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Gen Z Adoption of AI Virtual Assistants for Personalized Shopping: Motivations and Barriers in Ho Chi Minh City

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KEYWORDS

AI virtual assistants,
Attitudes,
Barriers,
Motivators,
Personalized shopping.

ABSTRACT

This study examines factors influencing Generation Z (Gen Z) in Ho Chi Minh City to adopt AI virtual assistants for personalized shopping. A quantitative survey of 308 Gen Z participants was conducted. The research integrates the Technology Acceptance Model (TAM), Technology Readiness Index (TRI), and Behavioral Reasoning Theory (BRT) to analyze how drivers (optimism, innovativeness) and inhibitors (insecurity, discomfort) affect reasons for adoption or rejection, attitudes, and behavioral intentions. Findings reveal that motivators strengthen adoption reasons, fostering positive attitudes and usage intentions, while barriers increase rejection reasons, reinforcing resistance and negative attitudes. Positive attitudes significantly enhance usage intentions and reduce rejection. This study advances technology acceptance research by focusing on young Vietnamese consumers and offers practical insights for promoting AI virtual assistant adoption in personalized shopping.

1. Introduction

Gen Z, defined by the Oxford Dictionary as "the generation reaching adulthood in the second decade of the 21st century" and known for growing up in the digital age, is becoming a dominant force in Vietnam's online shopping landscape (Oxford University Press, 2023). Vietnam provides a compelling context for this study due to its rapidly expanding e-commerce market and the significant presence of Gen Z as a driving consumer demographic. With 43% of its 57 million online shoppers in 2024 belonging to Gen Z, Vietnam showcases a dynamic, tech-savvy consumer base increasingly demanding personalized, instant, and interactive shopping experiences. Additionally, the rapid digital transformation driven by high smartphone penetration and internet usage growth underscores the relevance of examining AI adoption within this emerging market. Understanding the motivations and barriers faced specifically by Vietnamese Gen Z consumers can provide valuable insights for businesses aiming to leverage AI technologies effectively to enhance personalized customer engagement.

With increasing demand for speed, personalization, and convenience, Gen Z expects shopping experiences that are tailored, instant, and interactive. To meet these demands, many retailers are deploying AI-based virtual assistants (e.g., chatbots, voice assistants) that provide personalized, 24/7 customer service. These virtual assistants can help users find products, answer queries, and offer personalized recommendations. However, despite being digital natives, not all Gen Z consumers readily embrace this technology. Concerns about trust, privacy, and the lack of human interaction remain significant barriers.

This study explores the key motivators and barriers that affect Gen Z's intention to adopt AI virtual assistants for personalized shopping experiences. We

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integrate three theoretical frameworks to examine these influences: Technology Acceptance Model (TAM) (Davis, 1989), the Technology Readiness Index (TRI) (Parasuraman, 2000), and Behavioral Reasoning Theory (BRT) (Westaby, 2005). TAM emphasizes that two primary factors influencing the adoption of technology are how useful it is perceived to be and how easy it is to use. TRI introduces personal traits like optimism and innovativeness (motivators), as well as discomfort and insecurity (barriers), that influence an individual's openness to new technologies. BRT) describes how individuals develop particular justifications for or against adopting something, which in turn shape their attitudes and behaviors.

This study integrates TAM, TRI, and BRT to develop a holistic framework that explores how Gen Z consumers' individual readiness characteristics affect their motivations for embracing or avoiding AI virtual assistants, and how these motivations influence their attitudes and intended behaviors. A quantitative survey was conducted with 308 Gen Z individuals in Ho Chi Minh City. PLS-SEM was employed to examine the connections between motivators, barriers, reasons, attitudes, and behavioral intentions.

The study advances research on technology adoption by incorporating individual personality traits and cognitive reasoning into established acceptance models, with a particular emphasis on the Gen Z population in Vietnam. It also provides practical implications for businesses aiming to increase AI virtual assistant adoption by aligning with Gen Z's preferences and addressing their concerns.

2. Theoretical Model

2.1. Theoretical Basis

According to Parasuraman (2000), technology readiness describes the extent to which a person is inclined to adopt and utilize new technologies, influenced by a combination of encouraging factors (motivators) and discouraging ones (inhibitors).

Optimism and innovativeness are key motivators. Optimistic individuals believe technology improves life through convenience and efficiency, while innovative users are eager to explore new technologies and lead adoption trends (Parasuraman & Colby, 2015). These traits are linked to stronger tech adoption behavior (Blut & Wang, 2020; Jan et al., 2023).

In contrast, discomfort and insecurity act as inhibitors. Discomfort arises from a lack of control or complexity of technology, while insecurity involves distrust or fear of negative consequences (Parasuraman, 2000). These factors hinder adoption by increasing psychological resistance (Claudy et al., 2015; Jan et al., 2023).

Grounded in Behavioral Reasoning Theory (Westaby, 2005), reasons for usage capture the perceived benefits (e.g., personalization, time-saving) that justify adopting AI assistants. These reasons foster positive attitudes and intent to use (Claudy et al., 2015; Jan et al., 2023).

