SYSTEM SAFETY: HUMAN - TECHNICAL FACILITY – ENVIRONMENT
7(1), 2025, pp. 501-510

AI-ENABLED SERVICE QUALITY MANAGEMENT IN AUTOMOTIVE OUTSOURCING

DOI: 10.2478/czoto-2025-0046
Received: 14/11/2025
Accepted: 19/12/2025

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Abstract: The automotive industry increasingly relies on outsourcing engineering services, software development, and technical support to specialized providers. Extensive research exists on artificial intelligence applications for product quality in manufacturing and on service quality assessment using the SERVQUAL model. However, no studies have examined the integration of AI technologies with service quality dimensions for managing outsourced automotive services. This conceptual paper addresses this gap by developing an AI-enabled SERVQUAL framework for automotive service outsourcing. The framework integrates five SERVQUAL dimensions (reliability, responsiveness, assurance, empathy, and tangibles) with intelligent monitoring systems including automated quality assessment tools, natural language processing for communication analytics, predictive analytics for risk assessment, sentiment analysis, and infrastructure assessment technologies. The proposed framework enables real-time service quality monitoring, predictive quality alerts, automated supplier benchmarking, and continuous improvement recommendations. This research bridges service quality theory, technological innovation, and automotive outsourcing practice, providing actionable framework for improving supplier relationship management and service delivery in the automotive sector.
Keywords: service quality, SERVQUAL, artificial intelligence, automotive outsourcing

1. INTRODUCTION

The global automotive industry undergoes significant transformation driven by technological advancement and increasing vehicle complexity. Modern vehicles integrate sophisticated software, electronics, and mechanical systems requiring specialized expertise. Automotive original equipment manufacturers (OEMs) increasingly outsource engineering services, software development, and validation to specialized providers to maintain competitive advantage while managing costs. The automotive engineering services outsourcing market was valued at USD 150.7 billion in 2025, projected to reach USD 503.0 billion by 2034 (IMARC, 2025). However, outsourcing success depends critically on service quality management, as inadequate quality causes product defects, delays, and financial losses.

Research on automotive quality management predominantly focuses on product quality rather than service quality (Roy and Srivastava, 2024). AI applications concentrate on manufacturing defect detection, addressing tangible product quality rather than intangible service quality dimensions in outsourcing (Adesola et al., 2025).

The SERVQUAL model provides a validated framework for assessing service quality across five dimensions: reliability, responsiveness, assurance, empathy, and tangibles. While researchers have applied SERVQUAL in automotive after-sales contexts, its application to outsourced engineering services remains unexplored.

The literature identifies three significant gaps. First, no studies have integrated AI technologies with SERVQUAL to address service quality in business-to-business outsourcing relationships. Second, existing quality frameworks for automotive outsourcing focus on process compliance rather than actual service quality outcomes. Third, despite AI's proven capability for quality monitoring in manufacturing, researchers have not explored its potential for assessing service quality dimensions in outsourcing contexts.

The research objectives are: (1) identify gaps in service quality assessment literature for automotive outsourcing; (2) develop an integrated framework mapping AI technologies to SERVQUAL dimensions; (3) articulate theoretical and practical implications.

2. LITERATURE REVIEW

Service quality is a critical determinant of customer satisfaction, organizational competitiveness, and long-term business success. In the late 1980s, Parasuraman, Zeithaml, and Berry (1988) developed the SERVQUAL model as a comprehensive framework for measuring service quality across five dimensions: reliability (performing promised services dependably and accurately), responsiveness (willingness to help customers and provide prompt service), assurance (knowledge and courtesy inspiring trust and confidence), empathy (caring and individualized attention), and tangibles (physical facilities, equipment, and communication materials). The SERVQUAL model measures service quality through gap analysis, comparing customer expectations with perceptions of actual service received. Researchers have validated SERVQUAL across diverse service sectors. Recent studies have extended SERVQUAL by integrating it with other quality frameworks such as the Kano model and Quality Function Deployment (Beheshtinia and Farzaneh Azad, 2019; Rahmana et al., 2014; Tan and Pawitra, 2001).

