Brand Service Quality Evaluation Using the SERVQUAL Customer Algorithm

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Abstract

As the competitive landscape grows and customer expectations accelerate, brands are under increasing pressure to deliver quality service and ensure consumer retention and loyalty. This research presents an on-demand, data-driven evaluation of brand service quality. Utilizing the SERVQUAL model in conjunction with a robust Customer Feedback Algorithm, the SERVQUAL model assesses the gap between customer expectations and customer perceptions through the five critical perspectives on service quality: tangibles, reliability, responsiveness, assurance, and empathy. Our methodology collects customer feedback through systematic surveys and captures real-time feedback using customer digital interaction data. This feedback is then processed with a customer feedback algorithm that calculates gap scores, yielding a brand service quality index. To increase the reliability and the overall accuracy of the surveys, we integrate various advanced analytics features (including sentiment analysis and weighted scoring) to produce quality indicators based on customers' subjective responses. The algorithm also has a built-in dynamic learning capability to accommodate changes to customer expectations over time. We collected empirical data from brands across various service industries, including, but not limited to, service-based companies in retail, banking, and telecommunications. Quantitative analysis of data revealed the factors that customer satisfaction is significantly influenced by, and how they differ across sectors. Above all, this system has the potential to help brands identify service quality deficits and assist in strategic decision-making through real-time data-driven analytics. The formulation of the SERVQUAL model with the real-time and automated nature of dynamic data processing is not only scalable, it is scalable and replicable.

Keywords: SERVQUAL; Feedback; Service Quality; Brand Evaluation; Customer Perception.

I. INTRODUCTION

In our increasingly service-based global economy, brand performance is no longer only defined by product performance, but rather dominance of a service experience. Service quality has become an increasingly common identifier and performance measure for brand longevity and to limit customer churn. Brand service quality is critical for brands to sustain their competitive advantage since customer expectations change rapidly, and continuous improvement of service delivery becomes the only defensible position. As such, brand service quality assessment has emerged as a critical area of focus for strategic management. Brand service quality assessment can help organizations understand how their service delivery approaches meet customer expectations and the perceived value of service quality (Zadeh & Khalili, 2015).

One of the most important breakthroughs in service quality analysis has been the framework structuring demonstrated in the SERVQUAL model, which empowers brands to break service quality into 5 measurable dimensions: Tangibles, Reliability, Responsiveness, Assurance, and Empathy. This also allows brands to diagnose service quality gaps through a comparison process between what customers expected and what they perceived of the service performance (Parasuraman et al., 1988). Over time and by design, SERVQUAL is popular among industry sectors given the ease of use, diagnostic capabilities, and flexibility it offers. Often, service quality measurement using SERVQUAL is reliant on static survey data and typically does not capture real-time customer sentiment or service behavior reflected in the survey response (Buttle, 1996).

Customer feedback is a key component of service quality measurement, as it captures the voice of the customer and provides actionable output. The fact that customer feedback represents qualitative data allows for capturing what is working and what is not working. Digital communication channels have increased the volume, variety, and velocity of customer feedback. This is a double-edged sword; on one hand, on occasion, the opportunity of abundant customer data provides them with invaluable insights into the service experience, whereas when unstructured or large-scale customer feedback and service data require sophisticated analytical tools to isolate the patterns and classify the latent time behavior (Zhou et al., 2020). Brands relying on shallow and narrow customer data, such as occasional manual interpretation or sales administration of the survey, limit repeated responses from customers with respect to service value actualization (Çetinkaya, 2020).

This study addresses these limitations by suggesting a combination of the SERVQUAL framework and a Customer Feedback Algorithm that analyzes feedback data across the five SERVQUAL dimensions automatically. Specifically, the Algorithm will handle both structured and unstructured data, allow gap scores to be calculated, and produce a real-time evaluation of service performance. The significance of this contribution is that it closes the gap between traditional service quality frameworks and current, data-driven decision-making. The contribution of combining these two systems provides a more effective, responsive, and accurate evaluation of service quality, and fosters continuous service enhancement and strategic brand management (Kapoor et al., 2022).

This study aims to show how the SERVQUAL Customer Feedback Algorithm can be used as a good, scalable, and customized tool to evaluate brand service quality (Donkor & Zhao, 2023). The research design will empirically test the algorithms on customer feedback datasets, representing a range of service industries, in order to strengthen the argument of a model that can identify service quality gaps and make recommended adjustments, if and when it is needed. Through the combination of the humbler theoretical framework of SERVQUAL with more flexible real-time feedback algorithms, this study provides an example of an innovative response to managing service quality in the digital age (Ramanathan, 2018).

