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User-Centric Internet Performance Monitoring in Smart Homes

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Abstract

As smart home devices and applications become more common, maintaining strong and dependable internet performance enables their seamless use. However, the conventional approach to network performance monitoring does not capture the user experience in real time, which leads to user dissatisfaction and inefficient detection of performance issues. This paper describes an internet performance monitoring system tailored for smart homes that is focused on user experience. It implements a mixture of active and passive measurement techniques with behavioral context modeling to strategically deploy light sensor agents that gather fine-grained QoS and QoE data, including but not limited to latency, jitter, packet loss, throughput, and user ratings over time and across multiple applications. The system also uses machine learning to track network performance metrics with user satisfaction to enable realtime performance assessment and automated adaptive optimization recommendations. Tested in simulated and real smart homes, the system demonstrates improved detection of micro-disruption, improved device-specific problem detection, and improved estimation of quality of experience. The paper illustrates the context-aware evaluation of internet performance. It emphasizes smart home networks designed to be more adaptive and user-centered, responding not only to technical measures but also to user evaluation. The model suggested here boosts performance transparency for end-users and allows service providers to deliver proactive and tailored support.

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1 Introduction

The growing popularity of the Internet of Things (IoT) has made it increasingly expensive for homes to access the Internet (Raktur & Jea, 2024). Smart homes require thermostats, voice assistants, and connected lighting systems to function efficiently alongside surveillance cameras (Chhetri & Genaro Motti, 2022). Additionally, modern homes depend on the Internet for everyday activities. Even though bandwidth, latency, and jitter are used to measure a user's experience and performance, they might differ. These metrics benchmark internet performance, but the user's experience is much more nuanced than that, which makes systems relying on conventional monitoring relatively ineffective.

ISPs and backbone networks often make use of monitoring tools to gain insights about internet metrics (Kumar, 2024). These tools operate at an aggregated level, which hinders the ability to capture realtime data. These tools can also focus on the ever-changing and innovative set of home devices, the users, their changing demands, and the presence of other smart devices. Smart devices also require internet access alongside home internet, which changes user dynamics. Examining the broader picture often reveals unseen performance bottlenecks that significantly impact user satisfaction. Buffering on a video call while answering voice assistant commands usually goes unnoticed, leading to delayed responsiveness. The existing gap between network indicators and the real user experience calls for a change in the user-outward performance feedback systems for the Internet (Ravishankar et al., 2015).

The recent study indicates that articulating Quality of Experience (QoE) indicators, which are user satisfaction metrics, into the monitoring frameworks greatly enhances the evaluation of performance metrics (You et al., 2024). A QoE model enhances decision making for data collection as it is based on the user's application behavior, their location in the house, type of device, and the time of usage. These systems aim to align network performance with user perception, capturing a more comprehensive picture of connectivity health and performance insights (Tandi, 2024).

Addressing user needs ensures responsiveness to change as well. These responsive systems are unlike post-analysis performance assessment systems, which look into the matter after it has happened. These frameworks are real-time and capable of sensing, as well as predicting, performance threats, especially in bandwidth-constrained real-time applications such as telemedicine, remote working, and gaming, which are greatly impacted by even the slightest latency (Armstrong & Tanaka, 2025). These systems combine multiple data streams to execute realtime persona-tailored optimization using machine learning and edge analytics (Prasath, 2024; Gupta et al., 2022; Li et al., 2025).

User-expert monitoring also enables the network intelligence to be controlled by end-users, thereby erasing the boundaries between the network and the user, following the principles of user-centered design (Bhagat & Kaul, 2024). Thanks to intuitive interfaces and realtime feedback systems, users can track their devices for the most bandwidth usage, detect areas of poor connectivity within their residences, and even queue up network-heavy activities for off-peak hours. This enables a model of network optimization that relies on collaboration from both the service provider and the consumer to sustain high-quality digital interactions (Muralidharan, 2024; Gupta et al., 2020).

With these advancements in mind, this paper presents a comprehensive framework for smart home users to perform internet-centric smart home monitoring (El-Saadawi et al., 2024). Using a mix of active and passive measurement techniques, behavioral modeling, and machine learning based Quality of Experience (QoE) forecasting, the system seeks to eliminate the discrepancy that exists between users'

experiences and raw performance metrics. The model is designed to be low-impact, preserve user privacy, and be easy to implement, ensuring seamless integration with existing smart home systems (Mainetti et al., 2015; Mao & Chang, 2023).