While SERVQUAL has been extensively validated across service sectors, its application in B2B outsourcing contexts presents specific considerations. Gounaris (2005) demonstrated that SERVQUAL suffers from methodological problems when applied to business-to-business services, as it was developed using consumer markets as a frame of reference. Woo and Ennew (2005) similarly argued that service quality research predominantly examines consumer service perspectives with little reference to B2B services. However, the five SERVQUAL dimensions remain conceptually relevant in B2B contexts when appropriately adapted. In automotive outsourcing, reliability reflects contractual adherence and delivery performance, responsiveness captures collaborative effectiveness and problem-solving speed, assurance addresses technical competence and capability verification, empathy represents partnership orientation and customer-centric attitude, and tangibles encompass infrastructure and tool capabilities. Traditional SERVQUAL limitations – particularly its reliance on periodic survey-based assessment and subjective gap measurement (Buttle, 1996) – pose challenges in B2B relationships requiring continuous monitoring. The AI-enabled framework addresses these limitations through continuous, objective measurement, transforming SERVQUAL from a periodic survey instrument into a real-time monitoring system more suitable for complex B2B relationships.

The choice of SERVQUAL over industrial service quality models warrants explicit justification. Gounaris (2005) developed INDSERV specifically for B2B contexts, demonstrating that SERVQUAL suffers from methodological problems when applied to business-to-business services. INDSERV conceptualizes service quality through four dimensions: potential quality (supplier's capabilities and resources), hard process quality (technical service delivery elements), soft process quality (relational and interpersonal aspects), and output quality (delivered results). Similarly, Woo and Ennew (2005) developed a six-dimensional model emphasizing interaction quality in professional B2B services, arguing that industrial services require adapted measurement approaches reflecting relationship complexity and technical expertise. However, SERVQUAL remains appropriate for this AI-enabled framework for several reasons. SERVQUAL's five dimensions align directly with automotive outsourcing evaluation criteria identified in practice and literature (Cieśla, 2024; Srivastava et al., 2012). Reliability corresponds to contractual delivery performance and consistency, responsiveness to collaborative effectiveness and problem-solving agility, assurance to technical competence and capability verification, empathy to partnership quality and customer-centric orientation, and tangibles to infrastructure and tooling assessment. SERVQUAL's widespread adoption provides conceptual clarity and practitioner familiarity, facilitating framework implementation and adoption. SERVQUAL's dimensional structure enables straightforward mapping to AI technologies – each dimension corresponds to specific data sources, analytical techniques, and assessment mechanisms. Future research could explore hybrid approaches integrating INDSERV constructs. INDSERV's distinction between hard process quality (technical delivery) and soft process quality (relationship management) could enrich the framework by enabling separate AI model development for objective performance metrics versus subjective relationship assessments. This represents a promising direction for future conceptual refinement and empirical validation in diverse B2B service contexts.

In automotive contexts, researchers have applied SERVQUAL primarily to after-sales service evaluation. Studies identified gaps between expectations and delivery, with customer satisfaction and loyalty (Furaida et al., 2018; Karsh and Harb, 2021; Wang et al., 2019). Research has also demonstrated the potential for machine learning to predict customer behavior based on SERVQUAL dimensions (Komijan et al., 2024). However, application of SERVQUAL to business-to-business service relationships, specifically outsourcing partnerships, remains limited in automotive literature.