II. LITERATURE REVIEW

The topic of service quality has been the subject of much discussion in both academic and industry literature primarily because of its relationship with customer satisfaction, loyalty, and the ability of services to succeed within the brand overall. Service quality is generally defined as the difference between customer expectations and customer perceptions of the service experienced. Grönroos (1984) was one of the first people to conceive service quality as a dual-structure concept, consisting of technical quality (what you deliver) and functional quality (how you deliver it). Overall, researchers have become much more focused, with a move toward customer-perceived quality, as perceptions shape the overall brand experience in many service encounters (Davidians & Gelard, 2017).

The SERVQUAL model, designed by Parasuraman, Zeithaml, and Berry, is arguably the most widely used framework to evaluate service quality systematically, transforming service quality into five distinct dimensions (Tangibles, Reliability, Responsiveness, Assurance, Empathy) and defining a critical aspect of the service encounter. As noted by SERVQUAL has been validated and modified across different environments and cultures, confirming its flexibility and reliability in measuring service quality, in settings ranging from retail to hospitality to health care to finance (Anitha & Dhivya, 2019). The SERVQUAL model identifies service quality gaps as it measures the differences between the service expected versus the service received, thus providing a diagnostic portrait of organizational performance from the customer perspective.

Recent studies have started to adapt the original SERVQUAL tool, and reports have included more proactive measures for obtaining customer feedback, as well as enhancing the analytical approaches for processing customer feedback (Xie & Fang, 2024). For example, contended that adapting the SERVQUAL model into a predictive feedback model would enable service businesses to be relevant by enabling better utility legal; that is, in an environment where customer expectations are changing rapidly, and are continuously generated. Furthermore, the major drawback of original SERVQUAL efforts revolved around its static nature - that is, they relied on pre-developed surveys and then analyzed the customer experience and the survey inferential error measurement of service quality. The original SERVQUAL model fails to reflect the service experience and customers' expectations from the dynamic nature of the digital and omnichannel world (Alattas, 2024).

The use of SERVQUAL as a measure of brand service quality was the subject of a number of studies that used technological tools to automate feedback reviews (Verma & Banerjee, 2024). For example, Prentice investigated the extent to which customer satisfaction with hotel brands can be accurately predicted using a modified SERVQUAL scale that was related to automated feedback analysis from customer online reviews. Their result showed that sentiment data and digital perceptions are increasingly being used to complement existing survey methods (Menon & Rao, 2024). Likewise, discovered that by combining SERVQUAL and a machine-learning-based sentiment classifier, a more accurate representation of service quality measurement could occur in food delivery services. All of these studies demonstrated the advantages of adopting structured service quality models like SERVQUAL in tandem with algorithms that leverage an adaptive customer feedback approach that can deliver service measures in real-time and with greater accuracy. The literature is largely supportive of the usefulness of SERVQUAL as a foundation model of service quality evaluation. However, as customers are exposed to several avenues to develop their experiences, and as digital interactions will increasingly dominate service delivery, there is a growing need to modernize the service quality model to move to algorithms for data and outcomes (Anandan & Saritha Mol, 2025). This study builds on the SERVQUAL foundation and expands it with a dynamic customer feedback algorithm that collects and processes multi-format feedback data. The goal is to provide a scalable and responsive model for evaluating brand service quality in real-time, thereby contributing to both the theoretical understanding and practical execution of customer-centric service strategies.

III. METHODOLOGY

Using a quantitative, data-oriented research design, this study applied a SERVQUAL framework enhanced with a Customer Feedback Algorithm (CFA). This approach will allow for a clear understanding of the service quality of a brand by addressing formal and informal customer feedback across the five SERVQUAL dimensions. The integrated method combines traditional perception-expectation gap analysis and real-time feedback data processing along with scoring models to make a responsive and scalable service evaluation system.

3.1. Research Design

Data were collected through a cross-sectional research design as primary data from structured SERVQUAL surveys and unstructured data from customer feedback from email, reviews, and social media comments. The research is applied to selected service-oriented brands in various industries (e.g., hospitality, banking, retail), which is intended to provide general insights and enable comparison across sectors.