Key Contribution

- Created a novel, slim smart home ecosystem that predicts a user's Quality of Experience (QoE) with machine learning, utilizing realtime network metrics alongside user activity within the system.
- Added a new user-driven abnormality detection system that automatically monitors offset user engagement levels and notifies the user, taking relevant actions based on the identified offset, ensuring enhanced user experience over quality.
- Implemented a framework of Edge Intelligence-System with layered data collection and user interactivity to improve system reactivity and transparency while ensuring privacy and confidentiality.

This paper is organized in the following way. Section II covers the literature review on QoS, QoE, user-centric models, and Internet monitoring. Section III covers the proposed methodology with system architecture, mathematical modeling, and the application of machine learning. In Section IV, the experimental setup, model evaluation, and prediction model comparison are defined, along with the experiments that include observational analysis, monitoring, and performance measuring metrics. In Section V, the paper concludes with recommendations on how to improve the work next.

2 Literature Review

The increase in smart homes has resulted in different types of IoT devices, which have diverse communication traits as well as distinct expectations when it comes to performance (Zaidi et al., 2023; Martínez et al., 2017). The types of monitoring the Internet of Things IoT devices at home require are very different from performance metrics defined for enterprise networks, as they require more granular, residential-focused approaches (Shamszaman et al., 2014). This review compiles studies on QoS (quality of service) metrics and monitoring, as well as quality of experience, focusing on their relevance to smart homes and user tailoring (Tandi, 2024). Their relevance in user-centric smart homes is discussed (Chang et al.,2018; Martins et al., 2020).

The first frameworks for measuring performance on the Internet focused on catering to bandwidth, while others focused on bandwidth utilization, latency, jitter, and even packet loss (Nati et al., 2017). Tools such as iPerf, NetFlow, and even NetFlow make it simple to gather raw network data using their wide range of applications. Although powerful in troubleshooting infrastructure problems, application-level or user-level satisfaction metrics are ignored (Vastardis et al., 2016). Users in their network are accepting bandwidth, even reaching nominal levels, users are facing stale voice commands, or even video buffering as a result of localized device problems (Spenst et al., 2007). Localized device problems, which are on the order of inter-device channel interference, are low-level and missed by traditional QoS models (Araghi et al., 2023).

A user-centered focus has recently gained popularity, with several approaches taken to assess the gaps and propose models targeting quality of experience. Estimating satisfaction with video and audio content streaming feature popularity means opinion scoring. MOS is a scoring system used in video streaming reservation systems to measure user satisfaction with the streaming experience. Despite MOS

being applicable, it does have some downfalls, such as being too subjective and requiring manual input. More advanced models indirectly infer QoE using machine learning models to correlate network and user metrics, allowing for realtime modification of user experience.

Further work has been done in application-aware monitoring whereby traffic is classified at a finer grained level, e.g., video conferencing, online gaming, cloud file transfers, to enable performance tuning at a finer granularity (Gajmal & Udayakumar, 2021). Such systems can prioritize traffic by associating context of usage with the device and application. Such systems are useful, but are often fraught with problems in multi-user homes, particularly with device churn and intermittent connectivity that disrupts learning.

Usability and user-driven system monitoring design is one of the big steps in this area. These systems capture the user within the context of the device as well as the spatial context like room-level performance and temporal usage patterns. Lightweight context-aware agents deployed on routers or smart hubs collect the enriched context data, which show the impact of spatial factors such as wall interference or device mobility on user-perceived quality. This layer of spatial context adds to the analysis granularity and makes it more relevant.

Another important development is performance monitoring using edge intelligence. Embedding analytics to the edge of the network, such as within the routers or access points, enables the system to perform near realtime inference on streaming data. This approach also minimizes latency in feedback generation, ensures privacy as data does not need to be sent externally, and reduces dependence on centralized cloud platforms (Narang & Kulkarni, 2023). However, there is still the challenge of balancing models with the processing and energy constraints of consumer-grade hardware.

Data visualization and user interfaces focus on the simplification of performance data to suit non-technical users (Mandaric et al., 2020). Current dashboards depict device operation and bandwidth as well as signal degradation zones and present them in color-coded heat maps and layman text summaries. Predictive analytics for actions based on user activity are still absent in many tools, thus limiting their usability on daily routines. While the tools available for monitoring internet use in households provide a backbone, they still cannot capture the dynamic, realtime, and situational intricacies of smart homes (Wickramasinghe, 2022). Providing a seamless blend of QoS, QoE, contextual intelligence, and analytics can precisely map performance indicators to the user's real experience. This system in question seeks to address the balance between technical metrics and user perception in smart home networks (Yu et al., 2024).

