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Original Article

Predicting Service Quality in Primary Healthcare Centres Using SERVQUAL Indicators: A Data-Driven Approach using CatBoost Machine Learning

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Abstract *- This study evaluates the Quality of Service (QoS) in Primary Healthcare Centres (PHCs), which serve as the first point of contact for healthcare services in rural and urban areas. The research aims to identify key service quality dimensions influencing healthcare performance and patient perceptions in PHCs. Service quality was assessed using patient-reported indicators based on the SERVQUAL framework, which includes five dimensions: tangibility, reliability, responsiveness, assurance, and empathy. Data collected from patient surveys were analysed using a CatBoost regression model to examine the relationship between service attributes and overall QoS. The model achieved strong predictive performance with R^2 = 0.856, RMSE = 0.027, and MAE = 0.021. The results indicate that SERVQUAL-based patient perceptions provide meaningful insights into service performance and can effectively support predictive evaluation of healthcare service quality in PHCs. The findings provide evidence for healthcare administrators and policymakers to improve service delivery by focusing on key service quality dimensions identified through data-driven analysis. The approach can support more efficient monitoring and improvement of healthcare services in resource-constrained environments. This study integrates SERVQUAL-based service quality assessment with machine learning techniques to provide a predictive framework for evaluating healthcare service performance in Primary Healthcare Centres.*

Keywords *- Quality of Service, Primary Healthcare Centres, SERVQUAL, CatBoost, Healthcare Analytics.*

1. Introduction

Investment in PHC has increased to improve healthcare among people in rural and urban areas. PHC provides services such as basic treatment, health education, disease control, and promotes healthy lifestyles in rural and urban areas. Therefore, to increase the quality of service of PHC, upgrading the facilities, digitizing the services, and strengthening the quality of health officers are important [1, 2].

The increased investment alone is not sufficient to improve the QoS of PHC. Furthermore, QoS depends on staff availability and the organization of service delivery at the PHC level. Such variations may influence patient satisfaction, healthcare utilization, and the effectiveness with which publicly funded healthcare resources are used. From a health economics perspective, evaluating service quality is therefore important for understanding whether public expenditure on primary healthcare translates into effective service delivery and improved patient outcomes [3].

Assessment of healthcare service quality is based on patient-reported feedback collected through structured survey instruments. The SERVQUAL framework has been widely applied to measure perceived service quality across five key dimensions: tangibility, reliability, responsiveness, assurance, and empathy [4], [5]. These dimensions include patient experience, including the condition of healthcare facilities, the reliability of services, the responsiveness of staff, professional competence, and interpersonal communication during service delivery. Existing SERVQUAL studies have provided useful insights into patients' perceptions of healthcare services. These analyses are frequently limited to descriptive evaluation and do not support systematic comparison or predictive assessment of service performance across healthcare facilities.

The healthcare data has created new opportunities for analysing service performance using data-driven approaches. Administrative records, health information systems, and patient surveys collectively generate large volumes of structured healthcare data that can support performance evaluation in public health systems [6]. These data sources are primarily used for routine monitoring and reporting and for analytical evaluation of service quality [7]. Advances in machine learning methods have demonstrated the ability to analyse complex datasets and identify patterns that are not easily captured by conventional statistical techniques [8], [9].

Primary Healthcare Centres use integrated analytical frameworks that combine patient-reported service indicators with predictive modelling techniques. Existing studies focus on specific operational indicators or clinical outcomes rather than providing a comprehensive assessment of service quality across multiple dimensions of healthcare delivery [10]. Addressing this gap improves the evaluation of service performance at the primary healthcare level. A data-driven framework for assessing and predicting the Quality of Service (QoS) of Primary Healthcare Centres using patient-reported SERVQUAL indicators. A composite QoS index is constructed using normalized service quality dimensions derived from patient survey responses. The relationship between service attributes and overall QoS is analysed using a CatBoost regression model. Integrating service quality measurement with predictive analytics supports evidence-based decision-making and improves the efficiency of primary healthcare service delivery.

