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Enhancing Gen Z Consumer Engagement through AI: The Role of AI Chatbots in Shaping Purchase Intentions in Vietnam's E-commerce Market

Thong Tien Nguyen[*1], Chi Quoc Nguyen[2]

[*1]Ho Chi Minh City University of Foreign Languages – Information Technology
Email ID: thongnt@huflit.edu.vn
[2]Ho Chi Minh City University of Foreign Languages – Information Technology
Email ID: chinq@huflit.edu.vn
***Corresponding author:**
Thong Tien Nguyen
Faculty of Business Administration, Ho Chi Minh City University of Foreign Languages – Information Technology, 828 Su Van Hanh Street, HCMC, Vietnam.
Email ID: thongnt@huflit.edu.vn

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KEYWORDS

AI Chatbot, Gen Z, Stimulus-Organism-Response model, Vietnam.

ABSTRACT

This paper investigates the role of AI-powered Chatbots in enhancing consumer engagement among Gen Z consumers in Vietnam's rapidly growing e-commerce market. The purpose of this study is to explore how chatbot experiences, including accuracy, insight, and interactivity, influence perceived value and, in turn, affect purchase intentions. A quantitative survey was conducted to examine Gen Z consumers' interactions with AI chatbots in online shopping environments, focusing on their perceptions and purchase intentions. The findings reveal that experience factors positively influence both perceived utility and hedonic value, which significantly enhance purchase intentions. This research contributes to the understanding of AI's impact on e-commerce by highlighting the personalized and efficient shopping experiences that chatbots provide, particularly for Gen Z consumers. This paper explores on Gen Z's response to AI chatbot interactions, offering valuable insights for businesses looking to optimize customer engagement strategies.

1. INTRODUCTION

E-commerce in Vietnam has grown rapidly and become an important sector in the national economy, reflecting general trends globally. E-commerce began in Vietnam in the 2000s, and up to now, the Vietnamese e-commerce market has expanded strongly thanks to technological advances, increased internet connectivity and a growing middle class. The size of Vietnam's e-commerce market is expected to reach around $32 billion by 2024, representing a growth rate of 27% year-on-year. Online retail alone accounts for $22.5 billion of this total, contributing around 12% of total retail sales of consumer goods and services. The market is expected to grow even further in the future, with forecasts suggesting that the market will continue to expand significantly by 2030, potentially reaching between $90 and $200 billion (VECOM, 2025).

Driving this boom is digitalization, which is revolutionizing the way businesses connect with consumers. One of the standout tools in this revolution is the AI chatbot. With 24/7 availability, instant response times, and the ability to process massive amounts of data, chatbots have become indispensable for e-commerce operations (Kedi, Ejimuda, Idemudia, & Ijomah, 2024). Lazada's survey shows that up to 88% of respondents in Southeast Asia said they made purchasing decisions based on content and product suggestions generated by AI (Lazada, 2024).

AI chatbots not only automate customer service but also personalize experiences, learning from each interaction to tailor suggestions and improve satisfaction. With their growing capabilities, including understanding emotional tones through sentiment analysis, they're not just digital assistants—they're becoming digital companions in the shopping journey.

The unique behavioral patterns of Generation Z (Gen Z), who were raised surrounded by social media and mobile technology, are changing online commerce. AI chatbots have become essential tools in e-commerce environments due to consumers' demands for instantaneity, personalization, and seamless digital experiences. According to studies, AI-powered customer support improves perceived utility, emotional fulfillment, and trust—all of which have a big impact on younger consumers' intentions to make a purchase (L. Guo & Cai, 2024). By utilizing machine learning and natural language processing, AI chatbots provide real-time assistance that satisfies Gen Z's need for both hedonistic engagement and utilitarian efficiency (Kelly, 2024). Understanding how Gen Z interacts with intelligent digital assistants is crucial for improving conversion rates and optimizing online retail strategies as this generation of consumers becomes more and more dominant.

In the context of Vietnam's rapidly expanding digital economy, the integration of AI chatbots has become increasingly significant. The country's e-commerce sector is experiencing robust growth, fueled by rising internet penetration and widespread smartphone usage, which are reshaping consumer behavior. As Vietnamese e-commerce enterprises strive to maintain a competitive edge in this dynamic environment, AI chatbots offer promising potential for enhancing customer satisfaction and streamlining operations. Against this backdrop, a key research question emerges: To what extent do AI chatbot-driven user experiences—particularly in terms of accuracy, insight, and interactivity—shape Gen Z's perceived value and online shopping intentions? Addressing this question is essential for understanding how AI technologies can be strategically deployed to foster value-driven consumer engagement.

