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Factors Influencing the Intention to Use AI Chatbots in E-Commerce Customer Service

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Abstract

While Vietnamese e-commerce has quickly integrated AI tools into customer service, the actual uptake of chatbots hinges on how shoppers in this market appraise their value and experience. In Vietnam, where online shopping is growing rapidly, little empirical evidence exists on the drivers of chatbot adoption. This research aims to investigate the behavioural, psychological, and technological factors that determine Vietnamese consumers' intention to use AI chatbots in e-commerce customer service. Specifically, it seeks to identify the most influential determinants of usage intention and to propose managerial implications for improving chatbot design and implementation in Vietnam's digital marketplace. The research was conducted based on a Technology Acceptance Model (TAM) framework incorporating Trust, Social Influence, Application Design, Efficiency, and Enjoyment. Data from 304 online shoppers were analyzed using reliability assessment, Exploratory and Confirmatory Factor Analyses (EFA and CFA), and Structural Equation Modeling (SEM) for hypothesis testing. This process ensured measurement validity and offered theoretical insights into chatbot adoption in Vietnam's e-commerce context. The analysis reveals that Perceived Usefulness and Perceived Enjoyment serve as the most influential determinants of behavioral intention, whereas Social Influence and Efficiency affect intention indirectly via usefulness, with Trust and Application Design demonstrating comparatively weaker impacts than anticipated. The evidence adds an emerging-market perspective and indicates concrete levers (utility, responsiveness, and engaging interaction) that Vietnamese platforms can act on.

Keywords: AI chatbots, behavioral intention, customer service, E-commerce, perceived usefulness, structural equation modeling (SEM), online shopping, technology acceptance model, Vietnam.

1. Introduction

Recent digitalization waves have reconfigured service operations; in Vietnam's online retail, AI-mediated support is now routine. Among the technologies driving this shift, artificial intelligence (AI) has emerged as a core enabler of customer service innovation. AI-powered chatbots have been widely adopted to simulate human conversation, provide instant support, and manage customer inquiries efficiently. According to research in the Gartner customer service & support practice [1], by 2027 around 25% of customer service operations worldwide are expected to be handled by AI chatbots, underscoring their increasing strategic significance in digital commerce. In this study, attention is directed to the Vietnamese retail context, where major platforms have already adopted such technologies at scale. Chatbots have become an integral part of Vietnam's e-commerce landscape, being deployed by leading platforms such as Shopee, Lazada, and Tiki to deliver 24/7 customer support, facilitate order tracking, and resolve post-purchase issues. Global research consistently emphasizes that user acceptance of these technologies depends on multiple determinants, including perceived usefulness (PU), ease of use, trust, and enjoyment [2, 3]. For instance, research identified convenience and productivity as dominant motivations [4], while Adam *et al*. (2021) [5] showed that trust mitigates perceived risks and strengthens adoption. In the Vietnamese context, however, empirical studies remain limited. Most chatbot-related research to date has examined banking and telecommunications, whereas e-commerce adoption has yet to be thoroughly investigated [6, 7]. Despite these advances, limited attention has been paid to the use of AI chatbots in e-commerce platforms, where customer interaction dynamics differ substantially from banking or telecommunications services. E-commerce transactions often involve high-frequency, and low-value purchases that rely on instant responses, emotional engagement, and convenience. Investigating chatbot adoption in this setting therefore provides new insight into how PU, enjoyment, and trust operate in quick-decision environments. Extending the Technology Acceptance Model (TAM) framework to include social influence (SI), application design, and efficiency offers a more comprehensive understanding of users' behavioral intentions, reflecting both technological and experiential factors unique to the online retail context. The TAM has been widely applied to explain adoption behavior, but contemporary studies extend it by incorporating trust, anthropomorphism, application design, and SI to capture socio-psychological dimensions of chatbot use [8, 9]. Building on this foundation, the present study develops