Conversely, reasons against usage such as privacy concerns or incompatibility rationalize resistance. Strong opposing reasons diminish favorable attitudes and increase rejection (Ram & Sheth, 1989; Claudy et al., 2015).

Attitude toward usage reflects the user's general evaluation of AI assistants and mediates the effect of beliefs on behavioral outcomes (Ajzen, 1991; Jan et al., 2023). A positive attitude enhances usage intention, defined as the user's plan to engage with the technology (Davis, 1989)

Lastly, resistance intention denotes deliberate rejection of new technologies, driven by perceived risks and costs. It represents a distinct process from acceptance, shaped by the dominance of negative over positive reasoning (Claudy et al., 2015; Jan et al., 2023).

2.2. Hypothesis Development

2.2.1. Technology Readiness and Reasons for/against Using AI Chatbots

The concept of technology readiness, as defined by Parasuraman (2000), describes an individual's propensity to use new technologies, a tendency determined by the interplay of positive factors known as motivators and negative factors called inhibitors. This framework is composed of four core dimensions: optimism and innovativeness as motivators, and discomfort and insecurity as inhibitors.

Users who exhibit high levels of optimism and

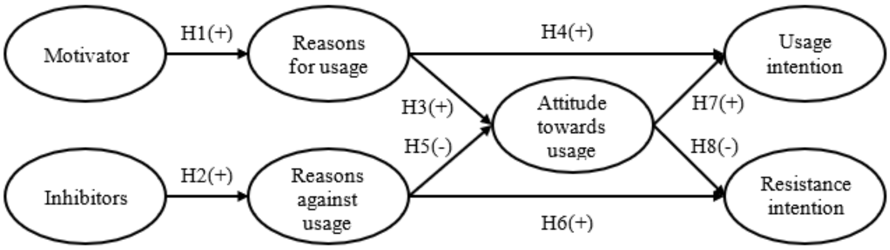

Figure 1. Research model

innovativeness tend to perceive AI chatbots as useful and valuable, which strengthens their intention to use such technology (Blut & Wang, 2020). In contrast, people who feel uncomfortable with technology tend to reject chatbots due to concerns over control, privacy, or complexity (Parasuraman & Colby, 2015).

H1: Technology readiness motivators positively influence reasons for using AI chatbots.

H2: Technology readiness inhibitors positively influence reasons against using AI chatbots.

2.2.2. Reasons for and Against Using AI Chatbots

Behavioral Reasoning Theory (Westaby, 2005) argues that an individual's decision-making is distinctly shaped by their specific 'reasons for' and 'reasons against' an action. Supporting reasons reflect beliefs about usefulness, efficiency, and value, while opposing reasons often center on risks, complexity, or emotional resistance (Claudy et al., 2015).

These two types of reasoning play distinct roles: positive reasons promote favorable attitudes and usage intent, while negative reasons foster resistance or rejection. Thus, we propose four more hypotheses:

H3: Reasons for using AI chatbots positively influence user attitudes.

H4: Reasons for using AI chatbots positively influence usage intention.

H5: Reasons against using AI chatbots negatively influence user attitudes.

H6: Reasons against using AI chatbots positively influence resistance intention.

2.2.3. Attitude and Behavioral Intentions Toward AI Chatbots

Attitude is a key predictor of behavioral intention, a core principle established in both the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991). When users form a positive evaluation of AI chatbots, their intention to use them is more likely to increase (Kasilingam, 2020).

Furthermore, attitude not only drives adoption but also inversely affects resistance: the more favorable the attitude, the lower the resistance. Based on this, we propose:

H7: User attitude toward AI chatbots positively influences usage intention.

H8: User attitude toward AI chatbots negatively influences resistance intention.

2.3. Research Methodology

A quantitative research approach was adopted in this study, utilizing a structured online questionnaire to gather data from Gen Z participants residing, studying, or working in Ho Chi Minh City. The survey instrument was developed using theoretical constructs derived from prior research and was customized to align with the specific context of adopting AI virtual assistants for personalized shopping experiences.

The questionnaire was divided into four sections, with the first section outlining the purpose of the study and assuring participants of the confidentiality of their responses. The second section collected demographic details and screening information, such as age, gender, educational background, job, income level, and previous experience using AI assistants on platforms like Tiki. Only respondents aged 18 to 27 who had at least some experience with AI virtual assistants were included in the valid sample.

The third section measured the theoretical constructs through a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The key constructs measured included: (1) motivators (Optimism, Innovativeness); (2) inhibitors (Discomfort, Insecurity); (3) reasons for usage; (4) reasons against usage; (5) attitude toward usage; (6) usage intention; and (7) resistance intention. These constructs were measured using 49 observed variables, all of which were adapted and localized from well-established prior studies to ensure conceptual alignment and relevance.

