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QoE Aware Semantic Computing and Edge Intelligence for Adaptive XR Broadcasting over 6G Networks

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ABSTRACT

The rapid evolution of Extended Reality (XR) broadcasting over sixth-generation (6G) networks introduces significant challenges related to ultra-low latency, heterogeneous traffic, intensive computation, and dynamic Quality of Experience (QoE) requirements. Conventional resource allocation and edge computing approaches often process immersive content uniformly, resulting in inefficient bandwidth and computational utilization while failing to prioritize semantically important XR information. **semantic computing** and edge intelligence framework that enables adaptive XR broadcasting by prioritizing perceptually and contextually important content according to network conditions and user experience requirements. **Integrates semantic** feature extraction, intelligent edge processing, QoE-aware resource allocation, and adaptive transmission within a simulated 6G edge network environment. The proposed framework is evaluated under different traffic loads and network conditions using end-to-end latency, bandwidth consumption, computational efficiency, QoE score, and transmission reliability as the primary performance indicators and is compared with a conventional resource allocation approach. Demonstrates that the proposed approach reduces transmission latency and unnecessary bandwidth consumption while maintaining higher QoE stability, particularly under congested and highly dynamic network conditions. Semantic prioritization further enables edge resources to focus on XR components with greater perceptual importance without significantly degrading overall immersive quality. **Confirms that combining** semantic computing with edge intelligence provides an effective mechanism for adaptive XR broadcasting and offers a scalable foundation for delivering responsive, resource-efficient, and QoE-oriented immersive media services over future 6G networks.

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1. INTRODUCTION

The rapid development of Extended Reality (XR) technologies is transforming digital broadcasting from conventional two-dimensional media delivery into interactive, immersive, and highly personalized experiences [1]. XR, which encompasses Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), enables users to interact with digital objects and environments through high-resolution visual content, spatial

audio, three-dimensional objects, and real-time sensory information [2]. These capabilities create new opportunities for immersive broadcasting in entertainment, education, healthcare, tourism, remote collaboration, sports, and live events. However, XR broadcasting imposes considerably higher communication and computational requirements than conventional multimedia services [3]. High-resolution panoramic video, interactive objects, spatial information, and continuous user movement generate large volumes of heterogeneous data that must be processed and transmitted within very short time intervals. Delayed frames, unstable throughput, packet loss, or insufficient computational resources can immediately affect visual continuity and user perception, potentially causing poor immersion and discomfort . Sixth-generation (6G) networks are therefore expected to provide an important technological foundation for next-generation XR broadcasting through extremely high data rates, ultra-low latency, massive connectivity, intelligent network management, and integrated computing capabilities . Nevertheless, increased network capacity alone cannot guarantee satisfactory Quality of Experience (QoE), particularly when large numbers of XR users simultaneously compete for limited communication and computational resources. Future immersive broadcasting consequently requires intelligent mechanisms capable of understanding not only how much data should be transmitted, but also which content has greater semantic and perceptual importance to users[4].

Existing XR delivery mechanisms generally focus on network-centric performance indicators such as throughput, latency, bandwidth availability, and packet-loss rate. Although these parameters remain essential, conventional approaches frequently treat multimedia components relatively uniformly and allocate resources without sufficiently considering the semantic importance of individual content elements [5] . In an immersive environment, however, not every component contributes equally to perceived quality. A user's current field of view, interactive objects, human faces, text, speech information, and objects related to ongoing activities can be substantially more important than background elements or content outside the user's immediate attention [6]. Allocating equivalent transmission and computational resources to all XR components may therefore create unnecessary network traffic and processing overhead, especially during congestion. Semantic computing provides a promising alternative by enabling communication systems to identify, interpret, and prioritize information based on contextual and perceptual relevance rather than simply transmitting all available data with identical priority . At the same time, edge intelligence extends artificial intelligence and advanced computing capabilities closer to end users, allowing semantic analysis, prediction, rendering decisions, and resource management to occur without continuous dependence on distant cloud infrastructure. The combination of these technologies has the potential to transform conventional XR transmission into an adaptive process in which communication and computing resources are dynamically concentrated on content that contributes most significantly to the user experience . However, effectively coordinating semantic importance, edge computational capacity, network conditions, and QoE requirements remains a complex problem, particularly within highly dynamic 6G broadcasting environments [7].

