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AI-Driven Service Quality in E-Commerce: Expectation–Perception Gaps Using Interval-Valued Pythagorean Fuzzy Analysis

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Abstract: Digital commerce is transforming through Artificial Intelligence (AI), which has redesigned the interaction with customers, delivery of services, and personalizing of customer experience. Nevertheless, the expectations and perceptions of the customers regarding the quality of the AI-driven service (AISQ) are still poorly comprehended, in particular, in regard to trust and reliability throughout the digital purchasing experience. This paper analyses consumer expectations and consumer perception of AISQ in e-commerce through Interval- Valued Pythagorean Fuzzy (IVPF) framework to deal with uncertainty in human judgments. According to 684 online customers, the results of this study reveal that there are wide differences between the expected and perceived performance of AI and that the highest degree of dissatisfaction is registered in terms of efficiency of problem solving, personalization with contexts, timely updates and emotional assurance with the uniformity of cross-platform system, which is satisfactory. The research has both theoretical and methodological implications in that it analyses the AISQ dimensions gaps as a multidimensional construct, and methodologically by enhancing gap analysis by IVPF to include trust and user satisfaction assessment in online commerce. In practice, the results give practical recommendations to the improvement of reliability, responsiveness, personalization, privacy assurance, and empathetic interaction design, allowing e-commerce companies to provide more reliable and user-friendly AI-based services to people in various regional markets.

Keywords: Artificial Intelligence, Service Quality, E-Commerce, User's Expectations and Perceptions, Interval-Valued Pythagorean Fuzzy

1. Introduction

Artificial Intelligence (AI) enabled innovations are driving significant changes in customer service and businesses practices (Svetlana *et al.,* 2022). The Mckinsey analytics report (Mckinsey report 2024) determine AI as a major driver of enhanced customization and improved operational efficiency. A survey of 41 cases of AI usage showed a significant increase in revenue with use of AI adoption in business (Chaturvedi and Verma, 2023). In the global economy, cumulative GDP could increase by up to 18% by 2031 as a result of integration of AI into business operations (Hui *et al.,* 2024). Prior research defines AI-enabled technologies and the pivotal role of AI in developing business. It is the time for practitioners and researchers to mull over the AI opportunities and issues in revamping the industries all over the world (Mckinsey report 2024). Prescriptive analytics indicates that AI will play a pivotal role in customer service soon, and personalization-based conversational chat bots (customer care service-based AI tools) will instrumentalize customer satisfaction (Mckinsey report 2024). Rana *et al.* (2022) introduces the discussion on AI-driven customer-care service using AI chat bots, recommender systems, Internet of Things (IoT), extended reality, and service robots. Businesses adopt AI-based technologies to gain competitive advantages by enhancing the quality of service to customers (Chen *et al.,* 2021). AI is increasingly redefining the e-commerce landscape, powering chatbots, recommender systems, automated service agents, predictive analytics, and generative models that permeate the entire customer journey. In online retail, consumers no longer only interact with human representatives: they engage with AI at every stage, from product search and comparison, through inquiry resolution and order support, to post-purchase service. This shift not simply technological, but deeply experiential raises critical questions about how customers evaluate the quality of AI-mediated service.

Despite its growing prevalence, the character of AI-based Service Quality (AISQ) is minimal. More recent research highlight a few of the most salient dimensions: responsiveness of AI systems to real-time demand (e.g., cloud-edge collaborative frameworks to serve customers); the effectiveness and psychological experience of personalised recommendations (e.g. AI-personalised product suggestions in Chinese e-commerce); and the issue of algorithmic fairness, especially in recommender systems (Vashishth *et al.,* 2024). Concurrently, trust and emotional comfort are key elements of customer acceptance that have been delicate due to users having to make trade-offs between privacy, transparency, and perceived bias. Thus, their correspondence (or dis-correspondence) with the real impressions of customers regarding AI interactions have been under little empirical analysis (Mckinsey report 2024; Kreps and Neuhauser, 2013). The current models of service quality such as SERVQUAL, e-SERVQUAL, or e-TailQ are developed in the human-centric service context and are not capable of capturing the peculiarities of AI-mediated services in a wholesome manner (Chen *et al.,* 2021; Svetlana *et al.,* 2022). Such traditional paradigms disregard such essential features as AI autonomy, algorithm transparency, decision making machinery and non-human responsiveness. The issue of risk perceptions regarding automated interactions and trust to the judgment of the algorithms is the arising problem which demonstrates the inadequacy of classical models. With the growth of AI agents performing their functions with minimum human participation, the main assumptions in the classic theory of service quality (e.g., service failure attribution, expectation formation, and competency evaluation) should be reconsidered.

The benefits and effects of AI-based service interventions in e-commerce have been discussed by a great number of scholars. Additionally, most existing literature has been targeted at a more advanced tier of digital environments, e.g., logistics platforms (Fried and Goodchild, 2023), advanced markets (Lucas *et al.,* 2023), and a scenario where the use of AI technologies (chatbots, recommender systems, and virtual assistants) is widespread (Badouch *et al.,* 2024). On the other hand, it is not found that the studies have analyzed the minor effects of AISQ at specific customer touchpoints or whether the customers have consistent expectations in their interaction with AI. Individual elements of AI-based services have been studied by other studies, such as the quality of personalization (Kim and Kim, 2025), perceived fairness and transparency (Chen *et al.,* 2021), or trust in automated recommendations (Hassan *et al.,* 2025; Chaturvedi and Verma, 2023). Nevertheless, these studies hardly integrate these dimensions into a logical system, and they are less concerned with the fact of the possibility of expectation and perception gaps that define trust, satisfaction, and subsequent involvement. In addition, the classical approaches to the quality of the traditional service cannot be applied to the uncertainty and unwillingness to evaluate AI systems among the customers, particularly, regarding the explainability, reliability, and equity. Based on the literature, there are various observations that come out pertinent to the current study. First, the bulk of research is being focused on technologically advanced e-commerce environments, and there is a gap in the knowledge regarding how AISQ is viewed through different customer interactions. Second, although there are studies which have taken into account personal AI service aspects, few of these have conducted systematically the expectations and perceptions of customers or correlated it with trust results. Finally, there is no standardized or universal set of AISQ dimensions that managers can use to improve customer satisfaction and trust during digital transactions which accelerated reliance on AI-mediated services (Badouch *et al.,* 2024). Therefore, this research study addresses this gap by identifying and analysing various dimensions of AISQ in the context of user's perceptions and expectations across digital buying processes. To achieve this, the Interval-Valued Pythagorean Fuzzy (IVPF) technique that is typically applied to analyse the service quality in other areas of life is modified to meet the needs of the e-commerce interactions with AI. The quality of services measured by human judgment is vague, uncertain or subjective and, therefore, is subject to influence. IVPF approach has a clear advantage in managing such vagueness, giving a more sophisticated test than the traditional service quality measurement methods, which generally lack the ability to measure hesitation or ambiguity in human behavior. In line with this, the following objectives will be developed in this study:

- To establish the important dimensions of AI-based service quality in e-commerce by conducting systematic literature review.
- To establish the relative significance and interrelationships of these AISQ dimensions with the expectation and perception of customers.
- To examine how e-commerce managers and AI service operators can utilize IVPF-based analysis outcomes to prioritize improvements and allocate resources effectively across AISQ dimensions.

