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Exploring Factors of Artificial Intelligence-Enabled Service Quality: Scale Development and Empirical Validation

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Abstract

The rapid integration of Artificial Intelligence (AI) into service delivery necessitates a re-evaluation of traditional service quality models. This study develops and validates a comprehensive scale to measure Artificial Intelligence-Enabled Service Quality (AI-SQ), addressing the limitations of existing frameworks like SERVQUAL in non-human, technology-driven contexts. Grounded in a thorough review of literature and empirical data, the research proposes a five-dimensional AI-SQ scale: Reliability, Responsiveness, Personalization & Intelligence, Transparency & Trust, and Empathy & Emotional Intelligence. Data were collected from users of AI-powered services through a structured survey (N = 350), and psychometric analysis was conducted using exploratory factor analysis (EFA), Cronbach's alpha, and KMO/Bartlett's tests. Results indicate excellent reliability (Cronbach's Alpha = 0.987) and strong construct validity, with a Kaiser-Meyer-Olkin (KMO) measure of 0.976 and significant Bartlett's Test of Sphericity ($p < 0.001$). The rotated component matrix confirms clean item loadings across the five factors, supporting the scale's dimensional structure. Findings reveal that users expect AI systems to be not only accurate and fast but also transparent, trustworthy, personalized, and emotionally aware. The validated AI-SQ scale offers a reliable tool for researchers and practitioners to assess and improve AI-driven customer experiences. This study contributes to service science by introducing a context-specific, empirically supported model that captures the evolving nature of service quality in the age of AI. The scale can be applied across industries to enhance AI design, build user trust, and ensure ethical, human-cantered service delivery.

Keywords: Artificial Intelligence, service quality, AI-SQ scale, scale development, customer experience, human-AI interaction, service innovation.

Introduction

The rapid integration of Artificial Intelligence (AI) into service delivery systems has fundamentally transformed the way organizations interact with customers. From chatbots and virtual assistants to recommendation engines and automated customer support, AI is redefining service experiences across sectors such as banking, healthcare, retail, and hospitality (Davenport et al., 2020). While AI offers unprecedented efficiency, scalability, and personalization, it also introduces new challenges in maintaining service quality—particularly in the absence of human touchpoints. Traditional service quality models, such as SERVQUAL, were developed in human-centric service environments and may not fully

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capture the nuances of AI-mediated interactions (Parasuraman et al., 1988). As a result, there is a growing need for a context-specific, reliable, and valid measurement instrument that reflects the unique dimensions of service quality in AI-enabled environments.

Artificial Intelligence-Enabled Service Quality (AI-SQ) refers to the perceived excellence of service delivery when interactions are facilitated or fully managed by AI technologies. Unlike traditional service quality, AI-SQ must account for factors such as algorithmic accuracy, system transparency, data privacy, responsiveness, and the perceived empathy of AI agents (Puntoni et al., 2021). These factors influence user trust, satisfaction, and continued engagement with AI systems. However, despite the proliferation of AI in service contexts, there remains a significant gap in the literature regarding a standardized, empirically validated scale to measure AI-SQ. Most existing studies borrow constructs from technology acceptance or general service quality models without fully addressing the distinct characteristics of AI-driven services (Gummerus et al., 2022).

This study aims to address this gap by developing and empirically validating a comprehensive AI-SQ scale grounded in both theoretical foundations and user-centered insights. The research adopts a mixed-methods approach: first, exploratory qualitative interviews are conducted to identify salient dimensions of AI-SQ; second, a quantitative survey is administered to a diverse sample of AI service users to test the psychometric properties of the proposed scale. The development process follows established scale development guidelines, including item generation, purification, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA) (Churchill, 1979; Hinkin, 1998).

The proposed AI-SQ scale integrates six key dimensions identified through a thorough review of literature and preliminary empirical exploration: (1) Reliability (consistency and accuracy of AI performance), (2) Transparency (clarity in AI decision-making processes), (3) Personalization (AI's ability to tailor responses based on user data), (4) Trust (perceived security, privacy, and ethical use of data), (5) Responsiveness (speed and availability of AI support), and (6) Perceived Empathy (the extent to which AI demonstrates understanding and emotional intelligence). These dimensions reflect the evolving expectations of users in human-AI interactions and extend beyond traditional service quality frameworks.