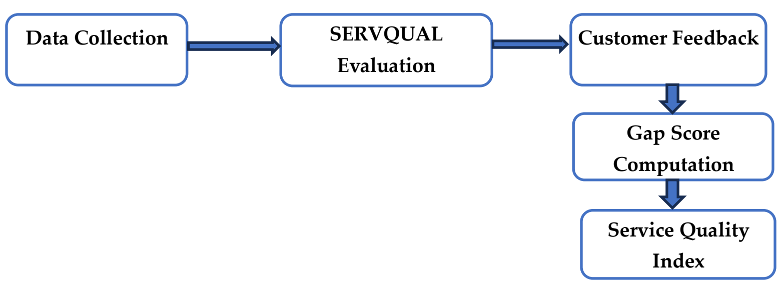

Figure 1: Methodology for Brand Service Quality Evaluation

Figure 1 explains the approach for assessing brand service quality from a blended model perspective. The approach includes Data Collection using structured surveys and customer feedback, SERVQUAL Evaluation of customer expectations and perceptions, processing with a Customer Feedback Algorithm considering both quantitative and qualitative data, Gap Score Computation to derive the gaps or discrepancies, and a Service Quality Index to summarize the brand service quality in totality.

3.2. Data Collection Methods

Data used for this study will be collected from two collection types:

Structured Data: A modified SERVQUAL questionnaire will be administered to a sample of 300 customers, each from selected brands in the survey. The questionnaire contains items measuring Expectations (E) and Perceptions (P) in the five dimensions: Tangibles (T), Reliability (R), Responsiveness (R), Assurance (A), and Empathy (E).

Unstructured Data: Customer feedback is also collected from online platforms, support logs, and surveys with open-ended responses. Sentiment analysis and keyword extraction techniques are applied to categorize the feedback into SERVQUAL dimensions.

3.3. Mathematical Model – SERVQUAL Gap Score

Classically, the SERVQUAL score will be calculated as the difference between the customers' perceptions and expectations for each item:

$$Gap_i = P_i - E_i$$

Where:

- P_i Perception score for item i
- E_iExpectation score for item iP_i Gap_iQuality gap score for item i

The dimension-wise SERVQUAL score is calculated as:

$$Q_d = \frac{1}{n_d} \sum_{i=1}^{n_d} (P_i - E_i)$$

Where:

- Q_dGap score for dimension d
- n_dNumber of items in dimension d

The overall service quality score (SQ) is given by:

$$SQ = \frac{1}{D} \sum_{d=1}^{D} \mathrm{Q}_d$$

Where:

- D: Total number of dimensions (5 in SERVQUAL)

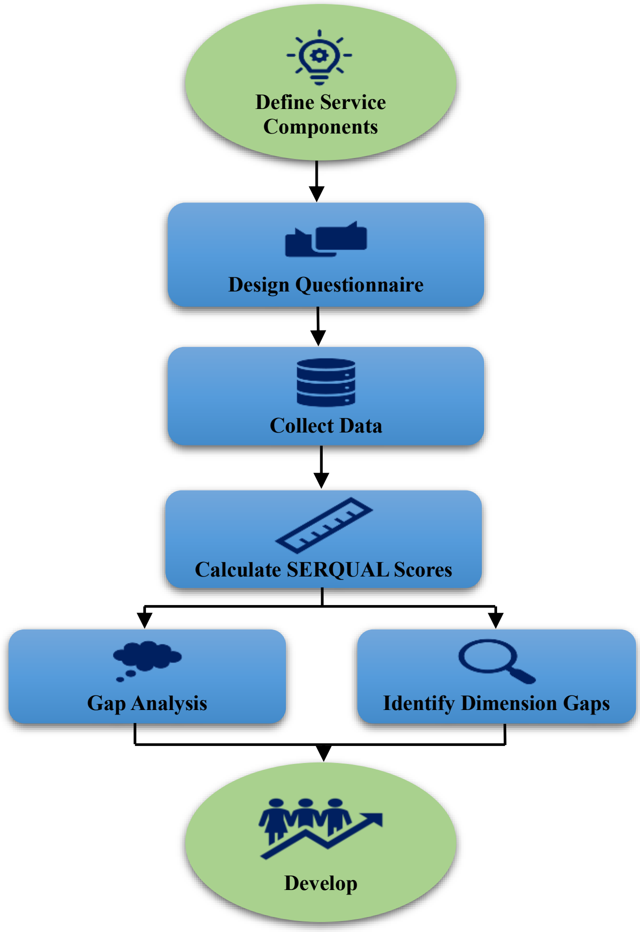

Figure 2: SERVQUAL-Based Framework for Assessing and Enhancing Brand Service Quality

