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AI AS A TOOL FOR SUPPORTING RESEARCH ON THE QUALITY OF E-SERVICES – A METHODOLOGICAL PERSPECTIVE

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Purpose: The main objective of this paper is to present how artificial intelligence can support research on e-service quality and to propose methodological frameworks integrating traditional and AI-based research methods.
Design/methodology/approach: The study reviews classical approaches to e-service quality research (e.g., Servqual, Kano model, surveys, opinion analysis) and examines AI applications such as natural language processing (NLP), machine learning, and behavioral data analytics. A conceptual framework is proposed that integrates declarative, behavioral, and textual data sources to enable comprehensive, real-time analysis.
Findings: AI enhances traditional research by enabling faster, more objective analysis, revealing hidden patterns in user behavior, and supporting predictive modeling of satisfaction and churn. The proposed framework demonstrates the potential for a holistic, data-driven assessment of e-service quality across sectors such as e-commerce, e-education, and e-government.
Research limitations/implications: The framework is conceptual and requires empirical validation in diverse e-service contexts. Limitations include data quality, standardization challenges, ethical considerations, and the need for researcher expertise to interpret AI-generated insights. Future research should test the model in multiple sectors and develop AI tools tailored to management and quality science.
Practical implications: Organizations can use AI to monitor and improve e-service quality in real time, optimize user experience, and inform decision-making processes. Implementation of the framework can enhance service delivery, reduce customer churn, and support adaptive service design.
Social implications: Improved e-service quality can increase accessibility, trust, and satisfaction for digital service users, contributing to higher quality of life and more inclusive digital environments. Insights may also guide public policy and corporate social responsibility initiatives in digital service provision.
Originality/value: The paper presents a novel, integrated methodological framework that combines classical e-service research with AI-driven analytics. It provides guidance for researchers and practitioners seeking to enhance the evaluation, monitoring, and prediction of e-service quality in a data-rich digital environment.
Keywords: e-service quality, artificial intelligence (AI), methodological framework, customer satisfaction, data integration.
Category of the paper: Conceptual paper.

1. Introduction

E-services play an increasingly important role in the digital economy, encompassing areas such as online commerce, distance education, and public administration. The growing number of digital platforms makes the quality of provided services a key determinant of user satisfaction, trust, and loyalty (Parasuraman et al., 2005; Kim, 2006; Pilarz Kot, 2019). Maintaining high service quality in the online environment has become a strategic challenge for organizations seeking to strengthen their competitive advantage and build long-term relationships with users (Kowalik, Klimecka-Tatar, 2018; Bagińska, 2022).

At the same time, the rapid development of artificial intelligence (AI) in management and business research opens new opportunities for improving the understanding and measurement of service quality. AI techniques such as machine learning, natural language processing (NLP), and predictive analytics enable the analysis of large and diverse data sets, providing insights that are difficult to obtain using traditional research methods (Alnor et al., 2026; Mukala et al. 2025; Elkharrat et al., 2026).

Traditional approaches to studying e-service quality, such as surveys, Servqual models, or manual content analysis, remain valuable but have clear limitations. These methods required modification due to the very fact that traditional services and e-services differ fundamentally and therefore need to be evaluated based on completely different attributes. They are often time-consuming, rely heavily on subjective assessments, and provide only static results, which may not capture the dynamic nature of user experience in digital environments. It is particularly challenging, mainly due to the fact that customer requirements are constantly changing, and service enterprises need up-to-date information on how their services are perceived by customers.

Therefore, there is a growing need to develop integrated methodological frameworks that combine the strengths of traditional methods with the analytical potential of AI-based tools. Such integration can enable researchers to obtain more comprehensive, real-time, and context-sensitive insights into how users perceive and evaluate e-services.

Despite the growing body of literature on e-service quality and the increasing use of artificial intelligence in management research, existing studies remain methodologically fragmented. Prior research typically applies classical service quality models or selected AI techniques in isolation, focusing on single data types or specific sectors, most often e-commerce. As a result, there is a lack of integrated research frameworks that systematically combine declarative, behavioral, and textual data and use artificial intelligence to analyze their interrelationships in the context of e-service quality. This methodological gap limits the ability to capture the dynamic, multidimensional nature of digital service quality and to translate analytical results into actionable insights.

