Department of Management Faculty of Islamic Economics and Business
Universitas Islam Negeri Walisongo Semarang

email: jdmhi@walisongo.ac.id

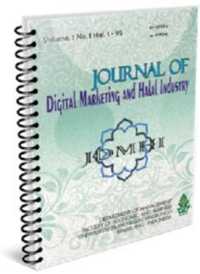
Journal of Digital Marketing and Halal Industry

ISSN: 2716-4810 (print) ISSN: 2716-4802 (online)

Modeling AI-Chatbot Service Quality and Purchase Intention: Mediating Mechanisms and the Moderating Role of Intrusiveness

Muhammad Syarifudin*, Edy Yulianto, Agung Nugroho L.I.F
Universitas Brawijaya, Indonesia

ARTICLE INFO



Article history:
Received 4 January 2025
Accepted 1 June 2025
Published 30 June 2025

Keywords:
AI chatbot, service quality, perceived privacy risk, consumer engagement, S–O–R, purchase intention

ABSTRACT

The rapid integration of AI-powered chatbots in e-commerce has reshaped how digital service quality influences consumer behavior. However, limited studies have examined how chatbot service quality impacts purchase intention through internal psychological mechanisms, particularly under the influence of perceived intrusiveness. This study investigates how AI-chatbot service quality affects consumer purchase intention, mediated by user trust, consumer experience, consumer engagement, and perceived privacy risk, and moderated by perceived intrusiveness. Employing the Stimulus–Organism–Response (S–O–R) framework, this research applies a quantitative explanatory method using a survey of 387 Zalora Indonesia users who have interacted with the platform's AI chatbot. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4. The results show that chatbot service quality significantly enhances user trust, experience, and engagement, while reducing perceived privacy risk. These organism-level variables significantly influence purchase intention: trust, experience, and engagement positively, while privacy risk negatively. Moreover, perceived intrusiveness significantly strengthens the relationship between service quality and consumer experience. The findings offer new insights into the psychological pathways of AI-based service interaction and provide theoretical contributions to the S–O–R framework. Practically, the study guides e-commerce platforms in developing AI-chatbot systems that are not only efficient but also psychologically acceptable to users.

* *Corresponding author. Muhammad.syarifudin@hangtuah.ac.id*
DOI: https://doi.org/10.21580/jdmhi.2024.6.2.27893

Introduction

The integration of Artificial Intelligence (AI) in digital commerce has redefined customer interaction, particularly through AI-powered chatbots that support real-time, personalized service delivery (Adam et al., 2020; Huang & Rust, 2018). These systems are no longer limited to informational functions but increasingly facilitate product recommendation, transactional support, and consumer engagement (Aguirre et al., 2023; Chakraborty et al., 2024).

Indonesia stands as one of the world's fastest-growing e-commerce markets. From 2018 to 2024, e-commerce transaction values surged from IDR 105.6 trillion to a projected IDR 689 trillion (Kontan.co.id., 2022). The country also leads global forecasts in e-commerce revenue growth (30.5%) and is expected to surpass 99 million online consumers by 2029 (DataIndonesia.id., 2024; Statista, 2023). These developments underscore the urgency for local digital platforms to adopt AI technologies that not only scale efficiently but also align with evolving user expectations and psychological comfort.

Zalora Indonesia, a leading B2C fashion e-commerce platform, exemplifies this transformation. Operating with a curated marketplace and inventory-based model unlike conventional open marketplaces Zalora ensures higher product control and more personalized consumer experiences (Vizologi, 2023). Through its TITAN system, developed with OpenAI, the platform integrates intelligent chatbots, visual search, automatic sizing, and augmented reality to streamline the shopping journey (CIO World Asia, 2023; Insideretail Asia, 2023). This makes Zalora a strategically relevant context for examining AI-chatbot service quality and its implications for consumer behavior in Southeast Asia. Moreover, Indonesia's fashion e-commerce sector is experiencing rapid growth, driven by a young demographic, social media dynamics, and increasing demand for personalized shopping. These factors make Zalora not only a major industry player, but also an ideal case for examining how AI-chatbots influence user experience in high-involvement digital environments.

Although the literature supports the idea that AI-chatbot service quality encompassing responsiveness, accuracy, usability, and credibility can influence user perception and behavior (Bleier et al., 2018; Chung et al., 2020), empirical findings remain inconsistent. Most prior studies have focused on isolated pathways, such as trust or engagement, but lack an integrated model that incorporates both mediating and moderating mechanisms (Shahzad et al., 2024; Zhu et al., 2023).

One particularly underexplored factor is perceived intrusivenessthe feeling that chatbot interactions are overly invasive or psychologically disruptive (Chakraborty et al., 2024). While often examined as a dependent outcome, this study reconceptualizes it as a moderator that potentially weakens the relationship between chatbot service quality and consumer experience. This approach reflects a theoretical shift from seeing intrusiveness as merely an effect to a boundary condition that interacts with stimulus-organism mechanisms. To date, no empirical studies have explicitly tested perceived intrusiveness as a moderating variable within the S–O–R framework, particularly in AI-chatbot service settings.

To address this gap, the study adopts the Stimulus–Organism–Response *(S–O–R)* framework (Mehrabian, 1974), which posits that external stimuli trigger internal cognitive-affective processes (organism), which then influence behavioral responses. In this context, AI-chatbot service quality functions as the stimulus, while user trust, consumer experience, engagement, and perceived privacy risk represent organismic evaluations. Purchase intention serves as the behavioral response (Donovan & Rossiter, 1982). Meanwhile, perceived intrusiveness is introduced as a moderating variable that disrupts the stimulus-organism pathway.

Accordingly, this research addresses two core questions: (1) To what extent does AI-chatbot service quality influence purchase intention both directly and indirectly through user trust, consumer experience, consumer engagement, and perceived privacy risk? (2) To what extent does perceived intrusiveness moderate the relationship between service quality and consumer experience?

This study contributes in three key ways. Theoretically, it expands the S–O–R framework by integrating perceived intrusiveness as a novel moderator in AI-based digital environments. Empirically, it proposes and tests a comprehensive model using Partial Least Squares Structural Equation Modeling (SmartPLS 4), based on survey data from 387 Zalora chatbot users in Indonesia. Practically, it offers strategic insights for e-commerce platforms in designing chatbots that balance personalization with psychological comfort.

Literature Review

Theoretical Foundation: From Stimulus–Response to Stimulus–Organism–Response

The theoretical basis of this study is grounded in the development from the classical Stimulus–Response (S–R) model to the more comprehensive Stimulus–Organism–Response (S–O–R) framework. The S–R model, rooted in behaviorist psychology, views human behavior as a direct consequence of external stimuli, where internal cognitive processes are largely disregarded (Holland, 1992; Thorndike, 2017). Although this model has been instrumental in explaining reflexive and habitual behaviors, it fails to account for psychological complexities in decision-making.

To overcome this limitation, Woodworth (1921) introduced the S–O–R framework, which inserts the "Organism" component as the internal mechanism through which stimuli are perceived, processed, and interpreted before producing a behavioral response. Further developed by Mehrabian and Russell (1974), the S–O–R model has become a dominant paradigm in digital consumer behavior, particularly when investigating psychological states such as trust, emotional responses, and cognitive evaluations in technology-mediated environments (Brodie et al., 2011; Donovan & Rossiter, 1982).

In this study, AI-chatbot service quality functions as the external stimulus (S), while the internal organism comprises user trust, consumer experience, consumer engagement, and perceived privacy risk. The response is operationalized as purchase intention. Furthermore, perceived intrusiveness is introduced as a moderating factor that weakens the stimulus–organism relationship, in line with research on digital boundary violations (Lee et al., 2022; Shoukat et al., 2024).

AI-Chatbot Service Quality as a Stimulus

The evolution of service quality theory from Parasuraman et al. (1988) SERVQUAL model to digital and AI-based services has prompted a reevaluation of quality dimensions in automated systems. Traditional service quality dimensions such as tangibles, reliability, and empathy have been adapted into constructs more appropriate for non-human interaction, such as responsiveness, informativeness, usability, and personalization (Shahzad et al., 2024; Wirtz et al., 2018).

In the context of AI-chatbots, service quality is defined as users' perception of the system's ability to deliver fast, accurate, and relevant responses through natural language interfaces (Ciechanowski et al., 2019; Huang & Rust, 2018). Key factors such as system reliability, response time, interface design, and degree of personalization influence users' judgments regarding service quality. When users perceive the chatbot as helpful, efficient, and capable of adapting to their needs, they are more likely to develop trust, experience positive interactions, and feel engaged with the system (Cheng et al., 2022; Chen et al., 2022).