2. Literature Review

Table 1 summarises recent studies examining healthcare service performance using statistical and machine learning approaches. Many of these studies focus on specific operational aspects such as waiting time, patient satisfaction, appointment behaviour, or healthcare demand prediction. A large proportion of the existing literature is concentrated on hospital or emergency care settings rather than Primary Healthcare Centres. Studies examining PHC service quality often rely on descriptive survey analysis and rarely integrate multiple service quality dimensions within a unified analytical framework. The comprehensive evaluation of Quality of Service across PHCs remains limited. This gap is addressed by combining SERVQUAL-based service quality indicators with a data-driven analytical approach to predict QoS across Primary Healthcare Centres.

Table 1.

Authors (Year)	Health-care setting & data type	Features used	Models used	Key limitation	Research gap identified
Garedew et al. (2025)	Primary and outpatient healthcare; waiting-time and service-process data	Waiting-time variables, service-process indicators	Hybrid ML and lean-management framework (regression and classification)	High computational cost and context-specific implementation	Scalable ML-based waiting-time-driven PHC service-quality prediction models remain limited
Mujawar et al. (2024)	Oncology / cancer-care settings; patient clinical datasets	Clinical and demographic variables	Explainable AI techniques (SHAP, LIME)	Disease-specific focus; not applicable to general PHC services	XAI-driven PHC-level service-quality and trust-building frameworks are not well explored
Rahman et al. (2025)	Primary health care; patient-satisfaction survey data	Waiting time, communication, staff attitude, cleanliness, facility attributes	Explainable tree-based ML models with SHAP	Relies on subjective satisfaction data rather than objective service indicators	An integrated ML-based PHC service-quality prediction combining objective and subjective indicators is needed.
Değer & İşsever (2024)	Primary health care services: cross-sectional survey data	Facility availability, staffing, waiting time, communication, outcome indicators	Statistical modelling (e.g., regression)	Descriptive and non-predictive; no ML-based forecasting	ML-based prediction and clustering of PHC service-quality levels across facilities are not addressed
Setyaneva et al. (2025)	Hospital and clinic settings; cost-related administrative data	Diagnosis codes, length of stay, resource-use indicators	Light Gradient Boosting Machine (LightGBM)	Hospital-centric focus; limited applicability to PHC	LightGBM-based PHC-level service-quality and cost-efficiency prediction models are lacking
Salhieh et al. (2024)	Healthcare purchasing and	Strategic purchasing	Structural equation	Focuses on purchasing	The The relationship

	management; organizational survey data	practices, purchasing involvement, and leadership style	modelling	strategy rather than service-quality prediction	between healthcare management practices and service quality in PHCs remains insufficiently explored.
Datt et al. (2025)	Healthcare service management; mixed-source data (surveys and operational metrics)	Service-quality dimensions, operational indicators	Hybrid statistical and machine-learning models	Broad healthcare scope with limited PHC specificity	PHC-focused, infrastructure-based ML QoS prediction models remain underdeveloped
Farrokhi et al. (2023)	Outpatient healthcare services; patient and provider survey data	Perceived service-quality dimensions from patients and providers	Descriptive and comparative analysis	Non-predictive; lacks machine-learning modelling	ML-based outpatient service-quality prediction integrating patient and provider perspectives is not yet developed.
Georgiev et al. (2025)	Post-emergency care; electronic health records	Post-discharge demographics, comorbidities, prior healthcare contacts	Tree-based and ensemble machine-learning models	Focuses on healthcare-contact prediction rather than service quality	ML-based service-quality prediction following emergency hospitalisation remains unexplored
Orhan & Kurutkan (2025)	General healthcare systems; population-level service-utilisation data	Predisposing, enabling, and need-based factors	Machine-learning models for demand prediction	Addresses demand rather than service quality	Service-quality implications of ML-predicted healthcare demand are not modelled.
Yang et al. (2024)	General healthcare: appointment and demographic datasets	Socioeconomic, clinical, and behavioural factors	Machine-learning models for no-show prediction	Focuses on appointment equity rather than overall service quality	The study focuses on appointment behaviour rather than overall service quality evaluation in PHCs.
Leiva-Araos et al. (2025)	Primary healthcare centres: appointment and no-show data	Appointment history, patient demographics, prior no-shows	ML-based no-show prediction and optimisation models	Concentrates on no-show management, not comprehensive QoS	Integrated ML-based PHC service-quality prediction incorporating no-show effects has not yet developed
Liu et al. (2023)	Online healthcare platforms: usage and satisfaction data	Platform features, user demographics, interaction patterns	Machine-learning models for satisfaction prediction	Limited to online platforms; not applicable to physical PHCs	ML-based PHC service-quality prediction integrating online and offline service channels is unexplored
Moreno-Sánchez et al. (2024)	Emergency departments: patient-flow and EHR data	Arrival patterns, triage level, clinical indicators	Explainable AI using tree-based ML models	Emergency-department-focused; not PHC-oriented	XAI-enabled PHC patient-flow and service-quality prediction frameworks have not been developed.
Petsis et al. (2022)	Public-hospital emergency departments; visit-log data	Temporal visit patterns, patient characteristics, triage level	Machine-learning models for visit forecasting and explanation	ED-specific context limits generalisation to PHC	ML-based forecasting and explanation of PHC-level visit patterns and service quality remain immature.

