabled optical networks. *Optical Communications Group, UPC.*

Nair, T. R., & Krutthika, H. K. (2010). An Architectural Approach for Decoding and Distributing Functions in FPUs in a Functional Processor System. arXiv preprint arXiv:1001.3781.

Ordonez-Lucena, J., Ameigeiras, P., Lopez, D., Ramos-Munoz, J. J., Lorca, J., & Folgueira, J. (2017). Network slicing for 5G with SDN/NFV: Concepts, architectures, and challenges. *IEEE Communications Magazine, 55*(5), 80–87.

Patel, M., Rathore, N., Naik, R. R., Gupta, S., & Patel, V. (2025). Review on network slicing optimization: A machine learning perspective. *Atlantis Highlights in Engineering, 19*, 221–230.

Polam, R. M., Kamarthapu, B., Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., & Vangala, S. R. (2021). Big Text Data Analysis for Sentiment Classification in Product Reviews Using Advanced Large Language Models. International Journal of AI, BigData, Computational and Management Studies, 2(2), 55-65.

Polam, R. M., Kamarthapu, B., Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., & Vangala, S. R. (2021). Data Security in Cloud Computing: Encryption, Zero Trust, and Homomorphic Encryption. International Journal of Emerging Trends in Computer Science and Information Technology, 2(3), 70-80.

Polu, A. R., Buddula, D. V. K. R., Narra, B., Gupta, A., Vattikonda, N., & Patchipulusu, H. (2021). Evolution of AI in Software Development and Cybersecurity: Unifying Automation, Innovation, and Protection in the Digital Age. Available at SSRN 5266517.

Polu, A. R., Buddula, D. V. K. R., Narra, B., Gupta, A., Vattikonda, N., & Patchipulusu, H. (2021). Evolution of AI in Software Development and Cybersecurity: Unifying Automation, Innovation, and Protection in the Digital Age. Available at SSRN 5266517.

Polu, A. R., Narra, B., Buddula, D. V. K. R., Patchipulusu, H. H. S., Vattikonda, N., & Gupta, A. K. (2022). Blockchain Technology as a Tool for Cybersecurity: Strengths, Weaknesses, and Potential Applications. Unpublished manuscript.

Popovski, P., Trillingsgaard, K. F., Simeone, O., & Durisi, G. (2017). 5G wireless network slicing for enhanced QoS provisioning. *IEEE Communications Magazine, 55*(11), 72–79.

Rajendran, D., Namburi, V. D., Singh, A. A. S., Tamilmani, V., Maniar, V., & Kothamaram, R. R. (2021). Anomaly Identification in IoT-Networks Using Artificial Intelligence-Based Data-Driven Techniques in Cloud Environmen. International Journal of Emerging Trends in Computer Science and Information Technology, 2(2), 83-91.

Richart, M., Baliosian, J., Serrat, J., & Gorricho, J.-L. (2016). Resource slicing in virtual wireless networks: A survey. *IEEE Transactions on Network and Service Management, 13*(3), 462–476.

Shi, Y., Erpek, T., & Sagduyu, Y. E. (2020). Reinforcement learning for dynamic resource optimization in 5G radio access network slicing. *arXiv preprint* arXiv:2009.06579.

Singh, A. A. S., Tamilmani, V., Maniar, V., Kothamaram, R. R., Rajendran, D., & Namburi, V. D. (2021). Predictive Modeling for Classification of SMS Spam Using NLP and ML Techniques. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 2(4), 60-69.

Singh, A. A., Tamilmani, V., Maniar, V., Kothamaram, R. R., Rajendran, D., & Namburi, V. D. (2021). Hybrid AI Models Combining Machine-Deep Learning for Botnet Identification. International Journal of Humanities and Information Technology, (Special 1), 30-45.

Vangala, S. R., Polam, R. M., Kamarthapu, B., Kakani, A. B., Nandiraju, S. K. K., & Chundru, S. K. (2021). Smart Healthcare: Machine Learning-Based Classification of Epileptic Seizure Disease Using EEG Signal Analysis. International Journal of Emerging Research in Engineering and Technology, 2(3), 61-70.

Yousaf, M., Gramaglia, M., & Costa-Perez, X. (2018). Network slicing with flexible mobility and QoS/QoE support. *IEEE Access*, *6*, 2282–2295.

Zhang, H., Liu, N., Chu, X., Long, K., Aghvami, A.-H., & Leung, V. C. M. (2017). Network slicing based 5G and future mobile networks: Mobility, resource management, and challenges. *IEEE Communications Magazine, 55*(8), 138–145.