This study aims to explore the determinants influencing Gen Z's online shopping behavior in Ho Chi Minh City, specifically through the use of AI chatbots. The research primarily investigates how various experiential dimensions—namely accuracy experience, insight experience, and interactive experience—affect two key value perceptions: perceived utility value and perceived hedonic value. Furthermore, the study examines how these perceived values, in turn, influence Gen Z's online shopping intentions, employing the Stimulus–Organism–Response (S-O-R) model as the theoretical framework. The findings are expected to provide practical implications for the development of AI chatbots, particularly in enhancing value recognition capabilities.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 AI and AI Chatbot Applications in E-Commerce

Artificial Intelligence (AI) refers to machine-generated intelligence that imitates human intellectual functions such as perception, decision-making, and language processing (Ellis & Teo, 2024; Fleurence et al., 2024). It involves developing computer systems capable of tasks requiring human-like intelligence (Akerkar, 2019).

AI Chatbot, a specific application of AI, simulates human conversation through text or voice interactions (Haristiani, 2019). Utilizing natural language processing and machine learning, chatbots analyze user input and context to deliver relevant responses (Cheng, Bao, Zarifis, Gong, & Mou, 2021; Gupta, Hathwar, & Vijayakumar, 2020). In e-commerce, they offer personalized support, enhancing user experience and engagement (Li & Wang, 2023).

2.2 Generation Z & Online Shopping Behavior

Generation Z (Gen Z) —individuals born between the mid-1990s and early 2010s—is widely recognized as the first digitally native consumer cohort, exhibiting unique behaviors shaped by constant connectivity and early exposure to technology (Ameen, Hosany, & Taheri, 2023; Bunea, Corbos, Misu, Triculescu, & Trifu, 2024). Gen Z makes up over one-third of the world's population, making it the largest generational group globally (Mason, Zamparo, Marini, & Ameen, 2022). Having grown up with constant internet access, Gen Z is inherently tech-savvy and digitally native. They frequently rely on smart technologies to shop for goods and services, and a significant portion—around 41%—tend to make spontaneous purchases (Djafarova & Bowes, 2021; W. Guo & Luo, 2023). Gen Z expects a seamless shopping experience with AI-driven personalization at every touchpoint. This demand pushes retailers to adopt AI and data analytics to deliver relevant, engaging content that builds stronger connections and brand loyalty (Bunea et al., 2024; W. Guo & Luo, 2023; Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2022).

2.3 Technology Acceptance Model

Davis (1989) developed the Technology Acceptance Model (TAM), which offers a fundamental perspective on how people embrace and interact with new technologies. It asserts that the main determinants of technology adoption are perceived utility and perceived usability. These concepts aid in the explanation of why users—especially Gen Z consumers—view chatbot interactions as beneficial or fulfilling in the context of AI chatbots. The accuracy, interactivity, and personalization of chatbots greatly increase users' utility and emotional satisfaction, according to recent studies that modified TAM to assess user responses to intelligent agents in e-commerce (Bunea et al., 2024; L. Guo & Cai, 2024).

2.4 S-O-R Model

The Stimulus–Organism–Response (S-O-R) framework explains how external stimuli affect internal evaluations that drive behavioral responses (Hamid, Sami, & Sidek, 2017; Pan, Ishak, & Qin, 2024). In online shopping, AI features such as chatbots serve as stimuli that shape consumer perceptions and emotional reactions, ultimately influencing purchase decisions (L. Guo & Cai, 2024; Sultan, Wong, & Azam, 2021). Prior studies have validated S-O-R as an effective model for examining how AI-driven design, interaction, and social elements impact trust, value perception, and purchase behavior (Cuong, 2024). Following this logic, this study defines User Experience (accuracy, insight, interactivity) as the stimulus, Perceived Value (utility and hedonic) as the organism, and Purchase Intention as the response.

2.5 User Experience

- Accuracy Experience

Accuracy experience refers to a user's perception that AI Chatbot provides precise, contextually relevant, and reliable information during interactions (Mazur, 2023). Beyond simply answering questions, accuracy involves the chatbot's ability to understand user intent and deliver responses that match their needs in real-time (Pathak, Prakash, Samadhiya, Kumar, & Luthra, 2025). In e-commerce, accurate chatbot responses are essential for product inquiries, order support, and decision-making (Ashfaq, Yun, Yu, & Loureiro, 2020). When accuracy is high, users feel more confident and satisfied, trusting the chatbot to offer dependable and helpful solutions (Halachev, 2024).