In this study, AI-chatbot service quality acts as the primary external stimulus in the S–O–R framework. It not only initiates a chain of psychological processing through user trust, consumer experience, consumer engagement, and perceived privacy risk but also exerts a direct influence on behavioral response, namely purchase intention. This dual-path model reflects both mediated and unmediated mechanisms through which service quality affects consumer behavior in AI-driven digital environments.

H1: AI-chatbot service quality has a positive and significant effect on purchase intention.

H2: AI-chatbot service quality has a positive and significant effect on user trust.

H3: AI-chatbot service quality has a positive and significant effect on consumer experience.

H4: AI-chatbot service quality has a positive and significant effect on consumer engagement.

H5: AI-chatbot service quality has a negative and significant effect on perceived privacy risk.

User Trust

User trust is a key psychological factor in digital service interactions. It refers to the consumer's belief that the chatbot is competent, honest, and has good intentions during service delivery (Mayer et al., 1995). In the context of AI-chatbots, trust emerges when users feel confident that the system can perform its functions reliably and securely.

Service quality is one of the most important drivers of trust formation. When users perceive that the chatbot delivers fast and relevant responses, provides consistent communication, and understands their needs, they are more likely to consider it trustworthy (Li et al., 2021; Zhu et al., 2023). Additional design aspects, such as empathetic tone or conversational intelligence, also contribute to building relational trust (Nguyen et al., 2021).

According to the Stimulus–Organism–Response (S–O–R) framework, user trust functions as an "organism" variable that mediates the relationship between external stimuli and behavioral responses. In this study, chatbot service quality is considered the stimulus, and user trust is one of the internal evaluations that leads to purchase intention.

H6: AI-chatbot service quality has a positive and significant effect on user trust.

Consumer Experience

Consumer experience is defined as the internal and subjective response consumers have when interacting with a digital platform, including emotional, cognitive, and sensory evaluations (Brakus et al., 2009; Schmitt, 1999). In AI-mediated environments, consumer experience extends beyond transactional efficiency to include feelings of personalization, enjoyment, and control over the interaction.

AI-chatbots, as service agents, can influence experience through their ability to simulate human-like dialogue, offer timely responses, and provide personalized recommendations (Chakraborty et al., 2024). A seamless and intelligent interaction can generate a sense of satisfaction, engagement, and comfort, contributing positively to overall user experience (Gnewuch et al., 2017). Conversely, poorly designed chatbots those that fail to understand queries or deliver irrelevant content may frustrate users and degrade their experience (Selem et al., 2024).

In the S–O–R model, consumer experience represents a core "organism" variable through which external stimuli such as chatbot service quality are cognitively processed before resulting in behavioral responses. When consumers perceive the interaction with chatbots as smooth, effective, and enjoyable, they are more likely to develop favorable attitudes that translate into purchase intention.

Prior studies support this linkage. For instance, Huang and Rust (2018) argue that AI interfaces that enhance user experience also increase consumers' willingness to transact. Similarly, Wirtz et al. (2018) show that high-quality chatbot interactions significantly boost perceived experience and behavioral loyalty.

H7: AI-chatbot service quality has a positive and significant effect on consumer experience.

Consumer Engagement

Consumer engagement reflects the degree of a consumer's emotional, cognitive, and behavioral investment in a brand or digital platform (Brodie et al., 2011). In the context of AI-chatbot interaction, engagement manifests through active participation, attentiveness, and a willingness to continue the interaction with the system.

Engagement is often triggered by stimulating, personalized, and context-aware interactions. Chatbots that understand consumer intent, respond meaningfully, and provide value-added services can generate a sense of involvement and enjoyment (Cheng et al., 2022). This engagement is not only functional but also affective consumers feel connected and valued, increasing their loyalty to the platform (Vohra & Bhardwaj, 2019).

Within the S–O–R framework, engagement is classified as part of the "organism" response a mediating psychological state influenced by external stimuli such as chatbot service quality. When chatbot interactions are perceived as helpful and human-like, they foster greater psychological immersion, which is instrumental in shaping downstream behavioral intentions.

Empirical evidence supports this relationship. (Chen et al., 2022) demonstrated that chatbot responsiveness and adaptiveness significantly enhance user engagement. Likewise, Gnewuch et al. (2017) found that perceived quality and richness of chatbot communication positively affect consumer involvement, which subsequently influences loyalty and intention.

H8: AI-chatbot service quality has a positive and significant effect on consumer engagement.

Perceived Privacy Risk

Perceived privacy risk refers to the consumer's subjective concern over the potential misuse, unauthorized access, or unintended exposure of personal data during digital interactions (Pavlou, 2003). In AI-driven service environments such as chatbots, privacy concerns arise due to the automated and opaque nature of data collection, personalization algorithms, and real-time tracking.

As chatbots increasingly utilize consumer data to offer personalized recommendations, users may perceive a trade-off between convenience and control (M. Song et al., 2022). While adaptive interactions may enhance relevance, they can also trigger discomfort if users feel their personal boundaries are being violated (Kronemann et al., 2023). This perception of intrusiveness often elevates the perceived risk, especially when users are uncertain about how their data is stored, processed, or shared.

From the S–O–R perspective, perceived privacy risk is positioned within the "organism" layer, as it represents an internal psychological evaluation triggered by external stimuli namely, the way chatbot services are delivered. High service quality, particularly in terms of transparency, credibility, and user control, may help reduce perceived risk and improve consumers' trust and willingness to engage

https://doi.org/10.21580/jdmhi.2024.6.2.27893

(Bleier et al., 2018; Selem et al., 2024).

Empirical studies reinforce this negative link. Kim et al. (2008) found that strong privacy concerns significantly undermine digital trust and behavioral intention. Likewise, (Kronemann et al., 2023) reported that perceived privacy risk mediates the effect of personalization on customer retention and satisfaction.

H9: AI-chatbot service quality has a negative and significant effect on perceived privacy risk.

Perceived Intrusiveness

Perceived intrusiveness refers to the user's feeling that a system is overly invasive, disruptive, or violates personal space, particularly when digital content is highly personalized or automated (Lee et al., 2022; van Doorn & Hoekstra, 2013). In the context of AI-chatbots, this perception arises when interactions feel overly pushy, contextually inappropriate, or excessively frequent regardless of their technical quality.

Although personalization is often associated with enhanced relevance and satisfaction, highly personalized AI responses can backfire if users perceive them as violating privacy norms or autonomy. According to psychological reactance theory, consumers may resist perceived attempts to control or manipulate their choices, especially when such influence is not explicitly consented to (Miron & Brehm, 2006).

Within the S–O–R framework, perceived intrusiveness operates not as a direct organismic state, but as a moderator that shapes the strength of the stimulus–organism linkage. Specifically, it may attenuate the positive impact of chatbot service quality on consumer experience. In such cases, even a technically proficient chatbot may fail to deliver positive experiences if users feel overwhelmed or psychologically threatened by the interaction style.

Despite growing attention to personalization and privacy, very few studies have empirically tested intrusiveness as a moderating variable in AI-chatbot contexts. This research addresses that gap by evaluating whether perceived intrusiveness weakens the relationship between perceived service quality and consumer experience an area still underexplored in digital service literature (Chakraborty et al., 2024; Van den Broeck et al., 2019).

H10: Perceived intrusiveness negatively moderates the relationship between AI-chatbot service quality and consumer experience.

Purchase Intention

Purchase intention refers to a consumer's conscious plan or willingness to buy a product or service in the near future (Ajzen, 1991). In digital contexts, it is often shaped by the consumer's psychological responses to platform interactions, including perceived trust, experience, engagement, and privacy concerns (Bleier et al., 2018).

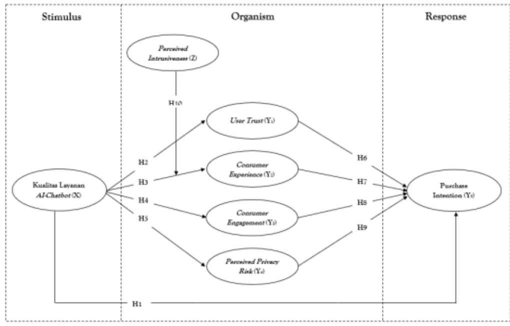
As the ultimate behavioral outcome in the Stimulus–Organism–Response (S–O–R) framework, purchase intention represents the "response" component. It emerges from consumers' internal evaluation of their interactions with AI-chatbots, which are shaped by both cognitive (e.g., trust, perceived risk) and affective (e.g., experience, engagement) processes.

High levels of user trust increase consumers' confidence in the platform's reliability, reducing hesitation to proceed with a purchase (Khan et al., 2024). Similarly, a positive consumer experience marked by smooth, helpful, and pleasant interaction increases the likelihood that users will convert intention into action (Huang & Rust, 2020). Engaged consumers also tend to develop emotional attachment to the brand, which strengthens their purchase motivation (S. W. Song & Shin, 2024).