The sample was selected through non-probability methods, specifically by integrating convenience sampling with purposive sampling techniques. The questionnaire was shared through social media channels and youth groups frequently accessed by Gen Z in Ho Chi Minh City. A total of 396 responses were received, with 308 valid responses remaining after excluding ineligible and duplicate entries. This sample size was considered adequate, surpassing the minimum threshold of 245 observations, following the guideline of five observations per measured item (Hair et al., 1998).

Data analysis was performed with SmartPLS4 software, utilizing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The analysis proceeded in two primary phases. Initially, the measurement model was assessed by examining indicator reliability (Outer Loadings), internal consistency (Composite Reliability), convergent validity (Average Variance Extracted – AVE), and discriminant validity using the Fornell-Larcker criterion alongside cross-loadings and Heterotrait-monotrait ratio (HTMT). Additionally, to address potential common method bias, a full collinearity assessment was conducted by examining the inner variance inflation factors (VIF) for all constructs in the model. Subsequently, to evaluating the structural model's explanatory power, the study also assessed its predictive relevance using the PLSpredict procedure in SmartPLS4. This analysis was conducted to evaluate how well the model predicts the outcomes for the endogenous constructs using Q^2predict statistic. Finally, the structural model was evaluated by analyzing path coefficients and R^2 values. To determine the significance of hypothesized relationships, bootstrapping with 5,000 resamples was employed. Also, while selecting the analytical approach, the Covariance-Based Structural Equation Modeling (CB-SEM) framework was considered to examinine fit model. However, the more important objective is maximizing the predictive power and explain the variance of dependent constructs, maintain consistency with the methodological objective, rather than to test the global fit of a theoretical model against the empirical data. For this reason, CB-SEM was not included.

This methodology was designed to ensure that the constructs of technology readiness, motivational and inhibitory factors, and behavioral responses of Gen Z toward AI virtual assistants could be rigorously examined within the context of personalized e-commerce experiences in Ho Chi Minh City.

3. Results and Discussion

3.1. Research results

3.1.1. Descriptive Statistics

The research data was collected from 308 satisfaction surveys over 396 participants, females constituted the most with 166 individuals (53.9%), while males accounted for 123 participants (39.9%), and 6.2% identified as other genders. Regarding age, the largest group of participants was aged 18 to 21, comprising 84.7% of the sample, followed by the 22 to 25 age group at 14%, and only 1.3% were between 26 and 28 years old. Majority of the respondents had high school education level (48%) and undergraduate/college (47.4%), only 4% held a postgraduate degree, and 0.6% had not completed high school. In terms of monthly income, the group earning between 2 to under 5 million VND was the largest (37.3%), followed by those with no fixed income or who are financially dependent on their families (21.4%), and the group with an income under 2 million VND (20.5%), very few participants have an income of 10 million VND or higher (8.8%), this aligns with the fact that majority of respondents are colleges (89%) and followed by office staff (6,8%), civil servant (0,6%) and finally public employee, businessmen share the proportion of (0,3%).

3.1.2. Evaluation of the measurement model

The outer loadings value ranged from 0.637 to 0.939. The majority of the measurement items achieved a loading greater than the recommended threshold of 0.7 suggested by Hair et al, except PUFN2, which belongs to the "Reasons for Usage" construct and had a loading of 0.637. Although the loading for PUFN2 did not meet the optimal threshold of 0.7, this indicator was still retained in the measurement model. This decision was justified as the overall quality metrics for the "Reasons for Usage" scale remained robust. Specifically, the AVE result for this construct was 0.649, well above the required 0.5, and its CR result was 0.963, significantly exceeding the 0.7 benchmark (Fornell & Larcker, 1981; Hair et al., 2019).

The Composite Reliability (CR) value ranging from 0.897 to 0.963 exceeding the 0.7 threshold recommended by Hair et al. This confirms that the scales used in this research ensure strong internal consistency among the items that constitute each latent concept. On the other hand, all VIF values are within the range of 1.511 to 4.331 which mean no serious multicollinearity among the independent variables.

In addition, convergent validity was assessed using the result of Average Variance Extracted (AVE). Fornell and Larcker (1981) suggested that AVE should be well more than 0.5 to establish convergent validity. Table 1 shows that AVE of all latent variables are within 0.649 and 0.804 well above the recommended 0.5 benchmark and confirm the convergent validity is strong between each latent construct.

Table 1. Outer Loadings, VIF, AVE, CR test results

		Outer Loadings	VIF	AVE	CR
Motivators	OPT1	0.812	3.154	0.713	0.949
	OPT2	0.834	3.424		
	OPT3	0.852	3.608		
	OPT4	0.837	3.443		
	INVO1	0.808	3.177		
	INVO2	0.859	4.331		
	INVO3	0.862	3.558		
	INVO4	0.817	3.021		
	INSEC5	0.867	3.527		
Reasons for usage	PEU1	0.791	3.178	0.649	0.963
	PEU2	0.778	3.054		
	PEU3	0.843	3.399		
	PUFN1	0.828	3.567		
	PUFN2	0.637	2.439		
	PUFN3	0.731	3.373		
	PTRND1	0.850	3.389		
	PTRND2	0.812	2.930		
	PTRND3	0.845	3.649		
	PINFOR1	0.811	2.781		
	PINFOR2	0.809	2.868		
	PINFOR3	0.851	3.562		
	PINFOR4	0.818	3.085		
	PINFOR5	0.851	3.537		

