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AI Chatbot Service Quality and Customer Engagement in Online Fast-Fashion Retail: An S-O-R Framework

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***Abstract*— The rapid adoption of artificial intelligence (AI) chatbots has transformed customer service in online retail, particularly in the fast-fashion sector, where customers increasingly expect immediate, accurate, and personalised assistance. However, the mechanisms through which specific chatbot service-quality dimensions translate into customer engagement remain insufficiently understood. Drawing on the Stimulus–Organism–Response (S-O-R) framework, this study examines the effects of chatbot accuracy, responsiveness, and personalisation on customer engagement, with customer trust and customer satisfaction serving as mediating mechanisms. A quantitative, explanatory research design was adopted, and data were collected through a structured questionnaire from 329 online fast-fashion consumers with prior experience interacting with AI-powered chatbots. The proposed model was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results demonstrate that chatbot accuracy, responsiveness, and personalisation significantly and positively influence both customer trust and customer satisfaction. Customer trust and customer satisfaction, in turn, significantly enhance customer engagement. The mediation analysis further confirms that both trust and satisfaction significantly mediate the relationships between the three chatbot quality dimensions and customer engagement. Among the examined relationships, personalisation showed the strongest effect on customer trust, while customer satisfaction demonstrated the strongest direct effect on customer engagement. The findings support the proposed S-O-R framework and demonstrate that effective AI chatbot interactions contribute to customer engagement not merely through functional performance but through the favourable psychological evaluations they generate. The study contributes to the literature on AI-enabled customer service by identifying the role of specific chatbot quality dimensions and provides practical insights for online fast-fashion retailers seeking to design chatbot experiences that build trust, enhance satisfaction, and foster stronger customer engagement.**

***Keywords*—Artificial intelligence; AI chatbots; chatbot service quality; customer trust; customer satisfaction; customer engagement; online fast-fashion retail; S-O-R framework.**

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has transformed the nature of customer interactions in digital retail environments.

Among the most visible applications of AI in customer service is the chatbot, which enables organisations to provide automated, real-time, and scalable assistance to customers. AI-powered chatbots are increasingly used to respond to customer enquiries, provide product-related information, facilitate navigation, assist with transactions, and resolve routine service issues. In online retail environments, these capabilities offer particular value because customers often expect immediate, accurate, and convenient support throughout their shopping journey. The growing integration of conversational AI therefore reflects a broader transformation in which digital service encounters are no longer limited to transactional exchanges but increasingly contribute to customers' overall experiences and relationships with retailers (Foroudi et al., 2026; Golalizadeh et al., 2023; Sandunima, 2026).

The relevance of AI-enabled customer service is particularly pronounced in online fashion retail. Fashion consumers frequently require assistance with product availability, sizing, styling, delivery, returns, and other purchase-related concerns. AI chatbots can address such needs through immediate responses, consistent information, personalised guidance, and continuous accessibility. In the context of online fashion retail, recent research identifies instant responses, real-time information, fast navigation, transaction support, and useful advice as important forms of value sought from AI chatbot interactions (Sandunima, 2026). Similarly, research on AI-enabled service quality suggests that chatbots can contribute to reliability, responsiveness, assurance, and empathy by providing accurate information, real-time assistance, credible guidance, and personalised communication (Foroudi et al., 2026; Golalizadeh et al., 2023).

Within the fast-fashion sector, the importance of these capabilities is amplified by the characteristics of the retail environment. Online fast-fashion platforms operate in markets characterised by speed, affordability, rapid trend responsiveness, and high volumes of customer interactions. Customers may seek assistance at different stages of the shopping journey, including product discovery, purchase, delivery, returns, and post-purchase service.

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Consequently, AI-powered chatbots are increasingly positioned as tools for improving convenience and operational efficiency by assisting customers with functions such as product recommendations, order tracking, returns, and size-related queries. However, the growing reliance on automated customer service also raises an important question: whether the quality of specific chatbot interactions is sufficient to generate meaningful customer engagement and stronger customer relationships.

Existing research indicates that customers evaluate AI-enabled interactions not only in terms of efficiency and speed but also according to the quality of the information provided, responsiveness of the system, personalisation of the interaction, and its ability to address individual customer needs. Research cited in the provided literature suggests that customers value chatbots that can answer queries accurately and efficiently, while human-like characteristics and social presence may improve the user experience and reduce discomfort associated with the absence of human interaction (Adam et al., 2021; Følstad & Skjuve, 2019; Gnewuch et al., 2018). At the same time, concerns relating to trust, privacy, and the limited emotional capabilities of AI may restrict the ability of chatbots to develop deeper relationships with customers (Gnewuch et al., 2018; Zamora, 2017). These findings suggest that chatbot performance should not be viewed as a single, broad concept of effectiveness; rather, specific quality dimensions such as accuracy, responsiveness, and personalisation may shape how customers evaluate and respond to AI-mediated service interactions.

