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THE IMPACT OF AI CHATBOT ATTRIBUTES ON CONSUMER PURCHASE INTENTION IN THE FAST-FASHION INDUSTRY: THE MEDIATING ROLE OF ATTITUDE

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ABSTRACT

This study investigates the AI Chatbot attributes that influence consumer purchase intentions for fast-fashion products on e-commerce platforms in Ho Chi Minh City. By extending the Technology Acceptance Model (TAM), the research framework incorporates Perceived Enjoyment, Personalization, Perceived Risk, and Trust to provide a comprehensive view of digital consumer behavior. A quantitative approach was employed, utilizing data collected from 169 valid respondents through an online survey. The data were subsequently analyzed using PLS-SEM in SmartPLS4. The empirical results reveal that Perceived Usefulness, Perceived Enjoyment, and Personalization exert significant positive impacts on Consumer Attitude. Furthermore, Consumer Attitude was found to be a powerful and significant predictor of Purchase Intention, acting as a critical mediator in the relationship between AI Chatbot attributes and behavioral intent. Interestingly, factors such as Perceived Ease of Use, Perceived Risk, and Trust did not show significant effects, suggesting that technology has normalized among digital-native consumers in the target region. The findings provide important theoretical contributions by validating the extended TAM in the AI context and offer practical managerial implications for e-commerce enterprises, suggesting ways to stimulate purchase intention towards fast-fashion products by optimizing their AI Chatbot tools.

Keywords: AI Chatbot, fast fashion, consumer attitude, purchase intention, E-commerce, Ho Chi Minh City.

1. INTRODUCTION

Due to the explosion of the Fourth Industrial Revolution, the internet has quickly become part of Vietnam's infrastructure. It is estimated to support more than 78.44 million users by 2024, representing about 79.1% of the country's population with internet access [1]. This development has laid the groundwork for the remarkable growth of e-commerce, especially in the post COVID-19 pandemic period. According to data from the Vietnam E-commerce and Digital Economy Agency (iDEA), the Vietnamese e-commerce market in 2024 exceeded 25 billion USD with a stable growth rate of 18% to 25% [2]. In this context, Artificial Intelligence (AI) has emerged as a key factor revolutionizing the online shopping experience. Notably, Vietnam currently leads Southeast Asia in AI adoption, with 92% of consumers using these tools on e-commerce platforms at least once a week to support their purchasing decisions [3].

In the AI ecosystem, chatbots are becoming a strategic solution for businesses to optimize customer interactions. Leading e-commerce platforms in Vietnam, such as Tiki [4] and Lazada [5], have quickly integrated advanced chatbot systems like ChatGPT and LazzieChat to provide personalized consultation services and instant answers to questions. Especially for the fast fashion industry, a sector that recorded an impressive revenue of 29 trillion VND in the first five months of 2024, the role of AI Chatbots is even more crucial [6]. Customers in this segment are often strongly influenced by new trends and the fear of missing out (FOMO), thus requiring quick responses regarding size, color, and style to make more decisive purchasing decisions.

AI has shifted from a competitive edge to a baseline requirement in the retail industry since the 2020 pandemic. In Ho Chi Minh City's fast-fashion market, AI-powered chatbots are becoming increasingly important to brands, helping them attract and retain customers. Nowadays, chatbots are expected to provide more personalized interactions and helpful information than just automated responses. Chi et al. [7] affirmed this point by showing that usefulness and personalization are the real drivers behind AI-assisted purchasing decisions. Rana & Jain (2024) [8] demonstrated this in the context of grocery stores, showing that chatbots deliver both practical and emotional value, thereby significantly improving consumers' perceptions of a brand. When an interaction goes beyond the transactional scope, it builds a connection. In a market where shoppers are constantly pulled in multiple directions, it is that connection that drives them to make a purchase.

Despite the enormous potential of AI Chatbots, current research in Vietnam still has certain gaps. Most previous studies have focused on technologies such as virtual reality (VR) or AI applications in the e-commerce sector in general [9]-[11]. Most existing research focuses on the Technology Acceptance Model (TAM). It leaves a clear gap in integrating functional and emotional factors to examine purchase intentions in the context of AI Chatbots in the fast-fashion industry. This study addresses this gap by extending the TAM framework to provide a more comprehensive understanding of consumer behavior in key markets, such as Ho Chi Minh City, the city with the highest purchasing power and access to technology.

The primary objective of this study is to analyze and evaluate the impact of AI Chatbot attributes on consumers' fast-fashion purchase intention on e-commerce platforms in Ho Chi Minh City. To achieve this, the study focuses on the following specific objectives:

Firstly, to identify and measure the extent to which various AI Chatbot attributes influence the attitude of consumers residing in Ho Chi Minh City.

Secondly, to analyze the relationship between consumer attitude and intention to purchase fast-fashion products via e-commerce platforms.

Thirdly, to propose actionable solutions for e-commerce enterprises to optimize AI Chatbot operations, thereby fostering positive consumer attitude and stimulating purchase intentions.

Fourthly, to examine the mediating role of consumer attitude in the relationship between AI Chatbot attributes and fast fashion purchase intention on e-commerce platforms.

Based on the aforementioned objectives, this study aims to address the following research questions:

RQ1: Which AI Chatbot attributes significantly influence the attitude of consumers toward e-commerce platforms in Ho Chi Minh City, and to what extent?

RQ2: How does consumer attitude toward AI Chatbots affect their intention to purchase fast fashion products?

RQ3: Does consumer attitude serve as a significant mediator in the relationship between AI Chatbot attributes and purchase intention?

RQ4: What strategic solutions should e-commerce enterprises implement to optimize AI Chatbot performance and stimulate consumer shopping behavior?

The research results not only contribute to the theoretical literature on user behavior in the AI era but also provide significant practical value. The research will provide important managerial implications, helping online retailers improve the efficiency of their chatbot operations, thereby enhancing the customer experience and strengthening their competitive advantage in the volatile fast-fashion market.

2. LITERATURE REVIEW

2.1. Underlying theories

2.1.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis (1989) [12], is a classic theoretical framework widely utilized to explain user behavior regarding the adoption and use of new technologies. According to TAM, the decision to utilize a technology is governed by two core determinants: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU reflects a user's belief that using a specific technology will enhance their performance or effectively meet personal needs [13], [14]. In contrast, PEOU assesses the degree of effort required to master technology.