- Insight Experience

Insight experience refers to a chatbot’s ability to understand and respond to users' deeper needs through personalized and predictive support (Wen, Zhang, Sheng, Li, & Guo, 2022). Rather than offering generic replies, AI Chatbot analyzes user behavior, such as past purchases and search patterns, to deliver tailored recommendations (Powell, Zhu, Xiong, & Yang, 2024; Sung, Bae, Han, & Kwon, 2021). This creates a sense of being understood and cared for, enhancing user comfort and emotional connection with the platform (Ho & Chow, 2024; Jordan & Mitchell, 2015). When chatbot responses feel personal and relevant, users are more likely to trust and rely on the technology (Chen & Prentice, 2024).

- Interactive Experience

Interactive experience refers to how naturally and smoothly an AI Chatbot can communicate with users, making the conversation feel more human and less robotic (Chen & Prentice, 2024; Wen et al., 2022). This involves using everyday language, giving fast replies, and adapting responses based on the user's tone, questions, or situation (Samadi, 2018). A well-designed chatbot can create the feeling that users are chatting with a real person, helping build comfort and engagement (Tian, Fan, Dai, Du, & Liu, 2018). When the interaction feels fluid and responsive, users enjoy the experience more and feel in control, which increases their satisfaction and likelihood of using the chatbot again (Sung et al., 2021).

2.6 Perceived Value

Perceived value represents the consumer’s overall assessment of the trade-off between the benefits received and the costs incurred in acquiring a product or service (Liu et al., 2024). It is shaped by both rational evaluations—such as functionality and price—and emotional responses, including enjoyment or trust, particularly in technology-enhanced environments like AI-driven platforms (Bai, Wu, Sha, & Gong, 2024; Su, Luo, Ji, & Tian, 2024). Drawing from prior experiences, consumers form subjective judgments about this value, which significantly influences their behavioral intentions, especially purchase decisions (Ragb, Peña, & Mahrous, 2024). In digital commerce, perceived value encompasses both utilitarian aspects (e.g., convenience, efficiency) and hedonic aspects (e.g., engagement, satisfaction), both of which are critical in determining purchase intention (Bai et al., 2024; W. Guo & Luo, 2023).

- Perceived Utility Value

Perceived utility value refers to how helpful users find AI Chatbot in achieving their online shopping goals (Etemad-Sajadi & Ghachem, 2015). This value is reflected in the chatbot’s ability to provide relevant information, assist in decision-making, and simplify the shopping process (Yu, Vahidov, & Kersten, 2021). When users feel that the chatbot saves them time and effort—by helping them find products quickly or complete transactions more easily—they see it as a practical and effective shopping assistant (Puspitasari, Rusydi, Nuzulita, & Hsiao, 2023). A high sense of utility contributes to user satisfaction and reinforces the belief that the chatbot and the e-commerce platform are meeting their needs efficiently (Kim & Lee, 2024).

- Perceived Hedonic Value

Perceived hedonic value refers to the enjoyment and emotional satisfaction users experience while shopping with the help of AI Chatbot (Kim & Lee, 2024). Unlike purely functional benefits, this value focuses on how fun, engaging, and comfortable the chatbot makes the shopping process feel (Kelly, 2024). When interacting with the chatbot feels enjoyable rather than tedious, users are more likely to explore the platform and make purchases. This positive emotional experience not only enhances user engagement but also strengthens the bond between the consumer and the platform, encouraging loyalty and repeat use (Fu, 2024).

2.7 Purchase Intention

Purchase intention refers to a consumer's readiness or willingness to make a purchase after interacting with an AI Chatbot (Bukari, Nnindini, Agbemabiase, & Nyamekye, 2024). It reflects the likelihood that a user will move from simply considering a product to actually deciding to buy it (Bai et al., 2024). As a key psychological indicator, purchase intention represents the final step in the consumer decision-making process, bridging the gap between initial interest and actual buying behavior (Erkan & Evans, 2016).

