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Understanding Gen Z's Perceptions and Acceptance of AI-Generated Advertisements: An Empirical Study in Vietnam

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Abstract

The 21st century marks the rapid adoption of artificial intelligence (AI) in advertising. However, to comprehensively evaluate the effectiveness of AI-generated advertisements, the consumers' perception and acceptance should be taken into consideration, especially among Generation Z. This study examines the factors influencing Gen Z's perceptions of AIGCs in Vietnam, using the Stimulus-Organism-Response (SOR) framework. Key characteristics include verisimilitude, vitality, imagination, synthesis, perceived eeriness, and perceived intelligence. Results find that perceived intelligence significantly enhances willingness to accept AI-generated ads, whereas perceived eeriness negatively affects it. Verisimilitude and imagination positively impact perceived intelligence but negatively on perceived eeriness. Synthesis contributes to perceived eeriness but does not influence perceived intelligence. This study contributes to the growing literature on AI applications in marketing by offering empirical evidence from a Southeast Asian context and provides actionable implications for advertisers seeking to effectively engage Gen Z consumers in Vietnam's dynamic digital marketplace.

Keywords: *Gen Z, AI-Generated Advertisements, Vietnam*

1. Introduction

In the 21st century, artificial intelligence (AI) is transforming how we create and communicate advertising messages. The role of AI in marketing is becoming increasingly essential, thanks to its ability to perform tasks that resemble human capabilities (Vlačić et al., 2021). From writing and designing visuals to generating videos and music, AI enables highly personalized advertising content at scale (Gujar & Panyam, 2024). However, while AI offers efficiency and customization, the success of AI-generated ads depends largely on how audiences perceive them and, crucially, whether they're willing to accept content made by machines (Gu et al., 2024).

These concerns are particularly relevant to Generation Z, who were born between 1996 and 2010, a cohort grown up in a digital environment and deeply familiar with algorithm-driven content. Despite their familiarity and experiences with AI, Gen Z consumers remain cautious regarding data privacy and the potential for manipulation through AI-driven marketing strategies (Jeffrey, 2021).

AI's impact has already been widely studied in areas like healthcare (Yin et al., 2021), education (Zawacki-Richter et al., 2019) and pharmaceutical research (Deng et al., 2021). Marketing, also, has adopted AI, using it for customer segmentation, content personalization, and campaign optimization (Kumar et al., 2022). However, there remains a lack of empirical investigation into how these dynamics play out in Southeast Asia,especially in Vietnam, where Gen Z comprises a rapidly expanding and influential consumer segment (Vlačić et al., 2021). In Vietnam, Gen Z is between the ages of 15 and 29, with a population of up to 20.46 million people, accounting for about 20.1% of the total population (GSO, 2025).

Advertisements are not only used for brand communication, but also a vital contributor to the business success. In 2025, Vietnam's advertising market is projected to reach USD 2.94 billion, reflecting the central role that advertising plays across industries (Statista, 2024). Globally, advertising spending has surpassed USD 1 trillion in 202, and is anticipated to increase by 10.7% in 2025, reaching $1.08 trillion (Warc, 2025).

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This study aims to investigate how Vietnamese Gen Z perceive AI-generated ads across various dimensions. By exploring these dimensions, the research seeks to offer a clearer understanding of the evolving relationship between young consumers and emerging advertising technologies. To support this objective, the study is guided by the following research questions, which aim to explore Gen Z's interpretations and attitudes in greater depth:

- **RQ1:** How does Generation Z evaluate essential characteristics—such as realism and dynamism—in AI-generated advertisements?
- **RQ2:** What are the dominant perceptions among Gen Z regarding the cognitive sophistication and potential uncanny or unsettling aspects of AI-created advertising?
- **RQ3:** How open is Generation Z to accepting and engaging with promotional content developed through artificial intelligence?

2. Research overview and hypothesis

2.1. SOR Theory

The Stimulus-Organism-Response (S-O-R) theory, initially developed by Mehrabian and Russell (1974), is a foundational framework for understanding how external environments influence human behaviors. This model conceptualizes stimuli (S) as external inputs that can be either physical or psychological, which then trigger the organism's (O) internal processes, such as perceptions, emotions, and cognitions, before resulting in a response (R) that manifests as approach or avoidance behaviors (Mehrabian & Russell, 1974).