In contemporary research, TAM continues to demonstrate its foundational value when applied to e-commerce and artificial intelligence. Ha & Stoel (2009) [15], Arachchi (2025) [16] demonstrated that TAM factors directly influence online shopping attitudes, with usefulness playing a dominant role. Notably, Fang (2023) [9], Ma (2025) [17] study on AI Chatbots expanded this model by integrating exogenous variables such as perceived risk, illustrating TAM's flexibility in explaining behavioral intentions when consumers interact with intelligent automated systems.

2.1.2. Theory of Reasoned Action (TRA)

Parallel to the technology-oriented approach, the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen (1975) [18] provides profound insights into behavioral psychology. This model posits that an individual's actual behavior is determined by their behavioral intention, which is influenced by two primary factors: Attitude and Subjective Norm. Attitude represents an emotional evaluative orientation based on beliefs about behavioral outcomes, while subjective norm reflects social pressure and an individual's perception of expectations from influential others [19], [20].

A significant advancement of TRA is its recognition of behavioral and normative beliefs as the foundation of intention. Expanding the model by incorporating external factors, such as environmental characteristics or technological context, allows researchers to identify indirect antecedents of purchase intention [21], [22]. Regarding AI Chatbot research, TRA clarifies that automated interactions not only influence individual attitudes but also shape behavioral norms within the digital consumer community, thereby driving the intention to purchase fast-fashion products on e-commerce platforms [23], [24].

2.2. Fast fashion

Fast fashion is a term used to describe low-cost clothing products produced quickly, mimicking catwalk designs or high-end brands to meet the ever-changing demands of the market. A key characteristic of this industry is its ability to shorten the design-to-distribution cycle, enabling consumers to access the latest trends at affordable prices. In the era of Industry 4.0, fast fashion has established a strong position on e-commerce platforms, particularly attracting young customers. This group prioritizes diverse designs and trendy styles in online shopping.

Within the scope of this study, fast fashion is defined as clothing and accessories that are highly up-to-date, feature modern and unique designs, and are distributed at competitive prices on digital platforms. This is also a pioneering field in the application of AI Chatbots as powerful support tools. Thanks to their intelligent interaction capabilities, AI Chatbots help users overcome barriers to searching for and receiving sizing and personal style advice, thereby optimizing the purchasing decision process in a market with an extremely fast product turnover rate.

2.3. AI Chatbot

An AI Chatbot refers to an artificial intelligence system designed to simulate human conversation and assist users. Chatbots are automated text or audio communication programs driven by algorithms [25]. Developing this view, Oktavia (2024) [26] emphasizes the machine learning mechanisms and natural language processing capabilities of AI Chatbots, which allow machines to provide relevant information and continuously refine responses based on their experiences interacting with humans over time. Fang (2023) [9] categorized chatbots into three main groups, including those performing specific tasks (e.g., shopping and scheduling), those providing information based on available data, and those focused on dialogue to maintain long-term interaction with users. This classification demonstrates the diversity and flexibility of chatbots in meeting the diverse needs of customers in the online space.

In e-commerce, AI Chatbot plays a strategic role, providing 24/7 assistance, personalized recommendations, and optimizing shopping decision-making processes to boost conversion rates [27], [28]. In recent years, the use of chatbots in the fast-fashion industry has been growing rapidly. Qi et al. (2024) [29] pointed out that chatbots have evolved into a new form of personalized style assistant rather than a basic customer service tool.

2.4. AI Chatbot attributes influencing Attitude and Purchase intention

2.4.1. Perceived Usefulness (PU)

According to Davis et al. (1989) [12], perceived usefulness is the degree to which an individual believes that utilizing a specific technology will enhance their performance. Within the scope of this study, PU is defined as consumers' perceptions in Ho Chi Minh City regarding the extent to which AI Chatbots provide practical, accurate, and valuable information, thereby effectively supporting the decision-making process for fast-fashion purchases.

Quan et al. (2023) [30] conducted a study on the influence of Augmented Reality (AR) technology on consumer attitude and online purchase intention. Their findings indicated that PU exerts the most significant positive impact on attitudes toward technology adoption. Chi et al. (2024) [7] conducted a study on AI-assisted online shopping intentions, focusing on the roles of perceived usefulness and personalization. The research findings demonstrated that perceived usefulness exerts a powerful influence on attitudes toward AI. Empirical evidence from Rana & Jain (2024) [8] indicates that perceived usefulness is a key determinant of attitudes toward chatbot use. These findings underscore the role of functional utility in technology adoption. In fast fashion, consumers face a multitude of choices, rapidly changing styles, and limited-time promotions. If a chatbot is viewed as a useful tool, it can simplify the purchasing decision process by helping customers filter products, provide the latest inventory data, and provide accurate purchasing guidance. If a chatbot helps consumers optimize shopping efficiency, their attitudes toward chatbots will become more favorable. Therefore, we formulated the following hypothesis:

H1: Perceived Usefulness has a positive impact on Consumer Attitude towards AI Chatbots in Ho Chi Minh City.

2.4.2. Perceived Ease of Use (PEOU)

Davis et al. (1989) [12] defined Perceived Ease of Use as “the degree to which a person believes that using a particular system would be free of effort.” In this research, this factor reflects the convenience, operational simplicity, and seamless interaction between customers and AI Chatbots when searching for, referencing information, and placing orders online.

Similarly, Quan et al. (2023) [30] indicated that PEOU significantly shapes Consumer Attitude toward emerging digital innovations. Moreover, there is extensive e-commerce research confirming that when people find an interface clear and easy to use, they experience fewer cognitive barriers and develop more positive attitudes toward the technology [31], [32]. Therefore, we suggested the following hypothesis:

H2: Perceived Ease of Use positively affects Consumer Attitude toward AI Chatbots in Ho Chi Minh City.

2.4.3. Perceived Enjoyment (PE)

According to Fang (2023) [9], Perceived Enjoyment derived from interacting with AI Chatbots generates a positive psychological state, which subsequently drives behavioral intentions. Kim et al. (2016) [11] also affirmed that in mobile commerce environments, perceived pleasure is a key catalyst for shopping intentions. When customers find interacting with an AI Chatbot engaging and entertaining, they form more positive attitudes and are more likely to execute a transaction.