Reasons against usage	PUSB1	0.865	3.343	0.704	0.955
	PUSB2	0.808	3.674		
	PUSB3	0.813	3.927		
	PFRB1	0.852	3.581		
	PFRB2	0.880	3.642		
	PFRB3	0.838	3.574		
	PINTRU1	0.896	4.327		
	PINTRU2	0.770	3.266		
	PINTRU3	0.823	4.307		
Attitude toward usage	ATTU1	0.920	3.700	0.804	0.943
	ATTU2	0.915	3.572		
	ATTU3	0.880	2.804		
	ATTU4	0.872	2.630		
Usage intention	UINT1	0.871	1.934	0.747	0.899
	UINT2	0.858	1.884		
	UINT3	0.863	1.901		
Resistance intention	RINT1	0.733	1.511	0.746	0.897
	RINT2	0.939	2.856		
	RINT3	0.905	2.597		

Table 2. Inner VIF

	MOTI	INHI	RFU	RAU	ATU	UI	RI
MOTI			1.000				
INHI				1.000			
RFU					2.444	**3.445**	2.243
RAU					2.444		2.243
ATU						**3.445**	
UI							
RI							

Furthermore, the study addressed the potential for common method bias (CMB) using a full collinearity test in order to seek out the inner VIFs for endogenous regressors. Most factor shown no dominated due to the conservative threshold of 3.3 suggested by Kock (2015) except two factor RFU (3.445) and ATU (3.445) to UI are slightly higher than the golden standard. Despite that, those values remained well below the more widely accepted threshold of 5.0 (Hair et al., 2019).

Table 3 shows the cross-loadings results of observation variables. According to this criterion, each indicator's loading on its corresponding latent construct must be higher than its loadings on any other construct within the model. Results from Table 3 confirms the strongest correlation between their respective latent variables, indicating a high degree of discriminant validity and ensuring that each construct represents a unique concept within the research scale.

Table 3. Cross-loadings results of observation variables

	MOTI	INHI	RFU	RAU	ATU	UI	RI
OPT1	0.812						
OPT2	0.834						
OPT3	0.852						
OPT4	0.837						
INVO1	0.808						
INVO2	0.859						
INVO3	0.862						
INVO4	0.817						
DISCOM1		0.840					
DISCOM2		0.864					
DISCOM3		0.864					
INSEC1		0.812					
INSEC2		0.833					
INSEC3		0.827					
INSEC4		0.848					
INSEC5		0.867					
PEU1			0.791				
PEU2			0.778				
PEU3			0.843				
PUFN1			0.828				
PUFN2			0.637				
PUFN3			0.731				
PTRND1			0.850				
PTRND2			0.812				
PTRND3			0.845				
PINFOR1			0.811				
PINFOR2			0.809				
PINFOR3			0.851				
PINFOR4			0.818				
PINFOR5			0.851				
PUSB1				0.865			
PUSB2				0.808			
PUSB3				0.813			
PFRB1				0.852			
PFRB2				0.880			
PFRB3				0.838			
PINTRU1				0.896			
PINTRU2				0.770			
PINTRU3				0.823			
ATTU1					0.920		
ATTU2					0.915		
ATTU3					0.880		
ATTU4					0.872		
UINT1						0.871	

	MOTI	INHI	RFU	RAU	ATU	UI	RI
UINT2						0.858	
UINT3						0.863	
RINT1							0.733
RINT2							0.939
RINT3							0.905

After that, the Fornell-Larcker criterion was applied as shown in Table 4. This method requires that the square root of each AVE must exceed its correlation with all other latent variables. The majority of the results tend to suit the criteria. However, a minor exception was noted, those were the correlation between MOTI and RFU, INHI and RAU, RFU and ATU. Despite that, other indices shown above held strong reliability and no severe multicollinearity was detected. Therefore, the original measurement model was retained.

Table 4. Discriminant Validity (Fornell-Larcker Criterion)

	MOTI	INHI	RFU	RAU	ATU	UI	RI
MOTI	0.835						
INHI	0.778	**0.845**					
RFU	0.843	0.763	**0.806**				
RAU	0.756	0.850	0.727	**0.839**			
ATU	0.797	0.716	0.841	0.722	**0.897**		
UI	0.726	0.678	0.777	0.623	0.813	**0.864**	
RI	0.557	0.600	0.530	0.753	0.591	0.437	**0.864**

Table 5. Heterotrait-monotrait ratio (HTMT)

	MOTI	INHI	RFU	RAU	ATU	UI	RI
MOTI							
INHI	0.825						
RFU	0.891	0.810					
RAU	0.830	**0.910**	0.807				
ATU	0.858	0.767	0.894	0.799			
UI	0.883	0.842	**0.926**	0.783	**0.966**		
RI	0.650	0.703	0.648	0.861	0.591	0.614	

The HTMT value between construct INHI and RAU, RAY and UI, ATU and UI, was found to be 0.910, 0.926, 0.966, which is slightly above the conservative threshold of 0.85. Although some of the HTMT are high, those constructs are conceptually distinct within Behavioral Reasoning Theory (BRT). Removing either construct would compromise the integrity of the theoretical framework. Therefore, they were retained for theoretical reasons despite the empirical overlap.