On the contrary, perceived privacy risk may inhibit purchase intention by triggering fear, uncertainty, and reduced confidence in the platform (M. Song et al., 2022). Therefore, while high service quality is necessary, it must be coupled with strategies to mitigate perceived intrusiveness and privacy concerns to fully influence consumer behavior.

Thus, purchase intention in this study is not treated as a direct consequence of the chatbot stimulus alone, but rather as a downstream result of multiple psychological mechanisms within the organism layer. To illustrate the theoretical foundation and proposed causal pathways, Figure 1 presents the conceptual model developed in this study.

Figure 1.
Proposed Research Framework Based on the Stimulus–Organism–Response (S–O–R) Model



Method, Data, and Analysis

This research adopts a quantitative explanatory approach using the Partial Least Squares–Structural Equation Modeling (PLS-SEM) method to examine the causal relationships among constructs in the Stimulus–Organism–Response (S–O–R) framework. Primary data were collected through a structured online questionnaire targeting users of Zalora Indonesia's AI-chatbot services within the last six months. The sampling technique employed was purposive sampling, appropriate due to the unknown population size and the specific inclusion criteria: respondents aged 18 years or older, residing in Indonesia, and having interacted with Zalora's chatbot.

To determine the minimum sample size, the Lemeshow et al. (1997) formula was used with a 95% confidence level and 5% margin of error, resulting in a required sample of at least 385 respondents. This meets the adequacy standard for SEM analysis (Hair et al., 2022). A pilot test involving 30 participants was conducted prior to the main survey to test the validity and reliability of the instrument. Construct validity was confirmed using item-total Pearson correlations ($r \geq 0.30$), and reliability was assessed via Cronbach's Alpha, with all constructs exceeding the 0.70 threshold except perceived privacy risk (0.615) and consumer experience (0.647), which are still acceptable for exploratory studies (Hair et al., 2022).

This study used reflective constructs adapted from established scales: AI-chatbot service quality (Shahzad et al., 2024; Zhang et al., 2022), user trust (Rajaobelina et al., 2021), consumer experience (Shahzad et al., 2024), consumer engagement (Jiang et al., 2022), perceived privacy risk (Dinev & Hart, 2006; Song et al., 2022), perceived intrusiveness (Lee et al., 2022; Youn & Kim, 2019), and purchase intention (Godey et al., 2016; Jiang et al., 2022). All items were rated using a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

The analysis process utilized SmartPLS 4 to estimate both the measurement model and structural model. Measurement model evaluation involved testing convergent validity through outer loadings (> 0.70), Average Variance Extracted (AVE ≥ 0.50), and composite reliability (CR ≥ 0.70). Discriminant validity was confirmed through the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratio, with values ≤ 0.85 considered acceptable. Structural model assessment used R^2 values to assess explanatory power (≥ 0.75 = substantial; 0.50–0.74 = moderate; 0.25–0.49 = weak), Q^2 values to confirm predictive relevance ($Q^2 > 0$), and f^2 to determine effect sizes (0.02 = small, 0.15 = medium, 0.35 = large).

Hypothesis testing was conducted using bootstrapping with 5,000 resamples. Path coefficients were deemed statistically significant if t-values ≥ 1.96 or p-values ≤ 0.05. Mediation effects were examined via bootstrapped indirect effects, classified as full or partial based on the significance of direct and indirect relationships. Moderation analysis tested the interaction term between AI-chatbot service quality and perceived intrusiveness to identify any weakening effect in the path from service quality to consumer experience.

This methodical and comprehensive procedure enabled empirical validation of the theoretical model and rigorous testing of causal pathways relevant to digital consumer behavior in AI-driven e-commerce environments.

Result and Discussion

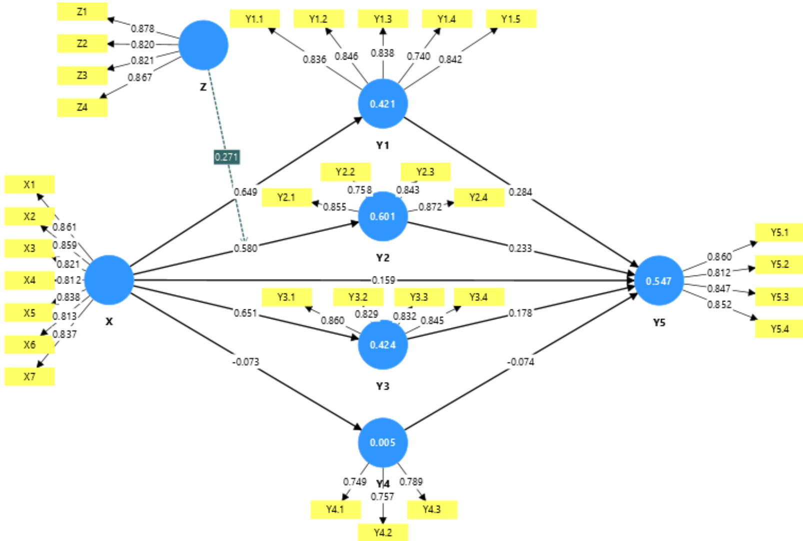
Outer Model Evaluation (Measurement Model)

This study employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to evaluate the measurement model, which includes the assessment of indicator reliability, internal consistency, convergent validity, discriminant validity, and multicollinearity. The evaluation was based on the guidelines recommended by Hair et al. (2022) for reflective constructs.

Before assessing the measurement quality in detail, the following figure illustrates the overall measurement and structural model developed in this study.

Figure 2.

Reflective Measurement and Structural Model



As shown in Figure 1, each construct is measured by multiple indicators with loading values that exceed the recommended threshold of 0.70. This visual representation serves as the basis for subsequent analysis of indicator reliability, convergent validity, discriminant validity, and multicollinearity diagnostics, as described in the following subsections.

The validity and reliability of the measurement model were assessed to evaluate the outer model in the PLS-SEM framework. This evaluation includes tests for convergent validity, discriminant validity, and construct reliability. Convergent validity is achieved when the outer loading of each indicator exceeds 0.70 and the Average Variance Extracted (AVE) value is greater than 0.50. All indicators in the model demonstrated adequate loading values, indicating strong convergence with their respective latent constructs. The outer loading values of each indicator are presented in Table 1.

Table 1.

Outer Loading

Variables	Code	Outer Loadings	Significance (>0.70)
AI-Chatbot Service Quality	X_1	0.799	VALID
	X_2	0.813	VALID
	X_3	0.794	VALID
	X_4	0.788	VALID
	X_5	0.774	VALID
	X_6	0.732	VALID
	X_7	0.743	VALID
User Trust	$Y_{1.1}$	0.826	VALID
	$Y_{1.2}$	0.870	VALID
	$Y_{1.3}$	0.866	VALID
	$Y_{1.4}$	0.819	VALID

	$Y_{1.5}$	0.812	VALID
Consumer Experience	$Y_{2.1}$	0.865	VALID
	$Y_{2.2}$	0.856	VALID
	$Y_{2.3}$	0.793	VALID
	$Y_{2.4}$	0.843	VALID
Consumer Engagement	$Y_{3.1}$	0.850	VALID
	$Y_{3.2}$	0.832	VALID
	$Y_{3.3}$	0.867	VALID
	$Y_{3.4}$	0.817	VALID
Perceived Privacy Risk	$Y_{4.1}$	0.758	VALID
	$Y_{4.2}$	0.792	VALID
	$Y_{4.3}$	0.774	VALID
Perceived Intrusiveness	Z_1	0.839	VALID
	Z_2	0.877	VALID
	Z_3	0.831	VALID
	Z_4	0.844	VALID
Purchase Intention	$Y_{5.1}$	0.855	VALID
	$Y_{5.2}$	0.825	VALID
	$Y_{5.3}$	0.867	VALID
	$Y_{5.4}$	0.817	VALID

Source: Processed data, 2025

As presented in Table 1, all outer loading values exceed the recommended threshold of 0.70 (Hair et al., 2022), indicating that each indicator demonstrates sufficient individual reliability in reflecting its respective latent construct. Since no indicator falls below the minimum criterion, none were removed from the model. These results confirm that the indicators are strongly associated with the constructs they are intended to measure, providing solid evidence of item-level validity.

Validity Test Results

Convergent validity refers to the extent to which indicators within a construct are highly correlated, thereby consistently representing the underlying latent variable. In the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), convergent validity is typically assessed through the Average Variance Extracted (AVE).

According to Hair et al. (2022), an AVE value of 0.50 or higher indicates that a latent construct explains at least 50% of the variance in its associated indicators, thereby confirming adequate convergent validity. Higher AVE values suggest stronger internal consistency among indicators. The AVE values for all constructs in this study are summarized in Table 2.