Although extensive literature exists on service quality, the literature is consistent with a lack of consensus about a unified set of dimensions or methods for measuring AISQ from the customer perspective in e-commerce. The majority of prior research is focused on isolated constructs, such as personalization, chatbots, or recommendation accuracy, without integrating them into a comprehensive framework or evaluating expectation and perception gaps. This study adopts an extended IVPF approach to conduct an in-depth analysis of AISQ, building on its successful application in other sectors (Sama *et al*., 2023). The key contributions of this research are outlined as it provides a robust set of service quality dimensions to evaluate the value of AI-enabled interactions from the user's perspective. Moreover, it determines the differences between perceptions and expectations, which helps predict the possibility of the user responding positively or negatively to AI services. It can also provide useful information to e-commerce operators so that they can maximize service deliveries by having a clearer insight into customer mindsets. The results can be applied in strategic decision making, focusing on the AISQ improvement, enabling managers to spend their resources efficiently, and creating interventions promoting trust, satisfaction, and loyalty in AI-mediated online purchasing activities.

2. Literature Review

The literature review is dedicated to AI-driven quality of service and users experience in e-commerce and how AI-mediated digital touchpoints, including chatbots, recommender systems, virtual try-ons, and AI-generated content, influence customer expectations and perceptions. The review also emphasizes the related research in the emerging markets to give insights into the trust, satisfaction, and adoption dynamics. This literature is discussed in detail as discussed in the succeeding sections.

2.1 AI in E-Commerce

Artificial Intelligence (AI) keeps reshaping e-commerce on a deeper level, not only by automating it but also by making it more personalized, efficient, and customer-centric. Transformer-based models, such as, are being used to understand and generate text in e-commerce systems to make intelligent product recommendations, create automated content, and improve customer-service interactions, and Ning *et al.* (2018) note that pre-trained transformer models outperform existing systems greatly in the comprehension of user intent, and accuracy of recommendations, but also mention that there are privacy and scalability issues (Vashishth *et al.,* 2024). At the same time, so-called end-cloud collaborative AI architecture are already becoming a promising technology. Abbass *et al.* (2025) proposes a hybrid solution combining cloud and device-level AI, to maximize the level of personalization and at the same time keep the privacy of the user intact, through local fine-tuning and reduced number of data transfers. In addition to technical complexity, AI in e-commerce evokes significant trust and ethical issues. Chen *et al.* (2025) shows that in the field of e-commerce AI, the issue of data privacy and the fairness of algorithms is especially acute because, in most cases, users do not trust how their information is gathered and how they are processed. Similarly, the debates on AI ethics show that the excessive amount of personalization, which is the primary advantage of AI, can ruin customer autonomy and trust when it seems intrusive or untransparent (Oshadi Karunanayaka *et al.,* 2024). The role of human-like interaction is also supported by the empirical evidence: Lucas *et al.* (2023) conclude that the interactivity of the chatbot and perceived humanness have a positive impact on trust and adoption intentions, and the effects of enjoying the chatbot enhancement increase with these factors, but the perceived misleading behaviour has a negative influence on adoption (Al-Adwan *et al.,* 2024). The mediating effect of perceived risk on the effects of the adoption of chatbots in Chinese e-commerce that authenticity, usefulness, and trust boost trust, perceived misleading behaviour reduce adoption is also demonstrated by Silva *et al.* (2023).

At the platform-level, it is shown that the largest online stores implement AI in customer service, supply chain, personalization, and security functions in a strategic way (Anshari *et al.,* 2019). The study of Pallathadka et al. (2023) discloses that e-commerce corporations such as Amazon, IKEA, or Temu implement AI implementation in a non-homogenous and non-technical manner. AI-based personalization can promote loyalty at the consumer behavior level: according to Hassan *et al.* (2025), when a user believes that AI systems know him, he or she would trust them, and commit to the platforms. However, such advantages come with significant trade-offs. The ongoing issues with ethical AI especially when it comes to data management, transparency, and equity are still a significant concern (Zanker *et al.,* 2019), and excessive automation can lead to a loss of trust when no human control and supervision take place (Kim and Kim, 2025). These developments in the framework of this paper point to the necessity of looking at AISQ through customer-centered lenses that would gauge the latter not by the technical performance alone but by such psychological constructs as trust, perceived risk, and emotional assurance. Accordingly, this research adopts five AISQ dimensions AI responsiveness, personalization intelligence, reliability, perceived safety/privacy, and emotional assurance and employs IVPF methods to rigorously capture customers' expectation and perception gaps and assess their implications for trust in AI-mediated e-commerce services.

2.2 E-commerce services and ongoing concerns

Even though AI has facilitated remarkable progress in e-commerce service provision, the same has remained a concern due to the services quality provided, trust, and the ethical utilization of data, which still remain pivotal in undermining the full potential of AI. One of the key problems is the conflict between individualization and privacy. On the one hand, AI-driven personalization in the form of intelligent recommendations, customized promotions, and adaptive customer support adds value to the perceived value, convenience, and the entire customer experience (Vashishth *et al.*, 2024). In addition, Kreps and Neuhauser (2013) discussed that the gathering and usage of vast amounts of personal information create severe questions about the consent of the users, their transparency, and the control of the data. Ethical AI models underline that online shopping platforms should be precised in algorithms and fair in that users are not profiled or discriminated against, which are not ethical (Pallathadka *et al.,* 2023). The second important issue is connected with the trust to the algorithmic decision-making. According to empirical evidence, the level of trust of consumers towards the AI systems depends on the transparency, perceived competence and the level of control that users possess over their personal data (Dao *et al.*, 2012; Zanker *et al.,* 2019). However, several platforms continue to demonstrate gaps in the major service quality areas including responsiveness, information accuracy, and data security that may destroy e-trust and customer loyalty in the long-term (Ping, 2019). To make the issue worse, the dark-pattern user interfaces architecture, which aims at covertly manipulating user behavior, only worsens the trust levels as it affects the consent and the choices regarding data-sharing, such as the forced opt-ins or the misleading privacy settings (Ping, 2019; Hui *et al.,* 2024).