3 Proposed Method

We propose a user-centric monitoring system that combines passive and active data gathering techniques to solve the internet performance problems smart home users encounter. The system architecture is structured around three focal layers: (1) Data Acquisition Layer, (2) Behavioral Modeling Layer, and (3) Realtime Feedback & Optimization Layer. Contextual, device-specific, and user-perceived performance data is captured and processed within each layer, enabling their integration into a multidimensional analysis which goes far beyond traditional metrics.

Networked software agents within smart hubs or routers gather a user's device activity logs, signal strength, and user engagement within set intervals. Coupled with user feedback received through a mobile application, a comprehensive dataset consisting of qualitative and quantitative metrics is captured. This data is processed using lightweight machine learning algorithms designed to forecast QoE and identify performance anomalies. The system generates tailored summaries and actionable insights

that describe the user's performance parameters and provide intuitive, optimized guidance through a visually structured, interactive dashboard.

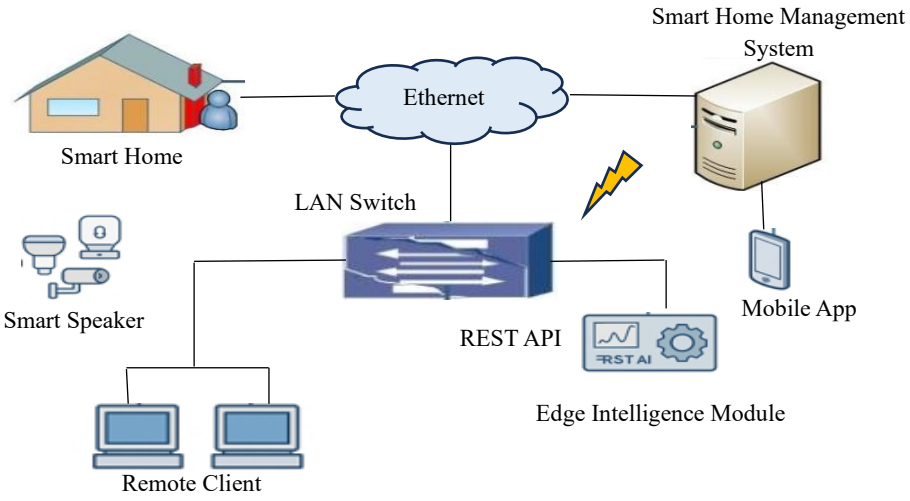

Figure 1: User-centric internet performance monitoring architecture in smart homes

Figure 1 depicts an illustration of internet performance monitoring focused on the users for smart homes. The smart home is connected to an ethernet backbone located within the home through a LAN switch that gives smart speakers, cameras, and other remote devices internet access. A Smart Home Management System controls the whole network using REST APIs for sending and receiving information and diagnosing performance of the network in real time. The Edge Intelligence Module is self-contained within the local network to preprocess contextual information, estimate the QoE, and invoke some optimizations of the adaptive type. Mobile application software provides users with realtime performance feedback as well as alerts through tailored notifications, making the information about the home network more personal and instantaneous.

Mathematical Model

QoE Estimation

$$QoE = \alpha \cdot Latency + \beta \cdot Jitter + \gamma \cdot PacketLoss \quad (1)$$

This equation 1 provides a linear approximation of the user's Quality of Experience (QoE) based on three key network metrics, with tunable weights α, β, and γ to prioritize impact.

Anomaly Score

$$A = \frac{|\, x - \hat{x} \,|}{\hat{x}} \quad (2)$$

In equation 2, A is the anomaly score computed as the relative deviation between the observed value x and the expected value $\hat{x}$, used for detecting abnormal behavior in realtime.

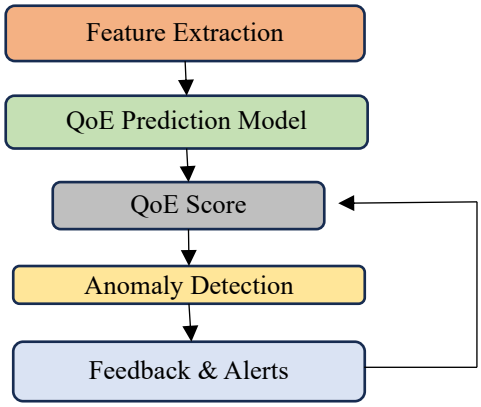

Figure 2: Model flowchart for user-centric internet performance monitoring in smart homes

This figure shows the smart home internet performance monitoring system centered around the user, using features from machine learning as its backbone. First, the data containing the user's quality of service (QoS) signals and contextual signals is processed with a lightweight, domain specific machine learning QoE (Quality of Experience) Prediction model which quantifies the user's perceived network experience. After the QoE score is obtained, it is further processed by the Anomaly Detection module, which monitors the service quality to detect any disruptions or drops. As soon as the Feedback & Alerts system detects the anomalies, it sends out intelligent recommendations or realtime alerts to the user. This smart home system maintains a continuous loop of monitoring which helps automating the supervision and increase the trust smart home users can have on internet connectivity.