A previous study by Marjerison et al. (2022) [31] examines consumer acceptance of Artificial Intelligence (AI) applications, specifically Chatbots, in the context of online shopping in China. The empirical evidence derived from the data analysis indicates that PE significantly contributes to a positive Consumer Attitude toward Chatbot usage. In the fast-fashion sector, where shopping has become a form of entertainment, the interactive, pleasurable experiences provided by chatbots encourage consumers to become interested in this technology and shift their traditional attitudes towards it. Accordingly, we proposed the following hypothesis:

H3: Perceived Enjoyment has a positive impact on Consumer Attitude toward AI Chatbots in Ho Chi Minh City.

2.4.4. Perceived Risk (PR)

While AI Chatbots enhance the shopping experience, the requirement for users to provide personal data (such as body measurements, preferences, and age) to receive accurate recommendations often triggers security concerns. Wang et al. (2018) [33] identified risk as a primary barrier to the adoption of new technologies. In the context of e-commerce, Marjerison et al. (2022) [31] observed that perceived risk negatively impacts AI utilization. This study defines perceived risk as consumers' subjective perceptions of potential undesirable consequences arising from sharing data with an AI Chatbot. Previous research findings demonstrated that Perceived Risk significantly influenced purchase intention [15], [34].

Also, Pavlou (2003) [35] demonstrated that perceived risk is a psychological barrier to both users' trust and system acceptance. In the context of e-commerce, when a customer believes that negative outcomes will result from providing personal information to an automated system, they will have negative attitudes towards the technology. Therefore, we proposed the following hypothesis:

H4: Perceived Risk has a negative impact on Consumer Attitude toward AI Chatbots in Ho Chi Minh City.

2.4.5. Personalization (PER)

Personalization allows retailers to provide products and services tailored specifically to each customer, meeting their exact needs and desires [36]. By utilizing AI algorithms to analyze search histories and user habits, Chatbots can offer relevant suggestions, creating a superior user experience [37].

Furthermore, Chi et al. (2024) [7] showed that customized recommendations improve users' preferences toward AI systems. In particular, by providing highly relevant, customized suggestions to users via chatbots, consumer search costs are reduced, and consumer attitude and satisfaction are enhanced. Based on these results, we proposed the following hypothesis:

H5: Personalization positively affects Customer Attitude towards AI Chatbots in Ho Chi Minh City.

2.4.6. Trust (TRU)

In an online shopping environment characterized by uncertainty, Trust acts as a catalyst that empowers consumers to conduct transactions with confidence [15]. Trust ensures that online retailers act transparently and protect customer interests. According to Pavlou et al. (2003) [35], trust indirectly influences purchase intention by fostering positive attitudes and reinforcing perceived usefulness. For an interactive emerging technology like AI Chatbots, trust in data processing, security, and advisory accuracy is an indispensable factor in maintaining customer relationships. Prior studies indicated that trust can be used to predict consumer attitude and intention [38], [8].

Likewise, trust reduces consumers' vulnerability and uncertainty regarding AI interactions. When consumers perceived that an AI Chatbot had a high level of honesty, sympathy, and skill, their uncertainty about automated decision-making was decreased [39]. This psychological assurance directly leads to a more positive evaluation of the system, laying the foundation for a positive user attitude [8]. Therefore, we proposed the following hypothesis:

H6: Trust will positively influence the Consumer Attitude towards the AI Chatbot in Ho Chi Minh City.

2.5. The relationship between Attitude and Purchase Intention

Consumer attitude is understood as positive or negative evaluations and emotions towards a specific object [8]. In the context of technology, Kasilingam (2020) [40] defines attitude as the emotional state of users when interacting with chatbots to make purchases. Based on the TAM, attitude plays a crucial role as an important prerequisite, directly and significantly influencing individuals' behavioral tendencies. When consumers form positive psychological responses to the intelligent characteristics of AI Chatbots, they tend to trust and be more open during the transaction process.

Purchase intention represents the likelihood that an individual will purchase in the future. According to Ajzen's Theory of Planned Behavior (TPB) (1991) [41], this intention is predicted through a combination of attitude, subjective norms, and perceived behavioral control. In the digital environment, Pavlou (2003) [35] emphasizes that online shopping intention reflects the willingness of customers to make transactions through e-commerce platforms. To stimulate this factor, businesses are now using AI Chatbots as tools for data analysis and personalized interaction, aiming to create incentives that encourage users to move from a research state to a purchase-intention state.

Numerous empirical studies have confirmed the relationship between attitude and purchase intention. Specifically, Fitzsimons and Morwitz (1996) [42] showed that attitudes are a driving factor in consumer intention, while Jain and Gandhi (2021) [43] demonstrated that positive attitudes toward AI technology led to a higher tendency to purchase. In the fast fashion industry, consumers' appreciation of artificial intelligence solutions is key to transforming technological experiences into concrete purchase intentions [44]. Thus, a favorable attitude towards AI Chatbots positively activates the intention to buy fast-fashion products on e-commerce platforms. Consequently, we proposed the following hypothesis:

H7: Positive Attitude towards AI Chatbots has a positive impact on consumers' intention to purchase fast fashion products in Ho Chi Minh City.

2.6. The Mediating Role of Consumer Attitude

The Theory of Reasoned Action (TRA) [18] states that an individual's attitude toward performing the behavior directly determines their behavioral intention. In the e-commerce context, Consumer Attitude serves as the central cognitive-affective process that converts external technological stimuli into behavioral intention. Previous AI adoption studies support this psychological linear progression by showing that chatbot attributes cannot be immediately translated into purchase decisions in economic transactions [8], [39]. Instead, functional, hedonic, and risk-related attributes were used as psychological inputs to form users' favorable or unfavorable attitudes. These stable internal attitudes directly influence final purchase intention. Based on TRA theory, Consumer Attitude is perceived as a mediator linking the six AI Chatbot attributes to purchase intention. Hence, we formulated the following hypotheses:

• H8a: Consumer Attitude mediates the relationship between Perceived Usefulness and Purchase Intention.

• H8b: Consumer Attitude mediates the relationship between Perceived Ease of Use and Purchase Intention.

• H8c: Consumer Attitude mediates the relationship between Perceived Enjoyment and Purchase Intention.

• H8d: Consumer Attitude mediates the relationship between Perceived Risk and Purchase Intention.