Outsourcing has become a strategic necessity in the automotive industry as manufacturers seek to reduce costs, access specialized capabilities, focus on core competencies (IMARC, 2025). The scope encompasses computer-aided design, embedded software development, testing and validation, technical documentation, and manufacturing engineering support. Market growth is driven by increasing vehicle complexity, shortened development cycles, cost considerations, and technological disruption in electric vehicles and autonomous driving. However, outsourcing presents challenges: geographic and cultural distance, intellectual property protection, quality

control complexity, and coordination across multiple providers (Srivastava et al., 2012; Cieśla, 2024). Cieśla (2024) identified significant gaps between standardized quality frameworks (ISO 9001 and IATF 16949) and practical requirements for evaluating service quality in automotive outsourcing. Existing standards focus primarily on process compliance rather than actual service delivery outcomes and customer satisfaction.
Artificial intelligence has transformed quality management in automotive manufacturing through applications addressing product quality. Computer vision systems achieve accuracy in detecting surface defects, dimensional deviations and assembly errors. AI-powered innovations continue to transform contemporary manufacturing procedures (Lodhi et al., 2024). Predictive maintenance applications employ machine learning to forecast equipment failures. Natural language processing enables automated analysis of quality reports and customer feedback.
Recent research demonstrates AI effectiveness in supply chain optimization through enhanced supplier performance management, predictive modeling, and real-time decision support (Adesola et al., 2025; Kufile et al., 2022). However, AI applications in automotive contexts concentrate on manufacturing and product quality rather than service quality.

3. METHODOLOGY

This research adopts design science methodology focusing on creating practical artifacts addressing real-world problems while contributing theoretical knowledge. Problem identification analyzed automotive trends, outsourcing practices, and quality challenges through industry reports and quality manager interviews. Literature analysis systematically reviewed service quality theory, SERVQUAL applications, automotive outsourcing, and AI quality management from recent publications (2010-2025). Framework design synthesized literature insights with practical requirements, mapping AI capabilities to SERVQUAL dimensions.
The framework adopts layered architecture: conceptual level defines SERVQUAL in automotive outsourcing; technological level specifies AI tools for each dimension; operational level describes implementation and management processes. While presenting conceptual development without empirical validation, the framework builds on validated SERVQUAL theory and proven AI technologies.

4. RESULTS

Figure 1 illustrates the framework architecture showing relationships among SERVQUAL dimensions, AI technologies, and management outcomes.

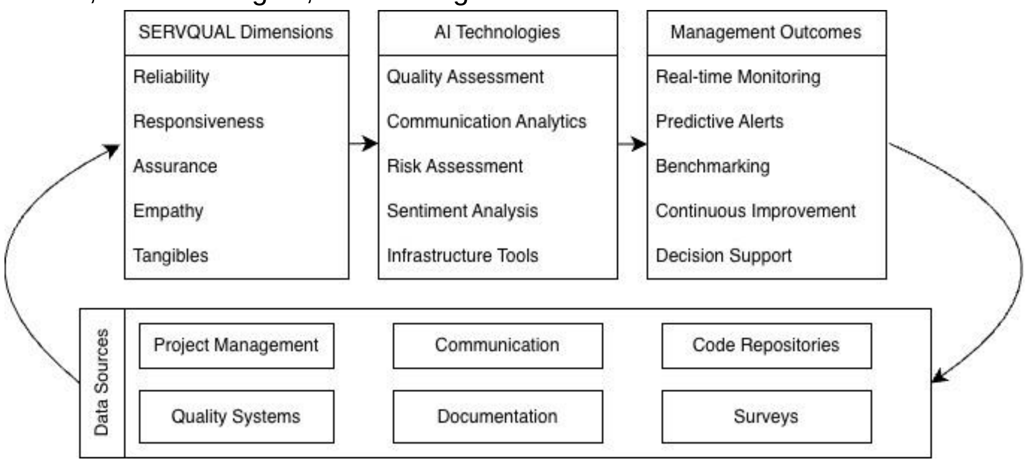

Fig. 1. AI-Enabled SERVQUAL Framework for Automotive Service Outsourcing.

4.1. Framework Overview

The framework integrates five SERVQUAL dimensions with corresponding AI technology clusters to enable continuous, automated service quality assessment in automotive outsourcing relationships. Each dimension connects to AI technologies that measure, monitor, and predict service quality indicators.