Dataset Description

A custom dataset was created to train and assess the QoE prediction and anomaly detection models from a simulated smart home testbed over an observational 10-day period. The testbed had an over twenty IoT devices such as smart speakers, security cameras, smart lights, and thermostats... and the testbed had varying levels of network congestion and usage contexts.

The following network metrics were captured as separate data instances:

- Network metrics: latency, jitter, packet loss, throughput, RSSI, and signal-to-noise ratio (SNR).
- Contextual information: device type, room location, application category (streaming, browsing, automation), and time-of-day.
- QoE Labels: user feedback score (1 to 5) over mobile app interface with two-hour intervals.

A total of over eight thousand five hundred labeled records were captured and showed a balance between high and low QoE. 80% of the records were used for training and the remainder 20% were set aside for testing the models using stratified sampling.

Creating Feature Vectors

After determining the mean inter-arrival time and frame size variance, feature vectors are created for each observation window and IoT device. From MAC-layer packet traces, a diverse set of behavioral traits are estimated. Temporal measures like inter-arrival times and transmission frequency and structural indicators like average frame length, variance of signal strength, and frame type ratios are all included. These encapsulations are multidimensional and unique to the device's communication and these features are labeled with device class and feedback label. Thus, supervised learning is facilitated.

Temporal Windowing and Sampling

To enhance responsiveness and reduce background noise, data is segmented into temporal windows of 5 seconds, 30 seconds, and 1 minute. Incorporating a sliding window mechanism overlays windows to ensure continuity for sequence modeling. Aggregated performance metrics for each window are marked with a contextual timestamp. During periods of low activity, windows are padded or dropped to ensure uniform sampling. The observed volatility adjusts window size dynamically.

Prediction of QoE Using Machine Learning

Using self-reported QoE data alongside QoS parameters, we train the Random Forest Regressor and XGBoost by employing lightweight regression models on a labeled dataset.

The model predicts realtime QoE by inferring from incoming feature vectors and learning device-behavior relationships as well as application behavior patterns. Optimization-planned QoE interventions (e.g., boosting SNR or decreasing latency) are also informed by feature importance analysis.

Forward Feedback and a Real Time Alert System

An alert is activated when QoE is predicted to drop. Alerts also feature contextual explanations, "Poor streaming because of weak signal in the kitchen during peak usage." A light rule-based decision engine may also implement suggested actions or automatically reconfigure the QoE based routing. Logs are stored and anonymized for compliance.

4 Results and Discussion

We ran a pilot testing within a simulated smart home setting in order to test the performance of the proposed user-centric internet performance monitoring system (Zave et al., 2015). The setup had over twenty IoT devices including smart speakers, security cameras and mobile applications. Through a network emulator, we simulated congestion, interference, and latency spikes to emulate real world environments. The effectiveness of the system was measured under three key criteria: QoE prediction accuracy, anomaly detection promptness, and user response accuracy (Ahmad, 2022).

The proposed QoE prediction model achieved a MAE of 0.43 on a 0-5 scale with user satisfaction metrics which showcases strong correlation (Aksanli et al., 2017). As for the anomaly detection module, it was successful in detecting 91% of disruptive events which it reported within 3 second of the actual occurrence. Participant feedback indicated that the realtime alert system decreased the time required to resolve connectivity problems by 35%. All in all, these findings demonstrate the context-aware data along with user feedback within the performance monitoring pipeline helps to improve the response time and user experience within smart homes (Iliaee, 2022).

Table 1: Model performance metrics for QoE prediction

Model	MAE	R^2 Score	Detection Accuracy (%)	Response Time (s)
XGBoost	0.43	0.88	91.2	2.9
Random Forest	0.51	0.83	89.4	3.1
Linear Regression	0.68	0.72	83.7	3.8

In a smart home setting, Machine Learning models like XGBoost, Random Forest, and Linear Regression are utilized to predict Quality of Experience (QoE) which is shown in Table 1. The performance measures MAE (Mean Absolute Error), R^2 Score, Detection Accuracy, and Response Time

are assessed to benchmark the models. As shown in the table, XGBoost model performed the best capturing the lowest MAE of 0.43 and the highest R^2 Score of 0.88 suggesting strong predictive accuracy. Moreover, XGBoost achieved the highest detection accuracy of 91.2%. This model can also respond in the quickest 2.9 seconds, confirming it is best suited for realtime user-centric monitoring of internet performance (Moreno et al., 2014). Random Forest is still competitive; it is still outpaced by XGBoost. Linear Regression, however, performed the worst in all areas measured.