The main objective of this paper is to present how artificial intelligence can support research on e-service quality and to propose methodological frameworks integrating traditional and AI-based research methods.

The following research questions guide the analysis:

- What classical methods are used to study e-service quality in management sciences?
- How can AI support or complement these traditional methods?
- What new methodological framework can be proposed for studying e-service quality using AI tools?

Addressing these issues provides a structured basis for identifying the potential of artificial intelligence in e-service quality research and for developing an integrated methodological approach that responds to the dynamic nature of digital services.

The novelty of this study lies in its methodological perspective on e-service quality research. Unlike existing studies that focus on isolated applications of artificial intelligence or single data sources, this paper proposes an integrated research framework that systematically combines declarative, behavioral, and textual data with AI-based analytical tools. By linking classical service quality methods with machine learning and natural language processing, the study introduces a coherent approach that enables dynamic, data-driven, and multidimensional assessment of e-service quality across different digital service sectors.

2. Literature review

2.1. Conventional approaches to e-service quality research

Research on e-service quality traditionally relies on well-established tools and conceptual models adapted from the study of offline services. The most frequently applied methods include the Servqual model, which measures the gap between customer expectations and perceptions of service performance, the Kano model, which distinguishes between basic, performance, and excitement attributes, as well as customer satisfaction surveys and opinion analysis based on qualitative data (Midor, Kučera, 2018; Cieśla, 2024, Sitinjak, Ober, 2025). These approaches have provided valuable insights into understanding how users evaluate digital interactions and what determinants shape perceived service quality.

Research on the quality of e-services is based both on the adaptation of classical service quality assessment methods and on the development of approaches specific to the digital environment. Traditional models, such as Servqual, Servperf, and Kano, were originally designed for traditional services; however, over time, they have been modified to account for the characteristics of interactions occurring in online contexts (Ingaldi, 2018; Nadziakiewicz, Mikolajczyk, 2019; Cao et al., 2025; Khouj et al., 2024). In e-service quality research, the E-Servqual model plays a particularly important role, as it adapts the original quality dimensions (tangibility, reliability, responsiveness, assurance, empathy) to the online context, focusing, among other aspects, on efficiency, fulfillment of promises, system availability, and privacy protection. The use of such models enables the measurement of users' subjective perceptions of quality, the analysis of gaps between expectations and actual experiences, and the identification of areas requiring improvement (Cotîrlea, 2011; Setiawan et al., 2025; Rol, Alaeddinoğlu, 2025).

Survey research is commonly employed to assess e-service quality, taking the form of traditional questionnaires or integrated online forms. These are complemented by focus group studies, in-depth interviews, and content analysis of user reviews posted on social media or review platforms. Increasingly, researchers focus on the analysis of user experience (UX), encompassing functional, aesthetic, emotional, and cognitive aspects of interaction with digital services. In this context, observational and experimental methods, such as clickstream analysis, eye-tracking studies, and usability testing, are gaining importance, as they provide deeper insights into user behavior in online environments (Melo, Monteiro, 2025; Njuguna, Qingfei, 2026; Kazakoff et al., 2025).

Contemporary e-service quality research increasingly adopts a holistic approach, combining the customer perspective with an analysis of organizational and technological processes. This implies that e-service quality is not perceived solely as a result of user satisfaction but also as an outcome of the quality of IT infrastructure, data security, system reliability, and the efficiency of service processes. Consequently, integrated quality measurement models, such as E-Servqual, WebQual, Sitequal, Piruqal, IRSQ, .comQ, E-TailQ, E-S-QUAL, E-SQ, e-RecS-Qual, E-A-S-Qual, eTransQual, eSelfqual, E-SQual-ERec-SQual are increasingly applied in research practice, enabling the assessment of both users' subjective perceptions and objective technical and functional parameters of the service (Webb, Webb, 2004; Wolfinbarger, Gilly, 2003; Ghosh, 2018; Ingaldi, 2022).

The entire process of e-service quality assessment can be illustrated using a diagram (Fig. 1). Taking into account customer expectations, a subjective evaluation of quality is conducted with respect to two key dimensions, such as organizational processes and technology. This evaluation results in information about the overall level of e-service quality.