Customer trust and customer satisfaction are particularly important in understanding these responses. Customer trust can be influenced by how consumers perceive the characteristics and communication capabilities of AI systems. Chi and Hoang Vu (2023) examined the role of anthropomorphism, empathy response, human–AI interaction, and communication quality in shaping customer trust in AI, indicating that the characteristics of AI-mediated interactions can influence customer acceptance, trust, and continued use. Customer satisfaction is similarly influenced by the quality of chatbot interactions. Previous research identifies response time, accuracy, problem-resolution capability, personalised responses, and proactive support as important factors influencing satisfaction with AI chatbot interactions (Chung et al., 2020; De Keyser et al., 2019). Service quality attributes such as reliability, responsiveness, assurance, and empathy can further shape customers' evaluations of service performance (Foroudi et al., 2026).

Thus, when chatbots provide accurate, responsive, and personalised assistance, they may contribute to more favourable customer evaluations and stronger relational responses.

Despite these potential benefits, efficient AI-enabled service does not automatically result in stronger customer engagement. Recent research in online fashion retail argues that functional attributes such as responsiveness and reliability may not independently generate behavioural outcomes unless they are translated into positive experiences and relational value (Sandunima, 2026). Consumers may seek not only functional convenience but also personalised assistance, interactive engagement, and emotional or relational value from AI-mediated service interactions. Furthermore, research on hyper-personalised fashion retail highlights the importance of trust, privacy management, personalised value, and reduced customer friction in sustaining consumer engagement (Mehmood et al., 2025). This suggests that the relationship between chatbot quality and engagement may operate through customers' internal evaluations rather than through functional performance alone.

Accordingly, the present study proposes an S-O-R-based framework to examine how AI chatbot quality dimensions influence customer engagement in online fast-fashion retail. Specifically, accuracy, responsiveness, and personalisation are conceptualised as stimulus-related characteristics of the AI chatbot interaction, while customer trust and customer satisfaction represent customers' internal evaluations of that interaction. Customer engagement is considered the resulting response. The study therefore investigates whether accuracy, responsiveness, and personalisation influence customer trust and satisfaction, whether trust and satisfaction subsequently influence customer engagement, and whether these two customer evaluations mediate the relationships between chatbot quality dimensions and engagement. By moving beyond a broad measure of chatbot effectiveness, the study seeks to provide a more specific explanation of how particular AI chatbot service-quality characteristics translate into customer engagement through trust and satisfaction in the context of online fast-fashion retail.

The study contributes to the emerging literature on AI-enabled customer service by examining the relationships among specific chatbot quality dimensions, customer evaluations, and customer engagement within an online fast-fashion retail context. It also provides practical insights for retailers seeking to move beyond the use of AI chatbots as purely functional service tools towards AI-enabled interactions capable of building trust, creating satisfaction, and fostering stronger customer engagement.

A. Research Objectives

To examine how AI chatbot quality dimensions: accuracy, responsiveness, and personalisation influence customer engagement in online fast-fashion retail, with customer trust and customer satisfaction as mediating mechanisms.

1. To examine the effect of chatbot accuracy on customer trust and customer satisfaction in online fast-fashion retail.
2. To examine the effect of chatbot responsiveness on customer trust and customer satisfaction in online fast-fashion retail.
3. To examine the effect of chatbot personalisation on customer trust and customer satisfaction in online fast-fashion retail.
4. To examine the effect of customer trust on customer engagement in online fast-fashion retail.
5. To examine the effect of customer satisfaction on customer engagement in online fast-fashion retail.
6. To examine the mediating role of customer trust in the relationships between chatbot quality dimensions: accuracy, responsiveness, and personalisation and customer engagement.
7. To examine the mediating role of customer satisfaction in the relationships between chatbot quality dimensions: accuracy, responsiveness, and personalisation and customer engagement.

II. Literature Review

A. AI Chatbots in Online Fast-Fashion Retail

The increasing adoption of artificial intelligence (AI) has transformed customer service in online retail, with AI-powered chatbots emerging as an important interface between retailers and consumers. Chatbots provide instant responses, product information, personalised assistance, and support for routine customer queries. In online fashion retail, AI-based customer service can improve service quality by providing consistent information, immediate assistance, and tailored interactions (Foroudi et al., 2026; Sandunima, 2026).

AI chatbots are particularly relevant to fast-fashion retail, where customers frequently seek information about product availability, sizing, styling, delivery, and returns. Previous research suggests that customers value chatbots that provide instant responses, useful information, personalised guidance, and effective problem-solving support (Adam et al., 2021; Følstad & Skjuve, 2019; Gnewuch et al., 2018).