Table 2.
Average Variance Extracted (AVE) for Each Construct

Code	Construct	AVE
X	AI-Chatbot Service Quality	0.697
Y_1	User Trust	0.675
Y_2	Consumer Experience	0.694
Y_3	Consumer Engagement	0.708
Y_4	Perceived Privacy Risk	0.586
Z	Perceived Intrusiveness	0.717
Y_5	Purchase Intention	0.710

Source: Processed data, 2025

As shown in Table 2, all constructs exhibit AVE values exceeding the recommended threshold of 0.50, indicating that each latent construct is able to explain more than half of the variance in its observed indicators. These findings confirm that the model achieves satisfactory convergent validity across all constructs. This provides a strong basis for continuing to assess other aspects of the measurement model, including construct reliability and discriminant validity.

Construct Reliability

Construct reliability refers to the degree of internal consistency among indicators within a latent variable. In Partial Least Squares Structural Equation Modeling (PLS-SEM), construct reliability is commonly evaluated using three metrics: Cronbach's Alpha, Composite Reliability (CR), and rho_A (Hair et al., 2022).

Cronbach's Alpha assesses internal consistency by assuming equal indicator weights, with values above 0.70 generally considered acceptable. However, values between 0.60 and 0.70 may still be deemed sufficient in exploratory studies. Composite Reliability (CR), regarded as a more accurate estimate of reliability than Cronbach's Alpha, accounts for actual indicator loadings and requires a minimum value of 0.70 to indicate good internal consistency. Likewise, the rho_A coefficient serves as a complementary reliability index, with an ideal threshold of ≥ 0.70. Table 3 presents the results of construct reliability testing across all latent variables in the model.

Table 3.

Cronbach's Alpha, Composite Reliability, and rho_A Values

Code	Construct	Cronbach's Alpha	Composite Reliability	rho_A
X	AI-Chatbot Service Quality	0.927	0.941	0.928
Y_1	User Trust	0.879	0.912	0.882
Y_2	Consumer Experience	0.852	0.900	0.858
Y_3	Consumer Engagement	0.863	0.907	0.864
Y_4	Perceived Privacy Risk	0.652	0.809	0.658
Z	Perceived Intrusiveness	0.869	0.910	0.886
Y_5	Purchase Intention	0.864	0.907	0.864

Source: Processed data, 2025

As shown in Table 3, all constructs demonstrate Composite Reliability and rho_A values above the 0.70 threshold, indicating satisfactory internal consistency. Although the Cronbach's Alpha value for Perceived Privacy Risk (Y_4) is 0.652 slightly below the conventional threshold it remains acceptable due to the limited number of indicators (three items), and is further supported by strong CR and AVE values. These findings affirm that all constructs are reliable and suitable for subsequent structural model evaluation.

Discriminant Validity: Fornell–Larcker Criterion

Discriminant validity assesses the extent to which a latent construct is truly distinct from other constructs in the model. One of the most widely accepted methods for assessing discriminant validity in reflective measurement models is the Fornell–Larcker criterion (Fornell & Larcker, 1981). This approach compares the square root of the Average Variance Extracted (AVE) of each construct with its correlations with other constructs. Discriminant validity is considered to be established if the square root of a construct's AVE is greater than its correlations with any other construct. Table 4 presents the results of the Fornell–Larcker test. The diagonal elements (in bold) represent the square root of the AVE for each construct.

Table 4.

Fornell–Larcker Discriminant Validity

Construct	X	Y_1	Y_2	Y_3	Y_4	Y_5	Z
X	0.835						
Y_1	0.649	0.821					
Y_2	0.614	0.629	0.833				
Y_3	0.651	0.641	0.654	0.841			
Y_4	-0.073	-0.039	-0.040	-0.053	0.765		
Y_5	0.608	0.651	0.629	0.620	-0.115	0.843	
Z	-0.237	-0.291	-0.308	-0.275	-0.483	-0.407	0.847

Source: Processed data, 2025

As shown in Table 4, the diagonal elements (square roots of AVE) are consistently higher than the off-diagonal correlation values between constructs. For instance, the square root of AVE for Purchase Intention (Y5) is 0.843, which exceeds its correlations with AI-Chatbot Service Quality (0.608), User Trust (0.651), Consumer Experience (0.629), Consumer Engagement (0.620), Perceived Privacy Risk (–0.115), and Perceived Intrusiveness (–0.407). A similar pattern is observed for all other constructs, including AI-Chatbot Service Quality (X = 0.835), Consumer Experience (Y_2 = 0.833), and Perceived Intrusiveness (Z = 0.847).

While some correlations between constructs are negative, this does not violate discriminant validity as long as the square root of AVE remains greater than those inter-construct correlations. These findings confirm that each construct in the model is empirically distinct and conceptually unique. Hence, the Fornell–Larcker criterion for discriminant validity is satisfactorily met in this study.

Discriminant Validity: Heterotrait–Monotrait Ratio (HTMT)

To complement the Fornell–Larcker analysis, this study also employs the Heterotrait–Monotrait Ratio of Correlations (HTMT) as a more sensitive measure of discriminant validity in reflective measurement models. As recommended by (Henseler et al., 2015) and Hair et al. (2022), HTMT is calculated as the ratio of the average heterotrait–heteromethod correlations to the average monotrait–heteromethod correlations. Values approaching or exceeding the threshold suggest a lack of discriminant validity between constructs.

A conservative threshold of 0.85 is used in this study, in line with recommendations for confirmatory research. As shown in Table 5, all HTMT values fall below this threshold. The highest value observed is 0.760, between Consumer Engagement and

Consumer Experience, which remains within acceptable limits.

Table 5.

Heterotrait–Monotrait Ratio (HTMT) of Correlations

Construct	X	Y1	Y2	Y3	Y4	Y5
Y1	0.718					
Y2	0.690	0.725				
Y3	0.725	0.734	0.760			
Y4	0.094	0.079	0.071	0.068		
Y5	0.678	0.746	0.731	0.716	0.151	
Z	0.263	0.334	0.353	0.315	0.646	0.469

Source: Processed data, 2025

As shown in Table 5, all HTMT values are below the conservative threshold of 0.85, with the highest value being 0.760. This confirms that all latent constructs in the model are empirically distinct from one another. The results also reinforce the discriminant validity previously established through the Fornell–Larcker criterion, indicating that the measurement model is conceptually sound and free from multicollinearity concerns.

Structural Model Evaluation (Inner Model)

The evaluation of the structural model (inner model) aims to assess the predictive power and causal relationships among latent constructs within the conceptual framework. Following the PLS-SEM approach, this evaluation includes the assessment of multicollinearity, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), direct path significance (path coefficients), as well as mediation and moderation testing (Hair et al., 2022). The results of the structural model assessment are presented in the following sub-sections.

Multicollinearity Test

Multicollinearity analysis was conducted to ensure that no significant linear relationships exist among predictor constructs in the structural model, which could distort the estimation of path coefficients and bias causal interpretations. In the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), multicollinearity is assessed using the Variance Inflation Factor (VIF) values, computed for each path within the inner model (Hair et al., 2022).

According to Hair et al. (2022), VIF values below 5.0 are generally acceptable, although a more conservative threshold of 3.3 is recommended for confirmatory research. VIF values exceeding these thresholds may indicate redundancy or overlap in explanatory power, which can compromise the validity of parameter estimates. Table 6 summarizes the VIF values for all predictor constructs in the structural model.

Table 6.

VIF Values in the Inner Model

Construct (Endogenous Variable)	VIF Value
Consumer Experience	1.060

Consumer Engagement	1.000
User Trust	1.000
Perceived Privacy Risk	1.000
Purchase Intention	2.270
Moderation Term (X × Z)	1.089

Source: Processed data, 2025

As shown in Table 6, all VIF values range from 1.000 to 2.270, well below the conservative threshold of 3.3. For instance, the highest VIF value is observed for Consumer Engagement (Y_3) predicting Purchase Intention (Y_5) at 2.270, which is still within acceptable limits. Similarly, the VIF for AI-Chatbot Service Quality (X) in predicting the interaction construct Z × X is only 1.089, indicating minimal redundancy.

These findings confirm that the structural model is free from problematic multicollinearity. Each predictor construct contributes unique and non-overlapping information, supporting the stability and validity of the estimated regression parameters. Therefore, the model is statistically appropriate for subsequent evaluation of causal relationships among constructs.

Coefficient of Determination (R^2)

The coefficient of determination (R-square or R^2) is one of the most fundamental indicators in assessing the predictive accuracy of the structural model within the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. R^2 measures the extent to which the variance in an endogenous construct is explained by one or more exogenous constructs linked to it. Thus, higher R^2 values indicate greater explanatory power of the model in capturing the behavior of the dependent variable (Hair et al., 2022).

Chin (1998) and Hair et al. (2022), R^2 values are commonly interpreted using three thresholds: values around 0.75 are considered substantial, around 0.50 are moderate, and around 0.25 are weak. Nevertheless, in social science and digital behavior research—where latent variables are influenced by complex, interrelated psychological and technological factors R^2 values above 0.20 are still deemed acceptable, especially when theoretically grounded. The R^2 results for this study are summarized in Table 7.