2.8 User Experience and Perceived Value

- Accuracy Experience and Perceived Value

Accuracy experience of AI Chatbot provides highly reliable and precise information that aligns with users' specific needs (Valdez Mendia & Flores-Cuautle, 2022). In the context of online shopping, Gen Z consumers increasingly demand accurate product and service information to make informed decisions. As such, an AI Chatbot's capability to deliver relevant, trustworthy responses enhances the perceived value of the technology during the shopping experience (Chung, Wedel, & Rust, 2016). Moreover, providing accurate information not only supports functional decision-making but also improves user comfort by reducing the time and effort spent on product selection (Kumar, Rajan, Swaminathan, & Johnson, 2022). Based on these insights, the following hypotheses are proposed:

H1a: Accuracy experience with AI Chatbots positively influences Gen Z's perceived utility value in online shopping.

H1b: Accuracy experience with AI Chatbots positively influences Gen Z's perceived hedonic value in online shopping.

- Insight Experience and Perceived Value

An AI Chatbot's ability to deliver personalized suggestions based on user preferences or purchase history enhances the overall shopping experience. This insight experience supports tailored interactions, helping Gen Z users discover relevant products more efficiently while increasing engagement and satisfaction (Micu et al., 2022). Personalized recommendations not only contribute to functional convenience but also add enjoyment to the shopping process, thereby reinforcing both utility and hedonic value perceptions (Valdez Mendia & Flores-Cuautle, 2022). Based on this rationale, the following hypotheses are proposed:

H2a: Insight experience with AI Chatbots positively influences Gen Z's perceived utility value in online shopping.

H2b: Insight experience with AI Chatbots positively influences Gen Z's perceived hedonic value in online shopping.

- Interactive Experience and Perceived Value

A well-designed interactive experience with AI Chatbots allows users to engage smoothly with the platform, improving both functional outcomes and emotional satisfaction. For Gen Z consumers, the ability to communicate naturally—by asking questions, receiving real-time responses, and navigating conversations easily—enhances their perception of the AI Chatbot's usefulness and enjoyment (Puspitasari et al., 2023; Yu et al., 2021). Accordingly, the following hypotheses are proposed:

H3a: Interactive experience with AI Chatbots positively influences Gen Z's perceived utility value in online shopping.

H3b: Interactive experience with AI Chatbots positively influences Gen Z's perceived hedonic value in online shopping.

2.9 Perceived Value and Purchase Intention

Perceived value reflects Gen Z users' subjective evaluation of the benefits gained from using AI Chatbots compared to not using them (Kim & Lee, 2024). When users perceive strong functional and emotional benefits—such as time-saving, convenience, and shopping enjoyment—their intention to purchase increases (Singh & Milan, 2025). A positive shopping experience, both practically and emotionally, reinforces their motivation to engage in transactions. Therefore, the following hypotheses are proposed:

H4: Perceived utility value positively influences Gen Z's online shopping intention.

H5: Perceived hedonic value positively influences Gen Z's online shopping intention.

The following diagram illustrates the relationship between AI Chatbot User Experience, Perceived Value, and Purchase Intention, aligned with the S-O-R framework.

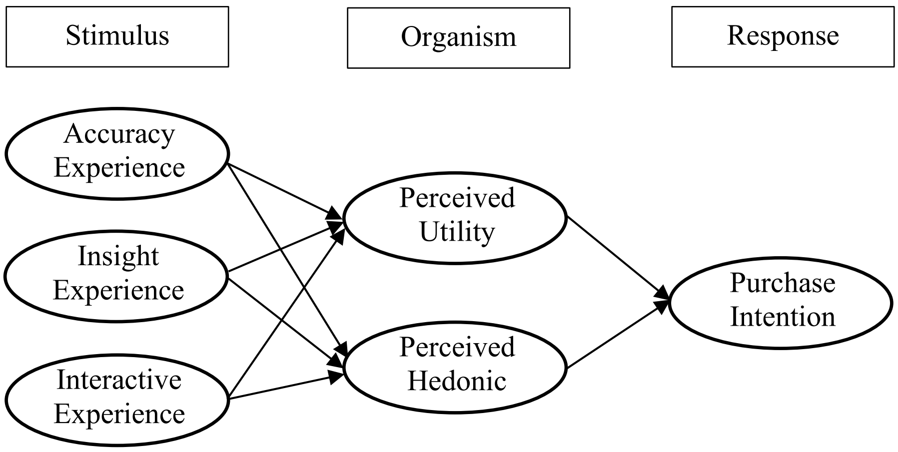

Figure 1. Research Model

3. DATA AND METHODOLOGY

3.1 Data

This study collected data through a structured survey distributed to Gen Z respondents residing in Ho Chi Minh City who have used or are familiar with AI Chatbots. A total of 200 valid responses were obtained, meeting the recommended sample size guidelines proposed by Tabachnick, Fidell, and Ullman (2007), which suggest a minimum of 74 for models with three independent variables, and Hair Jr, Matthews, Matthews, and Sarstedt (2017), who recommend at least 150 for models with fewer than seven constructs.