However, chatbot performance may also be affected by concerns regarding trust, privacy, and limited emotional capabilities (Gnewuch et al., 2018; Zamora, 2017). Therefore, the present study focuses on three specific chatbot quality dimensions: accuracy, responsiveness, and personalisation.

B. Chatbot Accuracy

Accuracy refers to the extent to which a chatbot provides correct, relevant, and dependable information. This is important in online fashion retail because customers may rely on chatbots for information regarding products, sizing, availability, delivery, and returns. Incorrect information can increase uncertainty and reduce confidence in the chatbot.

Previous research identifies accuracy as an important factor in chatbot-enabled service and customer satisfaction (Chung et al., 2020). Reliable and consistent information can also improve customers' evaluations of AI-enabled services (Foroudi et al., 2026). Thus, accurate chatbot responses may strengthen customer trust by reducing uncertainty and improve customer satisfaction by meeting customers' information and service needs.

C. Chatbot Responsiveness

Responsiveness refers to the chatbot's ability to provide prompt, timely, and accessible assistance. A major advantage of AI chatbots is their ability to provide immediate responses and continuous availability, reducing waiting time and customer effort.

Responsiveness is recognised as an important component of AI-enabled service quality (Foroudi et al., 2026; Golalizadeh et al., 2023). Prompt assistance can improve convenience and reduce uncertainty during online shopping. Responsive digital services may also contribute to trust and engagement, while credible service can enhance satisfaction and loyalty (Mousavizadeh et al., 2016; Selter et al., 2023; Srinivasa Raja et al., 2026). Therefore, responsiveness is expected to positively influence both customer trust and customer satisfaction.

D. Chatbot Personalisation

Personalisation refers to the extent to which chatbot responses and assistance are tailored to individual customer needs and preferences. Personalised interactions can make chatbot assistance more relevant and valuable, particularly in fashion retail where customers have different preferences regarding products, styles, and sizes.

Previous research suggests that personalised and context-aware communication can create more positive AI-enabled service experiences (Foroudi et al., 2026; Golalizadeh et al., 2023).

Research on hyper-personalised fashion retail also highlights the importance of personalised value, trust, and reduced customer friction in sustaining engagement (Mehmood et al., 2025). Therefore, personalisation may strengthen customer trust and customer satisfaction by making chatbot interactions more relevant to individual needs.

E. Customer Trust

Customer trust refers to the customer's confidence in the chatbot's ability to provide reliable, credible, and dependable assistance. Trust is particularly important in AI-mediated interactions because customers rely on automated systems without direct human assistance.

Chi and Hoang Vu (2023) examined anthropomorphism, empathy response, human–AI interaction, and communication quality in relation to customer trust in AI. Their findings indicate that AI characteristics and interaction quality can influence trust and continued use. In online retail, accurate, responsive, and credible AI-enabled services can reduce uncertainty and strengthen customer confidence (Mousavizadeh et al., 2016; Selter et al., 2023). Thus, customer trust is expected to contribute positively to customer engagement.

F. Customer Satisfaction

Customer satisfaction represents customers' overall evaluation of their chatbot-assisted service experience. Satisfaction is likely to increase when chatbots provide timely, accurate, relevant, and useful assistance.

Chung et al. (2020) identify response time, accuracy, problem resolution, personalised responses, and proactive support as important factors influencing chatbot satisfaction. Similarly, reliability, responsiveness, assurance, and empathy can influence customers' evaluations of AI-enabled service (Foroudi et al., 2026). Therefore, accurate, responsive, and personalised chatbot interactions may improve customer satisfaction, which in turn may contribute to customer engagement.

G. Customer Engagement

Customer engagement represents customers' cognitive, emotional, and behavioural involvement with a retailer. Although AI chatbots can improve convenience and service efficiency, functional performance alone may not automatically generate stronger engagement. Recent research suggests that responsiveness and reliability need to be translated into positive experiences and relational value to generate stronger behavioural outcomes (Sandunima, 2026).

Research on hyper-personalised fashion retail further highlights trust, personalised value, and reduced customer friction as important factors in sustaining customer engagement (Mehmood et al., 2025). Therefore, customer engagement may result not simply from chatbot functionality but from the trust and satisfaction generated through chatbot interactions.

H. Mediating Role of Customer Trust and Customer Satisfaction

The literature suggests that chatbot quality dimensions may influence customer engagement through customers' internal evaluations. Accuracy, responsiveness, and personalisation can shape customers' perceptions of the chatbot, which may subsequently influence their trust and satisfaction.

This logic is consistent with the Stimulus–Organism–Response (S-O-R) framework, where chatbot quality dimensions represent the stimulus, customer trust and satisfaction represent the organism, and customer engagement represents the response. Previous research indicates that AI-enabled service characteristics can influence customer perceptions and behavioural outcomes through relational and experiential mechanisms (Sandunima, 2026; Mehmood et al., 2025).