Traditional e-service quality frameworks such as efficiency, system availability, fulfillment and security are also applicable from a service quality perspective. Research revealed that the responsiveness and information delivery accuracy play an important role in repurchase intention and customer satisfaction (Sama *et al.,* 2023). However, the high pace of the AI adoption creates new and underresearched dimensions of service quality, including algorithmic fairness, data transparency, and emotional assurance, that the available models fail to address comprehensively (Bhardwaj *et al.,* 2025). Although AI in e-commerce continuously advances rapidly, there are still a number of gaps in the research that should be addressed. To begin with, the personalization-privacy trade-off is a burning issue as platforms are becoming more and more customized in their suggestions and offers, and the consent to this practice is being questioned, along with the data management and privacy, particularly in the markets with unequal regulatory systems (Cloarec *et al.*, 2024). Second, the processes of the established trust do not exist in AI and there is a paucity of the empirical studies of factors influencing trust or distrust in AI advice, particularly where the workings of the algorithm appear to be non-understandable or incorrect (Silva *et al.,* 2023; Hui *et al.,* 2024). Third, the impact of ethical interface design, including the use of dark-pattern interfaces that trick people into consenting to the use of their data or share data, is a less studied phenomenon but has a significant impact on user trust and acceptance (Oshadi Karunanayaka *et al.*, 2024). Fourth, the available models of service quality are not able to capture the new aspects of AI, such as emotional assurance, perceived fairness, and efficient personal data management, which are fundamental to overall customer satisfaction (Hui *et al.,* 2024). Moreover, cross-cultural research is still at a very poor level and the majority of the studies are done on the Western market, and new markets such as India and

Taiwan have not been sufficiently examined despite the differences in the user expectations, the degree of risk-taking, and regulatory laws (Badouch *et al.*, 2024). These exclusions propel the present study AISQ model, which involves five dimensions; AI responsiveness, personalization intelligence, reliability, perceived safety/privacy, and emotional assurance. This study can define the subtle customer expectations and perceptions by the IVPF approach, and the priorities will be on those domains where the component of trust, uncertainty, and emotional elements towards AI adoption and customer satisfaction.

2.3 Identify the AISQ Dimensions and Items

The AISQ dimensions according to selected customer views in the digital buying processes are the first aim of the current research.

Table 1. Determined AISQ dimensions and its items

AISQ dimensions	Measuring items	Source	Expert opinion
AI responsiveness	AR1: AI responds promptly to queries and requests.	Hui *et al.* (2024)	Major
	AR2: AI solves problems effectively and instantly.	Chen *et al.* (2021)	Major
	AR3: Messages and the news are shared on time.	Kreps and Neuhauser (2013)	Major
	AR4: AI technology is flexible to customer needs.	Ning *et al.* (2018)	Major
	AR5: The communication between customers and AI is perfect and continuous.	Chen *et al.* (2021)	Major
Personalization intelligence	PI1: Services are customized to personal tastes.	Anshari *et al.* (2019)	Major
	PI2: AI takes previous interactions with the user to direct and improve future responses.	Zanker *et al.* (2019)	Major
	PI3: Suggestions of products are context-related.	Dao *et al.* (2012)	Major
	PI4: AI analyzes the behavior of customers to improve the experience.	Vashishth *et al.* (2024)	Major
	PI5: The recommendations of AI are correct and applicable.	Pallathadka *et al.* (2023)	Major
Reliability	R1: The use of AI-based services operates without mistakes.	Ping (2019)	Major
	R2: Transactions and orders are error-free.	Chen *et al.* (2025)	Major
	R3: System outputs are accurate and dependable.	Stefani and Xenos (2008)	Major
	R4: The AI has a consistent and predictable functionality across platforms and devices.	Christopher and Sundjaja (2024)	Major
	R5: Services are at any time required.	Stefani and Xenos (2008)	Major
Perceived safety/privacy	SP1: Customer information is secured and safely managed.	Alharbi *et al.* (2021)	Major
	SP2: AI complies with regulatory and technical data privacy and security regulations.	Kwilinski *et al.* (2024)	Major
	SP3: Fraud or error in transactions is avoided.	Khalek *et al.* (2024)	Major
	SP4: The use of personal information is done in a responsible manner.	Saxena and Thakur (2024)	Major
	SP5: Customers are comfortable exchanging information with AI systems.	Chen *et al.* (2021)	Major

Emotional assurance	EA1: The interactions between AI produce emotional comfort and develop trust.	Hossain (2025)	Major
	EA2: AI guidance makes customers comfortable.	Christopher and Sundjaja (2024)	Major
	EA3: AI demonstrates empathy and attentiveness.	Khan *et al.* (2025)	Major
	EA4: System creates confidence in the purchasing decisions.	Chen *et al.* (2021)	Major
	EA5: AI interactions enhance customer satisfaction and trust.	Hassan *et al.* (2025)	Major

This analysis resulted in the recognition of the most critical AISQ items related to the e-commerce interactions. Based on a systematic review of the literature, five AISQ dimensions were found to be essential to comprehend customer expectations and perceptions, namely AI responsiveness, personalization intelligence, reliability, perceived safety/privacy, and emotional assurance. These dimensions are functional and psychological in nature and can be used to assess the level of trust, satisfaction, and engagement of AI-mediated services.

The significance of these dimensions in service interaction has been noted in previous studies. As an illustration, AI responsiveness of virtual assistants and chatbots influences the perception of customers in terms of service efficiency and timeliness (Stefani and Xenos, 2008). The relevance of service interactions and customer satisfaction are improved with personalization intelligence, which contains recommendation accuracy and adaptive learning (Christopher and Sundjaja, 2024). Reliability is the stability and precision of the AI processes, including the failure of transactions, continuous service, and reliable AI results (Srivastava *et al.,* 2025). The idea of the perceived safety and privacy prevails over the customers who believe in the integrity of the processing of their personal and payment information during the interactions with AI (Alharbi *et al.,* 2021). Lastly, emotional assurance introduces the psychological security, sympathy, and trust that customers have in AI systems, such as the confidence in the decision-making procedure and believed AI interface responsiveness (Kwilinski *et al*., 2024). Table 1 presents these five AISQ dimensions and their items in a tabular form in a systematic format and adjusted to suit e-commerce. The systematic mapping of these items will help the study to create a complete framework by which the expectations and perceptions of AISQ are to be evaluated and analyzed through the IVPF approach. This method will enable the research to capture uncertainty and ambiguity of customer evaluation of AI systems, which will give practical information to e-commerce managers to maximize the use of AI-based service delivery, build trust, and customer loyalty.

3. Methodology of this Study

3.1 Research Design

In the present study, this cross-sectional survey purpose is to identify users' perceptions and expectations of AISQ across digital buying processes and to assess their impact on trust, satisfaction, and engagement in e-commerce platforms. Previous studies in service quality research, such Palese and Usai (2018), have applied SERVQUAL to measure SQ in conventional service industries, with the methodology showing weaknesses in measuring subjective customer perceptions. In the same fashion, Musasa and Tlapana (2023) utilized the Retail Service Quality Scale (RSQS) to evaluate SQ for customer satisfaction, yet these tools fail to provide the most important dimensions of services in the eyes of customers. Ighomereho *et al.* (2022) also used RSQS and SERVQUAL to evaluate SQ in urban transport, but these tools have the weakness of not converting customer expectation scores into actionable information.