• H8e: Consumer Attitude mediates the relationship between Personalization and Purchase Intention.

• H8f: Consumer Attitude mediates the relationship between Trust and Purchase Intention.

2.7. Proposed Research Model

Based on a synthesis of the TAM, TRA, and the specifics of the fast-fashion industry, this study proposes an integrated model to clarify the mechanism by which AI Chatbots impact purchase intention. This model focuses on six antecedent factors related to AI Chatbot characteristics and the mediating role of Consumer Attitude. Specifically, six AI Chatbot attributes, including Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, Perceived Risk, Personalization, and Trust, are predicted to be the main factors shaping Consumer Attitude in Ho Chi Minh City towards the use of this technology on e-commerce platforms.

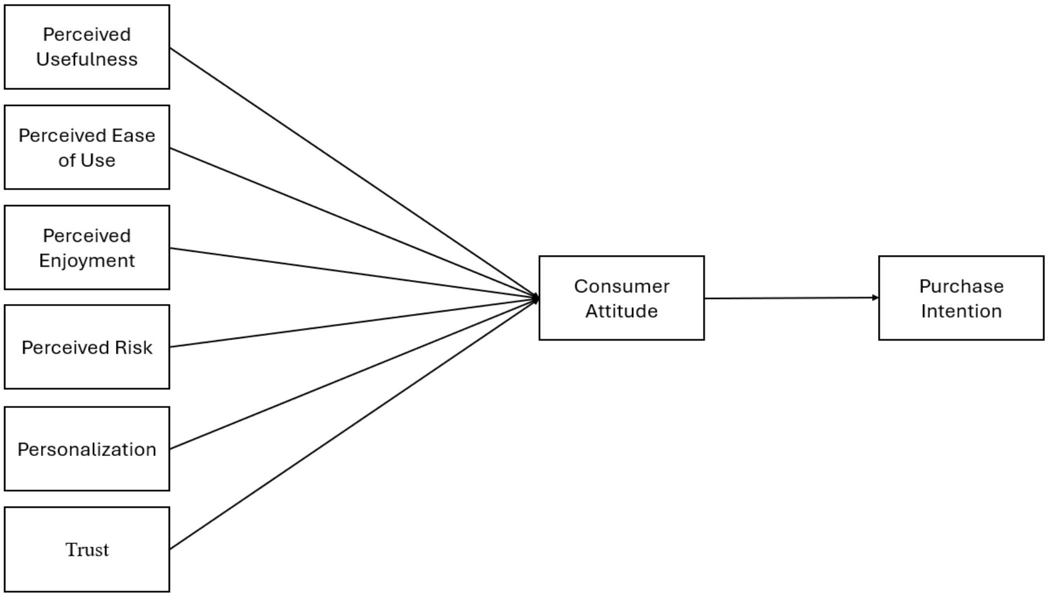

Figure 1. Conceptual Framework

(Source: Proposed by authors based on literature review)

3. METHODOLOGY

3.1. Research design

The research was conducted in three stages: preliminary, pilot, and formal research. First, preliminary qualitative research consists of literature synthesis to construct a conceptual framework and expert interviews to refine concepts and ensure that the measurement scales are appropriately adapted to the practical context of Ho Chi Minh City. Second, a pilot study with 30 respondents was executed to assess questionnaire clarity and eliminate linguistic or technical errors. Finally, the main quantitative research was conducted to test the proposed model and hypotheses. Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected for data analysis because it is well-suited for smaller sample sizes, which can lead to convergence issues in CB-SEM (Hair et al. 2022) [45]. Moreover, since this study extends the existing TAM framework to a specific emerging scenario (AI Chatbots in the fast-fashion context), its nature is fundamentally predictive and exploratory rather than confirmatory (as in the case of CB-SEM). Finally, PLS-SEM also imposes fewer assumptions about data distribution, which can be a major benefit when dealing with non-normal data often found in consumer behavior research surveys.

3.2. Measurement scales

The measurement scales for this study comprise eight constructs with 30 items, adapted from established previous studies. Perceived Usefulness (PU) includes four items (PU1 - PU4) adapted and modified from the studies of Rana & Jain (2024) [8] and Fang (2023) [9], while Perceived Ease of Use (PEOU) consists of four items (PEOU1 - PEOU4) derived from the same two sources. Perceived Enjoyment (PE) is measured by three items (PE1 - PE3) inherited from Fang (2023) [9], and Perceived Risk (PR) comprises three items (PR1 - PR3) adopted from Chi et al. (2024) [7]. Furthermore, Personalization (PER) includes four items (PER1 - PER4) developed based on the study by Marjerison et al. (2022) [31], and Trust (TRU) contains four items (TRU1 -TRU4) sourced from Chong et al. (2012) [38]. Finally, Consumer Attitude (AT) is measured through four items (AT1 - AT4) adapted from Rana & Jain (2024)

[8], and Purchase Intention (PI) includes four items (PI1 - PI4) derived from the research of Fang (2023) [9] and Chi et al. (2024) [7].

3.3. Questionnaire design

Primary data were collected using an online questionnaire structured into three main sections. The first section contains screening questions to ensure respondents reside, study, or work in Ho Chi Minh City and have prior experience interacting with AI Chatbots on fast-fashion e-commerce platforms. The second section captures demographic information (gender, age, education, income, etc) and online shopping behaviors. The final section measures the constructs in the proposed framework using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.4. Sampling method and Data collection

In this study, the respondents' information was collected using a non-probability convenience sampling technique This research focuses on respondents who live in Ho Chi Minh City, have previously bought fast-fashion products via e-commerce platforms, and have experience interacting with an AI Chatbot.

To ensure the model had adequate statistical power, we strictly followed the recommendations of Hair et al. (2010) [46]. They suggest that, in multivariate research, the minimum sample size should be at least 5 times the number of items on the measurement scale. Since the measurement scale of this research consists of 30 items; therefore, the required sample size was at least 150 respondents (30 x 5).

Data were collected from both secondary and primary sources. Secondary data were synthesized from academic literature (articles, dissertations on AI Chatbots, consumer behavior, TAM, TRA, PLS-SEM, etc.) and official reports from reputable organizations such as the Vietnam E-commerce and Digital Economy Agency (iDEA) and the Vietnam E-commerce Association (VECOM). Primary data were gathered via an online survey on Google Forms, distributed across social networks (Facebook, Zalo), e-commerce community groups, and emails. The collected primary data were subsequently screened and cleaned to remove invalid entries before quantitative analysis using SmartPLS 4.