Accordingly, this study proposes that customer trust and customer satisfaction mediate the relationships between chatbot accuracy, responsiveness, personalisation, and customer engagement.

I. Research Gap

Although previous studies have examined AI chatbot service quality, customer trust, satisfaction, experience, and loyalty, fewer studies have specifically examined how accuracy, responsiveness, and personalisation influence customer engagement through trust and satisfaction in online fast-fashion retail.

Existing research often considers chatbot effectiveness or AI-enabled service more broadly, making it difficult to identify which specific chatbot characteristics contribute to customers' internal evaluations and subsequent engagement. Therefore, this study addresses the gap by applying the S-O-R framework to examine:

Accuracy + Responsiveness + Personalisation → Customer Trust + Customer Satisfaction → Customer Engagement

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III. Theoretical Framework

A. Stimulus–Organism–Response (S-O-R) Framework

The present study is grounded in the Stimulus–Organism–Response (S-O-R) framework, which provides a suitable theoretical foundation for explaining how characteristics of AI-mediated service interactions can influence customers' internal evaluations and subsequent behavioural responses. The S-O-R framework proposes that external environmental stimuli influence an individual's internal psychological state, which subsequently generates a behavioural or attitudinal response. In the context of AI-enabled retail services, this framework provides a logical basis for examining how specific characteristics of chatbot interactions influence customers' perceptions and ultimately their engagement with the retailer.

The application of the S-O-R framework is particularly relevant to AI chatbot interactions because customers encounter a series of technological and service-related characteristics during their interactions with automated systems. The reference literature demonstrates the applicability of S-O-R to AI-enabled customer experiences by conceptualising AI-related characteristics as stimuli, customer relationship and psychological variables as organismic states, and subsequent customer outcomes as responses. Building on this logic, the present study adapts the S-O-R framework to the context of online fast-fashion retail by focusing specifically on three chatbot quality dimensions: accuracy, responsiveness, and personalisation.

B. Stimulus: AI Chatbot Quality Dimensions

In the proposed framework, accuracy, responsiveness, and personalisation represent the Stimulus (S) component. These dimensions capture important characteristics of the customer's interaction with an AI chatbot and represent the external qualities of the chatbot service that customers experience.

Accuracy refers to the extent to which an AI chatbot provides correct, relevant, and dependable information in response to customer queries. Accuracy is particularly important in online fashion retail because customers may depend on chatbot-provided information concerning product availability, product characteristics, sizing, delivery, returns, and other purchase-related issues. Previous research identifies accuracy and reliable information as important elements of effective AI-enabled service interactions and customer satisfaction (Chung et al., 2020; Foroudi et al., 2026).

Responsiveness refers to the chatbot's ability to provide prompt and accessible assistance when customers seek information or support. AI chatbots can provide immediate responses and continuous availability, thereby reducing customer effort and uncertainty during online shopping interactions. Responsiveness has been identified as an important service-quality characteristic because timely assistance can improve convenience and customers' evaluations of service performance (Foroudi et al., 2026; Golalizadeh et al., 2023).

Personalisation refers to the extent to which the chatbot provides responses and assistance that are relevant to an individual customer's needs, preferences, or circumstances. Personalised and context-aware communication can create more relevant service experiences and may strengthen the perceived value of AI-mediated interactions. In online fashion retail, personalisation is particularly relevant because customers may seek recommendations or assistance based on their individual preferences, product requirements, and shopping circumstances (Foroudi et al., 2026; Mehmood et al., 2025).

Thus, the three dimensions represent distinct but related aspects of the chatbot stimulus. Rather than treating chatbot effectiveness as a single broad construct, the present study examines whether accuracy, responsiveness, and personalisation independently influence customers' internal evaluations of their AI-mediated service experience.

C. Organism: Customer Trust and Customer Satisfaction

The Organism (O) component represents the internal psychological and evaluative states that arise in response to external stimuli. In the present study, customer trust and customer satisfaction represent the organismic mechanisms through which chatbot quality characteristics are expected to influence customer engagement.

Customer trust refers to the customer's confidence in the chatbot and its ability to provide reliable, credible, and dependable assistance. Trust is particularly important in AI-mediated interactions because customers must rely on automated systems when receiving information and assistance without direct human intervention. Chi and Hoang Vu (2023) demonstrate that characteristics of AI interaction, including communication quality, empathy response, and human–AI interaction, can influence customer trust. Therefore, accurate information, responsive assistance, and personalised communication may contribute to customers developing greater confidence in the chatbot and the service environment.

Customer satisfaction represents the customer's overall evaluation of the chatbot-assisted service experience. Satisfaction may arise when the chatbot successfully meets customer expectations by providing useful, accurate, timely, and relevant assistance.