To overcome these shortcomings in the AI-based services, this paper uses the IVPF technique to examine the scores of expectation and perception variables in the five best AISQ dimensions, including AI responsiveness, personalization intelligence, reliability, perceived safety/privacy, and emotional assurance. An extension of the Fuzzy Set (FS) theory is known as IVPF sets, which are especially useful when dealing with uncertainty and vagueness of human judgment (Sama *et al.,* 2023). Since its beginning, FS theory has been effectively implemented in multi-attribute decision-making problems in a wide variety of fields (Nalluri *et al.,* 2025), such as technology selection (Zanker et al., 2019), and supply chain performance evaluation (Anshari *et al.,* 2019). Long-term Fuzzy models, including IVPF offer powerful mechanisms to deal with real-life ambiguity in customer ratings (Sama et al., 2023). The IVPF approach is therefore adopted in this study to systematically evaluate customers' expectations versus perceptions of AISQ, enabling a detailed gap analysis and ranking of AI service improvement priorities. The research methodology and data analysis flow for the study are illustrated in Figure 1.

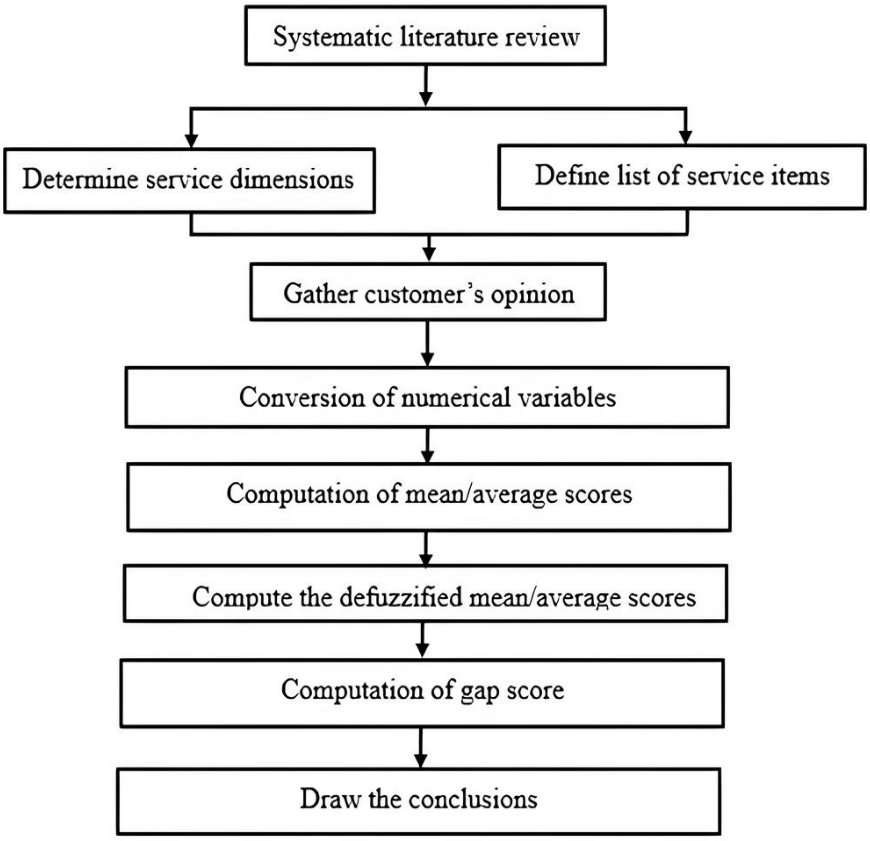

Figure 1. Research flow of this study.

3.2 Sampling Strategy

In accordance with the aim of the current research, data have been gathered in different parts of India and Taiwan, which are the largest e-commerce markets. In India, respondents were selected based on Andhra Pradesh and Telangana, which are diverse and large customer segments in terms of demographics, online shopping habits, and digital literacy. In Taiwan, the urban and semi-urban areas were sampled to get the views of a digitally-sophisticated e-commerce setting. The inclusion of the two countries will make sure that the study covers a wide range of customer expectations and perceptions of AISQ in the different digital buying touchpoints. The questionnaire was divided into two parts. The first part included the demographic data, such as age, gender, education, employment and experience in online shopping. The second part evaluated customers' opinions on the five AISQ dimensions AI responsiveness, personalization intelligence, reliability, perceived safety/privacy, and emotional assurance in terms of both importance and satisfaction. This dual assessment allows for the calculation of expectation and perception gaps and the evaluation of trust implications across AI-mediated services in both countries. The possibility of accessibility to low-digital literacy users or low access to AI-enabled platforms is one of the possible dimensions that were thought over but eventually omitted. Although it was significant, it was difficult to survey this group in India and Taiwan on a comprehensive level. This dimension may be handled by future research to make AI-driven e-commerce services inclusive in their evaluation. The next sections are devoted to the elaboration of the AISQ model development according to the principles of SERVQUAL, identification of the main AISQ dimensions, and the methodology of IVPF to analyze the gap between expectations and perceptions and make priorities to improve it. The study design will guarantee that the outcomes present a variety of customer experience in different markets and offer practical information to e-commerce managers seeking to improve the level of trust, satisfaction, and loyalty by implementing AI-based service delivery.

3.3 AISQ Model

Based on the prior research on AI-based service delivery, the perceptions and expectations of AISQ was measured by the AISQ measure among respondents. The test was testing 25 items statements that covered five key AISQ dimensions including AI responsiveness, personalization intelligence, reliability, perceived safety/privacy, and emotional assurance on a 5-point Likert scale. It has been demonstrated that the 5-point Likert scale has reliable test outcomes (Nalluri *et al.,* 2025).

The subscale (e.g. expectation and perception) provides a total score of 5-25. The greater the score on the expectation subscale, the greater is the level of anticipated AISQ and the greater is the score on the perception subscale, the greater is the positively perceived AISQ. The alpha of the perception and expectation subscales was 0.76 and 0.86, respectively, which implies that there was very good internal consistency. All the items of the scale, both expectation and perception components are shown in Table 1.

3.3.1 Steps for IVPF

The ability of e-commerce platforms to provide timely, accurate, and responsive AI-driven services and the design, usability, and visual appearance of online interfaces represent the responsiveness dimension of AISQ, as the system is able to satisfy users' needs and guarantee smooth service delivery.