3. Methodology

3.1. Analytical Framework for QoS Assessment

Primary Healthcare Centres (PHCs) are evaluated to assess and predict the Quality of Service (QoS). The proposed framework integrates patient-reported service quality information, data processing procedures, and model-based analysis in service performance across PHCs. Patient-level data were collected using a SERVQUAL-based survey administered to individuals receiving services at selected Primary Healthcare Centres. After data screening and validation, a total of 750 completed responses were retained for analysis.

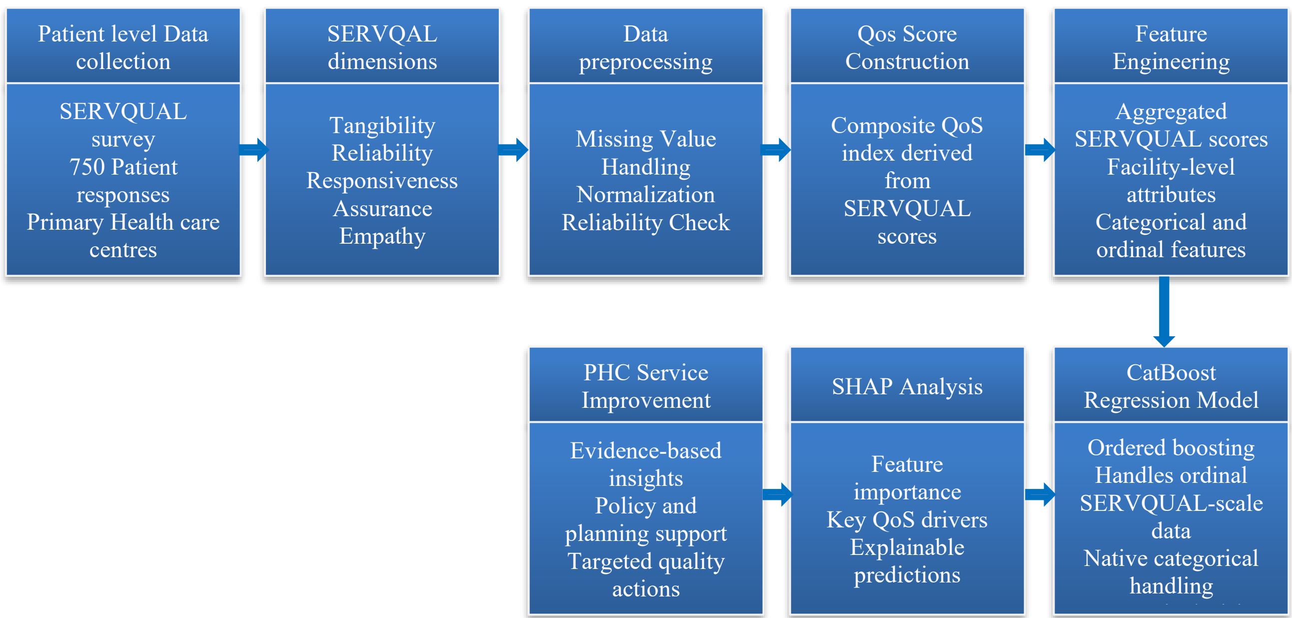

Fig. 1 Analytical framework for evaluating and predicting Quality of Service in Primary Healthcare Centres