Previous research identifies response time, accuracy, problem resolution, personalised responses, and proactive support as factors influencing satisfaction with chatbot-enabled services (Chung et al., 2020; De Keyser et al., 2019). Similarly, service-quality characteristics such as reliability and responsiveness can shape customers' overall evaluations of AI-enabled service encounters (Foroudi et al., 2026).

Within the S-O-R perspective, trust and satisfaction therefore function as internal mechanisms through which customers interpret and evaluate their chatbot experiences. The framework suggests that the characteristics of the chatbot alone may not be sufficient to produce stronger customer outcomes; rather, these characteristics must generate favourable internal evaluations that can subsequently influence customer responses.

D. Response: Customer Engagement

Customer engagement represents the Response (R) component of the proposed S-O-R framework. It reflects the customer's resulting involvement with the online fast-fashion retailer following the AI-mediated service experience. Engagement extends beyond a single transactional behaviour and can involve customers' cognitive, emotional, and behavioural involvement with the retailer.

The positioning of engagement as the response is consistent with the logic that positive experiences with AI-enabled services may encourage customers to develop stronger involvement with the retailer. However, previous research suggests that functional chatbot performance does not necessarily translate directly into stronger behavioural outcomes. Instead, functional characteristics may need to generate positive experiences and relational value before they can contribute to deeper customer engagement (Sandunima, 2026). Research on personalised fashion retail similarly highlights the importance of trust, personalised value, and reduced customer friction in sustaining customer engagement (Mehmood et al., 2025).

Accordingly, the present study proposes that customer engagement is not merely a direct consequence of chatbot functionality. Rather, customer trust and customer satisfaction are expected to act as psychological mechanisms that translate chatbot quality into customer engagement.

E. S-O-R Logic of the Proposed Model

Based on the above theoretical reasoning, the proposed model follows the sequence:

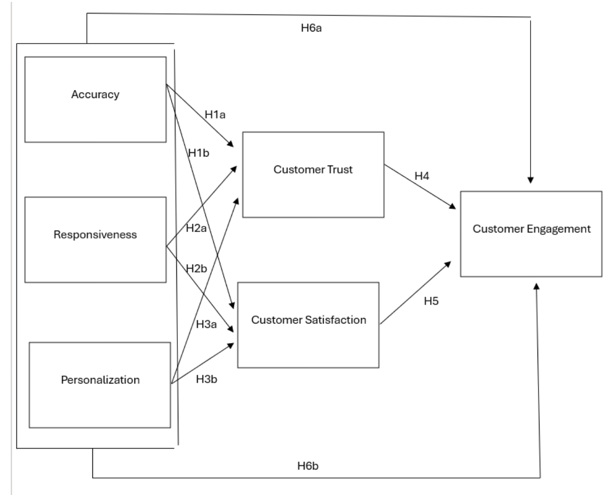

Fig. 1. Proposed Research Model

H1a: Chatbot accuracy positively influences customer trust.

H1b: Chatbot accuracy positively influences customer satisfaction.

H2a: Chatbot responsiveness positively influences customer trust.

H2b: Chatbot responsiveness positively influences customer satisfaction.

H3a: Chatbot personalisation positively influences customer trust.

H3b: Chatbot personalisation positively influences customer satisfaction.

H4: Customer trust positively influences customer engagement.

H5: Customer satisfaction positively influences customer engagement.

H6a: Customer trust mediates the relationships between chatbot quality dimensions and customer engagement.

H6b: Customer satisfaction mediates the relationships between chatbot quality dimensions and customer engagement.

IV. METHODOLOGY

A. Research Design

This study adopts a quantitative and explanatory research design to examine the relationships between AI chatbot quality dimensions and customer engagement in online fast-fashion retail.

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The study is guided by the Stimulus–Organism–Response (S-O-R) framework, where chatbot accuracy, responsiveness, and personalisation represent the stimuli, customer trust and customer satisfaction represent the organismic states, and customer engagement represents the response.

A structured questionnaire was used to collect data from respondents who had previous experience interacting with AI chatbots while shopping online.

B. Population and Sample

The target population consisted of online fast-fashion consumers who had interacted with an AI-powered chatbot during their online shopping experience. Respondents were required to have prior experience using a chatbot for purposes such as obtaining product information, receiving assistance, resolving queries, or seeking support during the online shopping process.

Sampling approach was used to ensure that only respondents with relevant chatbot experience participated in the study. Screening questions were included at the beginning of the questionnaire to confirm respondents' experience with online fast-fashion shopping and AI chatbot interactions. An attention-check question was also included to improve response quality.

A total of 329 valid responses were retained for the final analysis.