Let's say that X is a universal set. Then, the IVPF set $\widetilde{\mathrm{P}}$ are subsequently determined by using Equation (1) :

$$\widetilde{\mathrm{P}} = \left(\left[\mu_{\widetilde{\mathrm{P}}}^{-}(x), \mu_{\widetilde{\mathrm{P}}}^{+}(x)\right], \left[\upsilon_{\widetilde{\mathrm{P}}}^{-}(x), \upsilon_{\widetilde{\mathrm{P}}}^{+}(x)\right]\right) | x \in X \quad (1)$$

While the functions are consider as $\mu_{\widetilde{\mathrm{P}}}^{-}(x), \mu_{\widetilde{\mathrm{P}}}^{+}(x), \upsilon_{\widetilde{\mathrm{P}}}^{-}(x), \upsilon_{\widetilde{\mathrm{P}}}^{+}(x): \mathrm{X} \rightarrow [0,1]$ (lower degree membership) and $\mu_{\widetilde{\mathrm{P}}}^{-}(x)$ and $\mu_{\widetilde{\mathrm{P}}}^{+}(x)$ upper degree membership), where the non-membership functions as $\upsilon_{\widetilde{\mathrm{P}}}^{-}(x)$ (lower degree)and $\upsilon_{\widetilde{\mathrm{P}}}^{+}(x)$ (upper degree) respectively. The set $\widetilde{\mathrm{P}}$ ought to exceed the condition $0 \leq \left(\mu_{\widetilde{\mathrm{P}}}^{+}(\mathrm{x}) + \upsilon_{\widetilde{\mathrm{P}}}^{+}(\mathrm{x})\right) \leq 1$. The indeterminacy upper and lower measures are calculating by using Equation (2).

$$\pi_{\widetilde{\mathrm{P}}}^{-}(x) = \sqrt{1 - \mu_{\widetilde{\mathrm{P}}}^{+}(x) - \upsilon_{\widetilde{\mathrm{P}}}^{+}(x)} \text{ And } \pi_{\widetilde{\mathrm{P}}}^{+}(x) = \sqrt{1 - \mu_{\widetilde{\mathrm{P}}}^{-}(x) - \upsilon_{\widetilde{\mathrm{P}}}^{-}(x)} \quad (2)$$

3.3.2 Operations on Interval valued Pythagorean Fuzzy numbers

In this stage, we have calculated the interval-valued Fuzzy number operations. Let $\widetilde{\mathrm{P}} = ([\mu^{-}, \mu^{+}], [\upsilon^{-}, \upsilon^{+}])$, $\widetilde{\mathrm{P}}_1 = ([\mu_1^{-}, \mu_1^{+}], [\upsilon_1^{-}, \upsilon_1^{+}])$ and$\widetilde{\mathrm{P}}_2 = ([\mu_2^{-}, \mu_2^{+}], [\upsilon_2^{-}, \upsilon_2^{+}])$ be three IVPF numbers. In addition, the operations are defined as follows (Sama *et al.* 2023):

$$\widetilde{\mathrm{P}}_1 \oplus \widetilde{\mathrm{P}}_2 = \left(\left[\sqrt{(\mu_1^{-})^2 + (\mu_2^{-})^2 - \mu_1^{-} \times \mu_2^{-}}, \sqrt{(\mu_1^{+})^2 + (\mu_2^{+})^2 - \mu_1^{+} \times \mu_2^{+}}\right], [\upsilon_1^{-} \times \upsilon_2^{-},\ \upsilon_1^{+} \times \upsilon_2^{+}]\right) \quad (3)$$

$$\widetilde{\mathrm{P}}_1 \otimes \widetilde{\mathrm{P}}_2 = \left([\mu_1^{-} \times \mu_2^{-},\ \mu_2^{+} \times \mu_2^{+}], \left[\sqrt{(\upsilon_1^{-})^2 + (\upsilon_2^{-})^2 - \upsilon_1^{-} \times \upsilon_2^{-}}, \sqrt{\sqrt{(\upsilon_1^{+})^2 + (\upsilon_2^{+})^2 - \upsilon_1^{+} \times \upsilon_2^{+}}}\right]\right) \quad (4)$$

$$\mathrm{k}\tilde{\mathrm{P}}\left(\left[\sqrt{1 - (1 - (\mu^{-})^2)^{\mathrm{k}}}, \sqrt{1 - (1 - (\mu^{+})^2)^{\mathrm{k}}}\right], [(\upsilon^{-})^{\mathrm{k}}, (\upsilon^{+})^{\mathrm{k}}]\right) \text{ where k > 0} \quad (5)$$

$$\widetilde{\mathrm{P}}^{\mathrm{k}} = \left([(\mu^{-})^{\mathrm{k}}, (\mu^{+})^{\mathrm{k}}], \left[\sqrt{1 - (1 - (\upsilon^{-})^2)^{\mathrm{k}}}, \sqrt{1 - (1 - (\upsilon^{+})^2)^{\mathrm{k}}}\right]\right) \text{ where k > 0} \quad (6)$$

The Equations (3-6) are defined to measure the various operations of two-interval valuated Pythagorean fuzzy numbers.

3.4 Numerical Variable Conversion

Using Table 3, the numerical variables provided by the customers in their questionnaire responses are translated to the relevant IVPF numbers.

Table 2. Numerical variables and their associated interval valued Pythagorean fuzzy numbers

IVPF numbers	Numerical variables
([0.1,0.2],[0.8,0.9])	1
([0.3,0.4],[0.6,0.7])	2
([0.5,0.6],[0.4,0.5])	3
([0.7,0.8],[0.2,0.3])	4
([0.8,0.9],[0.1,0.2])	5

3.4.1 Mean/average score calculation

Let us consider $\tilde{B}ei = \left([\mu_{\tilde{B}ei}^{-}, \mu_{\tilde{B}ei}^{+}], [\upsilon_{\tilde{B}ei}^{-}, \upsilon_{\tilde{B}ei}^{+}]\right)$ and $\tilde{B}pi = \left(\left[\mu_{\tilde{B}pi}^{-}, \mu_{\tilde{B}pi}^{+}\right], \left[\upsilon_{\tilde{B}pi}^{-}, \upsilon_{\tilde{B}pi}^{+}\right]\right)$ as the IVPF expectation and perception on the SQ of the i[th] customer (where i=1,2,…,n) and j[th] AISQ item (where j=1,2,…,m) respectively. Let's say that $\tilde{M}_e$ and $\tilde{M}_p$ are the IVPF mean expectation and perception of AISQ on the j[th] item for all of the customers. Equations (7-8) are then used to obtain the IVPF mean scores for each item.

$$\tilde{M}_e = \left(\left[\sqrt{1-\prod_{i=1}^{n}\left(1-\mu_{\tilde{B}ei}^{-\,2}\right)^{\frac{1}{n}}}, \sqrt{1-\prod_{i=1}^{n}\left(1-\mu_{\tilde{B}ei}^{+\,2}\right)^{\frac{1}{n}}}\right], \left[\prod_{i=1}^{n}\upsilon_{\tilde{B}ei}^{-\,\frac{1}{n}}, \prod_{i=1}^{n}\upsilon_{\tilde{B}ei}^{+\,\frac{1}{n}}\right]\right) \tag{7}$$

$$\tilde{M}_p = \left(\left[\sqrt{1-\prod_{i=1}^{n}\left(1-\mu_{\tilde{B}pi}^{-\,2}\right)^{\frac{1}{n}}}, \sqrt{1-\prod_{i=1}^{n}\left(1-\mu_{\tilde{B}pi}^{+\,2}\right)^{\frac{1}{n}}}\right], \left[\prod_{i=1}^{n}\upsilon_{\tilde{B}pi}^{-\,\frac{1}{n}}, \prod_{i=1}^{n}\upsilon_{\tilde{B}pi}^{+\,\frac{1}{n}}\right]\right) \tag{8}$$