By systematically integrating feedback from multiple data sources, researchers can obtain a more comprehensive and nuanced understanding of service performance. The model also allows for the identification of critical factors that influence user satisfaction and loyalty, supporting targeted improvements in both service delivery and technological infrastructure. Ultimately, this approach enables organizations to not only assess but also dynamically monitor and enhance the quality of digital services in response to evolving customer expectations.

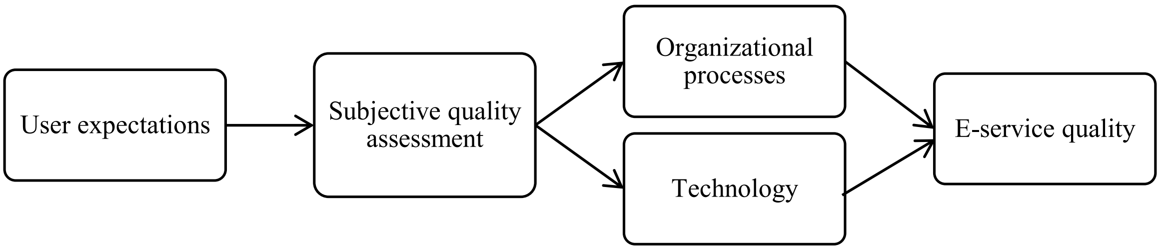

Figure 1. Conceptual Diagram of E-Service Quality Assessment Process.
Source: own study.

It should be remembered, that traditional tools have several methodological limitations when applied to the online environment. They are often time-consuming and rely on subjective user declarations, which may not fully reflect actual behavior. Moreover, they typically produce static results, offering only a snapshot of user perceptions at a specific moment in time, without capturing the dynamic and continuous nature of digital interactions.

As e-services become more complex and data-rich, there is a growing demand for research approaches that enable real-time measurement, automatic data processing, and integration of multiple data sources, including behavioral and textual data. This methodological shift creates a space for the application of AI-based analytical tools, which can complement and enhance classical research designs by providing more objective, scalable, and adaptive insights into service quality.

Building upon these traditional approaches, the following section explores how AI extends the methodological landscape of e-service quality research.

2.2. Applications of Artificial Intelligence in e-service quality research

The application of artificial intelligence (AI) in research on digital service quality significantly expands analytical and interpretative capabilities compared to traditional research methods. AI enables not only the processing of large and unstructured datasets but also the identification of hidden patterns in consumer behavior, relationships between variables, and changes in the perception of service quality over time (Chrysikou et al., 2026; Noor et al., 2022; Gerlich et al., 2021).

One key application is natural language processing (NLP), which allows for the analysis of user-generated texts, such as reviews, comments on social media, or customer service chat logs. NLP tools can automatically classify statements according to emotional tone (sentiment analysis), identify the most frequently occurring issues, and analyze satisfaction with specific aspects of a digital service (Alnor et al., 2026; Mukala et al., 2025; Elkharrat et al., 2026). The use of these techniques enables the creation of dynamic maps of quality perception, which can support customer experience management (CEM).

Another important area is machine learning (ML), which facilitates modeling the relationships between factors affecting customer satisfaction and their actual behavior. ML algorithms can predict satisfaction levels, user loyalty, or the risk of service abandonment (churn prediction). These models can be integrated with CRM systems or e-commerce platforms, allowing for personalized offers and early intervention when dissatisfaction is detected (Budhathoki et al., 2026; Zhan et al., 2025; Khabusi et al., 2025).

A third significant direction is the analysis of behavioral data, such as clickstream, time spent on a website, click sequences, or user navigation paths. The use of unsupervised learning algorithms (e.g., clustering or self-organizing neural networks) allows for the identification of typical behavior patterns and user segments (Suratno et al., 2025; Baek, 2025; Gerlich et al., 2021). This enables researchers to better understand how users interact with digital services and to identify key critical points influencing perceived service quality.

The application of AI in service quality research can also be seen as a new methodological dimension that combines classical approaches (e.g., surveys or interviews) with the analysis of digital data. Such an integrated approach enables triangulation of results and enhances the reliability of interpretations (Noor et al., 2022; Hamedani et al., 2025; Zachurzok-Srebrny, 2024). In the context of e-service quality research, AI thus serves not only as a computational tool but also as a method supporting the exploration and validation of phenomena that are difficult to capture in traditional social research.