C. Measurement of Variables

The questionnaire measured six constructs: chatbot accuracy, chatbot responsiveness, chatbot personalisation, customer trust, customer satisfaction, and customer engagement. The measurement items were adapted from established studies and modified to suit the context of AI chatbot interactions in online fast-fashion retail.

All items were measured using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

D. Data Collection Procedure

Data were collected through an online questionnaire distributed to eligible respondents. Before completing the main questionnaire, respondents were screened to ensure that they had experience with both online fast-fashion shopping and AI chatbot interactions.

The questionnaire consisted of three main sections. The first section included screening questions and demographic information. The second section measured respondents' perceptions of chatbot accuracy, responsiveness, and personalisation. The final section measured customer trust, customer satisfaction, and customer engagement.

Only complete and valid responses were included in the final analysis, resulting in a sample of 329 respondents.

E. Data Analysis

The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). This approach was selected because the study examines multiple relationships among latent constructs and includes both direct and mediating effects.

The analysis was conducted in two stages. First, the measurement model was assessed to evaluate the reliability and validity of the constructs. This included the assessment of indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity.

Second, the structural model was evaluated to test the proposed hypotheses. The assessment included collinearity statistics, path coefficients, coefficient of determination (R^2), and the significance of the hypothesised relationships. Bootstrapping with 5,000 resamples was used to determine the significance of the direct and indirect effects.

The analysis specifically examined the direct effects of accuracy, responsiveness, and personalisation on customer trust and customer satisfaction, the effects of customer trust and customer satisfaction on customer engagement, and the mediating effects of trust and satisfaction on the relationships between chatbot quality dimensions and customer engagement.

V. RESULTS

SPSS 27 was used to conduct the demographic analysis, while SmartPLS 4 was used for the measurement and structural model assessment. The analysis followed two stages: first, the reliability and validity of the measurement model were assessed, followed by structural model and hypothesis testing.

The final sample consisted of 329 respondents, with most aged 18–25 years (42.0%), followed by 26–35 (36.0%), 36–45 (12.0%), 46 years or above (6.0%), and below 18 (4.0%). In terms of gender, 59.0% were male, 38.0% female, and 3.0% other. Most respondents held a postgraduate degree (42.0%), followed by an undergraduate degree (35.0%), PhD (7.0%), diploma/some college (8.0%), and high school or equivalent (8.0%). Regarding occupation, students constituted the largest group (55.0%), followed by employed (25.0%), self-employed (12.0%), and other (8.0%) respondents.

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TABLE I
DEMOGRAPHIC PROFILE

Characteristics	Category	Percent age
Age	Below 18	4.0
	18–25	42.0
	26–35	36.0
	36–45	12.0
	46 or more	6.0
Gender	Male	38.0
	Female	59.0
	Other	3.0
Educational level	PhD	7.0
	Postgraduate degree	42.0
	Undergraduate degree	35.0
	Diploma/Some college	8.0
	High school or equivalent	8.0
Occupation	Student	55.0
	Employed	25.0
	Self-employed	12.0
	Other	8.0

A. Measurement Model Assessment

The measurement model was assessed using SmartPLS 4 to evaluate indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The assessment was conducted before testing the structural relationships among the study constructs.

1) Indicator Reliability: Indicator reliability was assessed through the outer loadings of the measurement items. All items demonstrated outer loading values above the recommended threshold of 0.70, ranging from 0.721 to 0.914, indicating satisfactory indicator reliability.

TABLE II
OUTER LOADINGS OF MEASUREMENT ITEMS

Construct	Item	Outer Loading
Accuracy	ACC1	0.842
	ACC2	0.811
	ACC3	0.816
Responsiveness	RES1	0.856
	RES2	0.879
	RES3	0.790
Personalisation	PER1	0.792
	PER2	0.834
	PER3	0.811
Customer Trust	CT1	0.872
	CT2	0.846
	CT3	0.867
Customer Satisfaction	CS1	0.835
	CS2	0.874
	CS3	0.819
Customer Engagement	CE1	0.887
	CE2	0.861
	CE3	0.857

The results indicate that all measurement items adequately represented their respective constructs. Therefore, no indicators were removed from the measurement model.

2) Internal Consistency Reliability and Convergent Validity: Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR). Convergent validity was assessed using the Average Variance Extracted (AVE). As shown in Table 3, all Cronbach's alpha and CR values exceeded the recommended threshold of 0.70, while all AVE values were above 0.50. These results confirm satisfactory internal consistency and convergent validity (Sarstedt et al., 2014; Fornell & Larcker, 1981).

TABLE III
RELIABILITY AND CONVERGENT VALIDITY RESULTS

Construct	Cronbach's Alpha	CR	AVE
Accuracy	0.842	0.894	0.679
Responsiveness	0.861	0.907	0.710
Personalisation	0.828	0.886	0.661
Customer Trust	0.879	0.916	0.732
Customer Satisfaction	0.865	0.908	0.712
Customer Engagement	0.892	0.925	0.755

Overall, the measurement model demonstrated satisfactory reliability and convergent validity.