3.2 Model and Variables

The research model is grounded in the S-O-R framework. In this model, Stimuli refer to user experiences with AI Chatbots, represented by three variables: accuracy experience, insight experience, and interactive experience. The Organism reflects users' internal evaluations, measured through perceived utility value and perceived hedonic value. Finally, the Response is defined as online purchase intention.

All constructs were measured using previously validated scales and adapted to fit the context of AI Chatbot use in e-commerce. Each item was evaluated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The final questionnaire included 18 measurement items, grouped as follows:

Table 1. Construct, Variable Descriptions, and Sources

Construct	Variable Name	Academic Description	Source
Accuracy Experience	AE1	Captures the extent to which the AI Chatbot delivers information perceived as accurate.	Valdez Mendia and Flores-Cuautle (2022)
	AE2	Measures the relevance of the AI Chatbot's responses to the user's specific shopping needs.	Chung et al. (2016)
	AE3	Assesses the user's perception of the AI Chatbot's reliability in providing real-time answers.	Valdez Mendia and Flores-Cuautle (2022)
Insight Experience	IS1	Reflects the AI Chatbot's ability to identify and adapt to individual user preferences.	Micu et al. (2022)
	IS2	Evaluates the degree to which the AI Chatbot provides recommendations based on past user behavior.	
	IS3	Assesses the chatbot's effectiveness in personalizing content to meet specific user needs.	
Interactive Experience	IT1	Represents the perceived ease of engaging in a two-way interaction with the AI Chatbot.	Yu et al. (2021)
	IT2	Measures the responsiveness and immediacy of communication with the AI Chatbot.	
	IT3	Evaluates the chatbot's adaptability to changing conversation flow and user input.	
Perceived Utility Value	UV1	Indicates the extent to which the AI Chatbot supports effective product discovery.	Kim and Lee (2024)
	UV2	Measures the perceived time and effort saved through AI Chatbot use during online shopping.	
	UV3	Assesses the overall usefulness of the AI Chatbot in facilitating shopping-related tasks.	
Perceived Hedonic Value	HV1	Captures the user's emotional enjoyment during interaction with the AI Chatbot.	Singh and Milan (2025)

	HV2	Reflects the extent to which the AI Chatbot contributes to a fun and engaging experience.	
	HV3	Measures the user's emotional satisfaction derived from the AI Chatbot interaction.	
Purchase Intention	PI1	Assesses the likelihood that users will make a purchase after using the AI Chatbot.	Zhang and Zhao (2024)
	PI2	Measures users' intention to continue shopping on the platform due to chatbot interaction.	
	PI3	Reflects the influence of chatbot use on strengthening the user's purchasing decision.	

3.3 Methodology

This research applies Structural Equation Model (SEM) design to examine the relationships between experiential factors (stimuli), perceived value (organism), and purchase intention (response), in line with the S-O-R framework (Ali Abumalloh et al., 2025). Data were collected through a self-administered online questionnaire, and statistical analysis was conducted using SmartPLS .

This methodological approach ensures rigorous testing of the proposed model and provides a reliable foundation for interpreting the behavioral impact of AI Chatbot experiences on Gen Z consumers in e-commerce.

4. RESULTS AND DISCUSSION

4.1 Data Description

The dataset includes responses from 200 Gen Z participants in Ho Chi Minh City who have used or are familiar with AI Chatbots in online shopping contexts. This section summarizes their online purchasing behavior and internet usage patterns.

The majority of respondents reported shopping online between 3 to 9 times per month, demonstrating a high level of digital engagement. In terms of daily internet usage, most participants spent over 4 hours online per day, consistent with prior research describing Gen Z as highly connected and comfortable with digital technology (Bunea et al., 2024). These behavioral traits align with the demographic's openness to AI-enhanced shopping environments, supporting the relevance of this study's focus on AI Chatbots in e-commerce.