Despite the growing number of studies, there is a lack of an integrated methodology combining traditional approaches with AI tools in the context of e-services. Most research focuses on a single sector, such as e-commerce, leaving gaps in areas like online education or digital administration. This highlights the need to develop frameworks that integrate declarative, behavioral, and textual data, which can be analyzed with AI support.

2.3. Identified gaps in the literature

Despite the growing interest in the use of artificial intelligence in research on e-service quality, there remains a lack of coherent and comprehensive methodological frameworks that integrate traditional research approaches with advanced AI analytical tools. Most existing studies are fragmentary in nature, focusing on selected aspects such as customer review analysis, satisfaction prediction, or user behavior modeling, while often neglecting the broader systemic context.

The dominant research trend mainly targets the e-commerce sector, which, due to its large data availability and measurable interactions, constitutes a natural testing ground for AI-based solutions. In contrast, other areas of digital services such as remote education, online public administration, or e-health, receive considerably less attention, even though they represent critical spaces for shaping user experiences and service quality in the digital society.

As a result, there is a lack of integrated research models that combine:

- declarative data (e.g., survey and interview results),
- behavioral data (e.g., user activity, click paths, response times),
- and textual data (e.g., reviews, comments, chats).

The integration of these three types of information, analyzed using AI algorithms (e.g., NLP, neural networks, predictive models), could enable a more comprehensive assessment of e-service quality and the identification of hidden relationships between user perceptions and actual behaviors.

Future research should therefore focus on developing an interdisciplinary methodological framework that combines knowledge from quality management, data analytics, and artificial intelligence. Such an approach could contribute to the emergence of a new research paradigm, e.g. "AI-driven quality research", which would not only diagnose but also dynamically forecast the quality of digital services in real time.

3. Methods

The proposed research model defines a methodological procedure for e-service quality analysis. However, it is not empirically applied in this study and serves as a conceptual reference framework for illustrating potential applications across different sectors.

3.1. Integration of data

The proposed research model for e-service quality (Tab. 1, Fig. 2) assumes the integration of three main categories of data: declarative, behavioral, and textual. Their combination enables a more comprehensive understanding of the user experience (UX) and a more reliable assessment of digital service quality. Table 1 summarizes the structure of the proposed research model, highlighting the role of AI in analyzing different data categories.

Table 1.
Research model for e-service quality

Data Type	Examples	Role of AI
Declarative Data	Surveys, SERVQUAL questionnaires, interviews	Statistical analysis, identification of key satisfaction factors, integration with behavioral data
Behavioral Data	System logs, clickstreams, UX data	Pattern detection, predictive analysis, user segmentation
Textual Data	Reviews, comments, chats, social media posts	NLP, sentiment analysis, topic classification, emotion detection

Source: own study.

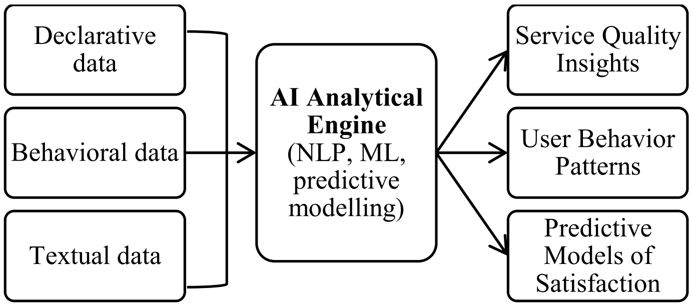

Figure 2. Conceptual model of data integration for e-service quality research.

Source: own study.

The integration of these three data sources enables methodological triangulation, enhancing the reliability and depth of the findings. Declarative data capture the subjective perception of quality, how users perceive the service. Behavioral data reveal actual patterns of user behavior, while textual data provide contextual qualitative information that can be automatically analyzed using AI algorithms, overcoming the limitations of manual content analysis.

From a methodological perspective, the model assumes the use of hybrid data analysis methods, in which AI supports the researcher in processing, classifying, and interpreting results. Supervised learning models (e.g., logistic regression, decision trees) can be applied to predict satisfaction or loyalty, while unsupervised learning (e.g., clustering) can be used to segment users based on behavioral patterns.

Figure 3 presents the proposed conceptual framework integrating declarative, behavioral, and textual data with AI analytical modules. The diagram illustrates how various data types are processed through natural language processing (NLP), machine learning (ML), and predictive models to generate actionable insights for improving e-service quality.