The SERVQUAL survey was organised into five service quality dimensions: tangibility, reliability, responsiveness, assurance, and empathy. These dimensions capture different aspects of patient experience, including the condition of physical facilities, the reliability and consistency of services, the responsiveness of healthcare staff, professional competence, and the quality of interpersonal interaction between patients and healthcare providers.

The data were examined to ensure consistency and suitability for statistical evaluation. Missing responses were addressed using appropriate imputation procedures, and the survey responses were normalised to allow comparison across service quality indicators. The internal consistency of the SERVQUAL items was also evaluated to assess the instrument's reliability.

SERVQUAL indicators, a composite Quality of Service (QoS) index, were constructed by aggregating the normalized dimension scores. This index represents the overall level of perceived service quality experienced by patients at the PHC level and serves as the outcome variable in the subsequent analysis.

The SERVQUAL dimension scores were combined with selected facility-level and categorical attributes related to Primary Healthcare Centres. These variables form the analytical feature set used to examine the relationship between service quality attributes and overall QoS. A CatBoost regression model was applied to estimate QoS, handling heterogeneous data and ordinal survey responses effectively.

SHapley Additive exPlanations (SHAP) were used to examine the relative contribution of individual variables to the predicted QoS values. This approach provides interpretable insights into the service quality factors that most strongly influence perceived healthcare performance across PHCs.

The analytical framework enables a systematic assessment of service quality in Primary Healthcare Centres. It provides evidence that can assist policymakers and healthcare administrators in identifying areas for service improvement and more efficient utilisation of healthcare resources.

3.2. Study Design and Framework Overview

The Quality of Service (QoS) of Primary Healthcare Centres using a quantitative approach grounded in patient-level data. Service quality perceptions collected from patients are analysed alongside statistical learning techniques to understand the factors associated with variations in healthcare service performance. The methodological framework integrates data preparation, service quality measurement, model-based analysis, and result interpretation to support evidence-informed decision-making at the policy level.

Let the complete dataset be represented as

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{1}$$

where N = 750 denotes the total number of patient responses, x_i represents the service quality attributes for the i^{th}patient, and
y_i denotes the corresponding Quality of Service score.

3.3. Data Collection

Primary data were collected using a structured SERVQUAL questionnaire administered to patients visiting Primary Healthcare Centres. A total of 750 valid responses were obtained from multiple PHCs. Each questionnaire item was measured using a Likert-scale format.

The patient-level response vector is expressed as

$$x_i = [x_{i1}, x_{i2}, \dots, x_{im}] \tag{2}$$

where x_{ij} denotes the response of i^{th}patient to the j^{th}SERVQUAL item and m represents the total number of items.

3.4. SERVQUAL Dimensions

The SERVQUAL instrument evaluates perceived healthcare service quality across five dimensions:

$$x_i = \{T_i, R_i, RS_i, A_i, E_i\} \tag{3}$$

where
T_i = Tangibility attributes,
R_i = Reliability attributes,
RS_i = Responsiveness attributes,
A_i = Assurance attributes, and
E_i= Empathy attributes.

These dimensions collectively represent patient perceptions of healthcare service quality.