3.4.2 Compute the Defuzzified average/mean scores.

The Defuzzified mean scores are calculated using the estimated IVPF mean scores for each item (for both expectation and perception of the AISQ). Let $\tilde{M}ej = \left(\left[\mu_{\tilde{M}ej}^{-}, \mu_{\tilde{M}ej}^{+}\right], \left[\upsilon_{\tilde{M}ej}^{-}, \upsilon_{\tilde{M}ej}^{+}\right]\right)$ and $\tilde{M}pj = \left(\left[\mu_{\tilde{M}pj}^{-}, \mu_{\tilde{M}pj}^{+}\right], \left[\upsilon_{\tilde{M}pj}^{-}, \upsilon_{\tilde{M}pj}^{+}\right]\right)$ are the IVPF average/ mean expectation and perception of the j[th] AISQ item. Further, the defuzzified average/mean expectation D_{ej} and perception D_{pj} of j[th] AISQ item is determined by using Equations (9-10) (Sama *et al.* 2023).

$$D_{pj} = \frac{\left(\begin{array}{c}\mu_{\tilde{M}pj}^{-\,2}+\mu_{\tilde{M}pj}^{+\,2}+\left(1-\pi_{\tilde{M}pj}^{-\,4}-\upsilon_{\tilde{M}pj}^{-\,2}\right)+\left(1-\pi_{\tilde{M}pj}^{+\,4}-\upsilon_{\tilde{M}pj}^{+\,2}\right)+\\ \mu_{\tilde{M}pj}^{-}\mu_{\tilde{M}pj}^{+}+\sqrt[4]{\left(1-\pi_{\tilde{M}pj}^{-\,4}-\upsilon_{\tilde{M}pj}^{-\,2}\right)\left(1-\pi_{\tilde{M}pj}^{+\,4}-\upsilon_{\tilde{M}pj}^{+\,2}\right)}\end{array}\right)}{6} \tag{9}$$

$$D_{ej} = \frac{\left(\begin{array}{c}\mu_{\tilde{M}ej}^{-\,2}+\mu_{\tilde{M}ej}^{+\,2}+\left(1-\pi_{\tilde{M}ej}^{-\,4}-\upsilon_{\tilde{M}ej}^{-\,2}\right)+\left(1-\pi_{\tilde{M}ej}^{+\,4}-\upsilon_{\tilde{M}ej}^{+\,2}\right)+\\ \mu_{\tilde{M}ej}^{-}\mu_{\tilde{M}ej}^{+}+\sqrt[4]{\left(1-\pi_{\tilde{M}ej}^{-\,4}-\upsilon_{\tilde{M}ej}^{-\,2}\right)\left(1-\pi_{\tilde{M}ej}^{+\,4}-\upsilon_{\tilde{M}ej}^{+\,2}\right)}\end{array}\right)}{6} \tag{10}$$

3.4.3 Calculation of the gap score among consumer perception and expectation

Let G_j be the gap score between the expectation and perception on SQ of jth item for all of the consumers. Next, Equation (11) is used to evaluate the gap score.

$$Gj = D_{pj} - D_{ej}\ , where\ j = 1, 2, 3, \ldots m \tag{11}$$

4. Discussion on Result

4.1 Data collection

In order to choose survey respondents, this paper used a multistage sampling, which combines simple random and purposive sampling methods. The sample was chosen among urban and semi-urban areas representing digitally active consumers during August 2024 and January 2025. The potential respondents were approached online or via e-commerce and asked to fill a structured questionnaire as defined in Section 2.3. In total, a sample of 909 respondents was collected across both countries. Following data screening (removed the user's response who do the shopping less than 3 time in a month), 684 (Taiwan=301, India=383) valid questionnaires were found and included in the analysis. Other questionnaires were omitted because of the unfinished ones or participants did not satisfy the minimum usage criteria. Such a strict sampling procedure allowed making sure that the data set will capture informed and frequent users of e-commerce platforms and conduct a valid analysis of AISQ expectations and perceptions gaps and trust implications.

Table 3. Demographics of users

Socio-demographics		Taiwan (n=301)	India (n=383)
Gender	Male	178	231
	Female	123	152
Age	Young	132	188
	Middle age	121	143
	Old age	48	52
Marital status	Unmarried	167	221
	Married	134	162
Education	Non-formal	8	19
	Basic	22	41
	UG	152	208
	PG and above	119	115
Employment	Unemployed	54	77
	Employed	247	306
Purpose of shopping	Daily needs	102	141
	Fashion & lifestyle	81	112
	Electronics	55	66
	Others	63	64
Number of times use e-commerce website (in month)	1–2 times	104 (removed)	121 (removed)
	3–5 times	243	284
	More than 5 times	58	99

4.2 Users' perceptions and expectations on AI service quality

Table 4 and Table 5 show the user perceived and expected defuzzied and IVPF values with AISQ item gaps. Each of the attributes of the AISQ was analysed by Sama et al. (2023), so that the necessary improvements can be prioritized according to the needs of the user and efficient distribution of resources. Based on Table 3, a summary of the user's characteristics on AISQ dimensions, most of the male users strongly criticized the current services provided by the e-commerce websites. When the expectation of AISQ is more than the service offered, there will be a gap that is captured by negative scores of the gap. The mean scores for perceived and expected e-commence websites AISQ varied among the 25 AISQ items. For instance, it is observed that, the perception of users on AISQ, the first item is messages and the news are shared on time (AR3), AI solves problems effectively and instantly (AR2), transactions and orders are error-free (R2), system outputs are accurate and dependable (R3), and AI responds promptly to queries and requests (AR1). According to the user's perception of AISQ dimensions in e-commerce websites, the dimensions are arranged as follows AI responsiveness (D1), personalization intelligence (D2), reliability (D3), perceived safety/privacy (D4), and emotional assurance (D5).

Regarding the expectations of users in all the dimensions of the AISQ, the ranking is highest to lowest are reliability (D3), AI responsiveness (D1), perceived safety/privacy (D4), personalization intelligence (D2), and emotional assurance (D5). The users have five high expectations in transactions and orders are error-free (R2), system outputs are accurate and dependable (R3), messages and the news are shared on time (AR3), customer information is secured and safely managed (SP1), and AI responds promptly to queries and requests (AR1).