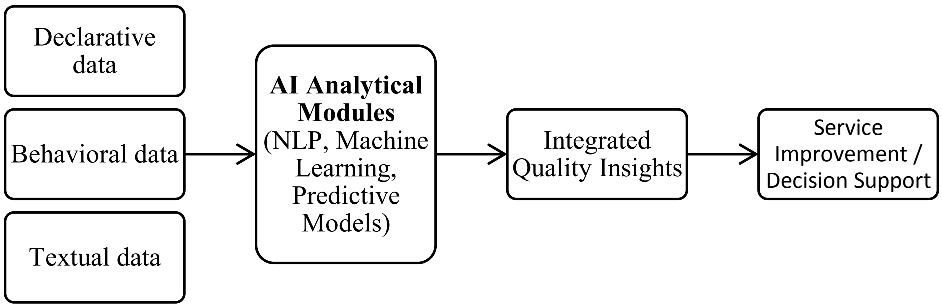

Figure 3. Conceptual AI-Driven Framework for E-Service Quality Research.

Source: own study.

This framework visualizes the data flow within the proposed model, emphasizing the integrative and iterative nature of AI-assisted quality analysis. It also demonstrates the transition from raw data to practical insights that can inform managerial decision-making and service improvement strategies.

3.2. Methodological Benefits

The implementation of the proposed model offers several methodological advantages:

- Faster and more efficient data analysis – the use of AI tools enables the analysis of large volumes of data in real time, which is particularly important in the dynamic environment of digital services.
- Integration of heterogeneous data sources – combining quantitative and qualitative information allows for a multidimensional assessment of e-service quality.
- Detection of hidden patterns and relationships – machine learning algorithms can reveal connections between user behaviors, their opinions, and survey results that would be difficult to identify using traditional analytical techniques.
- Increased objectivity and replicability of research – automating parts of the analytical process reduces the influence of subjective researcher interpretations while enabling repeatable analyses.

Thanks to these advantages, the model can serve as a foundation for the development of intelligent e-service quality monitoring systems and dynamic decision support tools (DSS) for managers responsible for customer experience.

3.3. Challenges and limitations

Despite numerous advantages, data integration and the use of artificial intelligence in e-service quality research also involve certain challenges:

- Data quality and standardization – data from different sources often vary in structure, level of detail, and reliability. It is essential to develop procedures for cleaning, harmonizing, and validating input data.
- Ethical and legal aspects – the use of user data, particularly textual and behavioral data, requires compliance with privacy principles and regulations such as GDPR. Ensuring participant anonymity is also crucial.
- Risk of algorithmic bias – AI models can reproduce or amplify existing biases in the data, potentially leading to incorrect conclusions. Therefore, the interpretation of results should be supported by expert researcher judgment.
- Interpretative complexity – although automated analyses provide rapid results, contextual interpretation in light of service quality theory and consumer behavior is necessary to ensure cognitive validity.

Developing ethical, technical, and interpretative standards for such research represents a key step toward fully leveraging the potential of AI in digital service quality analysis.

In summary, the proposed methodology combines traditional research approaches with advanced AI-based data analysis techniques. This approach enables a multidimensional assessment of e-service quality and provides a foundation for the development of new research tools and conceptual frameworks in quality management within the digital environment.

4. Results

The Results section presents objective methodological outcomes in the form of sectoral illustrations and structured examples demonstrating how the proposed research framework could be applied in different e-service domains, without empirical implementation or interpretative analysis.

The use of artificial intelligence in research on e-service quality is reflected across various sectors of the digital economy. Each sector is characterized by a specific user profile, data structure, and distinct quality assessment criteria. Below, three illustrative areas are presented in which AI methods can significantly support the research process.

E-commerce

In the e-commerce sector, artificial intelligence is used both to analyze service quality and to personalize user experiences. Natural Language Processing (NLP) tools allow for the analysis of customer reviews posted on sales platforms, social media, or customer service systems. This enables the automatic classification of statements according to quality-related categories (e.g., delivery time, customer service, product quality) as well as sentiment analysis.

Behavioral data, such as clickstreams, number of visits, purchase paths, or cart abandonment rates, can be analyzed using machine learning algorithms to predict purchase intentions and identify barriers in the buying process. Predictive models (e.g., gradient boosting, random forest) can estimate the likelihood of cart abandonment and suggest intervention strategies, such as automated reminders or personalized offers. This approach allows for both the improvement of service quality and the optimization of e-commerce processes from the perspective of customer experience.