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an extended TAM framework that integrates Trust, SI, Application Design, Efficiency, and Perceived Enjoyment. This approach allows for a comprehensive analysis that accounts for both utilitarian and hedonic motivations in shaping behavioral intentions. The application of AI chatbots in e-commerce is particularly significant for emerging digital economies like Vietnam. Unlike sectors such as banking or telecommunications, where chatbot interactions are often transactional and standardized, e-commerce involves more diverse, dynamic, and emotionally charged exchanges between consumers and digital interfaces. The sector's rapid expansion, fueled by increasing smartphone penetration and a young, tech-savvy population, has created new expectations for real-time, and personalized customer support. Chatbots therefore play a crucial role in addressing service scalability challenges, managing high inquiry volumes, and ensuring consistent user experiences across large customer bases. Moreover, from a strategic perspective, the integration of chatbots aligns with Vietnam's national digital transformation agenda (Decision No. 749/QD-TTg, 2020), which emphasizes the adoption of intelligent technologies to enhance service quality and operational efficiency. In this regard, examining chatbot adoption in e-commerce not only enriches the understanding of consumer behavior in a high-contact digital service environment but also provides evidence-based insights that support policymakers and businesses in accelerating smart retail transformation. Consequently, this research extends the TAM to capture both utilitarian and hedonic motivations that drive consumers' behavioral intentions in AI-mediated service contexts.

The purpose of this paper is to contribute to both theory and practice. Theoretically, it extends TAM by validating the joint impact of utilitarian and hedonic drivers in an emerging market context. Practically, it provides insights for e-commerce platforms to design chatbot systems that are not only efficient but also trustworthy and engaging, thereby enhancing consumer acceptance. The structure of this paper is organized as follows. Section 2 provides the theoretical foundation and formulates the hypotheses; Section 3 describes the research methodology; Section 4 reports the data analysis and findings; and Section 5 concludes with implications and suggestions for future studies.

2. Literature Review

AI has profoundly reshaped the interaction between businesses and consumers, particularly in the digital service environment. Among the most visible applications of AI are chatbots, which have gained prominence in e-commerce for their ability to provide immediate responses, reduce costs, and improve user experience. The increasing reliance on conversational agents highlights the necessity of understanding the factors influencing their adoption, a topic that has attracted significant scholarly attention across the globe. The TAM has long served as a foundational framework for understanding technology adoption, positing PU and perceived ease of use (PE) as primary antecedents of behavioral intention (BI) [10]. In the context of AI chatbots, PU reflects the degree to which consumers believe chatbots improve efficiency and decision-making, while PE indicates whether chatbots are simple and effortless to use. Empirical evidence across different contexts has consistently supported these constructions. In the case of Chinese e-commerce users, Gao *et al*. (2021) [3] found that PU exerted the most substantial influence on BI, while PE and interaction quality contributed to greater user satisfaction and continued usage. Similarly, in the hospitality industry, Gursoy *et al*. (2019) [11] found that PU, PE, and PJ collectively shaped user attitudes toward chatbots, demonstrating that utilitarian and hedonic drivers must both be considered.

Beyond TAM, trust has emerged as a critical factor in chatbot adoption. In AI-mediated environments, trust functions as a protective mechanism that alleviates users' perceived risks, notably in situations involving personal information disclosure or financial exchange. Gefen, Karahanna, and Straub (2003) [2] argued that in online contexts, trust plays a pivotal role in shaping user confidence and reducing uncertainty. More recent research has confirmed this view. It is found that privacy and security concerns directly influence trust, which subsequently shapes behavioral intention [12]. Adam, Wessel, and Benlian (2021) [13] further highlighted that when users perceive chatbots as reliable and competent, their willingness to adopt increases significantly. These insights reinforce the idea that technological features alone are insufficient; trust is indispensable for consumer acceptance.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has also provided valuable insights by emphasizing additional determinants such as SI and facilitating conditions [14]. Within collectivist environments, SI carries heightened significance, as individuals are more likely to align their choices with peer expectations and social norms. Lu *et al*. (2019) [15] applied UTAUT in mobile commerce and found that performance expectancy and SI were the strongest predictors of adoption, suggesting that endorsements from peers, family, or social networks can compensate for uncertainties about chatbot technology. This finding aligns with cultural contexts where individuals are likely to adopt technologies supported by their social circle.