This challenge reveals an important research gap in the integration of QoE-aware decision making, semantic computing, and edge intelligence for XR broadcasting [8] . Previous resource-management strategies commonly optimize communication efficiency or computational performance independently, whereas immersive media delivery requires coordinated decisions across content, computing, communication, and user-experience dimensions [9]. Moreover, purely network-oriented optimization may produce technically acceptable performance while still generating unsatisfactory perceptual results because objective network metrics do not always correspond directly to the user's immersive experience. This study therefore proposes a QoE-aware semantic computing and edge intelligence framework for adaptive XR broadcasting over 6G networks. The proposed approach evaluates the semantic relevance of XR components and combines this information with QoE requirements and real-time network conditions to support adaptive processing and transmission decisions at the network edge. Semantically important components are assigned higher priority, while less relevant data can receive reduced computational or transmission resources when network capacity becomes constrained. Edge intelligence further supports continuous adaptation by analyzing network states and determining appropriate resource allocation according to changes in traffic and user requirements . The framework is evaluated under multiple network-load scenarios and compared with a conventional resource allocation approach. Performance assessment considers end-to-end latency, bandwidth consumption, computational efficiency, transmission reliability, and QoE to determine whether semantic prioritization can improve resource utilization without sacrificing the perceptual quality required for immersive broadcasting . Through these mechanisms, the study seeks to establish a closer connection between technical network optimization and human-cen tered experience requirements [10].

The main contribution of this research is an integrated architecture that positions QoE as a central decision factor in semantic processing and intelligent edge resource management rather than treating it merely as a final performance indicator c [11]. The proposed framework is expected to reduce unnecessary transmission and processing by identifying the XR information that contributes most strongly to user perception and allocating resources accordingly [12]. This approach is particularly relevant during high and very high traffic conditions, where indiscriminate processing of immersive data can lead to congestion, increased latency, and unstable service quality. By placing intelligent decision-making functions at the edge, the framework can also respond more rapidly to changing network conditions, content characteristics, and user interactions. Accordingly, this study addresses three central research questions, how can semantic computing and edge intelligence be integrated to support adaptive XR broadcasting over 6G networks to what extent can QoE-aware semantic prioritization improve latency, bandwidth utilization, computational efficiency, and transmission reliability compared with conventional resource allocation and whether the proposed approach can maintain stable immersive QoE under increasing network loads . Answering these questions contributes to the development of intelligent 6G multimedia systems in which network efficiency and perceived experience are optimized jointly. Ultimately, this research provides a foundation for scalable, responsive, and resource-efficient XR broadcasting architectures capable of supporting the increasingly complex immersive services envisioned for future 6G ecosystems [10].

2. LITERATURE REVIEW

2.1. Extended Reality Broadcasting and Quality of Experience

Extended Reality (XR), including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), introduces demanding requirements for multimedia transmission due to its high-resolution visual content, spatial audio, interactive objects, and real-time user interactions. Compared with conventional multimedia services, XR broadcasting is more sensitive to end-to-end latency, packet loss, and fluctuations in available bandwidth [13] . Future sixth-generation (6G) networks are expected to support immersive applications through high data rates, low-latency communication, and integrated computing capabilities. However, network performance alone cannot guarantee satisfactory immersive experiences, particularly when multiple XR users compete for limited communication and computational resources [14].

Quality of Experience (QoE) is therefore an important consideration in adaptive XR broadcasting because it reflects the quality perceived by users during service delivery. Technical indicators such as latency, bandwidth consumption, and transmission reliability can influence QoE, but their optimization must also consider the perceptual importance of the transmitted content . For example, interactive objects and information within the user's field of view may contribute more to the immersive experience than less relevant background elements . Consequently, QoE-aware resource management should balance network efficiency with the preservation of essential XR information. This principle provides the foundation for the proposed framework, which jointly considers technical network conditions and perceptual quality when allocating resources.