The framework operates through continuous data collection from sources including project management systems, communication platforms, code repositories, documentation systems, and performance metrics databases. AI algorithms process this data to extract quality indicators, identify patterns, detect anomalies, and generate predictions, feeding into management dashboards, alert systems, and decision support tools. These AI-driven decision support capabilities enable proactive quality management interventions (Bokhonko et al., 2025).

4.2. Reliability Dimension and Automated Quality Assessment

Reliability in automotive service outsourcing reflects the supplier's ability to deliver promised services accurately, consistently, and dependably encompassing on-time delivery, accuracy of deliverables, consistency in meeting specifications, and Service Level Agreement (SLA) adherence. AI technologies enable reliability assessment through automated mechanisms. Code quality analysis tools examine software deliverables using static analysis, complexity metrics and defect prediction algorithms, assessing readability, maintainability, performance, and security (Roy and Srivastava, 2024). Deliverable validation systems employ machine learning models trained on historical project data to assess completeness and accuracy, flagging deviations. Pattern recognition algorithms analyze time-series delivery performance, identifying trends and anomalies. SLA compliance tracking systems monitor agreed indicators, generating alerts when thresholds are breached.

4.3. Responsiveness Dimension and Communication Analytics

Responsiveness captures the supplier's willingness and ability to help customers promptly, addressing questions, concerns, and issues with appropriate urgency. In automotive outsourcing, responsiveness manifests through responses to technical queries, problem resolution, and speed. Natural language processing and communication analytics enable automated responsiveness assessment through multiple mechanisms. Response time monitoring tracks time between inquiries and responses across communication channels. Issue resolution speed tracking analyzes the lifecycle of reported problems from reporting through resolution, with machine learning identifying factors associated with resolution speed. Communication pattern analysis employs NLP to assess communication quality beyond timing. Sentiment analysis reveals emotional tone. Topic modeling identifies recurring themes. Automated classification categorizes communications by urgency, and complexity. Automated escalation systems integrate responsiveness metrics with thresholds to trigger notifications when service levels decline.

4.4. Assurance Dimension and Predictive Risk Assessment

Assurance in service relationships reflects customer confidence in the supplier's competence, credibility, and ability to deliver promised results. In automotive outsourcing, assurance depends on technical expertise, track record, certifications, and capability to handle project complexity. Predictive analytics and risk assessment technologies enable evaluation (Adesola et al., 2025). Competence verification systems analyze deliverable quality metrics, and certification records to assess supplier capabilities. Machine learning identifies correlations between supplier characteristics and project outcomes, enabling performance prediction (Kufile et al., 2022). Risk scoring algorithms evaluate technical capability risks, capacity risks, financial stability, and relationship risks (Adesola et al., 2025). Performance prediction models employ historical project data to forecast outcomes on ongoing projects.

4.5. Empathy Dimension and Sentiment Analysis

Empathy reflects the supplier's understanding of customer needs, caring attitude, and individualized attention. In outsourcing relationships, empathy manifests through attentiveness to requirements, flexibility in accommodating needs, proactive issue identification, and commitment to customer success. Sentiment analysis enables empathy assessment through communication pattern analysis. Communication sentiment tracking applies NLP to email, messages, and transcripts to assess emotional tone. Customer satisfaction scoring aggregates sentiment indicators to generate satisfaction metrics. Problem-solving approach analysis examines how suppliers respond to challenges. NLP systems categorize responses as proactive versus reactive and solution-oriented versus excuse-focused. Relationship quality indicators synthesize signals including communication frequency, information sharing patterns, and conflict resolution.