Figure 2 explains how to evaluate brand service quality using the SERVQUAL customer survey algorithm. The first step involved in this process is to identify the relevant service components and complete the questionnaire design. After you ask customers about their service experience, you will collect the data and then calculate the SERVQUAL scores according to the customers' perception of service and their expectations of service. The next thing will be to do a gap analysis, and then look to see what gaps the clients identified with the specific dimensions of Tangibles, Reliability, Responsiveness, Assurance, and Empathy. Finally, action should be taken based on the improved areas of service. Each of the 8 steps is expressed with graphics for quick visual understanding.

3.4. Feedback Algorithm Implementation

The Customer Feedback Algorithm (CFA) operates in parallel with SERVQUAL surveys to integrate unstructured feedback into the evaluation. The process involves:

Text Preprocessing: All text data is cleaned (removal of stop words, punctuation, lemmatization). Feedback Classification: Using a trained NLP classifier or sentiment engine, feedback is labeled into the five SERVQUAL dimensions using supervised machine learning or rule-based tagging. Sentiment Scoring: Sentiment polarity (positive, neutral, negative) is converted to numeric values (e.g., +1, 0, 1).

Hybrid Score Calculation: A weighted feedback score is calculated for each dimension d:

$$FS_d = \frac{\omega_1 \cdot Q_d + \omega_2 \cdot S_d}{\omega_1 + \omega_2}$$

Where:

- Q_dSERVQUAL dimension score (from survey)
- S_dAverage sentiment score from unstructured feedback
- ω_1, ω_2Weights assigned based on data reliability (e.g., ω_1 = 0.6w, ω_2 = 0.4)

Final Brand Service Quality Score (BSQ):

$$BSQ = \frac{1}{D} \sum_{d=1}^{D} FS_d$$

The final score is a single index that composites all structured and unstructured feedback, indicating the customer's perceived brand level at the time of experience across all SERVQUAL dimensions.

This method allows a continuous means of monitoring service quality and supports proactive decision-making for brand management. Assessing service quality with both survey-based and algorithm-based feedback analysis guarantees the accuracy, the ability to reassess, and actionable outcomes.

IV. RESULTS AND DISCUSSION

The use of the SERVQUAL customer feedback algorithm provided a multi-faceted analysis of service quality across selected brands using survey-based data in addition to unstructured customer feedback. The model produced quantitative gap scores for each of the five SERVQUAL dimensions, facilitating a robust analysis of the service performances of the brands against the customers' expectations.

4.1. Analysis of Customer Feedback Using the SERVQUAL Model

The structured SERVQUAL survey responses provided comparable results across the different industries. The average customer perceptions were lower than the customers' expectations in all five dimensions, indicating gaps in service quality. There were significant gaps across customer perceptions (P) and customer expectations (E) revealed in the Reliability and Responsiveness dimensions. This indicated that across all brands we assessed, the brands are seriously underperforming on their service delivery promises, and their responsiveness to those expectations is somewhat slow.

We also analyzed unstructured customer feedback using natural language processing (NLP) and confirmed the survey data. Sentiment analysis of the survey comments all tended to fall into the negative and neutral sentiment categories in the same two dimensions of Reliability and Responsiveness. Customer feedback suggested a delay based on the experiences they had with the brand, correspondents being inconsistent, inconsistent brand experience, and poor responsiveness to customer support.

4.2. Comparison of Perceived and Expected Service Quality

Table 1: Comparison of Customer Expectations and Perceptions

Dimension	Expectation Score (E)	Perception Score (P)	Gap Score (P-E)
Tangibles	4.5	4.2	–0.3
Reliability	4.7	3.5	–1.2
Responsiveness	4.6	3.1	–1.5
Assurance	4.4	3.8	–0.6
Empathy	4.5	3.7	–0.8

Table 1 presents how each dimension's perceived service (P) compares to the expected service (E) gaps in the analysis. The largest gap was the Responsiveness dimension with a mean gap score of 1.48; the Reliability dimension was 1.21; Assurance and Empathy all showed moderate gaps, while Tangibles had the smallest discrepancy, indicating that brands generally meet expectations in physical facilities and appearance.