2.2. Semantic Computing and Semantic-Aware Communication

Semantic communication extends conventional data transmission by considering the meaning, context, or task relevance of information rather than focusing exclusively on the accurate delivery of every data element [15].Riviewed the fundamentals, applications, and challenges of semantic communication in future networks, highlighting its relevance to emerging 6G communication systems . Similarly,.Discussed context-, semantic-, and task-oriented communication as approaches that can adapt communication to the purpose and relevance of information. These concepts are relevant to XR broadcasting because immersive media contains components with different levels of perceptual importance. Prioritizing semantically significant information may help reduce unnecessary transmission and processing when network resources become constrained [16].

In the context of XR broadcasting, semantic computing can identify and prioritize content such as foreground objects, interactive elements, and visual information associated with the user's current activity. Less relevant content may receive lower transmission or processing priority when bandwidth or computational capacity is limited [17]. Such prioritization should be performed carefully to avoid degrading the overall immersive experience. In the proposed QoE-Aware Semantic Edge Intelligence (QSEI) framework, semantic analysis is used to estimate the importance of XR components and provide information for subsequent resource-allocation decisions. By integrating semantic relevance with network conditions and QoE requirements, the framework aims to improve resource efficiency while maintaining the quality of perceptually important content.

2.3. Edge Intelligence for Adaptive Resource Allocation

Edge computing enables data processing closer to end users, reducing dependence on distant cloud infrastructure and potentially improving response times for latency-sensitive applications. Zhou et al .Examined edge intelligence as the integration of artificial intelligence and edge computing, emphasizing the opportunities and challenges of deploying intelligent processing at the network edge. Similarly, Mao et al .Reviewed mobile edge computing from a communication perspective, including resource allocation and the coordination of communication and computation. These studies provide a theoretical foundation for XR broadcasting systems that require rapid content processing and efficient resource management . By placing intelligent functions near XR users, edge infrastructure can support semantic analysis, network-state monitoring, and adaptive transmission decisions [18].

Despite these advantages, edge nodes have limited computational capacity, and their workloads can increase significantly as the number of concurrent XR users grows [19]. Therefore, resource allocation needs to consider bandwidth availability, end-to-end latency, computational utilization, and the importance of the content being processed. In the proposed QSEI framework, edge intelligence combines semantic information with network conditions and estimated QoE to determine appropriate processing and transmission priorities [20] . This coordinated approach is intended to reduce unnecessary computational overhead and improve transmission reliability, particularly under high and very high traffic conditions. The framework is evaluated against Conventional Resource Allocation (CRA) to examine whether intelligent, adaptive allocation provides measurable benefits.

2.4. Research Gap and Proposed Framework

Previous studies on semantic communication have established the importance of considering information meaning and task relevance in communication systems. Research on edge intelligence and mobile edge computing has also demonstrated the importance of distributed processing and efficient resource management for latency-sensitive services . However, these research directions address different aspects of communication and computing challenges. For XR broadcasting, a remaining challenge is to coordinate semantic importance, edge computational capacity, dynamic network conditions, and user-perceived quality within a unified resource-allocation process. Optimizing bandwidth or latency independently may not adequately preserve the immersive experience when network congestion increases.

To address this challenge, this study proposes a QoE-Aware Semantic Edge Intelligence (QSEI) framework for adaptive XR broadcasting over 6G networks. The framework integrates semantic feature extraction, QoE estimation, intelligent edge decision-making, and adaptive transmission to prioritize perceptually and contextually important XR components [21] . Its performance is compared with CRA across four traffic scenarios using end-to-end latency, bandwidth consumption, edge computational utilization, transmission reliability, and QoE. The principal contribution is the integration and scenario-based evaluation of these mechanisms within one framework [22]. This evaluation aims to determine whether semantic-aware resource allocation can improve network efficiency while maintaining satisfactory immersive quality under increasingly constrained network conditions [23].