E-education

In the context of digital education, AI supports the analysis of educational service quality by processing both declarative and behavioral data. Based on survey results, student feedback, and activity on e-learning platforms, it is possible to examine course satisfaction, the effectiveness of learning materials, and participant engagement.

Machine learning algorithms can be used to cluster students according to activity patterns (e.g., login frequency, number of completed modules, forum interactions), enabling the identification of groups with high or low risk of course dropout. Additionally, textual analysis of open-ended responses or comments allows the detection of areas needing improvement, such as the quality of communication with instructors or the usability of the platform.

AI also facilitates the creation of adaptive e-learning systems that personalize content and learning paths according to user preferences and progress, directly impacting the perceived quality of the educational experience.

E-government

In the public online services sector, the application of AI is particularly important for improving the accessibility and efficiency of citizen interactions with government administration. The analysis of textual data from contact forms, inquiries to offices, or chatbot conversations enables the assessment of communication quality, the identification of recurring issues, and the automatic grouping of inquiry topics.

NLP-based systems can support administration in monitoring citizen service quality, for example, by analyzing emotions in statements, evaluating satisfaction after completed interactions, or detecting difficulties in understanding procedures. Similarly, the analysis of behavioral data, such as portal visit frequency, task completion time, or the number of incorrect form submissions, allows for the identification of bottlenecks in digital processes and their optimization.

As a result, AI can support not only the assessment of e-government quality but also the design of more user-friendly and inclusive digital systems, which is one of the pillars of modern public management in the digital era.

Tables 2 and Figure 4 present a summary of AI applications in assessing quality across the illustrated areas. The overview demonstrates that in each of the analyzed sectors, it is possible to leverage a combination of declarative, behavioral, and textual data. AI enables the transformation of these data into actionable knowledge on service quality, paving the way for more integrated, empirical models for evaluating user experiences in the digital environment.

Table 2.
Applications of AI in E-Service Quality Research

E-Service Sector	Types of Data Analyzed	AI Tools Applied	Potential Research Benefits
E-Commerce	Textual data (reviews, comments), behavioral data (clickstream, cart abandonment)	NLP – sentiment analysis, topic classification; Machine Learning – cart abandonment prediction, customer segmentation	Identification of key factors affecting customer satisfaction and loyalty; prediction of purchasing behavior; optimization of service quality
E-Education	Declarative data (student surveys), behavioral data (platform activity), textual data (comments)	Machine Learning – student clustering, predictive analysis of dropout risk; NLP – analysis of opinions and emotions	Understanding engagement patterns; personalization of educational content; improvement of e-learning experience quality
E-Government	Textual data (messages, inquiries, chatbot conversations), behavioral data (portal interactions, response time)	NLP – language and sentiment analysis, topic classification; Predictive analysis – identification of user issues	Assessment of citizen service quality; streamlining administrative processes; enhancement of accessibility and user satisfaction

Source: own study.

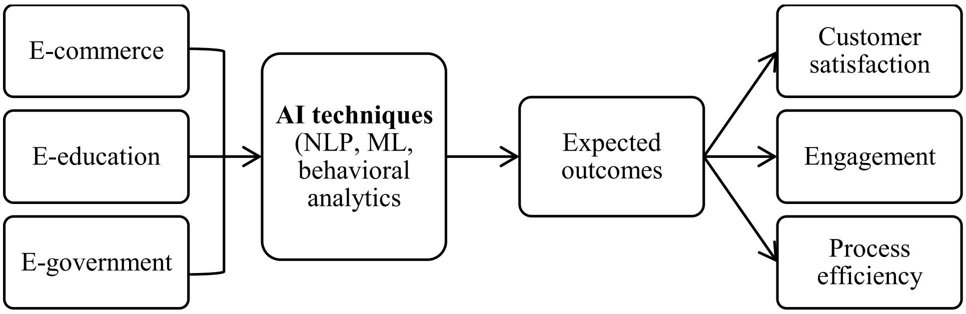

Figure 4. Overview of AI Applications in E-Service Quality Assessment Across Different Sectors.
Source: own study.