3.5. Data Preprocessing

To ensure data consistency, missing values in SERVQUAL items were handled using mean imputation:

$$x_{ij} = \begin{Bmatrix} x_{ij}, & if\ observed \\ \left(\frac{1}{n}\right)\sum_{k=1}^{n} x_{ij}, & if\ missing \end{Bmatrix} \tag{4}$$

To standardize the scale of responses, min–max normalization was applied:

$$x'_{ij} \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{5}$$

The internal consistency of the SERVQUAL instrument was verified using Cronbach's alpha:

$$\alpha = \frac{k}{k = 1}\left(1 - \frac{\sum_{j=1}^{k} \sigma_j^2}{\sigma_T^2}\right) \tag{6}$$

where k is the number of items, σ_j^2 is the variance of item j, and σ_T^2 is the total variance.

3.6. Quality of Service Score Construction

A composite Quality of Service score was constructed by aggregating normalized SERVQUAL item scores:

$$QoS_i = \frac{1}{m}\sum_{j=1}^{m} x'_{ij} \tag{7}$$

where QoS_i represents the aggregated perceived service quality score for the corresponding Primary Healthcare Centre.

The expectation–perception gap was examined as

$$G_i = P_i - E_i \tag{8}$$

where P_i denotes perceived service quality and E_i indicates the expected service quality of ith indicator.

The composite QoS score serves as the dependent variable for subsequent analysis.

The QoS score is calculated based on patient perceptions across different service quality dimensions, and categorical variables such as gender, age group, and PHC type. The final feature vector used for analysis is defined in equation (9).

$$Z_i = [X'_i, d_{i1}, d_{i2}, d_{i3}] \tag{9}$$

CatBoost is used to predict the QoS through learning complex non-linear patterns among the categorical data. The multiple regression tree is defined in equation (10).

$$\hat{y}_i = \sum_{k=1}^{K} f_k(Z_i) \tag{10}$$

The model is evaluated through using k-fold cross-validation to determine the predictive accuracy of the service quality of PHC.

The prediction accuracy is evaluated using the following metrics, which are defined in equations (11),(12), and (13).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \quad (11)$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i| \quad (12)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \quad (13)$$

From equations (11-13), y_i represents the observed QoS value, $\hat{y}_i$ denotes the predicted QoS value, and $\bar{y}$ is the mean of the observed QoS values.

4. Results and Discussion

4.1. Descriptive Analysis of SERVQUAL Dimensions

SERVQUAL responses were measured using an eight-point Likert scale, where higher scores indicate better perceptions of service quality. Table 2 shows the descriptive statistics of SERVQUAL dimensions at the Primary Healthcare Centre (PHC) level.

Table 2. Descriptive Statistics of SERVQUAL Dimensions

SERVQUAL Dimension	Mean	Std. Deviation	Minimum	Maximum
Tangibility	5.526	0.855	3.00	8.00
Reliability	5.462	0.761	3.40	7.40
Responsiveness	5.444	0.824	3.00	8.00
Assurance	5.549	0.848	3.25	8.00
Empathy	5.513	0.759	3.20	7.60

The mean SERVQUAL dimension scores range from 5.44 to 5.55, indicating a moderate level of perceived service quality across Primary Healthcare Centres. Assurance and tangibility show slightly higher mean scores, suggesting that patients generally view staff competence, physical condition and facilities positively.

Responsiveness records the lowest mean value, which may reflect delays in service delivery and possible inefficiencies in patient service management. These results indicate that overall service quality is moderate; improvements may be needed in service responsiveness.

4.2. Quality of Service (QoS) Score Analysis

Each Primary Healthcare Centre (PHC) was assigned a composite Quality of Service (QoS) score based on the normalised SERVQUAL dimension scores. The QoS index indicates the overall perceived service quality. Table 3 presents the SERVQUAL dimension scores and the QoS values for the selected PHCs.

Table 3. Composite Quality of Service (QoS) Scores

PHC ID	Tangibility	Reliability	Responsiveness	Assurance	Empathy	QoS
1	4.75	5.40	5.50	4.00	4.00	4.73
2	3.75	4.60	5.75	4.75	6.20	5.01
3	5.25	5.80	4.75	5.00	6.20	5.40
4	4.00	6.60	5.00	6.75	5.60	5.59
5	5.25	5.40	5.25	4.75	6.60	5.45

QoS values vary across PHCs. Centres with higher assurance and empathy scores generally exhibit higher QoS values, while lower scores across several dimensions correspond to lower QoS levels. Table 4 illustrates the comparative performance analysis of regression models to predict the QoS. The baseline models fail to capture non-linear relationships among categorical variables compared with the CatBoost model when handling heterogeneous features. Figure 4 shows the comparison of predicted and actual QoS scores.