3. RESEARCH METHODOLOGY

3.1. Research Design

This study employed a quantitative experimental approach to evaluate a QoE-aware semantic computing and edge intelligence framework for adaptive Extended Reality (XR) broadcasting over 6G networks. The experimental environment was designed to represent dynamic XR broadcasting conditions in which immersive media streams were processed at the edge and transmitted to multiple XR users . The proposed method, referred to as QoE-Aware Semantic Edge Intelligence (QSEI), was compared with a Conventional Resource Allocation (CRA) approach. The evaluation focused on whether semantic-aware processing could reduce unnecessary communication and computation while maintaining high perceptual quality . Four network scenarios, ranging from low to very high traffic load, were considered to examine system adaptability under different resource conditions. The overall methodology consisted of XR content acquisition, semantic analysis, QoE estimation, edge-intelligence decision making, adaptive resource allocation, 6G transmission, and performance evaluation.

The proposed framework, referred to as QoE-Aware Semantic Edge Intelligence (QSEI), integrates semantic feature extraction, semantic importance analysis, QoE estimation, and edge intelligence to support

adaptive decisions throughout the XR broadcasting process. Unlike conventional resource management approaches that primarily allocate network and computational resources based on traffic demand and predefined resource requirements, QSEI considers the semantic relevance of transmitted content and the perceived quality experienced by end users. This approach enables the system to prioritize important semantic information, optimize processing requirements, and dynamically adjust resource allocation according to changing network conditions and user experience requirements.

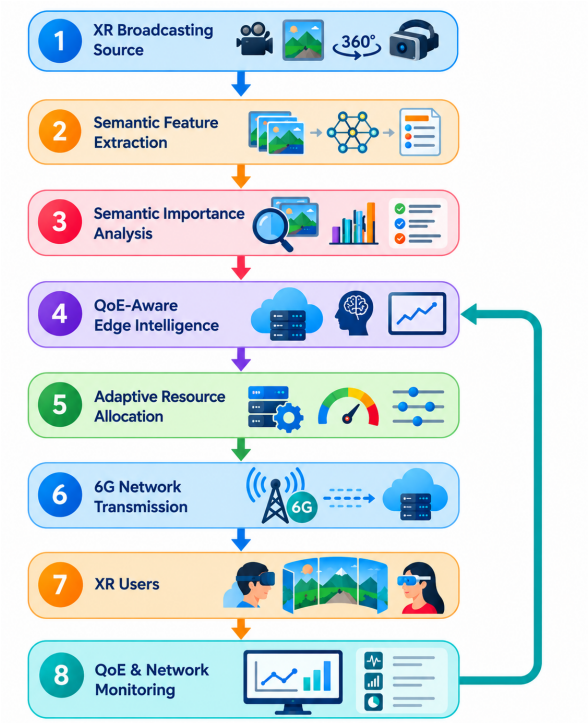


Figure 1. QoE-Aware Semantic Computing and Edge Intelligence Framework for Adaptive XR Broadcasting over 6G Networks

As illustrated in Figure 1, XR content is initially analyzed to identify semantically important information [24]. The resulting semantic information is combined with network and QoE conditions at the intelligent edge [25]. Based on this information, resources are dynamically allocated before the content is transmitted over the simulated 6G network. User-side performance information is subsequently returned to the edge intelligence module, forming a continuous adaptation loop [26].

3.2. System Architecture and Semantic Processing

The proposed framework consists of four principal layers: the XR source layer, semantic computing layer, intelligent edge layer, and 6G communication layer [27]. The XR source layer generates heterogeneous immersive media, including high-resolution video, spatial audio, interactive objects, and user-context information [28]. Instead of treating every component with equal importance, the semantic computing layer evaluates each element according to its contribution to the current immersive experience [29].

$$S_i = w_1 F_i + w_2 V_i + w_3 I_i + w_4 C_i \tag{1}$$

where F_i represents field-of-view relevance, V_i denotes visual saliency, I_i represents interaction relevance, C_i represents contextual importance, and w_1 to w_4 are weighting coefficients satisfying:

$$\sum_{j=1}^{4} w_j = 1 \tag{2}$$

Content with higher semantic importance receives greater transmission and computational priority [30]. Less important background information can be transmitted at a reduced quality when network resources become constrained [31].

3.3. QoE-Aware Edge Intelligence

The intelligent edge functions as the main decision-making component of the proposed framework [32]. It continuously collects information regarding available bandwidth, latency, computational utilization, packet loss, semantic importance, and estimated user QoE. These inputs allow the system to adapt resource allocation according to changes in network conditions.