Table 7.
R-Square and Adjusted R-Square Values for Endogenous Constructs

Endogenous Construct	R-Square	Adjusted R-Square
User Trust (Y_1)	0.427	0.425
Consumer Experience (Y_2)	0.462	0.460
Consumer Engagement (Y_3)	0.562	0.560
Perceived Privacy Risk (Y_4)	0.255	0.253
Purchase Intention (Y_5)	0.676	0.673

Source: Processed data, 2025

As shown in Table 7, the construct with the highest R^2 value is Purchase Intention (Y_5) at 0.676, meaning that 67.6% of the variance in users' intention to purchase is explained by the predictive variables Consumer Experience, Consumer Engagement, and Perceived Privacy Risk. This suggests a strong explanatory power and supports the robustness of the model in predicting actual consumer behavior.

Consumer Engagement (Y_3) follows with an R^2 of 0.562, falling into the moderate-to-substantial category, indicating that users' engagement with the AI-chatbot is significantly influenced by prior interactions, particularly from their experience with the chatbot service. The constructs Consumer Experience (Y_2) and User Trust (Y_1) also show moderate R^2 values of 0.462 and 0.427, respectively, demonstrating that the perceived service quality of AI-chatbot substantially shapes both trust and experiential aspects of the user.

In contrast, Perceived Privacy Risk (Y_4) records an R^2 of 0.255, which, although categorized as weak, is still acceptable within the behavioral domain, particularly considering the complexity and externality of data privacy perceptions in digital platforms.

In summary, the R^2 values indicate that the proposed model has strong explanatory power for the core outcome Purchase Intention while also showing reliable performance across intermediate psychological constructs such as trust, experience, and engagement. These results validate the suitability of the Stimulus–Organism–Response (S–O–R) theoretical framework in explaining how AI-chatbot service quality impacts downstream consumer behaviors through internal psychological processes.

Effect Size (f^2)

Effect size (f^2) is a complementary indicator to R-square, used to assess the relative contribution of each exogenous construct in explaining the variance of an endogenous variable. While R^2 measures the overall explanatory power of the model, f^2 evaluates the individual impact of removing a specific predictor from the model. This allows researchers to understand which paths play the most crucial roles in shaping the outcome variables (Hair et al., 2022).

The guidelines for interpreting f^2 values were initially proposed by Cohen (1988) and later adapted for PLS-SEM by Hair et al. (2022). They are as follows: 0.02 = small effect, 0.15 = medium effect, 0.35 = large effect, while values below 0.02 are typically considered negligible and may be disregarded unless supported by theoretical importance. The effect size results for each predictive path in the structural model are presented in Table 8.

Table 8.

Effect Size (f^2) for Each Structural Path

Predictive Path	f^2	Interpretation
$X \rightarrow Y_1$ (User Trust)	0.726	Large
$X \rightarrow Y_2$ (Consumer Experience)	0.797	Large
$X \rightarrow Y_3$ (Consumer Engagement)	0.737	Large
$X \rightarrow Y_4$ (Perceived Privacy Risk)	0.005	Negligible
$X \rightarrow Y_5$ (Purchase Intention)	0.026	Small
$Y_1 \rightarrow Y_5$	0.082	Small
$Y_2 \rightarrow Y_5$	0.057	Small
$Y_3 \rightarrow Y_5$	0.031	Small
$Y_4 \rightarrow Y_5$	0.012	Negligible
$Z \rightarrow Y_2$	0.003	Negligible
$Z \times X \rightarrow Y_2$ (Interaction)	0.492	Large

Source: Processed data, 2025

https://doi.org/10.21580/jdmhi.2024.6.2.27893

As shown in Table 8, the construct AI-Chatbot Service Quality (X) exhibits large effect sizes on three endogenous constructs: User Trust (f^2 = 0.726), Consumer Experience (f^2 = 0.797), and Consumer Engagement (f^2 = 0.737). These results affirm that X plays a dominant role in shaping users' internal psychological responses (Organism), aligning strongly with the S–O–R theoretical foundation of this study.

The path from X to Purchase Intention (Y_5) shows a small but positive effect size (f^2 = 0.026), suggesting a direct but limited impact. Notably, this path is further complemented by the mediating roles of psychological constructs like trust and experience, as discussed in subsequent sections.

In contrast, the X → Y_4 (Perceived Privacy Risk) and Z → Y2 paths both exhibit negligible effect sizes, indicating that service quality and perceived intrusiveness alone do not have substantial individual impacts on users' risk perceptions or experiential evaluations, respectively.

The moderation effect (Z × X → Y_2) stands out with a large effect size (f^2 = 0.492), signifying that the interaction between service quality and perceived intrusiveness contributes strongly to shaping the consumer experience. This suggests that in certain contexts, perceived intrusiveness may intensify or alter the effect of chatbot service quality in a meaningful way.

In summary, the f^2 analysis highlights that while some direct paths carry minor or negligible contributions, the core pathways particularly those from service quality to trust, experience, and engagement, as well as the moderation interaction demonstrate substantial explanatory power. These findings underscore the central role of AI-chatbot quality as a technological stimulus and justify the inclusion of psychological and behavioral constructs as mediators and moderators within the model framework.

Predictive Relevance (Q^2)

To evaluate the predictive relevance of the structural model, this study employed the cross-validated redundancy approach (Q^2) using the blindfolding procedure in SmartPLS. As recommended by Hair et al. (2022), a Q^2 value greater than 0 indicates that the model has predictive relevance for a particular endogenous construct, whereas a Q^2 value less than or equal to zero suggests a lack of predictive capability. This test is especially important to verify whether the model can not only explain variance (as shown by R^2) but also accurately predict data points that were not used during estimation. The Q^2 values obtained for each endogenous construct are summarized in Table 9 below:

Table 9.
Predictive Relevance (Q^2) of Endogenous Constructs

Endogenous Construct	Q^2 Value
User Trust (Y_1)	0.404
Consumer Experience (Y_2)	0.581
Consumer Engagement (Y_3)	0.407
Perceived Privacy Risk (Y_4)	-0.001
Purchase Intention (Y_5)	0.436

Source: Processed data, 2025

As shown in Table 9, four of the five endogenous constructs exhibit Q^2 values well above zero, thereby confirming adequate predictive relevance. In particular, Consumer Experience (Y_2) demonstrates the highest Q^2 value of 0.581, indicating that the model is particularly effective in predicting this construct. Similarly, User Trust (Y_1) (Q^2 = 0.404), Consumer Engagement (Y_3) (Q^2 = 0.407), and Purchase Intention (Y_5) (Q^2 = 0.436) also demonstrate moderate to strong predictive capability.

On the other hand, Perceived Privacy Risk (Y_4) records a Q^2 value of −0.001, suggesting that the model lacks predictive relevance for this construct. This may be due to the complexity and context-specific nature of privacy perceptions, which are potentially influenced by unobserved variables beyond the scope of this model.

Despite this exception, the overall results support the predictive strength of the structural model, particularly with regard to constructs that play a key role in driving consumer behavioral outcomes. The high Q^2 value for Purchase Intention further reinforces the model's applicability in capturing users' decision-making tendencies in AI-chatbot service contexts.

Path Coefficient Analysis

The assessment of path coefficients in the structural model provides insight into the significance and strength of direct relationships between latent variables. In this study, path significance was tested using the bootstrapping procedure with 5,000 resamples via SmartPLS. Each path was evaluated based on the standardized beta coefficient (β), t-statistic, and p-value, with a significance level of 5% ($p < 0.05$) as the benchmark for statistical significance (Hair et al., 2022). The summary of path coefficients for all direct hypotheses is presented in Table 10 below:

Table 10.
Path Coefficient Results (Direct Effects)

Path	β Coefficient	t-Statistic	p-Value	Conclusion
AI-Chatbot Service Quality → Purchase Intention	0.159	2.033	0.042	Significant
AI-Chatbot Service Quality → User Trust	0.649	9.015	0.000	Significant
AI-Chatbot Service Quality → Consumer Experience	0.580	12.322	0.000	Significant
AI-Chatbot Service Quality → Consumer Engagement	0.651	9.446	0.000	Significant
AI-Chatbot Service Quality → Perceived Privacy Risk	-0.073	1.235	0.217	Not Significant
User Trust → Purchase Intention	0.284	3.228	0.001	Significant
Consumer Experience → Purchase Intention	0.233	2.897	0.004	Significant
Consumer Engagement → Purchase Intention	0.178	2.210	0.027	Significant
Perceived Privacy Risk → Purchase Intention	-0.074	1.159	0.246	Not Significant
Perceived Intrusiveness → Consumer Experience	-0.039	0.607	0.544	Not Significant

Interaction (AI-Chatbot Service Quality × Perceived Intrusiveness) → Consumer Experience	0.271	9.514	0.000	Significant

Source: Processed data, 2025

The results presented in Table 10 indicate that the direct effects of AI-Chatbot Service Quality are largely significant across most psychological and behavioral constructs. Specifically, this variable exerts a strong positive influence on User Trust ($\beta = 0.649$; $t = 9.015$; $p = 0.000$), Consumer Experience ($\beta = 0.580$; $t = 12.322$; $p = 0.000$), and Consumer Engagement ($\beta = 0.651$; $t = 9.446$; $p = 0.000$), with all p-values below the 0.05 threshold, suggesting that perceived service quality plays a pivotal role in shaping both cognitive and affective consumer responses. These findings confirm the stimulus–organism mechanism within the S–O–R framework, whereby responsive and credible chatbot interactions stimulate favorable internal evaluations.