3) Discriminant Validity: Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio. All HTMT values were below the recommended threshold of 0.90, indicating that the six constructs were empirically distinct from one another.

TABLE IV
HTMT RESULTS (ACC = ACCURACY, RES = RESPONSIVENESS, PER = PERSONALISATION, CT = CUSTOMER TRUST, CS = CUSTOMER SATISFACTION, CE = CUSTOMER ENGAGEMENT)

Construct	ACC	RES	PER	CT	CS	CE
ACC	—					
RES	0.642	—				
PER	0.614	0.681	—			
CT	0.576	0.548	0.723	—		
CS	0.601	0.664	0.695	0.748	—	
CE	0.492	0.536	0.589	0.701	0.782	—

Note: All HTMT values are below 0.90.

4) Summary of Measurement Model Assessment: The measurement model assessment confirmed that all constructs met the required criteria for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All outer loadings exceeded 0.70, Cronbach's alpha and composite reliability values exceeded 0.70, AVE values exceeded 0.50, and HTMT values remained below 0.90. Therefore, the measurement model was considered satisfactory and suitable for proceeding to the structural model and hypothesis testing.

B. Structural Model and Hypothesis Testing

The structural model was assessed using SmartPLS 4 to examine the proposed direct relationships among the constructs. Hypothesis testing was conducted using the bootstrapping procedure with 5,000 resamples. The assessment considered the path coefficients (β), (t)-values, (p)-values, and coefficient of determination (R^2).

As shown in Table 5, all proposed direct relationships were statistically significant and therefore supported. Accuracy positively influenced both customer trust and customer satisfaction, supporting H1a and H1b. Similarly, responsiveness and personalisation had significant positive effects on both trust and satisfaction, supporting H2a, H2b, H3a, and H3b. Furthermore, both customer trust and customer satisfaction significantly influenced customer engagement, supporting H4 and H5.

TABLE V
STRUCTURAL MODEL AND HYPOTHESIS TESTING RESULTS

Hyp.	Relationship	β	t	p	Decision
H1a	ACC → CT	0.241	4.126	<0.001	Supported
H1b	ACC → CS	0.218	3.874	<0.001	Supported
H2a	RES → CT	0.196	3.315	0.001	Supported
H2b	RES → CS	0.263	4.682	<0.001	Supported
H3a	PER → CT	0.337	5.741	<0.001	Supported
H3b	PER → CS	0.291	5.108	<0.001	Supported
H4	CT → CE	0.304	5.284	<0.001	Supported
H5	CS → CE	0.421	7.196	<0.001	Supported

Note: ACC = Accuracy; RES = Responsiveness; PER = Personalisation; CT = Customer Trust; CS = Customer Satisfaction; CE = Customer Engagement.

The coefficient of determination (R^2) was 0.624 for customer trust, 0.661 for customer satisfaction, and 0.687 for customer engagement. This indicates that the chatbot quality dimensions explained 62.4% of the variance in customer trust and 66.1% of the variance in customer satisfaction. Together, customer trust and customer satisfaction explained 68.7% of the variance in customer engagement.

Overall, the structural model results supported H1a to H5, demonstrating that chatbot accuracy, responsiveness, and personalisation positively influence customers' trust and satisfaction, while both customer trust and customer satisfaction positively influence customer engagement. Among the relationships, personalisation had the strongest effect on customer trust (β = 0.337), whereas customer satisfaction had the strongest direct effect on customer engagement (β = 0.421).

TABLE VI
COEFFICIENT OF DETERMINATION (R^2^)

Endogenous Construct	R^2
Customer Trust	0.624
Customer Satisfaction	0.661
Customer Engagement	0.687

C. Mediation Analysis

The mediation analysis was conducted using the bootstrapping procedure with 5,000 resamples in SmartPLS 4 to examine the indirect effects of chatbot quality dimensions on customer engagement through customer trust and customer satisfaction. The significance of the indirect effects was assessed using path coefficients (β), (t)-values, and (p)-values.

As shown in Table 7, all indirect relationships were statistically significant. Customer trust significantly mediated the relationships between accuracy, responsiveness, and personalisation and customer engagement, supporting H6a. Similarly, customer satisfaction significantly mediated the relationships between the three chatbot quality dimensions and customer engagement, supporting H6b.