4.6. Tangibles Dimension and Infrastructure Assessment

Tangibles represent physical evidence of service capability including facilities, equipment, tools, and communication materials. In outsourced automotive engineering, tangibles encompass engineering software and tools, IT infrastructure, collaboration platforms, documentation quality, and workplace environments. Infrastructure assessment technologies evaluate tangible dimensions through automated analysis. Documentation quality evaluation employs NLP to assess technical documentation comprehensiveness, clarity, accuracy, and adherence to standards. Tool capability assessment examines the sophistication and appropriateness of engineering tools and software. Digital maturity scoring aggregates indicators of supplier digital capabilities including tool sophistication, process automation, and data analytics maturity. Infrastructure monitoring systems track availability, performance, and security of infrastructure supporting service delivery.

4.7. Integrated Framework Implementation

Implementation requires integration of technology, processes, and organizational capabilities Organizations must establish data collection mechanisms integrating multiple data sources: project management systems for delivery tracking, communication platforms for interaction analysis, version control systems for code quality assessment, documentation platforms for deliverable evaluation, and performance databases for SLA monitoring. Automated data pipelines should ensure continuous flow from these heterogeneous sources into the AI processing layer. AI models require training on historical data representing service quality. Integration with management processes transforms AI-generated insights into decisions through service quality dashboards, automated alert systems, and AI-enhanced supplier performance reviews.

4.8 Operational Implementation Guidelines

The framework operationalization builds on the AI technologies described in sections 4.2-4.6. For reliability assessment, organizations should monitor delivery performance metrics, defect rates, and SLA compliance using automated code quality analysis and validation systems. Responsiveness assessment requires tracking response times and resolution speeds through NLP-based communication analytics. Assurance evaluation employs competence verification and risk scoring algorithms analyzing certification data and historical performance. Empathy assessment utilizes sentiment analysis and satisfaction scoring from communication transcripts and surveys. Tangibles assessment applies NLP documentation analysis and infrastructure monitoring systems. Implementation requires establishing baseline measurements during initial 3-6 months, configuring continuous monitoring with automated data pipelines, and setting performance thresholds triggering alerts when quality indicators deteriorate. Specific indicators and thresholds should be adapted based on service type (e.g., software development versus testing), organizational priorities, and supplier characteristics.

5. DISCUSSION

This research makes three theoretical contributions that distinguish it from existing digital service quality and supplier performance frameworks. First, unlike digital service qualityframework (e-SERVQUAL) that addresses technology-mediated service delivery channels, our framework addresses AI-enabled assessment of traditional service quality dimensions in outsourcing relationships. Second, while existing supplier performance management systems (Adesola et al., 2025; Kufile et al., 2022) concentrate on procurement metrics, risk scoring, and transactional performance, our framework provides comprehensive service quality assessment integrating relationship, technical, and operational dimensions through SERVQUAL's validated structure. Third, it extends SERVQUAL theory by operationalizing its dimensions through AI-enabled continuous assessment rather than periodic gap analysis, enabling real-time visibility and proactive management unavailable in traditional approaches (Buttle, 1996).

Automotive outsourcing faces significant quality management challenges, including limited real-time visibility and reliance on manual monitoring (Srivastava et al., 2012; Cieśla, 2024). The proposed framework addresses these challenges through several mechanisms. Automated assessment reduces manual monitoring effort, allowing quality managers to focus on analysis and improvement. Objective quantitative metrics supplement subjective perceptions, providing evidence-based foundation for supplier discussions. Predictive capabilities enable proactive rather than reactive management. AI-driven decision support systems facilitate this proactive approach in strategic management contexts (Bokhonko et al., 2025). The framework supports informed supplier selection through consistent metrics (Kufile et al., 2022).

The framework offers significant benefits (Srivastava et al., 2012; Cieśla, 2024). Real-time visibility enables early problem identification before escalation. Automated assessment reduces manual monitoring effort, allowing quality managers to focus on analysis and improvement. Objective quantitative metrics supplement subjective perceptions, providing evidence-based foundation for supplier discussions.