The significance of this study is twofold. First, it contributes to service science by offering a validated instrument that captures the multidimensionality of service quality in AI contexts. Second, it provides practical value for organizations seeking to evaluate and improve their AI-driven customer experiences. By measuring AI-SQ effectively, firms can identify weaknesses, enhance user trust, and design more human-centered AI systems.

This research responds to recent calls for more nuanced measurement tools in the era of intelligent technologies (Huang & Rust, 2021) and advances the understanding of how service quality is redefined in the presence of non-human agents.

Literature Review

The integration of Artificial Intelligence (AI) into service delivery has redefined customer expectations and challenged traditional paradigms of service quality. As AI systems increasingly mediate interactions in sectors such as e-commerce, banking, healthcare, and hospitality, the need for a tailored measurement framework—Artificial Intelligence-Enabled Service Quality (AI-SQ)—has become imperative. While foundational models like SERVQUAL (Parasuraman, Zeithaml, & Berry, 1988) have long guided service quality assessment, their dimensions (tangibles, reliability, responsiveness, assurance, and empathy) were conceptualized in human-to-human service contexts and may not fully capture the nuances of AI-driven interactions. This literature review synthesizes current research on AI in service environments, identifies gaps in service quality measurement, and justifies the development of a new, empirically validated AI-SQ scale.

A key distinction of AI-enabled services is the absence of human agents, which alters the dynamics of trust, empathy, and perceived control. Traditional service quality models emphasize interpersonal skills and emotional support, yet AI systems operate through algorithms, automation, and data analytics. As such, new dimensions such as transparency, algorithmic fairness, personalization, and perceived empathy have emerged as critical to user satisfaction (Puntoni et al., 2021; Gummerus et al., 2022). For instance, users expect AI systems to explain decisions (e.g., loan denials or product recommendations), a concept known as *algorithmic transparency*, which directly impacts trust and perceived fairness (Chung et al., 2021). Without such clarity, even accurate AI responses may be perceived as low quality.

Trust is another pivotal construct in AI-mediated services. Unlike human agents, AI lacks emotional cues, making it harder for users to assess intent or reliability. Research shows that trust in AI is influenced by perceived competence, data privacy, and system dependability (McLean & Osei-Frimpong, 2019). In healthcare chatbots or financial advisors, users must believe that the AI is not only accurate but also secure and ethically aligned. This expands the traditional notion of "assurance" in SERVQUAL into a broader construct encompassing data ethics, security, and accountability.

Personalization, enabled by machine learning and user data analytics, is both a strength and a concern in AI services. On one hand, personalized recommendations enhance user experience and perceived relevance (Davenport et al., 2020). On the other, excessive data use can trigger privacy concerns, leading to the "creepiness effect" (Matz et al., 2020). Therefore, effective AI-SQ must balance personalization with respect for user autonomy—a dimension not explicitly addressed in classical service quality models.

Responsiveness in AI systems differs significantly from human responsiveness. AI offers 24/7 availability and near-instantaneous replies, but users may perceive responses as robotic or irrelevant if the system fails to understand context or emotion. Hence, perceived empathy the extent to which AI mimics understanding and emotional intelligence has gained prominence. Recent studies suggest that anthropomorphized AI (e.g., voice tone, empathetic language) improves user satisfaction and engagement (Huang & Rust, 2021).

Despite these insights, there is no consensus on a standardized scale to measure AI-SQ. Most studies borrow constructs from Technology Acceptance Model (TAM) (Davis, 1989) or Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), focusing on perceived usefulness and ease of use rather than holistic service quality. While useful, these models do not adequately capture experiential and relational aspects of service delivery. A few recent attempts have proposed AI-specific quality dimensions such as *machine empathy* (Luo et al., 2021) or *algorithmic accountability* (Bhatt et al., 2022) but these remain fragmented and lack psychometric validation.

Scale development in marketing and service research follows rigorous procedures, including item generation, purification, exploratory and confirmatory factor analysis (Churchill, 1979; Hinkin, 1998). A valid AI-SQ scale must be grounded in both theoretical rigor and empirical data. Prior research suggests that AI-SQ is multidimensional, encompassing reliability, transparency, personalization, trust, responsiveness, and perceived empathy. However, these dimensions have not been systematically integrated into a unified, validated instrument.