While TAM and UTAUT traditionally highlight utilitarian constructs, subsequent research emphasizes the role of enjoyment and emotional engagement in driving adoption. Venkatesh *et al*. (2003) [14] argued that hedonic motivation has been identified as a significant determinant of technology adoption, particularly within consumer-oriented contexts. In chatbot contexts, PE positively influences satisfaction

and loyalty [5]. Ding and Najaf (2024) [9] provided further psychological evidence, demonstrating that interactivity and perceived humanness strengthen trust and enjoyment, which in turn increase BI. These results underscore that the experience of interacting with chatbots must be not only useful but also enjoyable if businesses wish to encourage adoption. Both design quality and efficiency play supportive roles in driving users' adoption intention. Diederich, Brendel, and Kolbe (2022) [16] found that clarity, layout, and anthropomorphic design cues significantly enhance user satisfaction, whereas poor design undermines trust. Similarly, Luo *et al*. (2019) [17] emphasized that speed and accuracy of responses determine PU and, consequently, BI. Together, these findings highlight that application design and efficiency represent distinct constructs that deserve attention beyond traditional TAM variables.

While international studies provide extensive evidence, Vietnamese research on chatbot adoption remains limited. Vietnam has witnessed rapid growth in e-commerce, driven by increasing internet penetration, smartphone usage, and the rise of platforms such as Shopee, Lazada, Tiki, and TikTok Shop. Chatbots have been integrated into these platforms to handle routine inquiries and support customer interactions, yet empirical research on consumer acceptance is still emerging. Nguyen, Chiu, and Le (2021) [6] examined banking chatbots using the DeLone & McLean IS Success Model and Expectation-Confirmation Model, finding trust, satisfaction, and PU strongly predicted continuance intention. Ngo and Nguyen (2022) [7] extended TAM to e-commerce and confirmed that PU, PE, trust, and enjoyment positively affect BI, although hedonic motivations were weaker compared to utilitarian factors. Tran (2022) [18] offered a cultural perspective, arguing that politeness and linguistic appropriateness are critical in Vietnam, as consumers show higher tolerance for errors when chatbots adopt culturally aligned communication styles. More recent studies of Gen Z users have revealed that subjective norms and peer influence significantly affect adoption, reinforcing the role of SI in collectivist cultures [19]. A synthesis of global and Vietnamese research reveals both similarities and differences. Across contexts, PU and PE are consistently validated as the strongest drivers of adoption, supporting TAM's foundational assumptions. Trust is also universally significant, serving as both a direct predictor of BI and as an antecedent of PU and PE. SI emerges as another common determinant, especially in collectivist cultures where peer and societal norms shape behavioral intentions. Hedonic motivations, including PJ, have gained increasing recognition worldwide, although they have been undervalued in Vietnamese contexts until more recently, particularly with the rise of younger, and digitally fluent users. Finally, application design and efficiency are increasingly recognized as critical constructs, though global studies emphasize anthropomorphism and empathy while Vietnamese research focuses on credibility and cultural alignment.

Although prior research has made notable progress, important gaps in understanding still persist. First, most Vietnamese studies have concentrated on banking and telecommunications, leaving e-commerce chatbots relatively underexplored despite their widespread use. Second, the indirect effects of constructs such as trust have not been fully examined; while Vietnamese research often treats trust as a direct predictor of BI, global studies suggest more complex pathways such as trust influencing PU, which then drives BI [13, 20]. Third, hedonic motivations have been consistently significant in global research but are underrepresented in Vietnam, even though younger demographics indicate their importance. Fourth, application design and efficiency have rarely been empirically tested in Vietnam, although global evidence shows that these constructs substantially shape perceptions of usefulness and ease of use. Finally, few studies explicitly consider how cultural norms, generational differences, or language expectations influence adoption, leaving an opportunity for contextually rich research.

In summary, the literature establishes a comprehensive understanding of chatbot adoption while also revealing gaps that justify further investigation. Global studies underscore the multifaceted nature of adoption, highlighting functional, psychological, and design-related factors. Vietnamese research confirms many of these insights but also points to the importance of cultural and contextual determinants. This study builds on these foundations by extending TAM with Trust, SI, Application Design, Efficiency, and PE, thereby addressing underexplored constructs and providing new evidence from Vietnam's rapidly growing e-commerce sector.