3.5. Data analysis

Primary data were processed using SmartPLS 4 software in four sequential stages, following the PLS-SEM approach. Initially, descriptive statistics were used to present data on respondents' demographics and to ensure sample representativeness. Next, the measurement model was assessed, including the evaluation of indicator reliability (outer loadings > 0.7 [45]), internal consistency reliability (composite reliability rho_c > 0.7) [47], convergent validity (AVE > 0.5) [45], and discriminant validity via the Fornell-Larcker criterion [48].

In the third stage, the structural model was then assessed. A full collinearity assessment was conducted in this study to ensure data quality and assess common method bias (CMB). Unlike conventional approaches, this method of assessing CMB computes the VIF values for all constructs in the structural model. Kock (2015) [49] states that if the VIF ≤ 3.3, the model may be free from CMB. Then, the model was assessed for multicollinearity (VIF < 5, as suggested by Hair et al., 2017 [50]). Hypothesis testing was conducted using the bootstrap technique with 5.000 resamples. Finally, overall model performance was evaluated using the Coefficient of Determination (R^2), effect size (f^2) (where 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively) [51], and predictive relevance ($Q^2 > 0$).

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistical Analysis

Table 1. Descriptive Statistics

Characteristics	Category	Frequency (n=169)	Percentage (%)
Gender	Male	29	17.2%
	Female	140	82.8%
Age	Under 18	0	0%
	18 – 24 years old	165	97.6%
	25 – 34 years old	0	0%
	35 – 44 years old	4	2.4%
	45 – 54 years old	0	0%
	Over 54	0	0%
Education	Undergraduate	168	99.4%
	Postgraduate (Master/PhD)	1	0.6%
Shopping Frequency	1 – 2 times total	9	5.3%
	Occasional (1 – 2 times/month)	34	20.1%
	Frequent (More than 2 times/month)	126	74.6%

Primary data were gathered through an online survey, yielding 200 responses. Following a rigorous screening process, 169 valid responses were retained and analyzed using SmartPLS 4. The data obtained has been presented in Table 1 and reflects a group of respondents with a high degree of digital literacy that aligns with the target market: mostly being female (82.8%), Generation Z aged 18–24 (97.6%), and undergraduate students (99.4%). Behaviorally, over 94% of respondents shop online regularly (74.6% shopping more than twice per month). This high interaction frequency ensures that the feedback collected is based on the actual experience of using AI Chatbots in fast-fashion e-commerce.

4.2. Measurement Model Assessment

4.2.1. Indicator reliability

Indicator reliability is assessed through outer loadings. According to Hair et al. (2021) [47], outer loadings should ideally be 0.708 or higher. Items with loadings between 0.4 and 0.7 should only be considered for removal if deleting them leads to a significant increase in Composite Reliability (CR) or AVE.

Table 2 shows that the majority of the observed variables in the model exhibit outer loadings significantly higher than the 0.7 threshold, confirming strong indicator reliability across most constructs. Although PER1 (outer loading = 0.639) and TRU1 (outer loading = 0.584) fall below 0.7, they remain above the 0.4 threshold. These items were retained to preserve the content validity of the constructs because AVE for Personalization and Trust exceed 0.5.

Table 2. Outer loadings

	1. PU	2. PEOU	3. PE	4. PR	5. PER	6. TRU	7. AT	8. PI
AT1							0.949	
AT2							0.89	
AT3							0.943	
AT4							0.881	
PE1			0.938					
PE2			0.93					
PE3			0.947					
PER1					0.639			
PER2					0.708			
PER3					0.866			
PER4					0.726			
PEOU1		0.896						
PEOU2		0.807						
PEOU3		0.899						
PEOU4		0.89						
PI1								0.868
PI2								0.719
PI3								0.895
PI4								0.845
PR1				0.941				
PR2				0.95				
PR3				0.938				
PU1	0.883							
PU2	0.886							
PU3	0.857							
PU4	0.905							
TRU1						0.584		
TRU2						0.786		
TRU3						0.728		
TRU4						0.836		

4.2.2. Internal Consistency Reliability

The internal consistency reliability of the constructs in this model is evaluated using Composite Reliability (rho_c). According to the recommendations of Hair et al. (2021) [47], these indicators should ideally exceed a threshold of 0.7 to confirm that the observed items consistently and reliably measure their respective latent constructs.

As shown in Table 3, all constructs achieved rho_c values ranging from 0.826 to 0.960. All indicators significantly exceed the minimum requirement of 0.7, confirming high internal consistency.

Table 3. Composite reliability and Average variance extracted (AVE)

	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
1. PU	0.934	0.78
2. PEOU	0.928	0.763
3. PE	0.957	0.88
4. PR	0.960	0.889
5. PER	0.827	0.547
6. TRU	0.826	0.547
7. AT	0.954	0.84
8. PI	0.901	0.696

4.2.3. Convergent validity

Convergent validity was confirmed via the AVE. As shown in Table 3, all constructs yielded AVE values greater than 0.5, ranging from 0.547 to 0.889. This demonstrates that the latent constructs explain more than 50% of the variance of their respective indicators, satisfying the criteria established by Hair et al. (2022) [45].

4.2.4. Discriminant validity

Discriminant validity is a measure of how well the construct is differentiated from the other constructs in the model. In this study, the author employed the Heterotrait-Monotrait Ratio (HTMT) to assess discriminant validity.

According to Table 4, most constructs satisfied the HTMT ratio (< 0.9). However, significant issues were identified regarding the PE - PER, PER - TRU and AT - PI pairs. The correlations among those constructs exceeded 0.9.

Table 4. Heterotrait-monotrait (HTMT) ratio

	1. PU	2. PEOU	3. PE	4. PR	5. PER	6. TRU	7. AT	8. PI
1. PU								
2. PEOU	0.777							
3. PE	0.723	0.878						
4. PR	0.171	0.208	0.168					
5. PER	0.698	0.794	1.038	0.234				
6. TRU	0.835	0.766	0.736	0.232	0.952			
7. AT	0.800	0.600	0.794	0.261	0.837	0.611		
8. PI	0.685	0.630	0.692	0.212	0.711	0.539	0.923	

To address this lack of discriminant validity, the author conducted a detailed examination using a correlation table. The main goal is to reduce a large cross-correlation coefficient, allowing the latent variables to share more variance with other latent variables (or leading to a higher HTMT). In particular, a step-by-step refinement process was performed by removing problematic items, starting with PER4, PER1, TRU1, PU2, and ending with PI1. Following these adjustments, the model was recalculated until the HTMT criterion was fully satisfied.