The coefficient of determination (R^2) is used to explain the power of the structural model. According to the guidelines from Hair et al (2013), these values are typically categorized as substantial (0.75), moderate (0.50), or weak (0.25). Overall, results displayed on Table 6 show that the research model has good explanatory power, with all R^2 values ranging from moderate to substantial. This indicates that the chosen theoretical framework is highly suitable and effective in explaining the psychological and behavioral factors of Gen Z related to the adoption of AI virtual assistants.

Table 6. R-Square Values

	R Square
RFU	0.723
RAU	0.711
ATU	0.733
UI	0.572
RI	0.690

3.1.3. Predictive power assessment

Table 7 presents the PLSpredict results of the structural model. All Q^2predict values are greater than zero, confirming that the model has predictive relevance (Hair et al., 2019). In particular, Reasons for Usage (RFU), Reasons against Usage (RAU), and Attitude toward Usage (ATU) show high Q^2predict values (0.711–0.733), indicating strong predictive accuracy for cognitive and attitudinal constructs. Meanwhile, Usage Intention (UI) and Resistance Intention (RI) record moderate but acceptable Q^2predict values (0.572 and 0.690), suggesting that the model is capable of predicting Gen Z's behavioral outcomes.

Table 7. PLSpredict LV Summary

Constructs	Q^2predict
Reasons for usage (RFU)	0.723
Reasons against usage (RAU)	0.711
Attitude toward usage (ATU)	0.733
Usage intention (UI)	0.572
Resistance intention (RI)	0.690

3.1.4. Testing of research hypotheses

Bootstrapping is a resampling method that repeatedly draws samples from the original data to estimate the accuracy of parameters. Bootstrapping helps reduce assumptions about data distribution and evaluate the stability of results in statistical models. Hair et al. (2014) recommends using 5,000 bootstrap samples to achieve stable results, with each bootstrap sample having the same size as the original dataset. The structural model test results using bootstrapping with the sample number of 5,000 are shown in Table 8.

Table 8. Hypothesis testing results

Hypothesis		Path coefficient	Standard Deviation	T Value	P Values	Conclusion
H1	MOTI → RFU	0.843	0.020	42.492	0.000	Acceptance
H2	INHI → RAU	0.850	0.027	31.916	0.000	Acceptance
H3	RFU → ATU	0.670	0.051	13.225	0.000	Acceptance
H4	RFU → UI	0.319	0.067	4.781	0.000	Acceptance
H5	RAU → ATU	0.236	0.055	4.261	0.000	Acceptance
H6	RAU → RI	0.683	0.050	13.622	0.000	Acceptance
H7	ATU → UI	0.544	0.067	8.148	0.000	Acceptance
H8	ATU → RI	0.097	0.064	1.534	0.125	Rejected

Table 9. Indirect effects

Hypothesis	Indirect effects	VAF	P Values	Conclusion
MOTI → RFU → UI	0.344	40.5%	0.000	Acceptance
INHI → RAU → RI	0.663	98.3%	0.000	Acceptance
RFU → ATU → UI	0.301	42.6%	0.000	Acceptance
RAU → ATU → UI	0.108	100%	0.000	Acceptance
RFU → ATU → RI	0.038	100%	0.000	Acceptance
RAU → ATU → RI	0.014	1.8%	**0.377**	Rejected
MOTI → RFU → ATU → UI	0.256	42.7%	0.000	Acceptance
INHI → RAU → ATU → UI	0.093	100%	0.000	Acceptance
INHI → RAU → ATU → RI	0.012	1.7%	**0.379**	Rejected
MOTI → RFU → ATU → RI	0.032	100%	**0.348**	Rejected

From the result, T-Statistics (T-Value) are obtained to assess the hypothesized influence of independent variables on dependent variables. T-Value > 1.96 indicates statistical significance at a 95% confidence level, which is generally acceptable for research. Additionally, Hair et al. (2013) said that, a T-Value ≥ 2.58 indicates statistical significance at 99%, and a T-Value ≥ 3.29 indicates statistical significance at 99.9%.

Moreover, P-value is used to assess the reliability of hypotheses. Hair et al. (2013) suggest that P-values < 0.05 are accepted as a reliable means for evaluating the validity of a research model.

To test the indirect mechanisms within the research model, a mediation analysis was conducted using the bootstrapping method of 5,000 resamples. The type and extent of mediation were determined by the Variance Accounted For (VAF) index. In line with the guidelines of Hair et al. (2019), VAF index was employed to assess the extent of mediation effects in the structural model calculated as the ratio of the indirect effect to the total effect, thereby indicating the share of variance in the dependent construct transmitted through the mediator. Conventionally, a VAF value below 20% suggests no mediation, values between 20% and 80% indicate partial mediation, while values above 80% reflect full mediation.