3. Research Model and Hypothesis Development

AI chatbots have become an essential tool in e-commerce customer service, yet their adoption depends on how consumers perceive both functional and psychological attributes. Building on the TAM, this study incorporates additional constructs validated in prior research to capture a more holistic view of chatbot acceptance. Alongside the core variables PU and PE, factors such as Trust, SI, Application Design, Efficiency, and PJ are introduced. Prior studies emphasize that PU and PE strongly predict adoption [3], while trust reduces risk perceptions [13, 21], and SI plays a crucial role in collectivist societies [14, 15]. Efficiency, reflected in speed and accuracy of chatbot responses, has also been linked to higher PU, whereas application design and interface quality contribute to PE [16]. In addition to utilitarian dimensions, hedonic motivations are included to reflect the affective side of user experience. Research indicates that PE significantly strengthens BI in interactive technologies [5, 11]. Integrating both functional and emotional factors allows

the model to capture the multidimensional nature of chatbot adoption. The proposed framework therefore assumes that PU and enjoyment are the strongest direct predictors of intention, while SI, efficiency, trust, and design indirectly shape adoption by affecting PU and ease of use.

The following hypotheses are posited to test the relationships within the proposed model as shown in Fig. 1:

H1: Social Influence enhances users' Perceived Usefulness of AI chatbots.

H2: Efficiency positively contributes to users' Perceived Usefulness of AI chatbots.

H3: Trust facilitates users' Perceived Ease of Use of AI chatbots.

H4: Application Design improves users' Perceived Ease of Use of AI chatbots.

H5: Perceived Usefulness strengthens users' Behavioral Intention to use AI chatbots.

H6: Perceived Ease of Use promotes users' Behavioral Intention to use AI chatbots.

H7: Social Influence fosters users' Behavioral Intention to use AI chatbots.

H8: Efficiency reinforces users' Behavioral Intention to use AI chatbots.

H9: Trust positively associates with users' Behavioral Intention to use AI chatbots.

H10: Application Design contributes to users' Behavioral Intention to use AI chatbots.

H11: Perceived Enjoyment stimulates users' Behavioral Intention to use AI chatbots.

The proposed framework builds upon the extended TAM by integrating constructs from prior research in human–AI interaction. Trust theory explains users' reliance on system integrity; SI is grounded in social cognitive theory, emphasizing peer and societal norms; and application design and efficiency reflect the system quality dimension of the IS success model. Together, these elements offer a holistic perspective of users' cognitive and affective responses to AI chatbots.

4. Data Analysis

4.1. Sampling and Data Collection

Data for this study were collected through an online survey distributed via Google Forms between early June and early July 2025. The target respondents were Vietnamese online shoppers who had prior experience interacting with AI chatbots on major e-commerce platforms such as Shopee, Lazada, Tiki, and TikTok Shop. A purposive sampling strategy was employed, as the research specifically required participants with firsthand exposure to chatbot-assisted services in order to ensure the reliability of their evaluations. This approach allowed the study to focus on relevant users who could provide meaningful insights into BI and adoption patterns. A total of 357 responses were initially obtained. After data screening, including the removal of incomplete entries and straight-lined responses, 304 valid observations were retained for analysis. This number of respondents exceeds the minimum sample size recommended for Structural Equation Modeling (SEM), which is generally set at 200 or a ratio of at least 10 participants per estimated parameter.

Furthermore, the diversity of respondents in terms of age, occupation, education, and income increases the representativeness of the dataset, despite the use of an online distribution channel. The collection period coincided with peak shopping activities on e-commerce platforms, particularly during mid-year promotional campaigns, which ensured that most participants had recent and relevant chatbot interaction experiences.

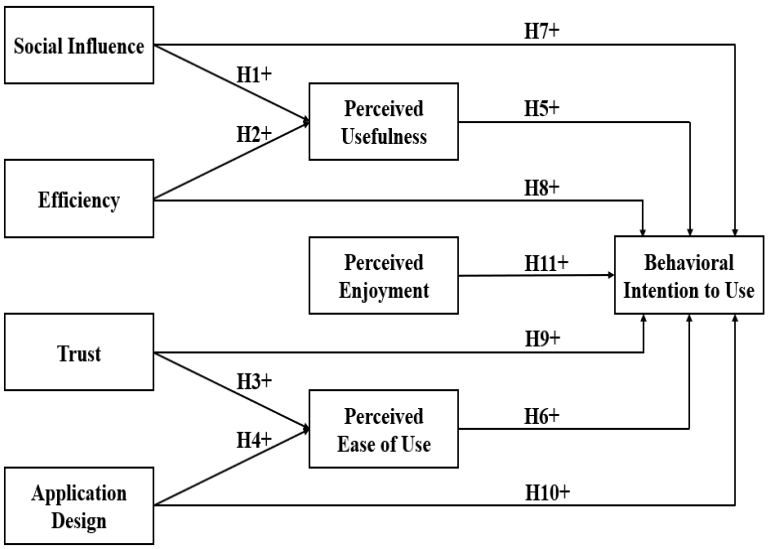


Fig. 1. Proposed research model

Consequently, the dataset can be considered robust and appropriate for advanced statistical analyses, including reliability testing, factor analysis, and structural model evaluation.