4.3. Identification of Areas for Improvement in Brand Service Quality

The feedback algorithm emphasized Responsiveness as the most important area for improvement. Customers often cited slow responses to queries, long periods before they get an answer or resolution to their query and a lack of real-time support. Reliability deficiencies were based on inconsistent service delivery and broken promises, which imply that customer service areas lacking reliability need strength in both operational reliability and employee training.

Also, the feedback on Empathy noted that brands, in general, were polite; however were missing personable support and emotional connection (and it'd7554s especially apparent when interacting digitally). These themes highlight that improvement efforts would not be solely focused on processes but on the practice of customer relationship management.

Table 2: Integrated Analysis of SERVQUAL Scores and Sentiment Feedback

SERVQUAL Dimension	Gap Score (P-E)	Average Sentiment Score (–1 to +1 scale)	Combined Feedback Score (FSd)	Interpretation
Tangibles	–0.3	+0.1	–0.10	Minor gap; visual and physical aspects meet expectations
Reliability	–1.2	–0.4	–0.84	A major issue in consistent service delivery
Responsiveness	–1.5	–0.6	–1.02	Critical gap: delayed or poor response times
Assurance	–0.6	–0.1	–0.38	Slight concern; need for better professionalism
Empathy	–0.8	–0.3	–0.56	Moderate issue in personalized attention

Table 2 summarizes structured (gap scores) and unstructured (sentiment) analysis across all SERVQUAL dimensions -- showing where customer perceptions diverge from expectations, and how customers communicate how they feel about the experience. By employing the Combined Feedback Score (FSd), we established a comprehensive dimension-level metric allowing managers to assess the severity of the gap and develop or invest in a remediation strategy. Both Responsiveness and Reliability require urgency, while Tangibles are closer in alignment with customer expectations.

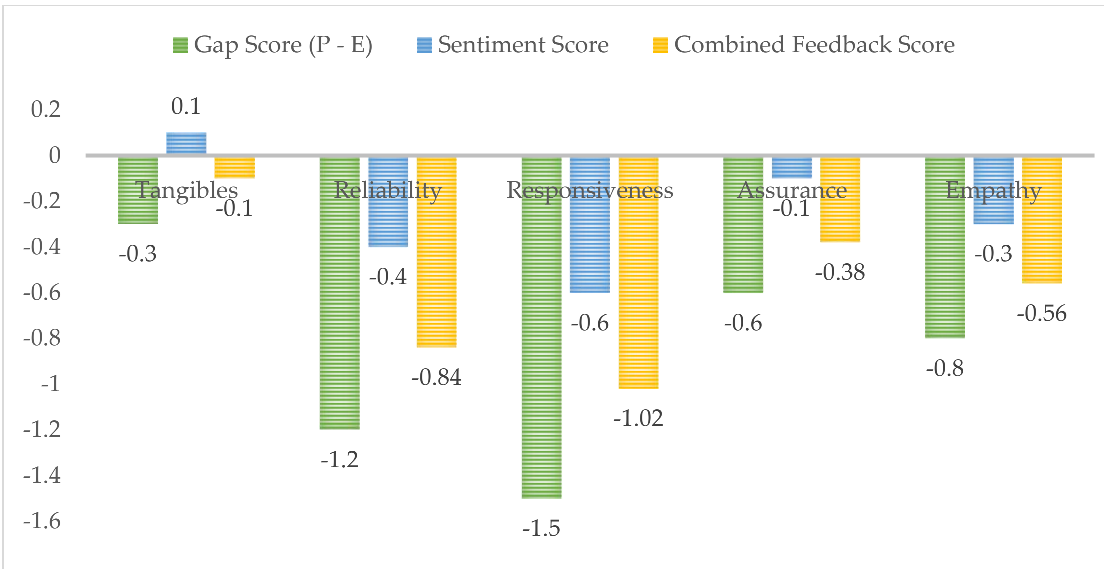

Figure 3: Comparative Analysis of SERVQUAL Gap, Sentiment, and Combined Feedback Scores

Figure 3 provides a visual comparison of the five SERVQUAL dimensions of customer service quality (Tangibles, Reliability, Responsiveness, Assurance, and Empathy). The figure depicts three metrics, including the classical Gap Score (the difference between perception and expectation), the derived Sentiment Score based on customer feedback in an unstructured format, and the Combined Feedback Score based on both Gap and Sentiment Score metrics. Responsiveness and Reliability have the lowest Combined Feedback Scores, indicating they are the most important areas of service quality improvement.