3.2. Discussion

H1: MOTI → RFU: The path coefficient is very strong and positive (β = 0.843, p = 0.000), indicating that technology readiness motivators have a powerful positive impact on the reasons to use AI assistants. This strongly aligns with Parasuraman's (2000) TRI model. Motivators like optimism and innovativeness are foundational drivers for technology adoption. This finding is also consistent with Blut & Wang (2020), who found that motivators have a stronger correlation with technology use than inhibitors do.

H2: INHI → RAU: This path is also very strong and positive (β = 0.850, p = 0.000), showing that technology readiness inhibitors strongly predict the reasons for not using AI assistants. This makes sense due to Parasuraman (2020), Inhibitors like discomfort and insecurity are the primary sources for forming specific reasons against usage.

H3: RFU → ATU: The path coefficient is strong and positive (β = 0.670, p = 0.000), meaning that having more reasons to use the technology leads to a more positive attitude towards it. This clarifies the role of reasons as mentioned in Westaby's (2005) BRT.

H4: RFU → UI: This path is positive and significant (β = 0.319, p = 0.000), but the effect is moderate, suggesting that while reasons for usage positively influence intention, other factors are also at play. Like above, Westaby's (2005) BRT play an important role the hypothesis.

H5: RAU → ATU: The path coefficient is positive and significant (β = 0.236, p = 0.000). This result conflicts with the hypothesized negative direction that has been predicted before. A positive coefficient suggests that having more reasons against using the technology is associated with a more positive attitude. While statistically significant, this finding requires careful interpretation; it may suggest a complex relationship where acknowledging barriers does not negate a positive overall attitude. H5 is accepted based on statistical significance, but the direction is noted.

H6: RAU → RI: The path coefficient is very strong and positive (β = 0.683, p = 0.000), indicating that reasons for not using the technology powerfully drive the intention to resist it. This finding strongly supports innovation resistance studies by Ram & Sheth (1989), Specific reasons against usage directly translate into an active intention to reject the technology.

H7: ATU → UI: The path is strong and positive (β = 0.544, p = 0.000), confirming that a positive attitude is a significant predictor of the intention to use the technology. This result reinforces technology acceptance models TAM (Davis, 1989) and the Theory of Planned Behavior (Ajzen, 1991), where attitude is a key predictor of behavioral intention. When Gen Z forms a positive attitude toward AI assistants, their intention to use them increases significantly.

H8: ATU → RI: This path was not statistically significant ($\beta = 0.097$, $p = 0.125$). This indicates that having a positive attitude does not significantly reduce the intention to resist using the technology in this model. So H8 is rejected. This hypothesis gives a view that users can form a positive attitude toward AI while still holding concerns to it. A positive attitude alone cannot easily overcome specific, powerful reasons for resistance.

About the indirect effect, the analysis revealed the partial mediating role of cognitive factors. Specifically, the indirect effect of MOTI on UI through RFU was significant with a VAF of 40.5% ($p = 0.000$), indicating partial mediation. Similarly, RFU also indirectly impacts UI through ATU), with a VAF of 42.6% ($p = 0.000$), again confirming partial mediation. These findings suggest that motivational drivers and reasons for usage influence behavioral intention not only directly but also by fostering a positive attitude.

The mediating role of RAU in the relationship between INHI and RI was exceptionally strong. This indirect path was highly significant with a VAF of 98.3% ($p = 0.000$), indicating full mediation. This means that the influence of psychological on the intention to resist is almost entirely channeled through the formation of specific reasons against adoption.

The result also shown the indirect effect of RAU on UI and ATU with VAF = 100% ($\beta = 0.108$, $p < .005$) indicating fully mediation. This result is contrary to the initial expectation that H5 predicted a negative RAU → ATU relationship and make more sense to protect the result of H5 discussed above.

Finally, most indirect paths leading to Resistance Intention via Attitude were found to be statistically non-significant ($p > 0.05$), which is consistent with the non-significant direct effect of ATU → RI reported in Table 8.

4. Conclusion and Implications

4.1. Conclusion

This research explores the psychological processes influencing Generation Z's behaviors toward AI virtual shopping assistants, focusing specifically on personalized e-commerce within Ho Chi Minh City. By integrating the Technology Readiness Model and Behavioral Reasoning Theory, the research offers a comprehensive perspective on how internal traits and contextual reasoning jointly influence adoption behavior.

Findings from 308 valid responses reveal that Gen Z's decision-making is not linear but dual-channeled. Technology-related optimism and a tendency toward innovativeness serve as primary motivators, strengthening favorable attitudes and encouraging the intention to adopt AI assistants. Conversely, feelings of discomfort due to usability issues and insecurities linked to privacy and data misuse concerns act as obstacles, leading to psychological resistance.