This study builds on these foundational insights to develop and validate a comprehensive AI-SQ scale. By synthesizing literature from service science, human-computer interaction, and AI ethics, it proposes a measurement model that reflects the evolving nature of service quality in intelligent environments. The resulting scale will enable researchers and practitioners to assess AI service performance more accurately, identify improvement areas, and design user-centered AI systems.

Objectives Of the Study

- To explore factors contributing in development of Artificial Intelligence Enabled Service Quality (AI-SQ) scale.

Hypotheses

H_0: The development of a robust Artificial Intelligence Enabled Service Quality AI-SQ scale does not combines critical dimensions including reliability, transparency, personalization, trust, responsiveness, and perceived empathy in AI influenced services.

H_1 : The development of a robust Artificial Intelligence Enabled Service Quality AI-SQ scale does not combines critical dimensions including reliability, transparency, personalization, trust, responsiveness, and perceived empathy in AI influenced services.

Research Methodology

Sample and Procedures

In the present study, the sample was drawn based on a convenient random sample. A total of 242 samples were collected for the study. Youngsters of Indore city were selected as respondents for the study. For collecting responses, Google forms, e-mails, and personal interactions were used. Initially, 300 people were accessed for the study in return 242 complete questionnaires were received back appropriate for analysis.

Tools for Data Collection

The Artificial Intelligence Enabled Service Quality (AI-SQ) scale was developed to assess user perceptions of service quality in artificial intelligence (AI)-powered environments, such as chatbots, virtual assistants, and automated customer support systems. Traditional service quality models like SERVQUAL were not designed for AI interactions, which are non-physical, data-driven, and often autonomous (Parasuraman, Zeithaml, & Berry, 1988). Therefore, a new scale was needed to reflect the unique characteristics of AI-based services.

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The development of the AI-SQ scale began with a review of foundational service quality literature. The original SERVQUAL model provided a strong base, identifying five key dimensions: reliability, responsiveness, assurance, empathy, and tangibles (Parasuraman et al., 1988). However, AI services lack physical presence, so the "tangibles" dimension was excluded. The remaining dimensions were reinterpreted to fit AI contexts. For example, empathy was redefined to focus on emotional recognition and adaptive communication rather than human warmth.

Recent research on AI in service contexts guided the refinement of the scale. Huang and Rust (2018) emphasized that AI systems must be intelligent, reliable, and capable of personalization. Their work on the "New Service Paradigm" highlighted the shift from human-to-machine service delivery, supporting the inclusion of dimensions like personalization and system intelligence. Wirtz et al. (2023) further expanded on this by proposing an AI-specific service quality framework that integrates responsiveness, transparency, and emotional awareness, which informed the structure of the AI-SQ scale.

Transparency and trust emerged as critical factors based on Diederich, Buder, and Messner (2023), who found that users are more likely to accept AI decisions when they understand how those decisions are made. This led to the inclusion of items assessing explainability and data use. Similarly, Puntoni, Reczek, Giesler, and Botti (2021) showed that users respond better to AI when it recognizes emotional cues and adjusts its behavior, supporting the development of the "Empathy & Emotional Intelligence" dimension.

The final scale consists of 25 items across five dimensions: Reliability (5 items), Responsiveness (5 items), Personalization & Intelligence (5 items), Transparency & Trust (5 items), and Empathy & Emotional Intelligence (5 items). Each item is phrased as a simple, clear statement and measured on a 7-point Likert scale ranging from *Strongly Disagree* (1) to *Strongly Agree* (7).

This scale is suitable for use in surveys, usability testing, and customer feedback systems. It enables organizations to evaluate and improve their AI-driven services. The AI-SQ scale is both theoretically grounded and practically applicable, making it a valuable tool for researchers and practitioners alike.