Furthermore, AI-Chatbot Service Quality also shows a statistically significant direct effect on Purchase Intention ($\beta = 0.159$; $t = 2.033$; $p = 0.042$), although the strength of this relationship is relatively lower compared to its effect on organismic variables. This implies that while consumers may be directly persuaded to purchase through perceived chatbot quality, the influence may be amplified when mediated by trust, experience, or engagement.

However, not all direct relationships were found to be statistically significant. The influence of AI-Chatbot Service Quality on Perceived Privacy Risk yielded a p-value of 0.217 ($\beta = -0.073$; $t = 1.235$), indicating an insignificant path. This suggests that even though users perceive chatbots as accurate and efficient, such perceptions do not necessarily reduce their privacy concerns likely because these concerns are shaped more by the nature of personal data exchanged than by service performance. Similarly, the relationship between Perceived Privacy Risk and Purchase Intention was also not supported ($\beta = -0.074$; $t = 1.159$; $p = 0.246$), suggesting that privacy apprehension may not substantially deter purchase behavior in the context of Zalora's chatbot services, at least within the perception of the current respondent pool.

Taken together, these results affirm that while chatbot quality significantly contributes to building trust, engagement, and experience eventually leading to purchase intention the role of privacy-related perceptions appears more nuanced and indirect. These patterns underscore the importance of evaluating both the direct and mediated pathways through which AI-driven service quality affects consumer decision-making in digital commerce settings.

Specific Indirect Effect (Mediation Analysis)

Mediation analysis tested whether the effect of AI-Chatbot Service Quality on Purchase Intention is transmitted through User Trust, Consumer Experience, and Consumer Engagement. Using PLS-SEM with 5,000 bootstrap resamples, indirect effects were evaluated based on t-statistics and p-values (significant if $p < 0.05$ (Hair et al., 2022). Table 11 summarizes the specific indirect effects for all hypothesized mediation paths.

Table 11.
Specific Indirect Effect (Mediation) Results

Mediation Path	Indirect Effect (β)	t-Statistic	p-Value	Conclusion
AI-Chatbot Service Quality → User Trust → Purchase Intention	0.184	2.612	0.009	Significant
AI-Chatbot Service Quality → Consumer Experience → Purchase Intention	0.135	2.498	0.013	Significant
AI-Chatbot Service Quality → Consumer Engagement → Purchase Intention	0.116	1.968	0.049	Significant
AI-Chatbot Service Quality → Perceived Privacy Risk → Purchase Intention	0.005	0.696	0.486	Not Significant
Perceived Intrusiveness → Consumer Experience → Purchase Intention	-0.009	0.449	0.654	Not Significant

Source: Processed data, 2025

The findings in Table 11 demonstrate that three mediation paths are statistically significant. First, User Trust significantly mediates the relationship between AI-Chatbot Service Quality and Purchase Intention ($\beta = 0.184$; $p = 0.009$), suggesting that user trust plays a pivotal role in translating perceived service quality into purchase intent. Second, Consumer Experience also serves as a significant mediator ($\beta = 0.135$; $p = 0.013$), implying that users' positive experiential perceptions enhance the likelihood of purchasing. Third, Consumer Engagement provides another significant pathway ($\beta = 0.116$; $p = 0.049$), reinforcing the idea that higher involvement with the chatbot service encourages stronger purchase intention.

On the other hand, two mediation paths are not supported statistically. The path through Perceived Privacy Risk ($\beta = 0.005$; $p = 0.486$) suggests that privacy concerns do not meaningfully mediate the relationship between service quality and purchase behavior. This may indicate that privacy perceptions are shaped by external or contextual factors rather than chatbot service performance. Similarly, Perceived Intrusiveness → Consumer Experience → Purchase Intention fails to show a significant mediating effect ($\beta = -0.009$; $p = 0.654$), implying that the perceived intrusiveness of chatbot interactions does not diminish or enhance users' experience in a way that influences purchasing decisions.

In summary, the mediation analysis confirms that User Trust, Consumer Experience, and Consumer Engagement serve as key psychological mechanisms through which AI-Chatbot Service Quality affects Purchase Intention. These findings highlight the importance of nurturing trust, delivering seamless experiences, and

http://journal.walisongo.ac.id/index.php/JDMHI/index
https://doi.org/10.21580/jdmhi.2024.6.2.27893

fostering engagement to enhance the impact of AI-based service innovations in digital commerce.

Interaction Effect (Moderation Analysis)

To examine whether Perceived Intrusiveness moderates the relationship between AI-Chatbot Service Quality and Consumer Experience, an interaction term was created and tested using the bootstrapping procedure in SmartPLS. This interaction term represents the product of the predictor variable (AI-Chatbot Service Quality) and the moderator (Perceived Intrusiveness), enabling the model to capture conditional effects based on users' perception of intrusiveness during their interaction with the chatbot. Table 12 summarizes the moderation test results:

Table 12.
Moderation Test Results (Interaction Effect)

Moderation Path	Interaction Coefficient (β)	t-Statistic	p-Value	Decision
Perceived Intrusiveness × AI-Chatbot Service Quality → Consumer Experience	0.063	2.885	0.004	Significant

Source: Processed data, 2025

The test results indicate that the interaction term has a positive and statistically significant effect on Consumer Experience ($\beta = 0.063$, $t = 2.885$, $p = 0.004$). Since the p-value is well below the 0.05 significance threshold, this confirms that Perceived Intrusiveness significantly moderates the effect of AI-Chatbot Service Quality on Consumer Experience.

Interestingly, the positive sign of the interaction coefficient suggests that higher levels of perceived intrusiveness enhance the positive impact of chatbot service quality on user experience. This result implies that in situations where the chatbot engages more actively even to the point of being perceived as intrusive it can still lead to improved user experiences, provided that the service remains relevant, responsive, and personalized. Such findings may reflect a paradoxical effect, where users tolerate or even appreciate higher intrusiveness when it is paired with high service quality, especially in digital environments where convenience and responsiveness are highly valued.

This result enriches the theoretical framework by highlighting that Perceived Intrusiveness does not necessarily diminish user experience; instead, under certain conditions, it may strengthen the perception of responsiveness and attentiveness thereby enhancing the overall experience. Consequently, chatbot designers and digital marketers may consider optimizing the balance between personalization and privacy to leverage this moderating effect effectively.

Discussion

This study investigated how AI-chatbot service quality influences consumer purchase intention through multiple organismic constructs namely user trust, consumer experience, engagement, and perceived privacy risk within the Stimulus–Organism–Response (S–O–R) framework. The results reveal several key insights that deepen our theoretical understanding and have practical relevance, especially within Indonesia's fast-evolving e-commerce landscape.

First, the analysis confirms that AI-chatbot service quality significantly increases user trust. This finding is consistent with the S–O–R proposition that external stimuli (i.e., chatbot responsiveness, credibility, and usability) initiate cognitive appraisals that reduce uncertainty in technology-mediated interactions (Mehrabian & Russell, 1974). In a market like Indonesia where digital commerce is expanding rapidly, yet trust in automation is still developing the role of quality chatbot service becomes essential in reinforcing consumer confidence. According to recent reports, over 99 million Indonesians are projected to engage in e-commerce by 2029 (DataIndonesia.id, 2024), illustrating the urgency of fostering digital trust as a prerequisite for behavioral acceptance.

Second, AI-chatbot quality also exerts a strong influence on consumer experience, validating the affective pathway within the S–O–R framework. High-quality chatbots enhance users' sense of control, enjoyment, and seamlessness during the shopping journey, particularly in fashion-based e-commerce where aesthetic interaction matters (Adam et al., 2021). In the case of Zalora Indonesia, the integration of augmented reality and visual search as part of its TITAN system likely contributes to the formation of emotionally engaging and frictionless experiences. This supports the theoretical claim that affective organismic responses are central to forming behavioral intention in immersive digital contexts.