The estimated QoE score is formulated as:

$$QoE = \alpha Q_v + \beta Q_a + \gamma I_q - \delta L - \theta P \tag{3}$$

where Q_v represents visual quality, Q_a represents audio quality, I_q represents interaction quality, L denotes normalized latency, and P represents packet loss. The coefficients determine the relative contribution of each parameter.

The optimization objective is defined as:

$$\max \sum_{i=1}^{N} S_i QoE_i \tag{4}$$

subject to bandwidth and computational resource constraints:

$$\sum_{i=1}^{N} B_i \leq B_{\text{available}} \tag{5}$$

$$\sum_{i=1}^{N} C_i \leq C_{\text{edge}} \tag{6}$$

where B_i is the bandwidth allocated to content i, $B_{\text{available}}$ is the available network bandwidth, C_i represents the required computational resource, and C_{edge} denotes total edge computing capacity.

3.4. Experimental Scenarios

Four experimental scenarios were established to represent variations in XR broadcasting traffic, as presented in Table 1. The same XR content characteristics and evaluation procedures were maintained for both QSEI and CRA to ensure a consistent and fair comparison [33]. Table 1 summarizes the experimental configurations used in each scenario, providing a common basis for assessing the performance of both methods under different traffic conditions [34].

Table 1. Experimental Scenarios

Scenario	Traffic Condition	Concurrent XR Users	Available Bandwidth	Network Latency	Edge Load
S1	Low	20	1,000 Mbps	5 ms	30%
S2	Moderate	50	750 Mbps	10 ms	50%
S3	High	100	500 Mbps	15 ms	70%
S4	Very High	150	300 Mbps	25 ms	90%

S1 represents an uncongested environment with sufficient communication and computational resources [35]. S2 introduces moderate competition among XR sessions. S3 represents a congested network, while S4 represents the most demanding condition, where limited bandwidth and high edge utilization require aggressive adaptive resource management.

3.5. Performance Metrics

The proposed framework was evaluated using communication, computational, and user-experience indicators, as summarized in Table 2 [36]. These measurements were selected because improvements in bandwidth utilization alone cannot demonstrate successful XR broadcasting if latency, computational efficiency, transmission reliability, or perceptual quality deteriorates.

Therefore, Table 2 presents a comprehensive evaluation of system performance by considering end-to-end latency, bandwidth consumption, edge computational utilization, transmission reliability, and Quality of Experience (QoE). Together, these indicators provide a balanced assessment of the proposed framework's ability to optimize network resources while maintaining reliable transmission and satisfactory immersive experiences across different operating scenarios.

Table 2. Performance Evaluation Metrics

Metric	**Measurement**	**Objective**
End-to-End Latency	Milliseconds (ms)	Minimize
Bandwidth Consumption	Mbps	Minimize
Edge Computational Utilization	Percentage (%)	Minimize
Transmission Reliability	Percentage (%)	Maximize
QoE Score	Percentage (%)	Maximize

End-to-end latency measures the time required for content to travel from the XR source through semantic and edge processing to the user. Bandwidth consumption represents the communication resources required for XR delivery [37].

Edge computational utilization measures processing demand at edge nodes, while transmission reliability represents successful and stable content delivery. Finally, the QoE score measures whether the system maintains acceptable immersive quality after semantic adaptation. Within the QSEI framework, semantic importance analysis supports the prioritization of relevant content, allowing the system to optimize transmitted information according to its perceptual and contextual significance. Consequently, bandwidth consumption provides an indication of how effectively the proposed approach manages communication resources compared with conventional resource allocation.

3.6. Experimental Procedure and Data Analysis

The experiment was performed independently for the four network scenarios [38]. Each scenario was tested using both QSEI and CRA under identical traffic conditions. During each experimental run, the system recorded latency, bandwidth consumption, computational utilization, transmission reliability, and QoE. Multiple runs were conducted for each scenario to reduce the influence of short-term network fluctuations, and the mean value of each performance indicator was calculated [39].