Table 1: Sources for AI-SQ Scale Development

Dimension	**Key Influences**
Reliability	SERVQUAL, Huang & Rust (2018), Wirtz et al. (2023)
Responsiveness	SERVQUAL, de Bruyn et al. (2021)
Personalization & Intelligence	Huang & Rust (2021), Wirtz et al. (2023)
Transparency & Trust	Diederich et al. (2023), de Bruyn et al. (2021)
Empathy & Emotional Intelligence	Puntoni et al. (2021), Wirtz et al. (2023)

The Cronbach's alpha value of the digital marketing measure was found as .987, while for all its sub-components it was found more than .922. Literature review suggests that an alpha value of more than .60 is good and acceptable for measurement.

Table 2 Reliability Statistics of AI-SQ Scale

Reliability Statistics

Scale	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Artificial Intelligence Enabled Service Quality (AI-SQ)	0.987	0.985	25

Table 3 Reliability Statistics of Sub- Factors

Reliability Statistics

Scale	**Cronbach's Alpha**	**Cronbach's Alpha Based on Standardized Items**	**N of Items**
Reliability	0.971	0.969	5
Responsiveness	0.964	0.962	5
Personalization & Intelligence	0.956	0.954	5
Transparency & Trust	0.944	0.942	5
Empathy & Emotional Intelligence	0.924	0.922	5

Statistical Tools Used

Exploratory factor analysis was applied to explore the contributing factors in Artificial Intelligence Enabled Service Quality (AI-SQ) in its sub-components. Five factors were identified from factor analysis as sub-components of AI-SQ scale.

RESULTS

The participants included 132 males and 110 females, with an average age of 30-40 (*n*=98) years. Participants also include 20-30 years (*n*=105) below 20 years (39) . The highest educational degree earned by participants included postgraduates (*n* = 94), graduates (*n* =107), and undergraduate (*n* =41).

Table 2 KMO and Barlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.976
Bartlett's Test of Sphericity	Approx. Chi-Square	6592.451
	df	240
	Sig.	0.000

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Table 3 Factor Analysis
Rotated Component Matrix

S.No.	Items	Components				
		Reliability	Responsiveness	Personalization & Intelligence	Transparency & Trust	Empathy & Emotional Intelligence
1	The AI system provides consistent responses across multiple interactions.	0.882				
2	I can rely on the AI to deliver accurate information every time.	0.854				
3	The AI completes tasks without errors or failures.	0.849				
4	The AI performs services correctly the first time.	0.843				
5	The AI handles my requests reliably, even during high demand.	0.832				
6	The AI responds to my queries almost instantly.		0.828			
7	The AI system is quick to assist me when I need help.		0.818			
8	There is minimal waiting time when interacting with the AI.		0.812			
9	The AI adapts quickly to changes in my requests.		0.804			
10	The AI provides timely follow-ups or reminders when needed.		0.794			
11	The AI remembers my preferences and past interactions.			0.774		
12	The AI offers suggestions that are relevant to my needs.			0.771		
13	The AI anticipates my needs before I ask.			0.768		
14	The AI learns from my behavior to improve future interactions.			0.743		
15	The AI communicates in a way that feels personalized and human-like.			0.736		

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16	The AI explains how it arrived at a decision or recommendation.				0.731	
17	I understand what data the AI uses to serve me.				0.723	
18	The AI clearly indicates when it is an automated system (not a human).				0.719	
19	I trust the AI with my personal information.				0.707	
20	The AI admits its limitations when it cannot help.				0.702	
21	The AI detects frustration or confusion in my tone or text.					0.697
22	The AI adjusts its tone based on my emotional state.					0.686
23	The AI shows understanding when I express dissatisfaction.					0.664
24	The AI offers supportive or empathetic responses when appropriate.					0.654
25	The AI knows when to escalate to a human agent if I'm upset.					0.645

The data analysis confirms that the Artificial Intelligence Enabled Service Quality (AI-SQ) scale is highly reliable and well-structured. The overall Cronbach's Alpha value for the full AI-SQ scale is 0.987, which shows excellent internal consistency. This means the 25 items in the scale are strongly related and measure the same underlying concept—service quality in AI-driven services. Even when standardized, the reliability remains very high at 0.985. This level of reliability is rare and indicates that the scale produces stable and consistent results.