Interestingly, the results underscore that these two pathways are not mutually exclusive. A Gen Z consumer may simultaneously feel optimistic about the potential convenience and personalization AI offers, while also harboring doubts that give rise to reluctance. This coexistence of acceptance and resistance within the same individual aligns with the assertions of Claudy et al. (2015) and Westaby (2005), thereby validating Behavioral Reasoning Theory in this emerging technology context.

Additionally, this research advances the use of Behavioral Reasoning Theory by emphasizing the mediating function of 'reasons for' and 'reasons against' as key explanatory factors. These constructs bridge the gap between innate traits (e.g., optimism/insecurity) and behavioral outcomes (e.g., intention to use/resist), offering a more granular understanding of Gen Z's logic in navigating technological choices.

In doing so, this research not only complements previous chatbot and AI assistant studies (e.g., Jan et al., 2023) but also provides empirical evidence from a rapidly developing market-Vietnam-where technological innovation and youthful consumer behavior are evolving in parallel. The results yield theoretical and managerial insights into how AI-powered retail experiences can be optimized to resonate with a highly discerning, digitally native demographic.

4.2. Theoretical and Practical Implications

Theoretically, this study adds to the technology adoption literature by combining TAM, TRI, and BRT to encompass both facilitators and barriers influencing AI adoption. It challenges conventional models that focus solely on acceptance, proposing that reasons against adoption such as security concerns or technological discomfort should be modeled independently. The findings reinforce that resistance should not be viewed as a mere absence of acceptance, but as an intentional behavioral outcome with its own cognitive antecedents. Moreover, by concentrating on Vietnamese Gen Z, the study offers localized insights into how contemporary digital consumers manage technological advancements while addressing inherent concerns. These results align with local research indicating that while perceived usefulness and personalization encourage adoption, trust remains a significant barrier (Thanh & Linh, 2023).

Practically, the study provides businesses with actionable strategies to enhance Gen Z's interaction and engagement with AI assistants. First, companies should clearly communicate the benefits of using AI tools such as time-saving features, instant support, and personalized experiences to build strong "reasons to use". Moreover, cultivating a community of early adopters, who are typically higher in technology innovativeness, can accelerate the diffusion of innovation by showcasing new features and generating positive social influence. Second, reducing complexity in AI interfaces is crucial, especially for users prone to tech discomfort. This includes user-friendly designs and simple onboarding tutorials that minimize friction. Third, despite the study reveals that recognizing and openly discussing potential risks may not necessarily weaken attitudes, strategies along thí theory should not be condered as a managerial implication until more trustworthy finding in the future typically about it. Finally, segmentation is recommended as a practical pathway to implementation. Technology-forward users with fewer concerns can be encouraged to explore advanced personalization features, while more skeptical consumers may benefit from a gradual onboarding process emphasizing simplicity, transparency, and user control. Continuous monitoring of core indicators like reasons for and against usage, attitudes, adoption intentions, and resistance intentions will allow firms to evaluate the impact of their interventions and adapt strategies in real time.

In the other hand, to neutralize the negative pathway, businesses must directly address user barriers, particularly since the findings show that a positive attitude alone is insufficient to reduce resistance. A core strategy is to adopt knowledge to privacy and user control. This approach directly targets "Reason agaist usage", the primary antecedent to "Resistance intention". Concurrently, reducing the uncomfortableness while using technology through frictionless interface design can help lower initial "inhibitors". In terms of communication, adopting a tone of optimism that balances benefits with risks aligns with the finding that acknowledging barriers can strengthen a positive attitude when paired with a commitment to resolving them. Finally, implementing risk-reversal policies at sensitive touchpoints, such as guaranteeing easy returns or providing users with an accessible log of their data access, helps transform reasons against usage into manageable and controlled barriers, thereby reducing resistance intention.

4.3. Limitations and Future Research

Although this study offers valuable insights, it has some limitations. The sample was restricted to urban Vietnamese Gen Z consumers, potentially limiting the applicability of the results to other regions or demographic groups. Cultural factors and levels of digital literacy in rural areas or other countries could influence how users perceive AI tools. Future research should replicate this model across diverse populations and consider cross-cultural comparisons to identify variations in motivator-barrier dynamics. Moreover, the use of self-reported, cross-sectional data introduces the risk of common method bias and restricts causal inference. Longitudinal studies or experiments such as exposing users to different AI scenarios would provide stronger evidence of causality. Further qualitative studies, such as interviews or focus groups, could provide deeper understanding of how users balance favorable attitudes with ongoing concerns.

Furthermore, the model did not account for potentially influential variables such as peer influence or prior experience with AI. Incorporating these could enhance explanatory power, especially in social or habitual contexts. Lastly, the rapid evolution of AI technology means that future research must update definitions and capabilities of AI assistants over time. As more advanced systems (e.g., GPT-based assistants) become mainstream, new inhibitors and ethical concerns may arise. Future studies should explore whether increased familiarity with AI reduces perceived risks or introduces new forms of resistance.