Originally, the SOR theory was adopted in environmental psychology, before being extended to various fields, including marketing to explain consumer responses to different marketing stimuli. Researchers have applied the S-O-R model in various digital marketing contexts, such as online shopping environments (Eroglu et al., 2001), social commerce (Zhao & Teo, 2023), and AI-generated advertisements (Gu et al., 2024). These studies collectively demonstrate the versatility of the S-O-R model in capturing the nuanced pathways through which external stimuli influence consumer behavior in technology-driven settings.

Given the rapid rise of AI-generated advertisements and their unique ability to simulate human creativity and agency, the S-O-R framework offers valuable insights into how Gen Z consumers in Vietnam perceive and respond to such ads. Specifically, the stimuli represented by AI-generated content may trigger varied organismic states, ranging from fascination to skepticism, that influence key behavioral responses like trust, engagement, and acceptance. This theoretical lens not only aligns with the empirical literature on AI in marketing (Gu et al., 2024) but also highlights the importance of considering both the technological and cultural contexts in shaping consumers' perceptions and decisions.

2.2. AI-generated ads

AI-generated content (AIGC) refers to digital content, such as text, images, audio, and video, produced by machines. These systems leverage advanced algorithms, including machine learning and natural language processing, to generate content based on user inputs or data patterns. AIGC has emerged as a transformative force in content creation, offering scalability and efficiency across various domains (Wu et al., 2023).

The integration of AIGC into marketing has brought substantial benefits, transforming traditional advertising into a more dynamic and efficient practice. Beyond traditional methods, AI can produce personalized content based on individual preference (Gao et al., 2023), (Xia, 2024), which can lead to increased campaign profitability (Boyko & Kholodetska, 2022) and consumer engagement and purchasing decisions (Ratta et al., 2024). Moreover, by analyzing data from social media and other platforms, these tools provide insights into consumer sentiments, allowing for the refinement of advertising strategies to target potential customers and meet audience needs (Choi & Lim, 2020).

However, there are several challenges about AI-generated advertisements that marketers must navigate to ensure ethical and effective communication with consumers. One significant concern is the presence of algorithmic bias in AI-generated advertisements. Because AI systems can potentially be trained on biased datasets, advertisements made by it can perpetuate stereotypes and discriminatory practices, resulting in unfair targeting and exclusion in advertising campaigns (Gao et al., 2023). Furthermore, advertisers are responsible for maintaining transparency and ethical standards in how they collect and use consumer information (Gao et al., 2023).

2.3. Factors influencing acceptance

Consumer acceptance of AI-generated advertisements is affected by several factors. One critical determinant is the perceived eeriness of AI-generated advertisements. When ads appear realistic, imaginative, and lively, they tend to reduce consumers' feelings of strangeness or discomfort, thereby enhancing their acceptance. Conversely, ads that appear overly synthetic or artificial increase perceived eeriness, which negatively impacts consumers' willingness to accept them (Gu et al., 2024).

Another important factor is perceived intelligence. Consumers are more likely to engage with AI-generated advertisements that they perceive as smart, thoughtful, and well-crafted, as these qualities foster a sense of relevance and connection with the brand (Gu et al., 2024). This highlights the importance of ensuring that AI-generated content demonstrates sophistication and creativity to align with consumer expectations.

Trustworthiness also plays a pivotal role in shaping consumer attitudes toward AI-generated advertisements. Trust can be affected by the degree of authenticity in the advertisement, the presence or absence of AI labels, and consumers' prior experiences with AI technology (Guerra-Tamez et al., 2024). Building trust through transparent and authentic advertising practices is thus essential for fostering positive consumer perceptions.

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Finally, the type of appeal used in AI-generated advertisements can impact their effectiveness. Research indicates that agentic (goal-oriented) appeals are generally better received than communal (relationship-focused) appeals. However, communal appeals can also be effective when the AI is presented with a relatable social role, such as a partner or servant, suggesting that the social context of AI representation matters in shaping consumer responses (Chen et al., 2024).