The final reassessment of discriminant validity following the removal of the aforementioned items is presented in Table 5. The result ensures that each latent variable represents a unique concept, thereby supporting good discriminant validity among the model's constructs.

Table 5. Heterotrait-monotrait ratio (HTMT) criterion (after removing PER4, PER1, TRU1, PU2 and PI1)

	1. PU	2. PEOU	3. PE	4. PR	5. PER	6. TRU	7. AT	8. PI
1. PU								
2. PEOU	0.709							
3. PE	0.736	0.842						
4. PR	0.161	0.208	0.171					
5. PER	0.672	0.761	0.874	0.235				
6. TRU	0.882	0.757	0.713	0.259	0.826			
7. AT	0.829	0.600	0.852	0.261	0.816	0.665		
8. PI	0.672	0.596	0.625	0.231	0.637	0.613	0.833	

4.3. Structural Model Assessment

4.3.1. Common Method Bias Assessment

To analyze the potential threat from common method bias we employed the full collinearity assessment technique [49]. As shown in the analysis results from Table 6, the inner VIF values for all latent variables ranged from 1 to 3.167. Since all VIF values are significantly below the 3.3 benchmark, it can be concluded that the data is not affected by common method bias. This confirms that the relationships observed in the structural model are not distorted by the measurement method, providing a reliable foundation for further hypothesis testing.

Table 6. The Variance Inflation Factor (VIF)

	1. PU	2. PEOU	3. PE	4. PR	5. PER	6. TRU	7. AT	8. PI
1. PU							2.345	
2. PEOU							2.687	
3. PE							3.167	
4. PR							1.186	
5. PER							2.381	
6. TRU							2.373	
7. AT								1.000
8. PI								

4.3.2. Collinearity Statistics Assessment

To ensure the structural model's validity, it is necessary to examine multicollinearity among independent variables. The VIF value is utilized in such situations, and values below 5 are generally considered acceptable [50].

According to Table 6, all VIF values in the model range from 1 to 3.167, which are well below the recommended threshold of 5. Therefore, multicollinearity is not a concern in this study, and the structural model results remain reliable for hypothesis testing.

4.3.3. Hypothesis testing

Table 7 summarizes the results of the structural model analysis, obtained via bootstrapping (5000 resamples). The significance of the hypothesized relationships is evaluated using path coefficients and p-values (p-value < 0.05).

PU has a strong and significant positive impact on AT (beta = 0.459, p-value = 0.000 < 0.05). When consumers perceive the AI Chatbot to be useful during their shopping process, they tend to develop a positive attitude towards using it. Similarly, PE significantly and positively influences AT (beta = 0.506, p-value = 0.002 < 0.05). This shows that the element of fun in the experience plays a significant role in consumers' attitudes towards using the technology. PER had a significant positive effect on AT (beta = 0.242, p-value = 0.000 < 0.05), suggesting that tailored experiences enhance users' positive evaluation of the technology. Hypotheses H1, H3, and H5 are accepted in this study.

Conversely, the relationship between PEOU and AT is found to be statistically insignificant (p-value = 0.266 > 0.05). This means that PEOU is not an important determinant in forming the consumer's attitude in this case. Furthermore, PR does not significantly affect AT (p-value = 0.068>0.05), suggesting that security concerns do not necessarily diminish overall attitude among the surveyed users in this case. The relationship between TRU and AT is not significant (p-value = 0.582 > 0.05). Simply trusting an AI Chatbot is insufficient to generate a positive attitude towards the system if it lacks other motivating factors, such as usefulness and enjoyment. Hypotheses H2, H4, and H6 are not supported in this study.

AT shows a very strong, highly significant positive impact on PI (beta = 0.742, p-value = 0.000 < 0.05). This is the strongest relationship in the model, confirming that a positive attitude toward the AI Chatbot is a critical precursor to the intention to purchase fast-fashion products. Hypothesis H7 is supported in this study.

Table 7. Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
1. PU -> 7. AT	0.459	0.488	0.114	4.040	0.000
2. PEOU -> 7. AT	-0.219	-0.293	0.197	1.113	0.266
3. PE -> 7. AT	0.506	0.566	0.161	3.140	0.002
4. PR -> 7. AT	0.065	0.059	0.035	1.828	0.068
5. PER -> 7. AT	0.242	0.257	0.068	3.540	0.000
6. TRU -> 7. AT	-0.059	-0.082	0.107	0.550	0.582
7. AT -> 8. PI	0.742	0.738	0.049	15.255	0.000

4.3.4. Coefficient of determination (R^2)

The coefficient of determination (R^2) was evaluated to measure the explanatory power of the structural model for the endogenous constructs. Table 8 shows the R^2 value for AT is 0.768, indicating that 76.8% of the variance in consumer attitude was explained by its predictor constructs. Also, the R^2 value for PI is 0.551, indicating that 55.1% of the variance in purchase intention among customers in the fast-fashion market is explained by consumer attitude. According to the thresholds suggested by Hair et al., (2019) [52], R^2 values of 0.75, 0.50, and 0.25 represent substantial, moderate, and weak levels, respectively. Consequently, the explanatory power of the model is substantial for AT (R^2 = 0.768) and moderate for PI (R^2 = 0.551). This proves that the selected AI Chatbot features are effective in predicting customers' attitudes and intentions towards purchasing fast-fashion products.

Table 8. The coefficient of determination (R-square)

	R-square	R-square adjusted
7. AT	0.768	0.760
8. PI	0.551	0.548

4.4. The Mediating role of Attitude (AT)

The analysis of the mediating role of AT in the relationships between AI Chatbot attributes and PI was shown in Table 9. The mediating effect of AT is evaluated based on the significance of the indirect paths from AI Chatbot attributes to PI through AT (p-value <0.05).