4.2. Descriptive Analysis

Among the 304 respondents, gender was relatively balanced, with a predominantly young sample concentrated in the 18–35 age range. Most participants were well educated, as nearly three quarters held a college/university or postgraduate degree, and students formed the largest occupational group. Income levels and online shopping frequency were diverse, with over half of respondents shopping online at least 3–5 times per month and a moderate monthly income being most common. While IT literacy was generally high, chatbot adoption remained low, with nearly half of respondents rarely using chatbots and fewer than one fifth using them frequently.

The descriptive statistics of the measurement factors and their items are presented in Table 1.

Table 1. A descriptive analysis of measurement factors and items

STT	Factor	Item	Min	Max	Mean	S.D	Mean of Factor	S.D of Factor
1	Social Influence (SI)	SI1	1	5	3.44	1.21	3.46	1.22
2		SI2	1	5	3.40	1.25		
3		SI3	1	5	3.54	1.22		
4		SI4	1	5	3.48	1.20		
5	Efficiency (EC)	EC1	1	5	3.52	1.16	3.50	1.18
6		EC2	1	5	3.51	1.18		
7		EC3	1	5	3.53	1.22		
8		EC4	1	5	3.44	1.16		
9	Trust (TR)	TR1	1	5	3.55	1.12	3.43	1.24
10		TR2	1	5	3.48	1.18		
11		TR3	1	5	3.51	1.22		
12		TR4	1	5	3.17	1.46		
13	Application Design (AD)	AD1	1	5	3.56	1.24	3.53	1.19
14		AD2	1	5	3.56	1.15		
15		AD3	1	5	3.51	1.22		
16		AD4	1	5	3.50	1.16		
17	Perceived usefulness (PU)	PU1	1	5	3.58	1.18	3.50	1.19
18		PU2	1	5	3.52	1.18		
19		PU3	1	5	3.45	1.20		
20		PU4	1	5	3.46	1.22		
22	Perceived Ease of Use (PE)	PE1	1	5	3.41	1.16	3.48	1.179
23		PE2	1	5	3.52	1.18		
24		PE3	1	5	3.50	1.19		
27	Perceived Enjoyment (PJ)	PJ1	1	5	3.49	1.16	3.53	1.18
28		PJ2	1	5	3.58	1.18		
29		PJ3	1	5	3.52	1.21		
32	Behavioral Intention (BI)	BI1	1	5	3.41	1.23	3.47	1.20
33		BI2	1	5	3.48	1.18		
34		BI3	1	5	3.51	1.21		

The mean scores of all constructs ranged between 3.43 and 3.53 on a five-point Likert scale, indicating that respondents generally held moderately positive perceptions toward the factors examined. Specifically, AD (*M = 3.53, SD = 1.19*) and PE (*M = 3.53, SD = 1.18*) reported the highest average values, suggesting that respondents appreciated the interface quality and the hedonic aspects of chatbot use. TR exhibited the lowest mean (*M = 3.43, SD = 1.24*), implying that while respondents acknowledged functional and design aspects, confidence in chatbot reliability remained limited. BI, the outcome variable, achieved a mean of 3.47 (*SD = 1.20*), reflecting a moderate willingness to adopt AI chatbots in e-commerce. Overall, the results demonstrate a balanced perception across constructs, with no extreme values, providing a sound basis for further reliability and validity testing.