Table 4. The perceptions and expectations of IVPF

AISQ Dimensions	IVPF Perceptions	IVPF Expectations
AI Responsiveness	[0.6315, 0.7442] [0.0738, 0.1520]	[0.6375, 0.7505] [0.0708, 0.1485]
AR1	[0.5978, 0.7102] [0.0952, 0.1822]	[0.6334, 0.7477] [0.0730, 0.1531]
AR2	[0.5748, 0.6865] [0.1121, 0.2052]	[0.6132, 0.7252] [0.0847, 0.1668]
AR3	[0.5721, 0.6836] [0.1151, 0.2091]	[0.6028, 0.7150] [0.0926, 0.1785]
AR4	[0.5751, 0.6865] [0.1124, 0.2056]	[0.6055, 0.7184] [0.0905, 0.1766]
AR5	[0.5968, 0.7091] [0.0968, 0.1849]	[0.6195, 0.7316] [0.0812, 0.1623]
Personalization Intelligence	[0.6242, 0.7377] [0.0776, 0.1582]	[0.6678, 0.7806] [0.0537, 0.1222]
PI1	[0.5829, 0.6946] [0.1064, 0.1976]	[0.5960, 0.7083] [0.0970, 0.1850]
PI2	[0.5249, 0.6364] [0.1556, 0.2651]	[0.6065, 0.7197] [0.0909, 0.1783]
PI3	[0.5641, 0.6756] [0.1218, 0.2183]	[0.6056, 0.7180] [0.0912, 0.1767]
PI4	[0.5338, 0.6441] [0.1452, 0.2485]	[0.5825, 0.6948] [0.1073, 0.1997]
PI5	[0.5944, 0.7073] [0.0981, 0.1872]	[0.6136, 0.7276] [0.0849, 0.1697]
Reliability	[0.5368, 0.6466] [0.1447, 0.2487]	[0.5847, 0.6966] [0.1065, 0.1983]
R1	[0.5607, 0.6714] [0.1238, 0.2206]	[0.5918, 0.7044] [0.0995, 0.1886]
R2	[0.1556, 0.2651] [0.1130, 0.2081]	[0.0970, 0.1850] [0.0537, 0.1222]
R3	[0.6070, 0.7218] [0.0903, 0.1789]	[0.6423, 0.7570] [0.0674, 0.1450]
R4	[0.5792, 0.6918] [0.1118, 0.2057]	[0.6271, 0.7404] [0.0779, 0.1585]
R5	[0.5234, 0.6331] [0.1565, 0.2640]	[0.5753, 0.6876] [0.1130, 0.2081]
Perceived Safety / Privacy	[0.5601, 0.6710] [0.1244, 0.2218]	[0.6058, 0.7181] [0.0909, 0.1768]
SP1	[0.5845, 0.6962] [0.1034, 0.1921]	[0.6354, 0.7472] [0.0709, 0.1465]
SP2	[0.5902, 0.7020] [0.1005, 0.1890]	[0.6333, 0.7463] [0.0724, 0.1503]
SP3	[0.5689, 0.6815] [0.1175, 0.2142]	[0.5984, 0.7106] [0.0949, 0.1816]
SP4	[0.6055, 0.7177] [0.0909, 0.1759]	[0.6237, 0.7371] [0.0789, 0.1603]
SP5	[0.5536, 0.6653] [0.1309, 0.2322]	[0.5857, 0.6984] [0.1049, 0.1971]
Emotional Assurance	**[0.6301, 0.7114] [0.2346, 0.6001]**	[0.4565, 0.5421] [0.1890, 0.2348]
EA1	[0.1120, 0.2079] [0.1569, 0.2642]	**[0.1291, 0.2286] [0.2346, 0.6301]**
EA2	[0.5107, 0.6200] [0.1680, 0.2785]	[0.5547, 0.6658] [0.1049, 0.1971]
EA3	**[0.5235, 0.6327] [0.6001, 0.7114]**	[0.5780, 0.6909] [0.1294, 0.2267]
EA4	[0.6288, 0.7403] [0.0751, 0.1525]	[0.6286, 0.7411] [0.0752, 0.1537]
EA5	**[0.5530, 0.6627]** [0.1294, 0.2267]	[0.6001, 0.7115] [0.0941, 0.1798]

Table 5. Defuzzified values on perception and expectation gap scores.

AISQ dimensions	Defuzzified perception values	Defuzzified expectation values	Gap values
AI responsiveness	0.5923 [1]	0.6146 [2]	-0.0209 [5]
AR1	0.5829 [5]	0.6270 [5]	-0.0414 [15]
AR2	0.6194 [2]	0.6198 [7]	-0.0003 [25]
AR3	0.6235 [1]	0.6311 [3]	-0.0069 [24]
AR4	0.5563 [11]	0.5924 [13]	-0.0402 [16]
AR5	0.5794 [7]	0.6028 [9]	-0.0241 [22]
Personalization intelligence	0.5536 [3]	0.5890 [4]	-0.0345 [4]
PI1	0.5654 [10]	0.5809 [16]	-0.0156 [23]
PI2	0.5109 [18]	0.5654 [19]	-0.0551 [6]
PI3	0.5819 [6]	0.6086 [8]	-0.0268 [21]
PI4	0.5561 [12]	0.6009 [10]	-0.0448 [12]
PI5	0.5503 [13]	0.5835 [15]	-0.0332 [19]
Reliability	0.5635 [2]	0.6192 [1]	-0.0557 [1]
R1	0.5399 [14]	0.5762 [17]	-0.0363 [17]
R2	0.6151 [3]	0.6685 [1]	-0.0534 [8]
R3	0.5956 [4]	0.6381 [2]	-0.0425 [14]
R4	0.5034 [19]	0.5940 [11]	-0.0906 [1]
R5	0.5561 [12]	0.6009 [10]	-0.0448 [13]
Perceived safety/privacy	0.5450 [4]	0.5928 [3]	-0.0478 [3]
SP1	0.5668 [9]	0.6276 [4]	-0.0608 [2]
SP2	0.5737 [8]	0.6259 [6]	-0.0522 [10]
SP3	0.5503 [13]	0.5835 [15]	-0.0332 [20]
SP4	0.5007 [20]	0.5574 [21]	-0.0567 [5]
SP5	0.5334 [16]	0.5694 [18]	-0.0360 [18]
Emotional assurance	0.5147 [5]	0.5682 [5]	-0.0481 [2]
EA1	0.5005 [21]	0.5611 [20]	-0.0606 [3]
EA2	0.4879 [22]	0.5339 [22]	-0.0460 [11]
EA3	0.5308 [17]	0.5851 [14]	-0.0543 [7]
EA4	0.5395 [15]	0.5925 [12]	-0.0530 [9]
EA5	0.4004 [23]	0.4403 [23]	-0.0599 [4]

The difference between the perceived score and expected score of the users is termed as the gap score. Gap scores should be positive, which means that the users are more satisfied than they thought with the services offered on e-commerce websites; a negative gap score means that the users are not as satisfied as they thought; and a zero-gap score means that the expectations of users are met. According to Table 5, the users seem to be only content with the coherent and predictable role of the AI in platforms and devices (R4) because the gap scores are nearly equal to zero. In terms of AISQ dimensions, which are not satisfied by the users of e-commerce websites from lowest to highest: AI responsiveness (D1), personalization intelligence (D2), perceived safety/privacy (D4), emotional assurance (D5), and reliability (D3), and. Table 5 shows the results of the Defuzzified expected, perception, and gap scores. The top 5 dissatisfied items with the services of e-commerce websites are the AI has a consistent and predictable functionality across platforms and devices (R4), customer information is secured and safely managed (SP1), the interactions between AI produce emotional comfort and develop trust (EA1), AI interactions enhance customer satisfaction and trust (EA5), and the use of personal information is done in a responsible manner (SP4).