2.4. Research hypothesis

Verisimilitude

Verisimilitude pertains to the degree to which AI-generated advertisements appear realistic and lifelike based on consumers' perception (Campbell et al., 2021). High verisimilitude improves consumer immersion by presenting a scene that closely reflects real-world contexts, thereby reducing the perceived artificiality that often triggers eeriness. Empirical findings indicate that greater verisimilitude is associated with lower perceived eeriness and higher perceived intelligence in AI-generated advertisements (Gu et al., 2024).

H1: Verisimilitude has a negative influence on the perceived eeriness of AI-generated advertisements.

H2: Verisimilitude has a positive influence on the perceived intelligence of AI-generated advertisements.

Vitality

Vitality is defined as the vital force, power, or principle possessed or manifested by creatures (Oxford English Dictionary). This quality emphasizes liveliness and emotional resonance, distancing the advertisement from static or mechanical representations. Results show that increased vitality not only enhances perceived intelligence but also mitigates perceived eeriness among viewers (Gu et al., 2024).

H3: Vitality has a negative influence on the perceived eeriness of AI-generated advertisements.

H4: Vitality has a positive influence on the perceived intelligence of AI-generated advertisements.

Imagination

Imagination describes the ability to create novel and creative works (Mun et al., 2013). By transcending conventional human cognitive boundaries, AI enables more inventive and unexpected visual narratives. The study reports that stronger imaginative content reduces perceived eeriness and boosts perceived intelligence, supporting its significance as a beneficial trait of AI-generated advertisements (Gu et al., 2024).

H5: Imagination has a negative influence on the perceived eeriness of AI-generated advertisements.

H6: Imagination has a positive influence on the perceived intelligence of AI-generated advertisements.

Synthesis

Synthesis refers to the way AI combines and reassembles diverse data inputs to generate new imagery (Campbell et al., 2021). While this capability underpins AI's creative potential, it can sometimes produce artifacts or incongruities that heighten perceived eeriness and diminish perceived intelligence in advertisements. The dual impact of synthesis signifies a key boundary condition in designing effective AI-generated ads (Gu et al., 2024).

H7: Synthesis has a positive influence on the perceived eeriness of AI-generated advertisements.

H8: Synthesis has a negative influence on the perceived intelligence of AI-generated advertisements.

Perceived eeriness

Perceived eeriness is defined as the uncomfortable, uncanny, or unsettling feeling that consumers experience when interacting with AI-generated advertisements (Li et al., 2022). This dimension is particularly important because it can inhibit consumer acceptance and lower trust in advertising content. The study underscores that higher levels of perceived eeriness can negatively impact consumer attitudes toward AI-generated advertisements (Gu et al., 2024).

H9: Perceived eeriness has a negative influence on the consumers' willingness to accept AI-generated advertisements.

Perceived intelligence

Perceived intelligence refers to the extent to which consumers view AI-generated advertisements as exhibiting technological sophistication, rationality, and competence (Kini et al., 2023). This perception can enhance the credibility and persuasive power of advertisements, contributing to greater consumer acceptance. The study highlights that perceived intelligence positively influences consumers' willingness to engage with AI-generated advertisements (Gu et al., 2024).

H10: Perceived intelligence has a positive influence on the willingness to accept AI-generated advertisements.

The research model of this study is shown in Figure 1.

Figure 1. Research Model and Hypotheses

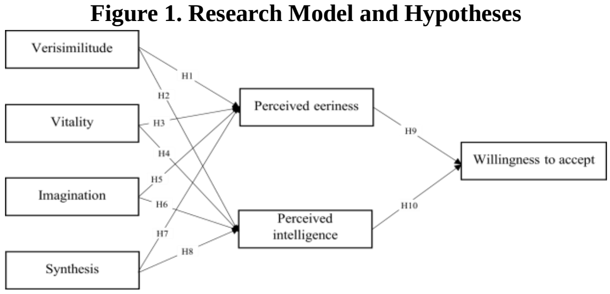

Table 1. The scales

Variable	Encoding	Scales
Verisimilitude	VE1	AI-generated advertisements present a realistic scenario.
	VE2	The details in AI-generated advertisements look realistic yet natural.