4.4. Discussion of Findings

This study provides important insights into the factors influencing Generation Z consumers in Ho Chi Minh City regarding their adoption of AI virtual assistants for personalized shopping. The findings support the integrated model of the Technology Acceptance Model (TAM), Technology Readiness Index (TRI), and Behavioral Reasoning Theory (BRT), extending existing literature by incorporating both positive drivers and negative barriers into technology acceptance analysis.

Our results align with previous research (Parasuraman, 2000; Blut & Wang, 2020), confirming that motivators such as optimism and innovativeness significantly enhance consumers' reasons for adopting AI technology. Specifically, Gen Z's optimistic outlook and innovativeness lead to strong positive reasons for using AI virtual assistants, such as perceived usefulness, ease of use, and personalized experiences. This positive reasoning fosters favorable attitudes, ultimately driving stronger behavioral intentions to use the technology.

Conversely, inhibitors including discomfort and insecurity were found to strongly contribute to reasons against adopting AI, which aligns with prior findings by Claudy et al. (2015) and Jan et al. (2023). Notably, concerns about privacy risks and complexity of AI interactions reinforce negative attitudes and resistance intentions. Contrary to initial expectations, the results indicate a statistically significant positive relationship between reasons against usage and attitudes toward AI, suggesting that Gen Z consumers acknowledge potential issues yet maintain a cautiously optimistic perspective towards AI technologies.

Additionally, our findings corroborate the central role of attitudes as a predictor of usage intentions, consistent with the Technology Acceptance Model (Davis, 1989) and Theory of Planned Behavior (Ajzen, 1991). Positive attitudes significantly increased Gen Z's willingness to adopt AI virtual assistants. However, contrary to hypotheses, attitudes did not significantly diminish resistance intentions, indicating that while consumers can maintain positive perceptions of AI, specific barriers like privacy concerns or technological discomfort remain potent enough to sustain resistance.

This study fills the research gap by focusing explicitly on Vietnamese Gen Z consumers and underscores the coexistence of adoption and resistance pathways within individual decision-making processes. Practically, these findings suggest businesses should prioritize clear communication of AI benefits, simplify user interfaces, and robustly address privacy concerns to mitigate resistance and strengthen positive attitudes and adoption intentions among Gen Z.

Despite its contributions, the study has limitations, notably the cross-sectional nature of the data and the restricted geographic focus on urban consumers in Ho Chi Minh City. Future research could extend this framework to other demographics and incorporate longitudinal methods to capture changes in attitudes and intentions over time. Additionally, qualitative research may provide deeper insights into how Gen Z consumers balance optimism and concern when interacting with AI virtual assistants.

REFERENCES

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

Blut, M., & Wang, C. (2020). Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, 48(4), 649–669. DOI: https://doi.org/10.1007/s11747-019-00680-8

Claudy, M. C., Garcia, R., & O'Driscoll, A. (2015). Consumer resistance to innovation—a behavioral reasoning theory perspective. *Journal of the Academy of Marketing Science*, 43(4), 528–544. DOI: https://doi.org/10.1007/s11747-014-0399-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. DOI: https://doi.org/10.2307/249008

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. DOI: https://doi.org/10.2307/3151312

Hair, J. F., Jr., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis (5th ed.)*. Prentice Hall.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM) (1st ed.)*. Sage.

Hair, J. F., Jr. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, 5(1), 105–115. DOI: https://doi.org/10.1016/j.jfbs.2014.01.002

Hair, J. F., Jr., Ringle, C. M., & Sarstedt, M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24. DOI: https://doi.org/10.1108/EBR-11-2018-0203

Jan, I. U., Ji, S., & Kim, C. (2023). What (de) motivates customers to use AI-powered conversational agents for shopping? The extended behavioral reasoning perspective. *Journal of Retailing and Consumer Services*, 75, 103440. DOI: https://doi.org/10.1016/j.jretconser.2023.103440

Kasilingam, D. L. (2020). Understanding the attitude and intention to use chatbots for customer service. *Journal of Retailing and Consumer Services*, 57, 102253. DOI: https://doi.org/10.1016/j.jretconser.2020.102253

Nguyễn Phúc Quý Thành & Châu Đình Linh (2024). Factors affecting the decision to use chatbots in e-banking services of GenZ customers in Vietnam. *Journal of Infrastructure, Policy and Development*, 8(13), 9688. DOI: https://doi.org/10.24294/jipd.9688

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307–320. DOI: https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research*, 18(1), 59–74. DOI: https://doi.org/10.1177/1094670514539730

Ram, S., & Sheth, J. N. (1989). Consumer resistance to innovations: The marketing problem and its solutions. *Journal of Consumer Marketing*, 6(2), 5–14. DOI: https://doi.org/10.1108/EUM0000000002542

Westaby, J. D. (2005). Behavioral reasoning theory: Identifying new linkages and arrangements of causes and effects. *Psychological Reports*, 96(3_suppl), 1227–1240. DOI: https://doi.org/10.1016/j.obhdp.2005.07.003