The analysis compared QSEI with CRA by calculating the relative improvement for each metric:

$$\text{Improvement}(\%) = \frac{M_{\text{CRA}} - M_{\text{QSEI}}}{M_{\text{CRA}}} \times 100 \tag{7}$$

For metrics requiring minimization, while the calculation was reversed for QoE and reliability metrics requiring maximization [40]. The experimental results were subsequently analyzed across S1–S4 to determine whether the proposed framework remained effective as network congestion increased. This methodology enables the study to evaluate not only technical resource efficiency but also whether semantic computing and edge intelligence can preserve the perceptual quality required for adaptive XR broadcasting over future 6G networks [41].

4. RESULTS AND DISCUSSION

4.1. Overall Performance of the Proposed Framework

The experimental results demonstrate that the proposed QoE-Aware Semantic Edge Intelligence (QSEI) framework consistently outperformed Conventional Resource Allocation (CRA), particularly as network traffic increased [42]. Under low traffic conditions, the performance difference between the two approaches was relatively small because sufficient communication and computational resources were available. However, the advantages of QSEI became increasingly evident under high and very high traffic conditions. Semantic importance analysis enabled the proposed framework to prioritize XR components that had a stronger influence on user perception, while edge intelligence dynamically adapted processing and transmission decisions according to current network conditions [43]. Consequently, QSEI reduced end-to-end latency, bandwidth consumption, and edge computational utilization while simultaneously maintaining higher transmission reliability and QoE.

Table 3. Overall Performance Comparison of QSEI and CRA

Scenario	Method	Latency (ms)	Bandwidth (Mbps)	Edge Utilization (%)	Reliability (%)	QoE (%)
S1	CRA	14.8	810	30	99.2	96.1
S1	QSEI	13.5	760	28	99.4	96.5
S2	CRA	22.7	690	50	97.6	92.8
S2	QSEI	18.4	610	45	98.5	94.9
S3	CRA	34.9	478	70	93.8	87.6
S3	QSEI	24.6	395	61	96.7	93.2
S4	CRA	47.6	292	90	88.9	82.7
S4	QSEI	31.2	238	73	94.8	91.8

The results show Table 3, QSEI maintained more stable performance from S1 to S4. In contrast, CRA experienced substantial performance degradation as network and edge resources became increasingly constrained. These findings demonstrate the importance of combining semantic awareness and intelligent edge processing rather than allocating resources uniformly to all XR information.

4.2. End-to-End Latency and Bandwidth Efficiency

End-to-end latency was evaluated to determine whether semantic computing and edge intelligence could improve the responsiveness of XR broadcasting. QSEI achieved lower latency across all experimental scenarios. Under S1, latency decreased from 14.8 ms with CRA to 13.5 ms with QSEI.

The difference became more significant under heavier traffic. In S3, QSEI recorded 24.6 ms compared with 34.9 ms for CRA, corresponding to a reduction of approximately 29.5 %. Under S4, latency decreased from 47.6 ms to 31.2 ms, representing an improvement of approximately 34.5%.

The proposed framework also reduced bandwidth consumption. Under S1, QSEI consumed 760 Mbps compared with 810 Mbps for CRA. Under S4, bandwidth consumption decreased from 292 Mbps to 238 Mbps, equivalent to a reduction of approximately 18.5%. This improvement occurred because QSEI did not transmit every XR component with identical resource priority. Instead, semantic importance analysis identified visually and contextually significant information such as the current field of view, interactive objects, foreground elements, and content relevant to user interaction. Less important information could consequently receive lower transmission priority during resource-constrained conditions.

These results indicate that semantic-aware adaptation becomes increasingly beneficial as network congestion increases. The latency and bandwidth reductions also demonstrate that resource efficiency can be improved without uniformly reducing the quality of the entire XR stream.

4.3. Edge Computational Efficiency and Transmission Reliability

Edge computational utilization increased for both approaches as the number of concurrent XR users increased. However, QSEI maintained lower utilization across all scenarios. Under S2, computational utilization decreased from 50% with CRA to 45% with QSEI. More substantial differences appeared under high traffic, where QSEI required 61% edge capacity in S3 compared with 70% for CRA. Under the most demanding S4 condition, CRA reached 90% utilization, whereas QSEI required only 73%.

This result suggests that the semantic processing mechanism successfully prevented edge nodes from allocating equal computational resources to XR elements with different perceptual importance. Consequently, computational capacity could be directed toward semantically important content and critical user interactions.