Table 2. Online Shopping Frequency and Internet Usage of Respondents

Online Shopping Frequency	< 2 hours/day	2–4 hours/day	4–6 hours/day	> 6 hours/day	Total (%)
Less than 3 times/month	17	4	13	15	**49 (24.5%)**
3–6 times/month	9	3	7	19	**38 (19.0%)**
7–9 times/month	6	3	10	10	**29 (14.5%)**
More than 9 times/month	13	9	8	54	**84 (42.0%)**
Total (%)	**45 (22.5%)**	**19 (9.5%)**	**38 (19.0%)**	**98 (49.0%)**	**100%**

The data reveals that a significant portion of Gen Z participants demonstrate strong digital purchasing behavior, with 42% shopping online more than nine times per month and an additional 33.5% making purchases three to nine times monthly, indicating that over 75% of the sample engage in frequent online shopping. Furthermore, nearly 49% of respondents spend more than six hours online per day, and another 19% spend between four to six hours, highlighting their deep integration into digital environments. These findings align with previous studies portraying Gen Z as a digitally immersed and tech-savvy generation that actively adopts AI-enhanced tools in e-commerce (Bunea et al., 2024; Kim & Lee, 2024). Interestingly, even those with relatively low daily internet use (under two hours) still report regular online shopping, suggesting that factors beyond time spent online—such as platform efficiency, ease of use, and AI Chatbot support—play a role in encouraging online purchase behavior (Yu et al., 2021).

4.2 Regression Analysis and Hypothesis Testing

- Reliability, Convergence, Discriminant Analysis

The evaluation of the measurement model begins with an assessment of reliability. To examine the internal consistency of the latent constructs, the study employs Cronbach's Alpha, rho_A, and Composite Reliability (CR) indices. A reliability threshold of 0.70 or higher is used to indicate acceptable consistency among the items (Rigdon, Sarstedt, & Ringle, 2017). In addition, outer loadings are used to assess the reliability of individual observed variables, where values exceeding 0.70 indicate satisfactory item reliability (Kurtaliqi, Miltgen, Viglia, & Pantin-Sohier, 2024). As presented in Tables 3 and 4, all constructs and their corresponding indicators meet these reliability standards.

Table 3.Reliability, Convergence Assessment

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AE	0.827	0.835	0.897	0.743
HV	0.858	0.859	0.913	0.779
IS	0.871	0.876	0.921	0.796
IT	0.863	0.866	0.916	0.785
PI	0.894	0.895	0.934	0.826
UV	0.764	0.768	0.865	0.681

To evaluate convergent validity, the Average Variance Extracted (AVE) is examined. An AVE value above 0.50 confirms that the construct explains more than half of the variance of its indicators, thus indicating adequate convergence (Batra, 2024). The results in Table 3 confirm that all latent variables satisfy this criterion.

Table 4. Outer Loading

	AE	HV	IS	IT	PI	UV
AE1	0.834					
AE2	0.842					
AE3	0.768					
HV1		0.840				
HV2		0.789				
HV3		0.784				
IS1			0.811			
IS2			0.846			
IS3			0.806			
IT1				0.859		
IT2				0.892		
IT3				0.837		
PI1					0.771	
PI2					0.802	
PI3					0.886	
UV1						0.832
UV2						0.866
UV3						0.846

Following reliability and convergence testing, the study proceeds to assess discriminant validity. First, the Fornell–Larcker criterion is applied to ensure that each construct shares more variance with its indicators than with other constructs (Hamid et al., 2017). This is verified when the square root of the AVE for each construct is greater than its correlations with other constructs. Furthermore, cross-loading analysis is conducted to confirm discriminant validity at the indicator level. An observed variable should load higher on its associated latent construct than on any other construct. The results, presented in Tables 5 and 6, confirm that both the latent constructs and their indicators possess acceptable discriminant validity.

Table 5. Fornell & Lacker

	AE	HV	IS	IT	PI	UV
AE	0.815					
HV	0.680	0.805				
IS	0.643	0.666	0.821			
IT	0.495	0.636	0.567	0.863		
PI	0.690	0.772	0.717	0.608	0.821	
UV	0.579	0.732	0.614	0.669	0.756	0.848