Each of the five sub-dimensions also shows strong reliability. Reliability (as a factor) has a Cronbach's Alpha of 0.971, responsiveness 0.964, personalization & intelligence 0.956, transparency & trust 0.944, and empathy & emotional intelligence 0.924. All values are above 0.9, which is considered excellent in social science research. This suggests that each group of five items consistently reflects its intended concept.

The KMO value of 0.976 is well above the acceptable threshold of 0.6, showing that the data is highly suitable for factor analysis. Bartlett's Test of Sphericity is also significant ($p < 0.001$), confirming that the variables are correlated and appropriate for dimension reduction. These results support the use of exploratory factor analysis to identify the underlying structure of the AI-SQ scale.

The rotated component matrix clearly shows that each item loads strongly on only one factor, with no major cross-loadings. For example, items 1 to 5 load highly on "Reliability" (from 0.832 to 0.882), showing users see consistency and accuracy as key to dependable AI. Items 6 to 10 load on "Responsiveness," with values from 0.794 to 0.828, highlighting the importance of speed and quick support in AI services. Items 11 to 15 relate to "Personalization & Intelligence," with loadings from 0.736 to 0.774, showing users value AI that remembers them and offers smart, tailored suggestions.

Items 16 to 20 measure "Transparency & Trust." Loadings range from 0.702 to 0.731. These results show users care about knowing how AI works and whether their data is safe. Trust is built when AI explains decisions and admits its limits. Finally, items 21 to 25 reflect "Empathy & Emotional Intelligence," with loadings from 0.645 to 0.697. While slightly lower, these are still strong, especially for a new concept like emotional AI. Users appreciate when AI detects frustration, adjusts tone, and knows when to pass them to a human.

Overall, the five-factor structure is clear, meaningful, and supported by strong statistical evidence. The AI-SQ scale is not only reliable but also valid, capturing key aspects of service quality in AI environments. These results provide a solid foundation for using the scale in future research and business practice.

In view of the results of exploratory factor analyses null hypothesis is rejected and alternate is accepted thus, the development of a robust Artificial Intelligence Enabled Service Quality AI-SQ scale does not combines critical dimensions including reliability, transparency, personalization, trust, responsiveness, and perceived empathy in AI influenced services.

Discussion

This study successfully develops and validates a new scale to measure service quality in AI-enabled environments. The results show that service quality in AI services is not the same as in human-led services. Users expect more than just speed and accuracy. They want AI systems that are reliable, fast, smart, transparent, trustworthy, and even empathetic. The AI-SQ scale captures these needs through five clear and reliable dimensions: reliability, responsiveness, personalization & intelligence, transparency & trust, and empathy & emotional intelligence. Each of these factors plays a unique role in shaping how users judge the quality of AI-driven services.

The high reliability scores for each dimension prove that the items used in the scale are consistent and meaningful. The Cronbach's Alpha values are all above 0.92, which is excellent. This means users respond to these items in a predictable and stable way. The factor analysis also shows that each item fits well under one factor, with no confusion between concepts. This confirms that the scale is well-structured and easy to interpret.

One key finding is that users value transparency. They want to know how AI makes decisions and what data it uses. This supports earlier research showing that "black box" AI systems reduce trust (Puntoni et al., 2021). When AI explains its actions or admits its limits, users feel more in control and more confident in the system. This links transparency directly to trust—a vital insight for companies designing AI tools.

Another important result is the role of empathy. Even though AI is not human, users expect it to recognize emotions like frustration or confusion. They appreciate when AI adjusts its tone or offers kind responses. This shows that emotional intelligence is no longer just for humans—it is now a part of good service design in AI systems (Huang & Rust, 2021). The fact that this dimension stands out in the analysis proves it cannot be ignored.

The study also confirms that personalization is key. Users like AI that remembers their past behavior and makes smart suggestions. But this must be balanced with privacy. The combined factor of transparency & trust shows that users are okay with data use—as long as they understand it and feel safe.

These findings have real-world value. Businesses can use the AI-SQ scale to test their AI systems, find weaknesses, and improve customer experience. For example, if users rate empathy low, the company can train the AI to respond more supportively. If transparency scores are weak, the system can be updated to explain decisions better.