4.3. Exploratory Factor Analysis and Regression Model

The reliability and validity of the constructs were assessed using Cronbach's Alpha and exploratory factor analysis (EFA). All constructs reported reliability coefficients met the generally accepted standard, with most Cronbach's Alpha values greater or equal 0.7, ranging from 0.772 (PU) to 0.831 (SI), except for TR which recorded a slightly lower value of 0.683. This indicates that most scales demonstrate strong internal consistency, and the TR construction remains acceptable for exploratory research. The rotated factor loadings further confirm the construct validity, with all observed variables loading significantly on their respective factors. Efficiency items loaded between 0.711 and 0.769, PU between 0.614 and 0.763, SI between 0.633 and 0.802, and AD between 0.655 and 0.759. PE showed loadings from 0.674 to 0.748, while TR items ranged from 0.689 to 0.757. BI items loaded between 0.588 and 0.803, and PE items between 0.631 and 0.750. Since most factor loadings exceed the minimum threshold of 0.5, the results confirm convergent validity and suggest that each set of indicators reliably represents its underlying latent construct. Collectively, these findings provide evidence of satisfactory reliability and construct validity, ensuring that the measurement model is appropriate for further confirmatory factor analysis (CFA) and SEM. The measurement model was assessed using Composite Reliability (CR) and Average Variance Extracted (AVE). All constructs achieved CR values above the recommended threshold of 0.7, ranging from 0.718 (TR) to 0.827 (SI), thereby confirming satisfactory internal consistency. Similarly, most constructions reported AVE values above 50%, indicating adequate convergent validity, with the exception of TR (AVE = 41.7%), which was slightly below the conventional benchmark. Despite this limitation, TR was retained in the model as its CR exceeded 0.7 and the construction was theoretically significant. Overall, these results suggest that the measurement scales are reliable and valid for further CFA and SEM.

The theoretical model of this study was assessed using a covariance-based structural equation modeling (CB-SEM) approach. CB-SEM was conducted using AMOS to assess construct reliability, validity, and overall model fit (Fig. 2).

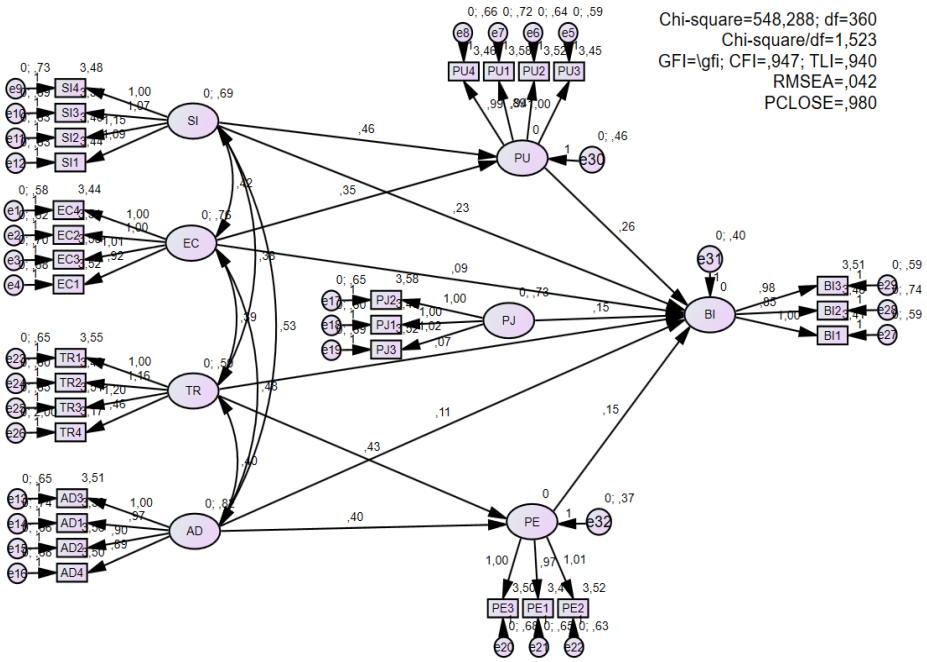


Fig. 2. Measurement model

Table 2. Estimated regression model results

Relationship of variables			Estimate	S.E.	C.R.	*P*-value
PU	←	SI	0.465	0.090	5.149	0.000***
PU	←	EC	0.349	0.083	4.185	0.000***
PE	←	TR	0.432	0.099	4.344	0.000***
PE	←	AD	0.396	0.082	4.808	0.000***
BI	←	PE	0.151	0.103	1.470	0.142
BI	←	PU	0.256	0.087	2.957	0.003
BI	←	PJ	0.153	0.063	2.430	0.015
BI	←	SI	0.229	0.121	1.897	0.058
BI	←	EC	0.087	0.097	0.893	0.372
BI	←	TR	0.065	0.118	0.549	0.583
BI	←	AD	0.113	0.115	0.981	0.327