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TABLE VII
MEDIATION ANALYSIS RESULTS

Hyp.	Indirect Relationship	β	t	p	Decision
H6a	ACC → CT → CE	0.073	3.421	0.001	Supported
H6a	RES → CT → CE	0.060	2.887	0.004	Supported
H6a	PER → CT → CE	0.102	4.436	<0.001	Supported
H6b	ACC → CS → CE	0.092	3.756	<0.001	Supported
H6b	RES → CS → CE	0.111	4.291	<0.001	Supported
H6b	PER → CS → CE	0.123	4.864	<0.001	Supported

Note: ACC = Accuracy; RES = Responsiveness; PER = Personalisation; CT = Customer Trust; CS = Customer Satisfaction; CE = Customer Engagement.

The results indicate that both customer trust and customer satisfaction act as significant mediating mechanisms between chatbot quality and customer engagement. The strongest indirect effect through customer trust was observed for personalisation (β = 0.102), while the strongest indirect effect through customer satisfaction was also observed for personalisation (β = 0.123).

Overall, the findings support H6a and H6b and are consistent with the proposed Stimulus–Organism–Response (S-O-R) framework. The chatbot quality dimensions of accuracy, responsiveness, and personalisation act as stimuli that shape customers' internal states of trust and satisfaction, which subsequently contribute to customer engagement.

VI. DISCUSSION

The findings provide support for the proposed S-O-R framework and demonstrate that AI chatbot quality plays an important role in shaping customer responses in online fast-fashion retail. All three chatbot quality dimensions: accuracy, responsiveness, and personalisation positively influenced both customer trust and customer satisfaction. Among these dimensions, personalisation showed the strongest influence on customer trust, while responsiveness and personalisation also demonstrated relatively strong effects on satisfaction. These findings suggest that customers are more likely to develop favourable evaluations when chatbot interactions are reliable, timely, and tailored to their individual needs.

The results further show that both customer trust and customer satisfaction positively influence customer engagement, with satisfaction demonstrating the stronger direct effect. This indicates that positive chatbot experiences can translate into greater customer involvement with the retailer. The mediation results provide further support for the S-O-R perspective. Customer trust and satisfaction significantly mediated the relationships between all three chatbot quality dimensions and customer engagement. Thus, chatbot characteristics do not only influence engagement directly; they also operate through customers' internal evaluations of trust and satisfaction.

Overall, the findings support the proposed pathway of Accuracy, Responsiveness and Personalisation → Trust and Satisfaction → Engagement. The results therefore reinforce the relevance of the S-O-R framework for explaining how AI-enabled service characteristics can influence customer behavioural outcomes in online fast-fashion retail.

VII. THEORETICAL AND MANAGERIAL IMPLICATIONS

A. Theoretical Implications

The study contributes to the literature by applying the Stimulus–Organism–Response framework to AI chatbot interactions in online fast-fashion retail. The findings demonstrate that chatbot quality dimensions can be conceptualised as stimuli that shape customers' internal states of trust and satisfaction, which subsequently influence engagement.

The study also extends existing chatbot research by considering accuracy, responsiveness, and personalisation simultaneously and by identifying trust and satisfaction as mediating mechanisms. The significant mediation effects demonstrate that customer engagement is partly explained by the psychological evaluations formed during chatbot interactions. This provides a more complete explanation of how chatbot quality translates into customer engagement.

B. Managerial Implications

The findings provide several practical implications for online fast-fashion retailers. First, retailers should prioritise accurate chatbot responses, particularly for product information, sizing, availability, delivery, and returns, because inaccurate information can undermine customer confidence.

Second, improving responsiveness should remain a priority. Fast and consistent responses can reduce customer effort and improve satisfaction during online shopping interactions.

Third, retailers should invest in personalisation, as it demonstrated the strongest relationship with customer trust and a strong relationship with satisfaction. Chatbots can use customer preferences, previous interactions, and shopping context to provide more relevant assistance.

Finally, managers should focus not only on chatbot functionality but also on the trust and satisfaction generated through chatbot interactions. Since both variables significantly mediated the relationships between chatbot quality and engagement, improving the overall customer experience can be an effective pathway for increasing customer engagement.

VIII. Limitations And Future Research

This study has several limitations. First, the study focuses specifically on online fast-fashion retail, which may limit the generalisability of the findings to other retail sectors or service contexts. Future research could examine the proposed model in areas such as banking, hospitality, healthcare, or general e-commerce.

Second, the study uses a cross-sectional survey design, which captures customer perceptions at one point in time. Future studies could adopt longitudinal designs to examine how trust, satisfaction, and engagement develop through repeated chatbot interactions.

Third, the model focuses on three chatbot quality dimensions: accuracy, responsiveness, and personalisation. Future research could incorporate additional factors such as privacy, perceived usefulness, anthropomorphism, empathy, ease of use, or perceived intelligence.

Finally, the study focuses on customer trust and satisfaction as mediators. Future research could examine additional psychological mechanisms, such as perceived value, customer experience, perceived risk, or emotional attachment, to provide a broader understanding of how AI chatbot interactions influence customer engagement.

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