5. Discussion on Results

Based on this study's key findings, the negative gap scores for reliability, emotional assurance, perceived safety/privacy, personalization intelligence, and (to a lesser extent) AI responsiveness in the present study suggest that expectations are not being satisfied by AI services used for e-commerce; only cross-platform consistency was found to be at the expected level. This pattern is in line with empirical work showing that the promise of AI in terms of personalization and automation is only converted to satisfaction when cues of quality (uptime, accuracy, timeliness) and trust are present in the system. Experimental and survey research conducted before indicates that chatbots and automated agents enhance convenience but are not very effective in solving complex problems and sustaining interaction except when their responsiveness and error-recovery are high. This study AISQ items based on results reflect the existing literature that speed/accuracy when solving problems, timely notifications, contextual recommendations and ongoing dialogue are critical failure points of AISQ when provider reliability and trust assurances are poor.

This study's results in India and Taiwan are compared, and it suggests that there are complementary policy and market leverages. In Indian market, consumers are rewarding of relevant recommendations and customized experiences, but negative gaps are eminent where personalization is bad or unpredictable, Quach et al., (2022) reported strong returns to better personalization but privacy and infrastructure are cited as binding factors. Thus, the detected discontent with personalization and perceived privacy is in line with the market of India where the pace of growth is high and the expectations are high and not met by some companies in their operations and ethical standards. Ling, H. C. (2025) indicates a fast AI adoption in all industries in Taiwan, but enterprise readiness, governance, and reliability are the most common barriers to AI adoption, users expect predictable and stable AI behavior and definite governance, which is why the score of reliability and emotional assurance is low in absence of these governance/quality indicators. Therefore, both markets converge on identical weak points that you discovered reliability, responsiveness, and trust but the gap profile of India is marked by personalization expectations and privacy sensitivity whereas Taiwan has the gap profile marked by the need to ensure the operational robustness and clarity of governance.

As the findings of the present study show, the four domains that the e-commerce firms should consider revolve around each other and enable them to enhance the quality of AI-based services and user satisfaction in India and Taiwan. It is important to enhance system reliability and error recovery mechanisms as users are particularly dissatisfied with the capabilities of AI to solve problems and maintain communications and companies should implement real-time monitoring, automated fault-diagnosis features, and human fallback mechanisms that enhance the performance of AI during complex queries (Karthikeyan *et al.,* 2026). Enhancing responsiveness especially real-time resolution and timely updates is also of high priority, where event-driven notification, latency optimization, and dynamic load balancing can be used to overcome delays that are exhibited (Rasool *et al.*, 2024). There is also a need to improve the contextual personalization using transparent ethics-regulated data practices, where dissatisfaction with PI1 and PI3 indicates to the expectations of relevant and adaptive recommendations, and constant A/B testing, contextual cues integration, explainable-AI functionalities, and opt-in privacy controls can both enhance the quality of personalization and address perceived privacy concerns. Finally, deficits in emotional assurance can be reduced by embedding emotional assurance through empathetic interaction design, the principles of affective computing, and models of human AI handoff to enhance user comfort with AI interactions (Oshadi Karunanayaka *et al.,* 2024). This study's recommendations will help to overcome the key weaknesses that have been stated in the gap analysis, and it is consistent with the previous research which proves that technical robustness, transparency, responsiveness, and emotional intelligence are core drivers of loyalty and satisfaction in AI-supported e-commerce settings.

5.1 Study's Implications

The theoretical contributions to the current research on the understanding of AISQ in e-commerce are significant as the study has revealed the gap in expectations and perception of the users on different dimensions. The presence of negative service gap recorded in the reliability, responsiveness, personalization, privacy, and emotional assurance areas show that the technical skills are not the only factors that define this user satisfaction but rather a trade-off between the AI capabilities and user expectations is of paramount importance. This result broadens previous studies on AI-based customer experience by confirming that the speed of resolving problems, recommendations based on the context, and constant interaction are the key factors of perceived service quality. Besides, the application of defuzzied gap scores is a methodologically sound strategy to represent the subtle differences in the expected and perceived AI performance to allow researchers and practitioners to determine areas of priority that need to be improved in service delivery. The research therefore adds to the theory by highlighting the fact that AISQ is a multidimensional concept and its influence on satisfaction is mediated by user expectations and context factors, including platform maturity and cultural predisposition to AI.

From a practical and regional perspective, the results can provide feasible advice to e-commerce companies in India and Taiwan, where the digital adoption trends and user anticipations are varied. Users in India are characterized by a high personalization and contextual relevance expectations because of the fast-paced digital markets, although there are worries about data privacy and unreliable infrastructure that increases dissatisfaction with the inability of AI to provide personalized and trustworthy experiences. In Taiwan, users, in turn, are more concerned with the reliability of the system, its operational robustness, and governance transparency due to the developed digital ecosystem in the region and regulatory orientation. Therefore, e-commerce companies will have to become region-specific: in India, personalization through AI should be improved, along with introducing open data-use policies and opt-in privacy features, which will address the key gaps, whereas in Taiwan, the focus should be on the reliability and responsiveness of the system and the transparency of AI management, which would fulfill the user expectations in a more efficient manner. All these lessons are worth noting the idea that the improvement of AISQ is impossible without not only technical optimization but also a special focus on the role of a market-specific digital readiness, cultural norms, and trust expectations which have a direct impact on satisfaction, loyalty, and acceptability of the use of AI-enabled services in the long term.

6. Conclusion

This research aims to determine the AISQ of the e-commerce sites. by juxtaposing the expectations and perceptions of the Indian and Taiwanese user with the objective of achieving the key points on how to increase user satisfaction. It is discovered that the similarity in AI functionality across platforms is the most frequent element that the user is content with, significant variation in reliability, responsiveness, personalization, perceived privacy, and emotional reassurance are noted, and the most unsatisfactory concerns the efficiency of solving the problem, promptness, tailored suggestions, and unlimited contact. The study contributes to theory because it provides a theoretically multidimensional, empirically validated theoretical framework in which AISQ assessment can be conducted and the usefulness of defuzzified gap analysis as a way of expressing nuanced user perceptions. On the part of management, it offers practical suggestions of the intervention based on the region, where technical reliability, empathetic interaction design, open personalization, and guarantee of privacy are the mean of enhancing the level of satisfaction and loyalty. In spite of these contributions, the study has limitations in the form of its cross-sectional design and use of self-reported measures which might limit causal inferences and generalizability. One of the main weaknesses is that the study was based on the use of online recruitment and only included the individuals who made at least three online purchases every month, which possibly skewed the sample towards the digitally fluent users. Thus, this study results can not be extended to less experienced or less digitally engaged groups. Longitudinal studies, experimental confirmation, and research on other cultural and regulatory settings and the integration of AI system logs could be considered in the future to expand on the present research to greater understanding of the dynamics of real-time performance and user behavior in e-commerce settings.

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