Third, the study finds that chatbot service quality positively affects consumer engagement, which reflects motivational activation triggered by interactive and responsive stimuli (Brandtzaeg & Følstad, 2018). This suggests that personalized, human-like chatbot interactions do not merely satisfy but also energize users to participate more actively, such as through feedback, information seeking, or even brand advocacy. From a practical standpoint, this becomes crucial in competitive B2C fashion platforms, where engagement often correlates with long-term loyalty and repurchase.

Interestingly, the relationship between chatbot quality and perceived privacy risk is found to be statistically insignificant. This challenges previous assumptions that better system design always reduces risk perception (Van den Broeck et al., 2019). Theoretically, it suggests that privacy-related concerns may operate through a separate evaluative lens more strongly shaped by contextual cues (e.g., data request sensitivity) than by service performance. Empirical data from the Indonesian context, where digital literacy and awareness of data misuse remain varied, might explain why service quality does not necessarily translate into lower privacy concerns. This aligns with privacy calculus theory (Dinev & Hart, 2006), which proposes that users weigh perceived costs (risks) against benefits independently, rather than as a linear function of system quality.

The direct effect of service quality on purchase intention though significant is relatively modest, implying that behavioral responses are more robustly activated through organismic mediators. This supports the original S–O–R assumption that internal psychological states are critical pathways through which stimuli exert influence (Donovan & Rossiter, 1982). The mediation analysis confirms this: trust, experience, and engagement each act as significant intervening variables. Notably, trust emerges as the strongest mediator, echoing prior findings that consumer trust is central in AI-mediated decision environments (Chung et al., 2020; Gefen et al., 2003). Meanwhile, experience and engagement reflect the role of affective and motivational processes that enhance user satisfaction and brand connectedness two increasingly valuable assets in post-pandemic digital commerce.

By contrast, perceived privacy risk does not significantly predict purchase intention, despite its theoretical importance. This finding may reflect contextual desensitization: Indonesian consumers, particularly urban fashion shoppers, may prioritize utility and convenience over abstract privacy concerns. Alternatively, consumers might engage in compensatory behavior, whereby trust or enjoyment offsets their latent privacy fears again consistent with privacy calculus and reactance theory (Miron & Brehm, 2006).

A major theoretical contribution of this study lies in its examination of perceived intrusiveness as a moderating variable, rather than as an outcome. The significant interaction between intrusiveness and service quality in shaping experience suggests a boundary condition within the S–O–R model. When users perceive chatbot interactions as too invasive such as being overly persistent, hyper-personalized, or intrusive the positive impact of service quality on experience weakens. This finding is novel, as prior research often treats intrusiveness as a direct outcome, not as a contextual disruptor. From the lens of psychological reactance theory, excessive personalization may trigger resistance or discomfort, thereby undermining the experiential benefits of chatbot engagement.

Taken together, these results confirm the multidimensional pathways through which AI-chatbot service quality affects consumer behavior. They also highlight the importance of designing chatbot systems that are not only technically proficient but also psychologically calibrated minimizing perceived intrusion while maximizing trust, experience, and engagement.

From a managerial standpoint, e-commerce platforms like Zalora must strike a balance between automation and human-centric design. Incorporating transparency, ethical data practices, and opt-in personalization settings may help reduce friction while sustaining engagement. As the Indonesian

https://doi.org/10.21580/jdmhi.2024.6.2.27893

digital commerce landscape continues to grow, such strategies will be pivotal in building long-term consumer relationships anchored in both performance and comfort.

Conclusion

This study aimed to investigate the influence of AI-chatbot service quality on users' purchase intention by integrating key psychological constructs user trust, consumer experience, consumer engagement, and perceived privacy risk within the Stimulus–Organism–Response (S–O–R) framework. Additionally, the moderating role of perceived intrusiveness was examined in shaping the user experience pathway.

The empirical findings, based on data from 387 Zalora Indonesia users and analyzed using PLS-SEM, confirm that service quality plays a central role not only in directly shaping purchase intention but also in activating multiple psychological mechanisms that mediate consumer behavior. Specifically, AI-chatbot service quality significantly enhances user trust, consumer experience, and engagement, while also reducing privacy risk perception. In turn, trust, experience, and engagement strongly predict users' intention to purchase, validating the S–O–R theoretical logic in the context of AI-driven digital commerce.

Interestingly, the study also identifies a privacy paradox: perceived privacy risk does not significantly hinder purchase intention, suggesting a pragmatic consumer mindset that prioritizes utility over privacy concern. Furthermore, perceived intrusiveness emerges as a significant positive moderator, indicating that in certain conditions, intrusive chatbot behaviors may enhance user experience particularly when perceived as functional or beneficial. This finding introduces the novel concept of *functional intrusiveness*, adding nuance to existing theories such as psychological reactance and privacy calculus.

Overall, this research enriches the theoretical discourse on AI-mediated service interaction by extending the S–O–R model and providing empirical support for the relevance of both trust-based and risk-based psychological factors. Practically, it offers actionable insights for e-commerce providers to design chatbot experiences that are fast, responsive, empathetic, and respectful of users' cognitive boundaries.

Suggestion

This study yields several managerial and theoretical recommendations for advancing AI-driven digital commerce. From a practical standpoint, enhancing chatbot responsiveness and interaction quality should be a priority. Delayed or impersonal responses often diminish user satisfaction; thus, improving server speed and employing real-time natural language processing can foster seamless communication. Moreover, adopting a humanized communication style friendly, empathetic, and personalized can enhance user trust, particularly in service recovery contexts.

Equally, intuitive interface design should guide user experience development. Clear navigation, low cognitive load, and contextual cues contribute to positive user journeys. AI-based personalization must also be implemented thoughtfully. While perceived privacy risk was not found to significantly deter purchase intention in this study, transparent data handling and visible privacy controls remain essential to foster long-term trust and loyalty.

Given the nuanced role of perceived intrusiveness, chatbot content delivery should be context-aware and non-repetitive. Irrelevant or excessive messaging can lead to user irritation. Thus, adaptive content algorithms are necessary to preserve relevance and engagement.

Theoretically, future research can extend the model to other industries (e.g., travel, healthcare) to increase generalizability. Incorporating variables such as emotional trust, perceived usefulness, or algorithm aversion may further enrich explanatory power. Additionally, longitudinal or mixed-method designs can better capture evolving user perceptions of AI, especially amid rapid advances in technology and policy.

Finally, future studies could explore the moderating role of perceived intrusiveness across other pathways, such as its potential to alter the effects of trust, engagement, or perceived risk offering a more granular view of consumer boundaries in AI-mediated interactions.

References

Adam, M., Wessel, M., & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*. https://doi.org/10.1007/s12525-020-00414-7

Aguirre, C., Ruiz de Maya, S., Palazón Vidal, M., & Rodríguez, A. (2023). Consumer motivations for engaging with corporate social responsibility on social media. *Spanish Journal of Marketing - ESIC*, *27*(2), 202–220. https://doi.org/10.1108/SJME-05-2022-0106

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/https://doi.org/10.1016/0749-5978(91)90020-T

Bleier, A., De Keyser, A., & Verleye, K. (2018). Customer Engagement Through Personalization and Customization. In *Customer Engagement Marketing* (pp. 75–94). https://doi.org/10.1007/978-3-319-61985-9_4

Brakus, J. Joško, Schmitt, Bernd H, & Zarantonello, Lia. (2009). Brand Experience: What is It? How is it Measured? Does it Affect Loyalty? *Journal of Marketing*, *73*(3), 52–68. https://doi.org/10.1509/jmkg.73.3.052

Brandtzaeg, P., & Følstad, A. (2018). Chatbots: changing user needs and motivations. *Interactions*, *25*, 38–43. https://doi.org/10.1145/3236669

Brodie, R. J., Hollebeek, L. D., Jurić, B., &

Ilić, A. (2011). Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research. *Journal of Service Research*, *14*(3), 252–271. https://doi.org/10.1177/1094670511411703

Chakraborty, D., Kumar Kar, A., Patre, S., & Gupta, S. (2024). Enhancing trust in online grocery shopping through generative AI chatbots. *Journal of Business Research*, *180*. https://doi.org/10.1016/j.jbusres.2024.114737

Cheng, X., Zhang, X., Cohen, J., & Mou, J. (2022). Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management*, *59*(3), 102940. https://doi.org/https://doi.org/10.1016/j.ipm.2022.102940

Chen, Q., Gong, Y., Lu, Y., & Tang, J. (2022). Classifying and measuring the service quality of AI chatbot in frontline service. *Journal of Business Research*, *145*, 552–568. https://doi.org/10.1016/j.jbusres.2022.02.088

Chin, W. W. (1998). Commentary: Issues and Opinion on Structural Equation Modeling. *MIS Quarterly*, *22*(1), vii–xvi. http://www.jstor.org/stable/249674

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587–595. https://doi.org/10.1016/j.jbusres.2018.10.004

Ciechanowski, L., Przegalinska, A., Magnuski, M., & Gloor, P. (2019). In the shades of the uncanny valley: An experimental study of human–chatbot interaction. *Future Generation Computer Systems*, *92*, 539–548. https://doi.org/https://doi.org/10.1016/j.future.2018.01.055

CIO World Asia. (2023). *Zalora Pioneers AI-Powered Fashion E-commerce in Southeast Asia*. Https://Cioworldasia.Com/2023/08/22/Zalora-Pioneers-Ai-Powered-Fashion-Ecommerce-in-Southeast-Asia/.