Table 6. Cross Loading

	AE	HV	IS	IT	PI	UV
AE1	**0.834**	0.614	0.609	0.454	0.624	0.515
AE2	**0.842**	0.587	0.520	0.394	0.530	0.477
AE3	**0.768**	0.443	0.425	0.355	0.531	0.415
HV1	0.616	**0.840**	0.569	0.573	0.680	0.632
HV2	0.544	**0.789**	0.509	0.407	0.611	0.543
HV3	0.475	**0.784**	0.527	0.550	0.566	0.589
IS1	0.624	0.574	**0.811**	0.469	0.660	0.534
IS2	0.498	0.543	**0.846**	0.451	0.617	0.460
IS3	0.453	0.521	**0.806**	0.476	0.483	0.516
IT1	0.488	0.628	0.497	**0.859**	0.644	0.683
IT2	0.439	0.550	0.506	**0.892**	0.492	0.539
IT3	0.327	0.434	0.461	**0.837**	0.394	0.474
PI1	0.578	0.653	0.596	0.403	**0.771**	0.560
PI2	0.559	0.565	0.543	0.514	**0.802**	0.572
PI3	0.568	0.678	0.624	0.575	**0.886**	0.718
UV1	0.521	0.589	0.568	0.576	0.647	**0.832**
UV2	0.448	0.611	0.486	0.564	0.641	**0.866**
UV3	0.501	0.662	0.507	0.561	0.633	**0.846**

- Hypothesis Testing

To test the proposed hypotheses, the study employed the bootstrapping technique with 5,000 subsamples using SmartPLS 4. Statistical significance was determined based on p-values, with hypotheses considered supported when $p \leq 0.05$ and rejected when $p > 0.05$, following the guidelines established by Batra (2024) and Akter et al. (2024). The analysis revealed that all hypothesized relationships yielded p-values less than or equal to 0.05, indicating that all hypotheses were statistically supported.

Table 7. Hypothesis Assessment

Hypo-thesis	**Path**	**Original Sample**	**Sample Mean**	**Standard Deviation**	**T Statistics**	**P Values**	**Result**
H1a	AE→UV	0.217	0.217	0.074	2.929	0.004	**Accepted**
H1b	AE→HV	0.360	0.357	0.076	4.730	0.000	**Accepted**
H2a	IS→UV	0.230	0.245	0.112	2.052	0.041	**Accepted**
H2b	IS→HV	0.258	0.254	0.092	2.814	0.005	**Accepted**
H3a	IT→UV	0.431	0.414	0.148	2.919	0.004	**Accepted**
H3b	IT→HV	0.312	0.314	0.099	3.160	0.002	**Accepted**
H4	UV→PI	0.411	0.412	0.091	4.533	0.000	**Accepted**
H5	HV→PI	0.472	0.479	0.087	5.404	0.000	**Accepted**

Accuracy experience significantly influenced both perceived utility value ($\beta = 0.217$, $p = 0.004$) and hedonic value ($\beta = 0.360$, $p < 0.001$), supporting hypotheses *H1a* and *H1b*. This suggests that Gen Z consumers value AI Chatbots that provide reliable and contextually relevant information, which enhances both the effectiveness and enjoyment of their online shopping experience. This finding aligns with Valdez Mendia and Flores-Cuautle (2022), who emphasized that accuracy reinforces the user's confidence in AI systems, and with Chung et al. (2016), who noted that high-quality information improves shopping satisfaction. Furthermore, Halachev (2024) suggests that when users perceive chatbot responses as accurate, they experience greater trust and cognitive comfort, leading to a stronger sense of practical benefit and emotional engagement.

Insight experience also showed a significant positive effect on both utility ($\beta = 0.230$, $p = 0.041$) and hedonic value ($\beta = 0.258$, $p = 0.005$), confirming *H2a* and *H2b*. These results highlight the importance of personalization—AI Chatbots that adapt to a user's past behavior and preferences are perceived as more helpful and emotionally rewarding. This is consistent with Micu et al. (2022), who argue that personalization strengthens perceived relevance and shopping efficiency. Wen et al. (2022) further emphasize that insightful recommendations create a sense of being understood, which enhances emotional satisfaction. For Gen Z, a generation accustomed to algorithmic customization, this reinforces loyalty and deepens user-platform connection (Ho & Chow, 2024; Powell et al., 2024).

Interactive experience was the strongest predictor of utility value ($\beta = 0.431$, $p = 0.004$) and also had a significant impact on hedonic value ($\beta = 0.312$, $p = 0.002$), supporting *H3a* and *H3b*. This underscores the critical role of fluid, responsive communication in shaping user perceptions of value. These findings are supported by Yu et al. (2021), who argue that ease of interaction increases usability, while Puspitasari et al. (2023) confirm that responsive systems enhance user satisfaction. The emotional dimension of interactivity also aligns with the work of Tian et al. (2018), who found that natural conversations reduce perceived friction and create a more enjoyable shopping experience. For Gen Z users, who expect real-time responsiveness, interactive design significantly drives engagement and value perception.