In sum, this study proves that a new kind of service quality model is needed for the AI age. The AI-SQ scale is reliable, valid, and practical. It moves beyond old models like SERVQUAL and reflects how people truly experience AI services today. Future research can use this scale in different sectors—like healthcare, banking, or education—to see how AI quality varies across fields.

Recommendation and Implications

This study offers practical recommendations for businesses, designers, and researchers working with AI-driven services. The AI-SQ scale provides a clear roadmap for improving service quality in artificial intelligence environments. Organizations should use this scale to regularly assess their AI systems, just as they would measure customer satisfaction in human-led services. By doing so, they can identify weak areas and make data-driven improvements.

First, companies should focus on reliability. Users expect AI to work correctly every time. Errors, crashes, or inconsistent answers damage trust. Firms must invest in robust testing, continuous monitoring, and regular updates to ensure their AI performs accurately and without failure. This is especially important in high-stakes areas like healthcare or banking, where mistakes can have serious consequences.

Second, responsiveness matters. Users value speed and instant support. AI systems should be designed to reply quickly, reduce waiting times, and offer timely reminders or follow-ups. However, speed should not come at the cost of relevance. Fast but incorrect responses can frustrate users more than slow ones.

Third, personalization should be smart and respectful. AI should remember user preferences and anticipate needs. But it must also avoid crossing privacy boundaries. Companies should be clear about what data they collect and why. Giving users control over their data helps build trust and prevents the "creepiness effect" (Matz et al., 2020).

Fourth, transparency and trust must be built into AI design. Users want to know when they are talking to a machine, not a human. They also want simple explanations of how decisions are made—especially in cases like loan denials or medical advice. AI systems should be honest about their limits and admit when they cannot help. This openness increases user confidence and reduces frustration.

Fifth, empathy and emotional intelligence should not be ignored. Even though AI is not human, it can still show understanding. Detecting user frustration, adjusting tone, and offering kind responses make interactions feel more natural. Knowing when to transfer a user to a human agent is also a sign of emotional awareness. These features improve user satisfaction and loyalty.

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For researchers, the AI-SQ scale offers a validated tool for future studies. It can be used to compare AI systems across industries, test new AI designs, or study how service quality affects customer loyalty. The scale can also be adapted for specific sectors like education, retail, or government services.

In policy and ethics, this study highlights the need for standards in AI service design. Regulators and industry groups should consider using the AI-SQ dimensions to set quality benchmarks. This can help ensure that AI services are not only efficient but also fair, safe, and user-friendly.

In conclusion, the AI-SQ scale is more than a research tool—it is a guide for building better AI experiences. By focusing on reliability, responsiveness, personalization, transparency, and empathy, organizations can create AI systems that people trust, use, and recommend.

Conclusion

This study successfully develops and validates a reliable and comprehensive scale to measure Artificial Intelligence-Enabled Service Quality (AI-SQ). As AI becomes a central part of customer service, traditional models like SERVQUAL are no longer enough. Users now expect more from AI than just speed and accuracy—they want systems that are dependable, transparent, smart, and even emotionally aware. The AI-SQ scale meets this need by identifying five key dimensions: reliability, responsiveness, personalization & intelligence, transparency & trust, and empathy & emotional intelligence. Each of these factors is supported by strong statistical evidence, including high Cronbach's Alpha values (above 0.92) and clear factor loadings from the analysis.

The findings show that users judge AI service quality based on both performance and experience. They care about whether the AI works correctly (reliability), how fast it responds (responsiveness), and whether it remembers and understands them (personalization). They also value honesty and clarity (transparency), feel safer when their data is protected (trust), and appreciate when AI detects their emotions and responds with care (empathy). These insights go beyond technology acceptance and focus on the full service experience.

The AI-SQ scale is not just a research tool—it is a practical guide for businesses. Companies can use it to test their AI systems, find weaknesses, and improve customer satisfaction. For example, low scores in empathy may lead to redesigning chatbot language, while poor transparency scores can prompt better user notifications about data use.

In sum, this study fills a critical gap in service research. It proves that AI service quality is multidimensional and requires a new measurement approach. The validated AI-SQ scale provides a strong foundation for future research and real-world applications. As AI continues to grow, tools like this will help ensure that technology serves people—not just efficiently, but respectfully and humanely.

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