An important mediating effect can be observed from PUto PI mediated by AT. The mediation effect from PU to PI by AT has a statistically significant (p-value = 0.000 <0.05). This shows that AT is an important mediator. When consumers perceive the chatbot as useful, it improves their attitude, which in turn drives their intention to buy. Similarly, the indirect path from PE to PI via AT is statistically significant (p-value = 0.002 <0.05). This confirms that the pleasure derived from using the AI Chatbot motivates purchases by first fostering a positive consumer attitude. PER has a significant indirect impact on PI through AT (p-value = 0.000 <0.05). Tailored interactions lead to a better attitude, which, in turn, increases PI. Hypotheses H8a, H8c and H8e are supported in this study.

Conversely, the indirect effect of PEOU on PI through AT is insignificant (p-value = 0.26 > 0.05), indicating that PEOU does not significantly influence PI through the mediation of AT. In addition, the indirect path for PR is insignificant (p-value = 0.073 > 0.05), suggesting that risk perception does not impact purchase intention through the attitude channel. TRU does not have a significant indirect effect on PI through AT (p-value = 0.580 > 0.05). This suggests that in the fast-fashion segment, trust in the AI Chatbot does not serve as a primary antecedent in shaping the psychological attitudes that lead to purchase decisions. Hypotheses H8b, H8d and H8f are not supported in this study.

Table 9. Mediating effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
1. PU -> 7. AT -> 8. PI	0.341	0.360	0.085	3.989	0.000
2. PEOU -> 7. AT -> 8. PI	-0.163	-0.215	0.144	1.126	0.260
3. PE -> 7. AT -> 8. PI	0.375	0.417	0.120	3.140	0.002
4. PR -> 7. AT -> 8. PI	0.048	0.043	0.027	1.793	0.073
5. PER -> 7. AT -> 8. PI	0.179	0.189	0.049	3.625	0.000
6. TRU -> 7. AT -> 8. PI	-0.044	-0.060	0.079	0.554	0.580

4.5. Effective size

An effect size (f^2) analysis was also computed using Cohen's (1988) [51] standards to assess the practical significance of each predictor variable, beyond its statistical significance level. The empirical findings show that AT had the largest effect size ($f^2 = 1.226$), indicating a very large practical effect on the outcome construct. PU showed a large effect size ($f^2=0.388$) and made a substantial contribution to the model. PE also approached the threshold for a large effect size ($f^2 = 0.348$) and provided some substantive explanation. PER had a small effect size ($f^2 = 0.106$), and PEOU had a small effect size ($f^2 = 0.077$). However, PR ($f^2 = 0.015$) and TRU ($f^2 = 0.006$) both fell below the 0.02 threshold for a small effect size; they had little to no effect on the outcome construct.

Table 10. Effective size

	1. PU	2. PEOU	3. PE	4. PR	5. PER	6. TRU	7. AT	8. PI
1. PU							0.388	
2. PEOU							0.077	
3. PE							0.348	
4. PR							0.015	
5. PER							0.106	
6. TRU							0.006	
7. AT								1.226
8. PI								

4.6. Predictive relevance

The predictive relevance was evaluated using the PLSpredict procedure based on the Q^2predict value. According to Shmueli et al. (2019) [53], a positive Q^2predict value (Q^2predict > 0) confirms acceptable out-of-sample predictive capability.

As shown in the PLSpredict output, all indicators for both AT and PI had positive Q^2predict values. Specifically, the values for AT items ranged from 0.423 to 0.655, with AT1 = 0.655, AT3 = 0.647, AT2 = 0.484, and AT4 = 0.423. Similarly, all PI items achieved positive Q^2predict values, including PI3 = 0.388, PI2 = 0.211, and PI4 = 0.043.

Overall, because all Q^2predict values for the key measurement indicators are greater than zero, the model has sufficient out-of-sample predictive relevance for predicting customers' attitudes and intentions.

Table 11. Predictive relevance

	Q^2predict
AT1	0.655
AT2	0.484
AT3	0.647
AT4	0.423
PI2	0.211
PI3	0.388
PI4	0.043

4.7. Discussion

The empirical results provide critical insights into the mechanism of fast-fashion purchase intention through AI Chatbot interactions. Based on the TAM and TRA, the model effectively explains consumer behavior in the modern e-commerce landscape of Ho Chi Minh City.

First, the empirical results of this study reveal that PU and PER exert significant positive impacts on Consumer Attitude. These findings are highly consistent with the prior research conducted by Chi et al. (2024) [7], reinforcing the idea that functional value and personalized experience remain fundamental drivers for consumers to have a positive attitude towards technology. Furthermore, PE was found to be a powerful predictor of attitude, with a strong beta coefficient of 0.506. This result is consistent with the work of Quan et al. (2023) [30], which indicates a big change in psychology. For Generation Z, online shopping is not just about buying things; it is a form of digital entertainment. When a chatbot is interactive and fun to the user, it makes shopping more emotionally satisfying. Therefore, in the context of fast fashion, both hedonic and experiential aspects of AI Chatbot interactions are just as critical as their utilitarian functions.

Notably, PEOU, TRU, and PR do not significantly impact consumer attitude. These results are inconsistent with previous TAM literature [12] [35], but they provide new theoretical insights. In the case of PEOU, insignificance can be attributed to the normalization of technology. Since 97.6% of consumers are Gen Z, using an AI Chatbot has already become an integrated, unconscious, and simple daily behavior. Therefore, PEOU is viewed as a basic prerequisite that users expect by default of any online system, rather than a driver that actively shapes their positive attitude. TRU and PR are insignificant because fast-fashion products are not high-value items, and online shops in general are so secure nowadays, thus minimizing consumer perceived risk. Since existing online purchasing platforms (Shopee, Lazada, TikTok Shop, etc.) offer secure payment and clear return policies, consumers trust the platform itself and automatically assume that using the AI Chatbot is safe. Therefore, in low-cost, fun shopping environments, emotional factors such as PE and PER completely replace traditional ones such as PEOU and PR.