Finally, both perceived utility value ($\beta = 0.411$, $p < 0.001$) and hedonic value ($\beta = 0.472$, $p < 0.001$) had strong positive effects on purchase intention, confirming *H4* and *H5*. These results indicate that both cognitive and emotional evaluations are crucial in influencing Gen Z consumers' decision-making. This dual pathway is consistent with Singh and Milan (2025), who suggest that rational benefits and emotional experiences jointly influence buying behavior. It also aligns with Kim and Lee (2024), who found that utility and hedonic values are equally important for digital natives. The strong statistical support for both relationships in this study confirms that AI Chatbots can drive online purchases not only by solving problems but also by creating pleasurable experiences.

5. CONCLUSION

This study looked at how Ho Chi Minh City's Gen Z consumers react to experiential elements in AI chatbot interactions, particularly accuracy, insight, and interactivity, and how these factors affect their opinions about value and intention to buy.

Based on the S-O-R framework, the results show that perceived utility value and perceived hedonic value are significantly influenced by all three experiential dimensions. Consequently, the intention to make an online purchase is strongly and favorably influenced by both value perceptions. These findings support Singh and Milan (2025) dual cognitive-affective pathway by indicating that Gen Z users not only anticipate AI chatbots to perform well but also look for emotional fulfillment from the interaction.

By applying the S-O-R model to AI-based chatbots in the context of e-commerce, this study theoretically adds to the body of literature. This study incorporates both viewpoints, whereas previous research has frequently concentrated on usability or emotional reactions separately (L. Guo & Cai, 2024; Micu et al., 2022). The significant influence of interactive experience on utility value reinforces the argument by Yu et al. (2021) that responsiveness and conversational fluidity are central to technology acceptance, especially among digital natives. Similarly, the role of insight experience in enhancing hedonic value aligns with Wen et al. (2022), who emphasized the importance of personalized experiences in driving emotional engagement. This dual-pathway validation extends the S-O-R model by empirically confirming that Gen Z consumers base their purchase decisions not only on task efficiency but also on the pleasure derived from the interaction.

Practically, the results provide insightful information for e-commerce companies and AI chatbot developers who want to better interact with Gen Z customers. This study supports Kim and Lee (2024) findings that for digital platforms to have an impact on behavior, utility and enjoyment must coexist. The robust relationship between accuracy experience and hedonic value implies that consumers find emotional fulfillment in systems that are not only accurate and context-aware but also functional (Valdez Mendia & Flores-Cuautle, 2022). The importance of memory-based personalization techniques and recommendation algorithms in enhancing user satisfaction is further highlighted by the noteworthy role of insight experience (Micu et al., 2022). Additionally, the data demonstrate that a well-designed interactive experience enhances utility and hedonic perceptions by fostering a sense of natural communication, in addition to providing a functional benefit. These results highlight the necessity for platform designers to make investments in chatbots' conversational and adaptive capabilities in addition to their technical prowess.

The study has a number of shortcomings in spite of these contributions. First, the results may not be as applicable to other cultural or demographic groups because they were gathered solely from Gen Z users in Ho Chi Minh City. While the findings are consistent with worldwide AI adoption trends, future studies should investigate whether comparable trends hold true in other national or regional contexts. Second, a cross-sectional design was used in the study to record user responses at a specific moment in time. According to Akter et al. (2024), long-term research is required to examine how technology perceptions may change as a result of repeated exposure or system design updates. Finally, because of social desirability effects and common method bias, survey data may not always accurately predict actual behavior, even though they are helpful for capturing perceptions and intentions.

Future studies should expand this work by observing how user experience and purchasing behavior change over time using experimental or longitudinal designs. Furthermore, studies comparing different AI chatbot modalities—such as text-based versus voice-enabled systems—may highlight significant variations in the ways that experiential factors affect perceived value. A more thorough grasp of the dynamics at work in AI-supported online shopping might also be obtained by extending the model to incorporate trust, privacy concerns, or brand attitude. Long-term engagement and business success will be largely dependent on the ability to create emotionally intelligent, adaptive, and context-aware chatbot systems as AI develops further, particularly in light of Gen Z's digital behavior.

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