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contexts (Bokhonko et al., 2025). The framework supports informed supplier selection through consistent metrics (Kufile et al., 2022).
Framework implementation faces technical, organizational, and ethical challenges requiring careful consideration. Data availability represents a primary constraint. Effective AI assessment requires comprehensive, high-quality data from multiple sources – project management systems, communication platforms, code repositories, and performance databases. Organizations with immature data infrastructure may lack sufficient data for reliable AI model training. AI bias poses significant risks requiring proactive mitigation. Models trained on historical data may perpetuate existing biases in supplier evaluation, potentially disadvantaging new suppliers, smaller providers, or those serving different market segments (El Mimouni and Bouhdadi, 2025). Research demonstrates that AI systems can amplify rather than eliminate human biases, creating feedback loops where biased assessments reinforce discriminatory patterns (Hanna et al., 2025). Regular bias audits, model validation against diverse supplier populations, and fairness metrics evaluation are essential mitigation strategies. Transparency and explainability challenges arise when complex AI models generate quality assessments. Black-box algorithms may produce accurate predictions but lack interpretability, creating difficulties when communicating assessment rationale to suppliers or justifying management decisions (Barredo Arrieta et al., 2020). The European Union's AI Act and similar regulations increasingly require explainable AI systems, particularly for high-stakes decisions affecting business relationships. Organizations should prioritize explainable AI techniques and attention mechanisms, to maintain transparency and enable constructive supplier dialogue while ensuring regulatory compliance. Governance structures must address data privacy, particularly when analyzing communication content and employee performance indicators. Clear policies regarding data collection, usage, retention, and access rights are essential. Organizations must establish human oversight mechanisms, ensuring that AI-generated insights inform rather than replace human judgment in critical supplier decisions. Technical implementation challenges include system integration complexity across heterogeneous platforms, ongoing model maintenance and retraining requirements, and the need for specialized AI and data science expertise. Organizations should adopt phased implementation approaches, beginning with less complex dimensions (reliability, tangibles) before addressing nuanced aspects (empathy, assurance) requiring more sophisticated natural language processing and sentiment analysis capabilities.
This conceptual paper lacks empirical validation. Future research should validate the framework through multiple complementary empirical approaches. Case study validation could implement the framework in automotive OEM-supplier relationships across different service types (software development, testing and validation, engineering design), documenting implementation processes, data integration challenges, and quality improvement outcomes. Survey-based assessment could gather perceptions from quality managers and supplier relationship managers regarding framework utility, usability, and decision-support value. Experimental validation could employ quasi-experimental designs comparing quality outcomes and relationship satisfaction between organizations using AI-enabled versus traditional SERVQUAL approaches. Longitudinal studies tracking quality improvements and relationship satisfaction would demonstrate long-term value and return on investment. Mixed-methods approaches combining quantitative metrics with qualitative

interviews would provide insights into implementation success factors and contextual adaptations.
Investigation of emerging AI technologies (large language models, generative AI) could enhance assessment capabilities. Predictive modeling of relationship outcomes based on service quality metrics represents another promising direction (Komijan et al., 2024).
Research examining how AI-enabled insights translate into quality improvements would advance the field. Cross-cultural considerations merit investigation given global automotive outsourcing.

6. CONCLUSION

This research addresses a gap in automotive quality management by developing an AI-enabled SERVQUAL framework for service quality management in automotive outsourcing. The framework integrates five SERVQUAL dimensions with AI technologies including automated quality assessment, communication analytics, predictive risk assessment, sentiment analysis, and infrastructure evaluation.
The framework provides theoretical and practical contributions. Theoretically, it extends SERVQUAL through AI-enabled continuous assessment, bridges service quality and AI literature, and expands automotive quality management from product to service domains. Practically, it enables real-time visibility, reduces monitoring effort, supports proactive management, and informs supplier decisions.
While presenting conceptual development without empirical validation, this establishes foundation for future validation through case studies and implementations. As automotive companies expand outsourcing, effective service quality management becomes essential for competitive success. The AI-enabled SERVQUAL framework provides systematic approach leveraging technology to improve assessment, monitoring, and management in automotive outsourcing, offering pathway toward effective and proactive service quality management supporting industry transformation.

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