Transmission reliability showed a similar pattern. Both approaches achieved reliability above 99% in S1, indicating that semantic optimization provides only limited additional benefits when resources are abundant. However, CRA reliability declined to 88.9% in S4, whereas QSEI maintained 94.8%. The approximately 5.9 percentage-point difference indicates that adaptive semantic processing can protect critical XR information from network degradation during congestion. Therefore, the framework provides improved resource efficiency without compromising transmission stability.

4.4. QoE Performance under Dynamic Network Conditions

QoE represents the central performance objective of the proposed framework because technical efficiency alone is insufficient if immersive user experience deteriorates. The experimental results demonstrate that QSEI consistently maintains higher QoE than CRA, particularly as network traffic increases.

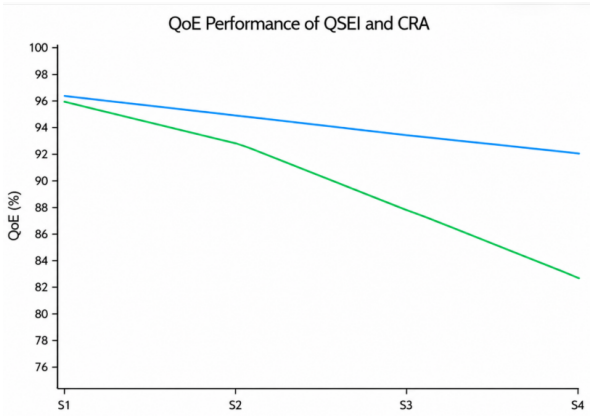


Figure 2. Figure X. QoE Performance Comparison of QSEI and CRA

Figure 2 shows that the performance difference between QSEI and CRA increases as network traffic becomes more demanding. Under S1, both approaches provide similar QoE because sufficient network resources are available. However, QSEI maintains QoE values of 93.2% and 91.8% under S3 and S4, respectively, while CRA decreases to 87.6% and 82.7%. These findings demonstrate that semantic prioritization enables the proposed framework to preserve perceptually important XR content even under highly congested network conditions.

QoE represents the central performance objective of the proposed framework because technical efficiency alone is insufficient if immersive user experience deteriorates. The experimental results show that QSEI maintained consistently higher QoE than CRA as network conditions became more demanding.

Table 4. QoE Performance across Network Conditions

Scenario	CRA QoE (%)	QSEI QoE (%)	Difference
S1	96.1	96.5	+0.4
S2	92.8	94.9	+2.1
S3	87.6	93.2	+5.6
S4	82.7	91.8	+9.1

Under S1, QSEI achieved a QoE of 96.5%, only slightly higher than the 96.1% obtained by CRA. This result was expected because both approaches operated with sufficient resources. In contrast, the QoE difference increased substantially under congestion. In S3, QSEI maintained 93.2% QoE compared with 87.6% for CRA. Under S4, QSEI maintained 91.8%, whereas CRA declined to 82.7%.

Table 4 indicate that bandwidth and computational savings achieved by QSEI did not result from indiscriminate XR quality reduction. Instead, semantic prioritization allowed the framework to preserve components with greater perceptual and contextual importance while reducing resources allocated to less critical information. This mechanism explains why QSEI simultaneously achieved lower resource consumption and higher QoE.

4.5. Effectiveness of Semantic Computing and Edge Intelligence

The experimental findings confirm the effectiveness of combining semantic computing with edge intelligence for adaptive XR broadcasting. Semantic computing provided information about which XR components should receive higher priority, while edge intelligence used this information together with network and QoE conditions to dynamically determine resource allocation. The feedback mechanism also allowed allocation decisions to be continuously adjusted when traffic and user conditions changed.

The proposed architecture therefore addresses the main research objective established in this study. First, semantic computing and edge intelligence can be successfully integrated through a continuous pipeline involving semantic feature extraction, importance estimation, QoE monitoring, and adaptive edge resource allocation. Second, QoE-aware semantic prioritization improved technical performance, with the greatest benefits observed under S3 and S4. At the highest traffic condition, the framework reduced latency by approximately

34.5%, bandwidth consumption by 18.5%, and edge utilization from 90% to 73%. Finally, the framework successfully maintained immersive service quality under resource-constrained conditions, achieving 91.8% QoE and 94.8% transmission reliability in S4.