Table 4. Comparative Performance of Regression Models for Quality of Service (QoS) Prediction

Model	RMSE	MAE	R^2
Linear Regression	0.089	0.071	0.598
Support Vector Regression	0.064	0.052	0.701
Random Forest	0.048	0.037	0.789
Gradient Boosting Regression	0.041	0.031	0.812
CatBoost (Proposed)	0.027	0.021	0.856

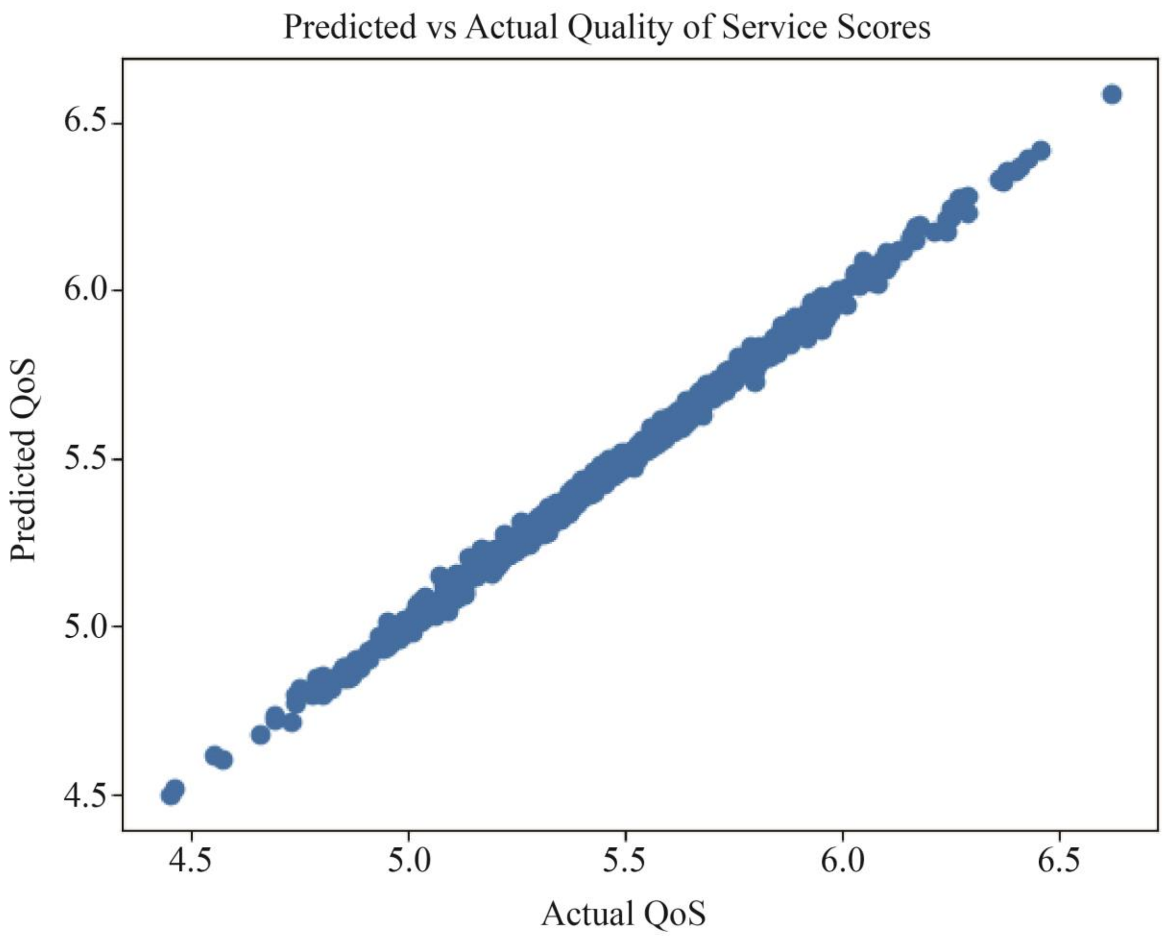

Fig. 4 Comparison of predicted and actual Quality of Service (QoS) scores

Table 5 shows the relative importance of each SERVQUAL dimension derived from the CatBoost regression model. Tangibility shows the highest contribution, compared to assurance and responsiveness.

Table 5. Feature Importance Ranking of SERVQUAL Dimensions

Rank	SERVQUAL Dimension	Importance Score
1	Tangibility	24.43
2	Assurance	20.78
3	Responsiveness	20.23
4	Reliability	17.85
5	Empathy	16.70

The importance values are normalised scores derived from the CatBoost model. The higher contribution of Tangibility indicates that factors related to physical facilities and infrastructure are closely associated with variation in QoS across PHCs. Assurance and responsiveness also play a meaningful role, reflecting the influence of staff competence and the timeliness of service delivery. Reliability and empathy, although relevant, have a smaller impact relative to the other dimensions.

Related to physical infrastructure and facility conditions, these factors may partly explain the stronger influence of Tangibility on perceived service quality. Overall, these results show that QoS is influenced by multiple service quality dimensions, with differences in their relative importance across Primary Healthcare Centres.

4.3. SHAP-Based Interpretation of QoS Drivers

SHAP-based analysis of individual SERVQUAL items to the predicted Quality of Service (QoS) scores. Figure 5 shows feature contributions across the dataset and how variations in SERVQUAL items are associated with changes in predicted QoS.

In the SHAP summary plot, labels represent the SERVQUAL dimensions: T, R, RS, A, and E correspond to Tangibility, Reliability, Responsiveness, Assurance, and Empathy, respectively. The numeric indices associated with each label refer to individual questionnaire items within the corresponding SERVQUAL dimension.