The results confirmed that the measurement items adequately represent their respective latent constructs, demonstrating both convergent and discriminant validity. Therefore, the measurement model provides a robust foundation for the subsequent structural model analysis, which examines the hypotheses and the direct, indirect, and total effects influencing the intention to adopt AI chatbots in e-commerce customer service. Model fit was assessed through several indices, all of which indicated acceptable values, confirming the measurement and structural models' adequacy in representing the data. Specifically, the discrepancy measures indicated a satisfactory ratio between chi-square and degrees of freedom. Incremental fit indices such as Comparative Fit Index - CFI (0.947), Tucker–Lewis Index - TLI (0.940), and Incremental Fit Index – IFI (0.948) all fell within the recommended range (from 0.9 to 1), demonstrating that the proposed model provided a significant improvement over the null model. Similarly, the parsimony-adjusted indices (Parsimonious Normed Fit Index – PNFI (0.764) and Parsimonious Comparative Fit Index – PCFI (0.840) were also within acceptable limits (0.5 – 1 for PNFI and (0.9 to 1 for PCFI) respectively, suggesting that the model is both parsimonious and well-specified. Collectively, these findings validate that the model adequately represents the data and can be reliably used for subsequent structural path analysis.

The results of the structural model in Table 2 show that SI (β = 0.465, p < 0.001) and Efficiency (β = 0.349, p < 0.001) exert significant positive effects on PU, confirming that both social validation and system performance strongly shape how users evaluate the practical value of chatbots. Among these, SI demonstrated the stronger impact, suggesting that recommendations from peers, influencers, or communities substantially enhance the perception of usefulness. Similarly, TR (β = 0.432, p < 0.001) and AD (β = 0.396, p < 0.001) were found to significantly improve PE, indicating that confidence in system reliability and a user-friendly interface directly support the perception of interaction simplicity. With regard to Behavioral Intention, two predictors emerged as statistically significant. PU (β = 0.256, p = 0.003) confirmed its central role as a utilitarian driver of adoption, while PE (β = 0.153, p = 0.015) highlighted the importance of hedonic motivation. These results suggest that users are more willing to adopt AI chatbots when they perceive them as both beneficial for task completion and enjoyable to interact with.

Notably, the impact of PU was stronger than that of PE, underscoring that pragmatic benefits remain the dominant determinant, while emotional engagement plays a complementary role. In contrast, the direct effects of several constructs on BI were not supported. PE (p = 0.142), SI (p = 0.058), Efficiency (p = 0.372), TR (p = 0.583), and AD (p = 0.327) failed to reach statistical significance. This implies that while these factors are important in shaping perceptions of usefulness and ease of use, they do not directly determine users' intention to adopt chatbots. The findings therefore highlight a nuanced adoption mechanism: utilitarian and hedonic values are decisive, whereas design, TR, and SI primarily function as indirect enablers rather than direct drivers of behavioral intention.

The regression results indicate that SI (β = 0.465, p < 0.001) and efficiency (β = 0.349, p < 0.001) significantly enhance PU, suggesting that users find AI chatbots more valuable when recommended by others and when the system operates effectively. TR (β = 0.432, p < 0.001) and AD (β = 0.396, p < 0.001) also have strong effects on PE, implying that reliability and intuitive design make the chatbot easier to interact with. In contrast, PE does not directly influence BI (β = 0.151, p = 0.142), indicating that ease alone is insufficient to encourage adoption. BI is more strongly influenced by PU (β = 0.256, p = 0.003) than by PE (β = 0.153, p = 0.015). The effects of social, design, and operational factors are primarily mediated through

Usefulness and Ease of Use. Furthermore, SI, efficiency, TR, and design show no significant direct impact on BI, implying their indirect effects through PU or ease of use as calculated in Table 3. Overall, the findings confirm that PU, TR, and PE are the most critical factors influencing users' intention to use AI chatbots in e-commerce customer service.

5. Conclusion

AI chatbots have rapidly emerged as an innovative tool transforming customer service in e-commerce. This study aimed to examine the factors influencing Vietnamese consumers' intention to adopt AI chatbots by extending the TAM with additional constructs such as SI, Efficiency, Trust, Application Design, and PE. Advanced statistical methods, including reliability analysis, EFA, CFA, and SEM, were employed to test the research model using 304 valid survey responses collected from online shoppers across major platforms such as Shopee, Lazada, Tiki, and TikTok Shop.