Finally, the analysis confirms that AT significantly and positively influences PI. This strong relationship aligns with a broad range of contemporary literature from previous studies [7], [8], [30]. Collectively, these results validate the study's theoretical framework, confirming that a favorable psychological attitude is the essential precursor to the actual intent to purchase via AI-driven platforms. In addition, AT acts as a mediating variable in the relationship between AI Chatbot attributes and PI. This has also confirmed the main logic of the Theory of Reasoned Action (TRA). In the context of fast-fashion e-commerce, a consumer's purchase behavior toward technologies such as an AI Chatbot is not a coping mechanism, but the result of a step-by-step psychological process. When an AI Chatbot offers valuable information alongside enjoyment of the shopping process, it shapes consumers' attitudes and subsequently reduces hesitation, turning them from passive shoppers to active purchasers.

5. CONCLUSION

5.1. Conclusion

This study explored the AI Chatbot attributes influencing fast-fashion purchase intentions in Ho Chi Minh City by using the Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA). Empirical results indicated that AT acts as a significant direct driver and an essential mediator of PI. Furthermore, the research highlighted the importance of PU, PE, and PER as the three vital catalysts driving these positive attitudes, with functional utility exerting the strongest effect. Conversely, PEOU, PR, and TRU showed no statistically significant impacts, indicating that consumers have a high level of digital literacy and a robust e-commerce security ecosystem in Ho Chi Minh City.

5.2. Implications

5.2.1. Theoretical Implications

The findings of this study make valuable theoretical contributions to the existing literature on the TAM and AI adoption by extending the classical TAM to the AI Chatbot in the e-commerce context. While confirming that PU is a key driver for technology adoption, the result implies that integration of the traditional model with hedonics and personalization aspects, i.e., PE and PER, into the structural model to represent customer motivations is essential in the fast fashion industry. The study confirms that today's digital consumer behavior is strongly driven by experiential value. Although classic TAM predominantly focuses on the utilitarian outcomes, our empirical evidence suggests that PER and PE are key drivers for a positive consumer attitude. Our investigation has also broadened the scope of TAM from purely utilitarian tools to experiential shopping companions, highlighting the importance of emotional engagement in AI interactions.

In addition, the results offer a new perspective on AI adoption. Because PEOU, PR, and TRU were not significant, we can see that AI is now a standard tool for digital natives. Theoretically, this shows that as technology grows, we should move away from analyzing whether a tool is easy or safe. Instead, research models should focus on exploring features that add real value to the user experience.

Finally, this study confirms that AT is a powerful mediator. It shows how people process AI features in their minds before they decide to buy. This provides a solid framework for future cognitive-affective research.

5.2.2. Managerial Implications

Based on the empirical findings, this study proposes a strategic framework to help e-commerce businesses optimize their AI Chatbot tools, thereby driving fast-fashion purchase intentions among consumers in Ho Chi Minh City.

Firstly, businesses should focus on improving the perceived usefulness of AI Chatbots, as this has a significantly positive impact on Consumer Attitude. Businesses should upgrade chatbots from passive tools to active consultants. A chatbot should also include functions such as recommending clothing sizes based on the user's height and weight and suggesting accessories to pair with the clothes. Hence, the customer has a better decision-making experience. Next, businesses should improve the quality of the information they provide to consumers. Product specifications (materials for clothing, washing care directions, etc.) and details on current stock, shipping policies, and return procedures should also be detailed and accurate.

Secondly, to enhance Perceived Enjoyment, chatbots need to provide immediate gratification of emotions. Given that fashion consumption among Gen Z in Vietnam has become more entertaining, chatbot interactions should include entertaining elements like “AI Virtual Try-On” applications that use images and allow customers to upload their pictures for a preview of clothes. The language used in chatbot conversations should include trending local slang and emoji-rich text, aligned with Gen Z culture, across platforms like Zalo or Messenger. This can mitigate the coldness of machine interaction, transforming shopping into an inspiring leisure activity. Lastly, the response latency must be kept within seconds to align with the rapid scrolling behaviors of young consumers.

Thirdly, enterprises need to strengthen Personalization in the user experience. E-commerce businesses should develop AI Chatbots capable of analyzing consumer data in real time to provide product recommendations tailored to individual style preferences. Platforms must encourage users to share personal data by clearly demonstrating the value of a tailored experience, such as offering exclusive personalized discounts or early access to collections based on their browsing history. To drive customer retention and repeat purchases, the chatbot should be capable of remembering and deeply analyzing previous sizes and style choices, significantly reducing the time spent on repetitive searches and making the shopping process more efficient. Finally, managers must implement transparent data privacy policies to ensure that consumers feel secure when exchanging their personal information for these highly customized and time-saving shopping experiences.

Finally, an effective Chatbot management strategy requires seamless coordination between technology and humans. Businesses should establish a flexible transition mechanism from Chatbots to human consultants for complex situations or when customers show signs of dissatisfaction. Periodically evaluating key performance indicators (KPIs), such as conversion rates and customer satisfaction scores, will serve as a vital basis for continuously refining conversation scripts, ensuring that AI Chatbots remain adaptable to the fast-paced, volatile nature of the fast-fashion market.

5.3. Limitations and Future Research

5.3.1. Limitations

Nevertheless, the present study has certain limitations that must be acknowledged. The first limitation is the sample size (n = 169), which is relatively small and limits its ability to represent all digital consumers in Ho Chi Minh City fully. Second, the use of convenience sampling led to a notable demographic bias, as the sample was heavily skewed toward females (82.8%), Generation Z (aged 18 - 24; 97.6%), and undergraduate students (99.4%). Finally, as the respondents belong to this generation, referred to as "digital natives," this young group possesses high levels of digital competence, low risk aversion, and strong familiarity with technologies such as artificial intelligence and Chatbots. These unique characteristics may have led to overly optimistic attitudes toward AI Chatbots. They could explain why factors such as PEOU and PR were statistically insignificant, thereby limiting the generalizability of the findings to older or less tech-savvy populations.

5.3.2. Future Research

To address the limitations in this study, suggestions for future research are provided. First, future studies should include larger samples with diverse demographics (age, gender, geographic locations, etc.) as well as use probability sampling methods, such as stratified random sampling, to improve generalizability. Second, it is necessary to focus on comparing different generations, particularly Gen X, Millennials, and those with low digital literacy, as perceived risk and ease of use might differ across these groups. Third, expanding the study across different geographical regions and conducting a comparative analysis would discover potential moderating factors. Additionally, combining online and offline data collection will enrich the sample beyond young "digital natives". Lastly, future research could include additional variables, such as individual personality traits or AI ethics, to provide a more understanding of human-AI interactions in e-commerce.

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