The applications of artificial intelligence across various e-service domains demonstrate that AI not only supports quality analysis but also serves as a tool actively shaping the user experience. The integration of declarative, behavioral, and textual data enables a more holistic understanding of digital service quality, opening new research opportunities in the fields of quality management and innovation.

5. Discussion

The integration of artificial intelligence with traditional research methods represents a significant step toward the development of modern approaches to analyzing e-service quality. Combining statistical, survey, and qualitative tools with machine learning algorithms and natural language processing (NLP) techniques enables research with a higher level of objectivity, speed, and precision. This makes it possible to process large, diverse datasets, e.g. declarative, behavioral, and textual, that were previously difficult to analyze using conventional methods.

From a methodological perspective, the application of AI opens new opportunities for data triangulation and result validation, as well as for detecting hidden relationships and patterns in user behavior. Such an approach supports a more in-depth diagnosis of service quality and the dynamic monitoring of changes in customers' perceived value. Consequently, AI can be seen not only as an analytical tool but also as a methodological partner for researchers, supporting the cognitive and decision-making processes.

At the same time, integrating AI into e-service quality research involves several challenges. Data quality and reliability are critical, as they form the foundation for machine learning algorithms. Incomplete, inconsistent, or contaminated data may lead to erroneous conclusions, even when using advanced models. Ethical and legal issues are also crucial, including user privacy protection, transparency of analytical processes, and compliance with regulations such as GDPR.

Equally important is the role of researcher competencies, as interpreting results generated by AI models requires not only knowledge of IT tools but also the ability to critically analyze and understand the socio-organizational context. Without this, there is a risk of overreliance on algorithmic outputs and potential misinterpretations.

The proposed model has several notable research limitations:

- Conceptual nature of the methodological framework – the model requires empirical validation across different e-service contexts to confirm its practical effectiveness.
- Data quality and standardization – data from various sources may be inconsistent, incomplete, or difficult to compare.
- Ethical considerations – ensuring privacy, anonymity, and compliance with legal regulations, such as GDPR, is essential.
- Expert interpretation of results – analyzing AI-generated outcomes requires researcher expertise to avoid erroneous conclusions due to algorithmic bias.

From the perspective of future research, the following directions appear particularly important:

- Testing the proposed data integration model across different e-service sectors (e.g., e-health, e-finance, e-government).
- Developing AI tools tailored to the needs of management and quality sciences.
- Advancing the concept of AI-driven quality research, in which artificial intelligence supports the research process at all stages, from data collection to result interpretation.

In summary, the use of artificial intelligence in e-service quality research does not replace traditional methods but serves as their natural extension. Integrating both approaches enables the creation of modern, adaptive research models that better reflect the complexity of contemporary digital environments and evolving user needs.

6. Conclusions

This paper critically reviewed existing approaches to e-service quality research and demonstrated their methodological limitations, particularly their reliance on subjective, declarative data, static measurement results, and limited ability to capture the dynamic nature of digital service interactions. The analysis showed that traditional models, although still valuable, are insufficient when used independently in contemporary, data-intensive digital environments.

Based on the results of the conceptual analysis and sectoral examples presented in the study, new knowledge is provided in the form of an integrated, AI-supported methodological framework for e-service quality research. The proposed model combines declarative, behavioral, and textual data and illustrates how artificial intelligence techniques such as machine learning and natural language processing can enhance data triangulation, pattern detection, and predictive analysis of user satisfaction and behavior.

From a theoretical perspective, the study contributes to the development of management and quality sciences by extending existing e-service quality research paradigms toward a more holistic and dynamic, data-driven approach. It supports the emerging concept of AI-driven quality research, in which artificial intelligence complements classical methods throughout the research process, from data collection to interpretation.

From a practical perspective, the results indicate that the proposed framework can be used by organizations to monitor e-service quality in real time, identify critical service weaknesses, and support evidence-based decision-making. The integration of AI tools enables faster response to changing user expectations and facilitates the design of adaptive, user-centered digital services across sectors such as e-commerce, e-education, and e-government.

The study is methodological and conceptual in nature, which constitutes its main limitation. The proposed framework requires empirical validation using real-world data from different digital service contexts. Nevertheless, the results provide a solid foundation for future research aimed at operationalizing the model, testing its effectiveness, and developing dedicated AI tools for quality management practice.

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