	VE3	The details in AI-generated advertisements are similar to scenes we see in real life.
	VE4	AI-generated advertisements present a credible image of the product or service.
	VE5	I feel that AI advertisements accurately reflect the nature of the product or brand.
	VE6	The images and content of AI-generated advertisements do not appear artificial.
Vitality	VI1	The AI-generated advertisements show the spirit of life and personality.
	VI2	The AI-generated advertisements show raw vitality.
	VI3	The AI-generated advertisements can be inherited and innovated.
	VI4	I feel that AI-generated advertisements have the potential to capture viewers' attention.
	VI5	I feel that AI-generated advertisements keep pace with modern media trends.
	VI6	AI-generated advertisements inspire and evoke positive emotions.
Imagination	IM1	AI-generated advertisements have creative ideas.
	IM2	AI-generated advertisements are innovative.
	IM3	AI-generated advertisements show originality.
	IM4	AI-generated advertisements are imaginative.
	IM5	I find that AI-generated advertisements introduce unprecedented approaches to content.
	IM6	AI-generated advertisements have the potential to shape future media trends.
Synthesis	SY1	There are obvious signs of synthesis between different elements in AI-generated advertisements.
	SY2	AI-generated advertisements as a whole give me the impression that they are cobbled together from different materials.
	SY3	Some of the detail articulation in the AI advertisements is unnatural.
	SY4	AI-generated advertisements as a whole give me a sense of disjointed combinations.
	SY5	I feel that the images, sounds, and content in AI-generated advertisements do not align with each other.
	SY6	Certain elements in AI-generated advertisements make me feel confused or unclear.
Perceived eeriness	PE1	I think the advertisements created by AI are creepy.
	PE2	I think AI-generated advertisements are weird.
	PE3	I think AI-generated advertisements are unnatural.
	PE4	I think AI-generated advertisements are bizarre.
	PE5	AI-generated advertisements make me feel uncomfortable when viewing it.

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	PE6	Certain images or movements in AI-generated advertisements make me feel uneasy.
Perceived intelligence	PI1	AI-generated advertisements are of great quality.
	PI2	I believe the products in AI-generated advertisements are functionally excellent.
	PI3	I think AI-generated advertisements demonstrate a high level of technology.
	PI4	I feel that AI-generated advertisements show an understanding of consumer needs and behaviors.
	PI5	I feel that AI-generated advertisements match the preferences of young people like me.
	PI6	I feel that AI-generated advertisements are built on smart data analysis.
Willingness to accept	WA1	I am willing (or will be willing) to accept AI-generated advertisements.
	WA2	I am willing to actively browse or watch incoming AI-generated advertisements messages.
	WA3	I am willing (or will be willing in the future) to purchase the product or service featured in the AI-generated advertisements.
	WA4	I feel positive about the application of AI in the advertising industry.
	WA5	I am willing to share AI-generated advertisements that I find attractive or interesting with others.
	WA6	I do not oppose the use of AI as a content creation tool in advertisements.

3. Methodology

Based on theoretical frameworks and literature reviews regarding the factors influencing the acceptance level of AI-generated advertising, the variables included in the research model are: "Verisimilitude" (VE), "Vitality" (VI), "Imagination" (IM), "Synthesis" (SY), "Perceived eeriness" (PE); "Perceived intelligence" (PI) và "Willingness to accept" (WI)

The survey was constructed with a 7-point Likert scale with:

1. *Completely disagree*
2. *Strongly disagree*
3. *Disagree*
4. *Neutral*
5. *Agree*
6. *Strongly agree*
7. *Completely agree*

A quantitative research method was employed to collect opinions on the acceptance level of AI-generated advertisements. After constructing the questionnaire, the research team conducted a pilot survey on the acceptance level of AI-generated advertisements, and preliminary results indicated agreement with the factors included in the model.