Overall, these findings support the central proposition of the study that future 6G XR broadcasting should consider semantic importance and perceptual experience alongside conventional network indicators. QSEI provides a more adaptive approach in which network, computing, content, and QoE requirements are jointly considered, enabling more efficient and stable delivery of immersive XR services over highly dynamic 6G environments.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for telecommunications operators and XR broadcasting service providers. The proposed QoE-Aware Semantic Edge Intelligence (QSEI) framework demonstrates that integrating semantic computing with edge intelligence can improve network resource utilization while maintaining a high-quality immersive experience. Managers can use this approach to support strategic decisions regarding bandwidth allocation, edge computing deployment, and adaptive content delivery. By prioritizing semantically important XR components, service providers can reduce unnecessary data transmission and improve service responsiveness, particularly during periods of high network traffic.

From an operational perspective, the results highlight the importance of implementing intelligent and adaptive resource management rather than relying solely on conventional resource allocation strategies. The reduction in latency from 47.6 ms to 31.2 ms and the decrease in edge computational utilization from 90% to 73% under very high traffic conditions indicate the potential for more efficient infrastructure utilization. Network operators can use these insights to improve congestion management, optimize edge computing capacity, and maintain transmission reliability as the number of concurrent XR users increases. Such improvements may also support more scalable service delivery across applications such as immersive entertainment, virtual events, remote collaboration, and interactive education.

For technology managers and decision-makers, the findings emphasize the need to evaluate network performance not only through technical indicators but also through user-perceived Quality of Experience (QoE). The improvement in QoE from 82.7% with conventional resource allocation to 91.8% with QSEI under very high traffic conditions illustrates the managerial value of aligning infrastructure decisions with user experience requirements. However, before large-scale implementation, organizations should validate the framework through real-world network testing and assess deployment costs, computational requirements, and integration with existing infrastructure. This approach can help managers develop more informed investment strategies and establish a foundation for reliable, efficient, and user-centered XR broadcasting services over future 6G networks.

6. CONCLUSION

This study proposed a QoE-Aware Semantic Edge Intelligence (QSEI) framework that integrates semantic computing, edge intelligence, and adaptive resource allocation for XR broadcasting over 6G networks. The experimental results demonstrate that QSEI consistently outperformed Conventional Resource Allocation (CRA), particularly under high and very high network traffic. Under the most demanding scenario, QSEI reduced end-to-end latency by approximately 34.5The research questions were addressed by demonstrating that semantic computing and edge intelligence can be integrated through semantic feature extraction, QoE monitoring, intelligent edge processing, and adaptive resource allocation. The proposed framework successfully prioritized contextually and perceptually important XR components and provided greater performance improvements as network congestion increased. These findings confirm that QoE-aware semantic prioritization can support efficient and reliable adaptive XR broadcasting over 6G networks. Nevertheless, this study has several limitations. The evaluation was conducted within a simulated network environment with predefined traffic scenarios and resource conditions. Furthermore, the QoE model was primarily based on technical and perceptual indicators rather than subjective evaluations involving real XR users. Future research should validate the proposed framework using physical 6G testbeds, real XR applications, and larger-scale multi-user environments to examine its performance under more realistic conditions. Subjective user studies could also be incorporated to strengthen the relationship between network-level performance and actual perceived experience. Furthermore, future studies may integrate deep reinforcement learning, federated learning, or predictive edge intelligence to

improve dynamic resource allocation and semantic prioritization. Additional investigations involving mobility, heterogeneous edge nodes, energy efficiency, security, and multi-access network environments are also recommended to support the development of scalable, intelligent, and sustainable XR broadcasting systems for future 6G ecosystems.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: MM; Methodology: ED; Software: ED; Validation: MM and AW; Formal Analysis: AW and ED; Investigation: MM; Resources: ED; Data Curation: AW; Writing Original Draft Preparation: MM and AW; Writing Review and Editing: MM and ED; Visualization: AW; All authors, ED, MM, and AW, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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