DataIndonesia.id. (2024, August 13). *Kumpulan Data Seputar Perkembangan E-Commerce di Indonesia pada 2023 dan 2024*. Https://Dataindonesia.Id/Ekonomi-Digital/Detail/Laporan-Kumpulan-Data-Seputar-Perkembangan-Ecommerce-Di-Indonesia-Pada-2023-Dan-2024. https://dataindonesia.id/ekonomi-digital/detail/laporan-kumpulan-data-seputar-perkembangan-ecommerce-di-indonesia-pada-2023-dan-2024

Donovan, R., & Rossiter, J. R. (1982). *Store Atmosphere: An Environmental Psychology Approach*. https://www.researchgate.net/publica tion/248766608

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Gefen, D., Karahanna, E., & Straub, D. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*, 51–90. https://doi.org/10.2307/30036519

Gnewuch, U., Morana, S., & Maedche, A. (2017). *Towards Designing Cooperative and Social Conversational Agents for Customer Service*.

Godey, B., Manthiou, A., Pederzoli, D., Rokka, J., Aiello, G., Donvito, R., & Singh, R. (2016). Social media marketing efforts of luxury brands: Influence on brand equity and consumer behavior. *Journal of Business Research*, *69*(12), 5833–5841. https://doi.org/10.1016/j.jbusres.2016.04.181

Hair, J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Holland, J. H. (1992). *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*. MIT Press. https://books.google.co.id/books?id=cyV7nQEACAAJ

Huang, M.-H., & Rust, R. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*, 109467051775245. https://doi.org/10.1177/1094670517752459

Huang, M.-H., & Rust, R. (2020). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*. https://doi.org/10.1007/s11747-020-00749-9

Insideretail Asia. (2023). *Zalora CTO talks OpenAI integration and future of e-commerce*. Https://Insideretail.Asia/2023/09/06/Exclusive-Zalora-Cto-Talks-Openai-Integration-and-Future-of-e-Commerce/.

Jiang, H., Cheng, Y., Yang, J., & Gao, S. (2022). AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior. *Computers in Human Behavior*, *134*, 107329. https://doi.org/10.1016/j.chb.2022.107329

Khan, H., Sararueangpong, P., Mathmann, F., & Wang, D. (2024). Consumers' promotion focus mitigates the negative effects of chatbots on purchase likelihood. *Journal of Consumer Behaviour*, *23*(3), 1528–1539. https://doi.org/10.1002/cb.2289

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544–564. https://doi.org/https://doi.org/10.1016/j.dss.2007.07.001

Kontan.co.id. (2022, December 22). *Laju pertumbuhan transaksi e-commerce di Indonesia melambat*. Https://Insight.Kontan.Co.Id/News/Laju-Pertumbuhan-Transaksi-e-Commerce-Di-Indonesia-Melambat. https://insight.kontan.co.id/news/laju-pertumbuhan-transaksi-e-commerce-di-indonesia-melambat

Kronemann, B., Kizgin, H., Rana, N., & K. Dwivedi, Y. (2023). How AI encourages consumers to share their secrets? The role of anthropomorphism, personalisation, and privacy concerns and avenues for future research. *Spanish Journal of Marketing - ESIC*, *27*(1), 3–19. https://doi.org/10.1108/SJME-10-2022-0213

Lee, J., Kim, C., & Lee, K. C. (2022). Exploring the personalization-intrusiveness-intention framework to evaluate the effects of personalization in social media. *International Journal of Information Management*, *66*, 102532. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2022.102532

Lemeshow, S., Hosmer, D. W., Klar, J., & Lwanga, S. K. (1997). Besar sampel dalam penelitian kesehatan. *Yogyakarta: Gajah Mada University*.

Li, L., Lee, K. Y., Emokpae, E., & Yang, S.-B. (2021). What makes you continuously use chatbot services? Evidence from chinese online travel agencies. *Electronic Markets*, *31*(3), 575–599. https://doi.org/10.1007/s12525-020-00454-z

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.2307/258792

Mehrabian, A. (1974). An approach to environmental psychology. *Massachusetts Institute of Technology*.

Miron, A., & Brehm, J. (2006). Reactance Theory - 40 Years Later. *Zeitschrift Fur Sozialpsychologie - Z SOZPSYCHOL*, *37*, 9–18. https://doi.org/10.1024/0044-3514.37.1.9

Nguyen, D. M., Chiu, Y. T. H., & Le, H. D. (2021). Determinants of continuance intention towards banks' chatbot services in vietnam: A necessity for sustainable development. *Sustainability (Switzerland)*, *13*(14). https://doi.org/10.3390/su13147625

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing*, *64*(1), 12.

Pavlou, P. (2003). Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model. *International Journal of Electronic Commerce*, *7*, 101–134.

Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing*, *38*(12), 2339–2356. https://doi.org/https://doi.org/10.1002/mar.21548

Schmitt, B. (1999). experiential-marketing. *Journal of Marketing Management*, *15*, 53–67.

Selem, K. M., Shoukat, M. H., Khalid, R., & Raza, M. (2024). Guest interaction with hotel booking website information: scale development and validation of antecedents and consequences. *Journal of Hospitality Marketing & Management*, *33*(5), 626–648. https://doi.org/10.1080/19368623.2023.2279174

Shahzad, M. F., Xu, S., An, X., & Javed, I. (2024). Assessing the impact of AI-chatbot service quality on user e-brand loyalty through chatbot user trust, experience and electronic word of mouth. *Journal of Retailing and Consumer Services*, *79*. https://doi.org/10.1016/j.jretconser.2024.103867

Shoukat, M. H., Elgammal, I., Selem, K., & Shehata, A. (2024). Fostering social media user intentions: AI-enabled privacy and intrusiveness concerns. *Spanish Journal of Marketing - ESIC*, 1–17. https://doi.org/10.1108/SJME-07-2023-0205

Song, M., Xing, X., Duan, Y., Cohen, J., & Mou, J. (2022). Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention. *Journal of Retailing and Consumer Services*, *66*. https://doi.org/10.1016/j.jretconser.2021.102900

Song, S. W., & Shin, M. (2024). Uncanny Valley Effects on Chatbot Trust, Purchase Intention, and Adoption Intention in the Context of E-Commerce: The Moderating Role of Avatar Familiarity. *International Journal of Human-Computer Interaction*, *40*(2), 441–456. https://doi.org/10.1080/10447318.2022.2121038

Statista. (2023, December 13). *Leading B2C e-commerce sites in the fashion category in Indonesia as of 2nd quarter 2022, by number of monthly visitors*. https://www.statista.com/statistics/1012489/indonesia-leading-b2c-ecommerce-sites-fashion/

Thorndike, E. (2017). *Animal intelligence: Experimental studies*. Routledge.

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? *Computers in Human Behavior*, *98*, 150–157. https://doi.org/10.1016/j.chb.2019.04.009

van Doorn, J., & Hoekstra, J. C. (2013). Customization of online advertising: The role of intrusiveness. *Marketing Letters*, *24*(4), 339–351. https://doi.org/10.1007/s11002-012-9222-1

Vizologi. (2023). *Zalora Business Model Canvas*. Https://Vizologi.Com/Business-Strategy-Canvas/Zalora-Business-Model-Canvas/.

Vohra, A., & Bhardwaj, N. (2019). Customer engagement in an e-commerce brand community: An empirical comparison of alternate models. *Journal of Research in Interactive Marketing*, *13*. https://doi.org/10.1108/JRIM-01-2018-0003

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, *29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Woodworth, R. S. (1921). *Psychology: A Study of Mental Life*. H. Holt. https://books.google.co.id/books?id=nLsEiExQLWAC

Zhang, S., Hu, Z., Li, X., & Ren, A. (2022). The impact of service principal (service robot vs. human staff) on service quality: The mediating role of service principal attribute. *Journal of Hospitality and Tourism Management*, *52*, 170–183. https://doi.org/10.1016/j.jhtm.2022.06.014

Zhu, Y., Zhang, R. (Renata), Zou, Y., & Jin, D. (2023). Investigating customers' responses to artificial intelligence chatbots in online travel agencies: the moderating role of product familiarity. *Journal of Hospitality and Tourism Technology*, *14*(2), 208–224. https://doi.org/10.1108/JHTT-02-2022-0041