The findings confirm that PU and PE are the strongest direct predictors of BI, highlighting that both functional value and hedonic motivation shape consumer decisions. PU is strongly influenced by SI and efficiency, while PE is determined by trust and application design. Interestingly, the study reveals those traditional determinants such as trust and design, though statistically significant for shaping ease of use-do not directly affect BI. Instead, they act as indirect enablers, reinforcing the perception of simplicity rather than serving as decisive adoption drivers. This reflects an important shift in consumer expectations: users now consider trust and design as "baseline requirements," while adoption is mainly driven by the chatbot's usefulness and the enjoyment of interacting with it. The results also emphasize that in a market dominated by young, and digitally fluent consumers, pragmatic benefits and hedonic engagement outweigh conventional factors in influencing adoption.

The findings confirm PU as the strongest determinant of BI, consistent with TAM and prior studies [3, 7]. The significant role of SI also supports UTAUT, particularly in socially influenced contexts [15, 19]. In contrast, PE shows no direct effect, diverging from traditional TAM [7, 10]. This suggests that ease of use has become a "hygiene factor," with adoption driven more by utility and engagement. Similarly, trust and application design influence intention only indirectly via PE, rather than directly [6, 13, 20]. Finally, PE plays an increasing role [5, 11], especially among younger users, though PU remains dominant.

The study shows that chatbot adoption differs by sector, transaction type, and stage of the e-commerce journey. Unlike banking and telecommunications where interactions are standardized and transactional, e-commerce involves high-frequency, low-value purchases with more dynamic and emotional exchanges. As a result, while usefulness remains important, enjoyment plays a stronger role in e-commerce contexts. Across stages, chatbot functions also vary. In pre-sale and during-sale phases, efficiency like speed and accuracy is critical, as users prioritize quick responses to support purchase decisions. In post-sale situations such as complaints or returns, trust and application design become essential baseline conditions that reduce perceived risk, though they do not directly drive usage intention. Additionally, while efficiency dominates transactional interactions, sustained engagement requires enjoyable features like personalization. Finally, due to the consumer-driven and trend-sensitive nature of e-commerce, SI strongly shapes perceptions of chatbot usefulness and adoption behavior.

Table 3. Estimated total effect, direct and indirect effect

Path			Total Effect	Direct Effect	Indirect Effect
SI	→	PU	0.423	0.423	0
SI	→	BI	0.322	0.212	0.110
EC	→	PU	0.333	0.333	0
EC	→	BI	0.171	0.084	0.087
TR	→	PE	0.383	0.383	0
TR	→	BI	0.111	0.055	0.056
AD	→	PE	0.416	0.416	0
AD	→	BI	0.173	0.113	0.060
PU	→	BI	0.260	0.260	0
PJ	→	BI	0.146	0.146	0
PE	→	BI	0.145	0.145	0

The study shows that chatbot adoption differs by sector, transaction type, and stage of the e-commerce journey. Unlike banking and telecommunications where interactions are standardized and transactional, e-commerce involves high-frequency, low-value purchases with more dynamic and emotional exchanges. As a result, while usefulness remains important, enjoyment plays a stronger role in e-commerce contexts. Across stages, chatbot functions also vary. In pre-sale and during-sale phases, efficiency like speed and accuracy is critical, as users prioritize quick responses to support purchase decisions. In post-sale situations such as complaints or returns, trust and application design become essential baseline conditions that reduce perceived risk, though they do not directly drive usage intention. Additionally, while efficiency dominates transactional interactions, sustained engagement requires enjoyable features like personalization. Finally, due to the consumer-driven and trend-sensitive nature of e-commerce, SI strongly shapes perceptions of chatbot usefulness and adoption behavior.

Based on these findings, several recommendations can be drawn up for e-commerce firms. First, companies should prioritize chatbot design that balances task efficiency with enjoyable interaction, moving beyond purely functional designs. Second, platforms should highlight the social credibility of their chatbots, for instance by showcasing customer testimonials or usage metrics. Third, firms should continuously update chatbot knowledge bases to reflect policies, promotions, and customer needs, ensuring sustained usefulness. Finally, introducing small rewards, personalization options, and playful features can enhance hedonic value and encourage repeat use. Balancing measurable benefits and interactive enjoyment enables e-commerce platforms to convert trial use into repeated engagement rather than limiting chatbot interactions to transactional support.

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