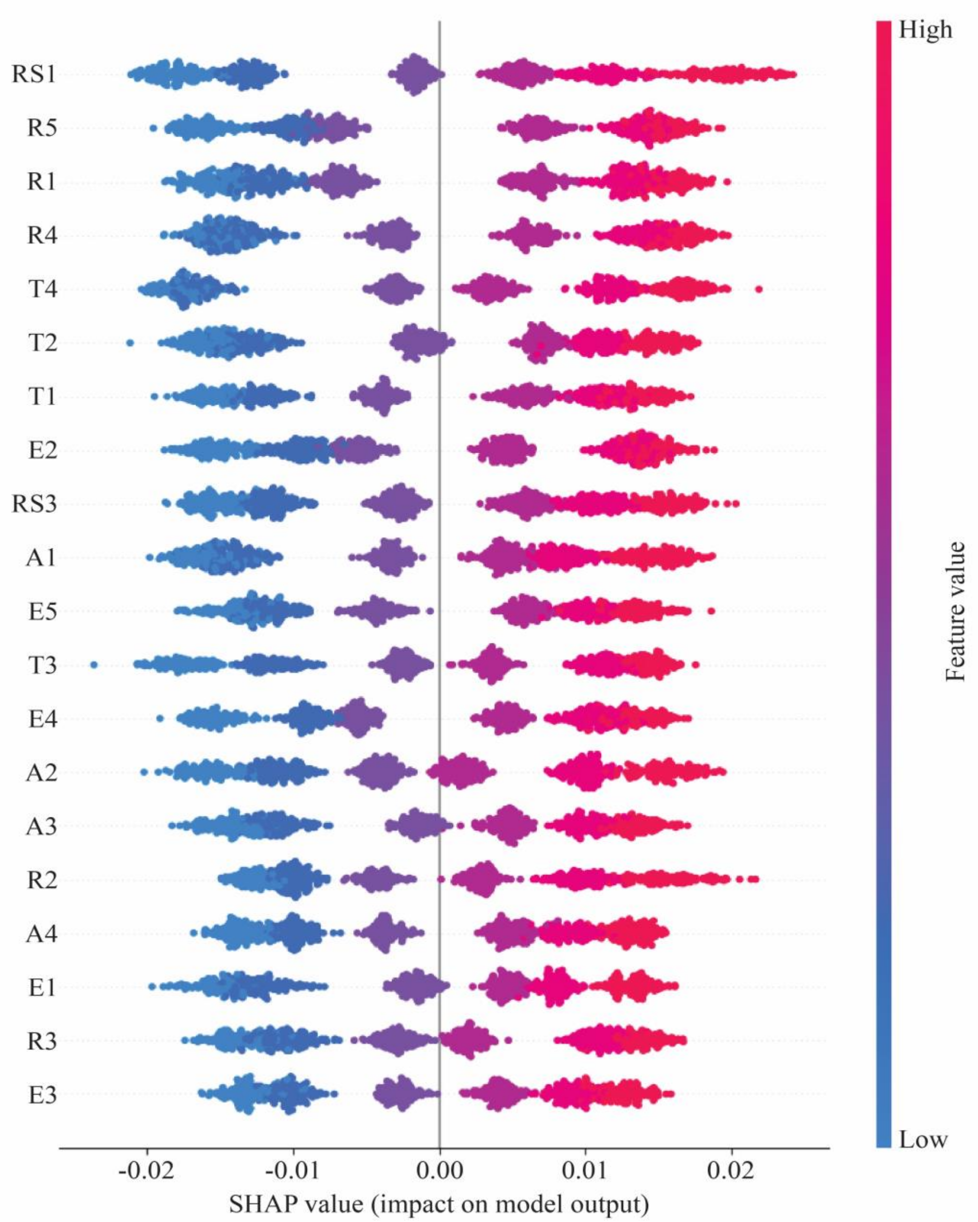

Fig. 5 SHAP summary plot showing the contribution of individual SERVQUAL items to the predicted Quality of Service (QoS) scores obtained using the proposed CatBoost regression model

Positive SHAP values indicate an increase in the predicted QoS, while negative values indicate a decrease. SERVQUAL items are related to tangibility and responsiveness for predicting QoS in PHC. Higher values for these items are linked to better perceived service quality, highlighting the importance of physical facilities and timely service delivery. Assurance also contributes to QoS prediction, reflecting the importance of staff competence and patient perceptions. In contrast, reliability and empathy show narrower SHAP value distributions, indicating a more moderate and consistent influence across PHCs. Overall, the SHAP result indicates that operational and facility-related SERVQUAL attributes have a stronger impact on predicted QoS. These findings can support data-informed evaluation of service quality and guide improvement efforts in Primary Healthcare Centres.

5. Conclusion

Service quality in Primary Healthcare Centres was evaluated using SERVQUAL indicators and a machine learning approach. The results show that service performance differs across SERVQUAL dimensions. Tangibility, Assurance, and Responsiveness have a stronger influence on Quality of Service (QoS) than the other dimensions. Among the tested models, CatBoost achieved the best prediction performance with the lowest RMSE and MAE values and the highest R^2 score. The results indicate that improvements in facility conditions, staff competence, and timely service delivery can enhance perceived service quality in PHCs. Future work may incorporate objective healthcare performance indicators and larger datasets to improve service quality evaluation in primary healthcare systems.

Limitations and Future Work

The analysis uses patient perception data based on SERVQUAL indicators, which may not fully reflect objective aspects of healthcare performance. The responses were also aggregated at the Primary Healthcare Centre (PHC) level, so individual differences may not be fully visible. Future research could incorporate objective performance indicators and broader datasets to improve the evaluation of service quality in primary healthcare systems.

Author Contributions

All authors have equally contributed to the investigation and implementation presented in this work. All authors have read and approved the final version of the manuscript.

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Data Availability Statement

The data presented in this study are available upon request from the corresponding author. 'Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

Conflicts of Interest

The authors declare no conflicts of interest.

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