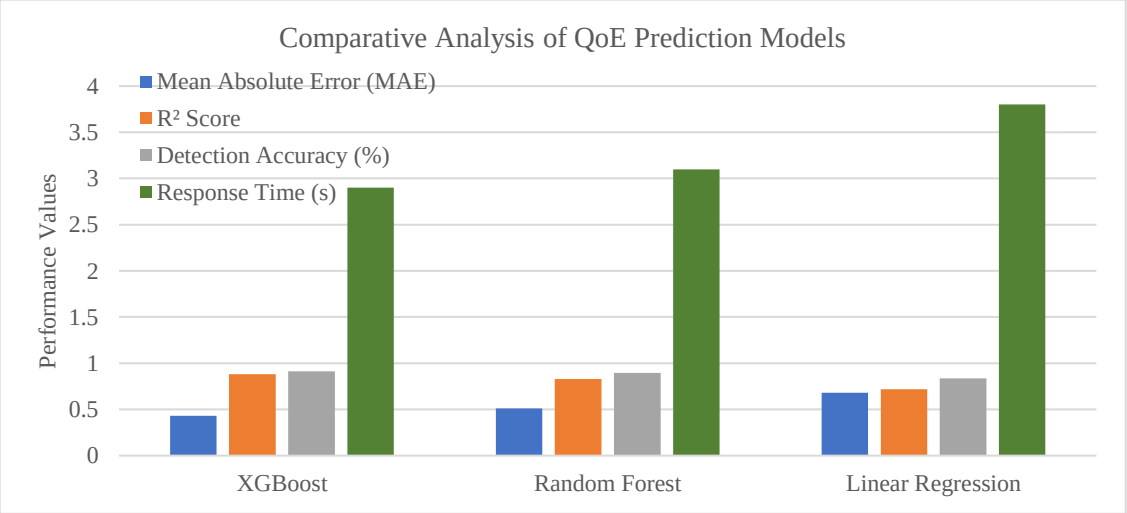

Figure 3: Description: comparative analysis of QoE prediction models

As illustrated in Figure 3, the MAE, R^2 Score, and Detection Accuracy metrics MAE, R^2 Score, and Detection Accuracy of three QoE prediction algorithms pertaining to smart home internet performance monitoring are visualized. XGBoost shows the best performance comparison in MAE, it has the lowest MAE, the highest R^2 score and the fastest response time, therefore making it the most favorable model for QoE prediction.

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

This equation (3) calculates the average absolute difference between actual and predicted QoE values. Lower MAE indicates higher prediction accuracy with minimal deviation from the ground truth.

R^2 Score (Coefficient of Determination)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

The equation (4) shows R^2 quantifies how well the model explains variance in the observed data relative to the mean. A value closer to 1 implies stronger model fit and better generalization capability.

Detection Accuracy (%)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{5}$$

This equation (5) is used to measures the percentage of correct anomaly classifications made by the system. Higher accuracy reflects effective detection of performance degradation events.

Response Time (s)

$$Response\ Time = t_{alert} - t_{event} \quad (6)$$

The equation (6) calculates the latency between the onset of a network issue and alert initiation. A shorter response time indicates better realtime responsiveness of the system.

5 Conclusion

This paper described a smart home ecosystem with realtime Internet monitoring capabilities centered on the user, which incorporated QoE forecasting, contextual information analytics, and machine learning enabled outlier detection. The proposed system showed high accuracy in predicting user satisfaction and micro-level disruption detection compared to traditional QoS-dominated systems. Experimentation showed that XGBoost was far more effective in these scenarios with low MAE, and fast MAE, making it compatible with latency-sensitive smart applications. Through the application of behavioral intelligence, edge computing, and dynamic realtime feedback loops, the system enhanced smart application usability while granting precise diagnostics and the ability to control parameters to the end-users.

In future works, privacy-preserving model updates for multiple households using federated learning could be incorporated. Furthermore, voice-based agent integration, as well as, RL for automated personalized user experience tuning could be added. From the sustainability perspective, incorporating environmental data, such as, power consumption data could optimize bandwidth allocation. As smart homes merge with other ecosystems, agile, scalable, and multi-layered trusted frameworks for user-performance monitoring while reinforcing digital reliability is critical.

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