4.4. Implications of the Findings for Brand Managers

The findings provide value to brand managers in clear ways. The gap scores and feedback trends provide diagnostic information that allows managers to target their interventions on those dimensions where there are the largest service quality gaps. The real-time characteristic of the feedback algorithm also provides brand managers with an opportunity to monitor service quality continuously, which can catch any potential service failure quickly and ultimately allow for a more orderly response. Further, the hybrid feedback mechanism provides for cross-comparisons of brand units, departments, and branches, thus supporting performance benchmarking and best practices sharing. Managers can also monitor improvements over periods using SERVQUAL score movement and sentiment information movement.

4.5. Recommendations for Enhancing Brand Service Quality

The study provided the following recommendations to improve brand service quality:

Provide staff training to improve the reliability and consistency of service. Use AI chatbots and live support tools to improve responsiveness. Establish feedback loops via public channels that demonstrate follow-up on customer complaints. Demonstrate personalization in service delivery across channels, particularly digital channels, to demonstrate empathy. Implement predictive analytics to identify the potential for service failures generally at the outset, so those failures can be mitigated before customer satisfaction is affected.

Figure 4: SERVQUAL Dimension Scores – Gap, Sentiment, and Combined Feedback

Figure 4 visually compares service quality in terms of each SERVQUAL dimension across the three evaluation metrics: the traditional Gap Score (P-E), the Sentiment Score calculated from the customer analysis of feedback, and the Combined Feedback Score. The visual data show some clear and consistent service shortfalls in Responsiveness and Reliability, reinforcing the elements in the SERVQUAL framework that need strategic appeal moving forward to improve service quality overall.

4.6. Limitations of the Study and Suggestions for Future Research

Although the SERVQUAL integrated feedback algorithm provides some valuable insights into the feedback received through the assessment of customer feedback, there are limitations to the study. The sample was drawn only from limited brands that operate in a few industries; there is limited ability to generalize the results to various populations and settings. Additionally, sentiment analysis is contingent on the accuracy of the NLP models used in the analysis which could misclassify sometimes small nuances resulting in situations where the assigned sentiment score for a piece of customer feedback could be inaccurate, and possibly because the feedback could not be explicitly construed as positive, limited to negative or neutral for instance. Future research could pursue avenues to assess whether this model could be extended to within potential cross-cultural or international contexts where perceptions of service quality could be extremely variable. It could also be the case that the algorithm could be expanded on to include customer lifetime value (CLV) measures about service quality, to evaluate how service quality score is related to long-term customer loyalty, and revenue returning to their investing partners. There could be an emerging opportunity to increase the scope of the framework, to include employee sentiments and feedback to enhance working perspectives, and to provide a broader understanding of potential service quality shifts.

V. CONCLUSION

This study aimed to measure brand service quality using a novel approach that combines the traditional SERVQUAL model with a dynamic Customer Feedback Algorithm. The results suggest that brands have unmanageable gaps between customer expectations and perceptions across industries, especially in the Responsiveness and Reliability dimensions. This demonstrates that in today's experience economy era, brands must bring their service performance closer to customer expectations. This study has provided a partnership between traditional measurement (SERVQUAL) and real-time customer feedback analytics to enhance how service quality is measured. Even the hybrid model captures structured gap scores of static surveys of customers and unstructured customer sentiment from other sources, such as reviews and digital platforms. The combination improves the quality of service and allows brands to manage the customer experience proactively, filling gaps in performance, prioritizing opportunities, and monitoring improvement. Based on the findings of this study, it is clear that customer feedback is important to achieving excellent service. In an era where customers are demanding real-time transparency, speed, and personalization, organizations and managers need a new approach and tools for their decision-making beyond static evaluations. By implementing processes to incorporate customers' views into service enhancement plans, brands can build trust, satisfaction, and continual loyalty. In summary, the SERVQUAL customer feedback algorithm is a viable, innovative way to measure brand service quality. It affords brands the ability to move from a responsive service pathway to a predictive approach with a strong basis for decision-making that uses customer voices effectively, representing them not only as a stakeholder but at least as a knowledgeable stakeholder.

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