Due to time and resource constraints for the survey, the author used a convenient sampling method. The minimum sample size required was calculated according to the formula n=50 + 8*m (m: number of independent variables) (Tabachnick and Fidell, 1996). In the case of a study with 7 variables, the minimum number of ballots needed to be collected was 50 + 8*7 = 106 ballots. The survey subjects were Gen Z, who had seen at least 1 AI-generated advertisement. From the perspective of collecting as many observation samples as possible to ensure the stability of the impact, the questionnaire was sent to the survey subjects by sending them online via the google form link https://forms.gle/2BvmGMrt58AbmQ2W7. The number of ballots collected was 182, of which 152 ballots were from people who had watched AI-generated advertisements, and 30 ballots from people who had not watched AI-generated advertisements.

Data processing method

Quantitative research methods were conducted to process research data collected from a survey of Gen Z who had watched AI-generated advertisements. The structural regression equation has the general form:

PE = a*VE + b*VI + c*IM + d*SY
PI = e*VE + f*VI + g*IM + h*SY
WA = i*PE + j*PI

SMARTPLS software is used to test hypotheses and evaluate the impact level of factors.

Step 1: Evaluating Measurement Model

Evaluating measurement model based on examining values of reliability, quality of observed variable, convergence, and discriminant

Testing the quality of observed variables (Outer Loadings)

Outer loadings represent the strength of the relationship between observed indicators and their corresponding latent constructs. In SMARTPLS, outer loadings are essentially the square root of the absolute R^2 value from a linear regression of the latent variable on its observed indicators. According to Hair et al. (2016), an outer loading of 0.708 or higher indicates that the latent construct explains at least 50% of the variance in the observed variable. In this research, the threshold is rounded to 0.7, serving as a benchmark for indicator reliability in measurement models.

Evaluating Reliability

Reliability assessment in SMARTPLS is primarily conducted using two key indicators: Cronbach's Alpha and Composite Reliability (CR). While both measures evaluate internal consistency, many researchers prefer CR, as Cronbach's Alpha tends to underestimate reliability (Chin, 1998). In exploratory studies, a CR value above 0.6 is acceptable, whereas for confirmatory research, a threshold of 0.7 or higher is recommended (Henseler & Sarstedt, 2013). This standard is also supported by Hair et al. (2010) and Bagozzi & Yi (1988), who suggest that a CR ≥ 0.7 ensures sufficient construct reliability.

Accordingly, reliability in SMARTPLS is considered acceptable when Cronbach's Alpha ≥ 0.7 (DeVellis, 2012) and Composite Reliability ≥ 0.7 (Bagozzi & Yi, 1988).

Testing Convergence

Convergent validity in SMARTPLS is assessed using the Average Variance Extracted (AVE). According to Hock and Ringle (2010), a construct is considered to have adequate convergent validity when its AVE value is 0.5 or higher. An AVE of 0.5 indicates that, on average, the latent construct explains at least 50% of the variance in its associated observed indicators. Therefore, convergent validity is confirmed when AVE ≥ 0.5 (Hock & Ringle, 2010).

Testing Discriminant Validity

Discriminant validity assesses whether a construct is truly distinct from other constructs within the research model. According to Sarstedt et al. (2014), discriminant validity can be evaluated using two primary approaches: cross-loadings and the Fornell–Larcker criterion.

The cross-loadings method is often the first step in assessing discriminant validity (Hair, Hult, et al., 2017). In this approach, each observed variable should load more strongly on its associated latent construct than on any other constructs in the model. In other words, the indicator's primary loading should be higher than all of its cross-loadings.

The Fornell–Larcker criterion (Fornell & Larcker, 1981) further supports discriminant validity by requiring that the square root of the AVE for each latent construct be greater than its highest correlation with any other latent construct.

More recently, Henseler et al. (2015) introduced the Heterotrait–Monotrait Ratio of Correlations (HTMT) as a more robust method for assessing discriminant validity. Simulation studies have shown HTMT to be more effective in detecting discriminant validity issues.

According to Garson (2016), discriminant validity is established when the HTMT value is below 1.0. Henseler et al. (2015) suggest a more conservative threshold of HTMT < 0.90. Clark and Watson (1995) recommend an even stricter threshold of 0.85, which is often adopted in SMARTPLS analyses as the preferred standard.

Testing Multicollinearity

In this study, the author uses a scale related to multicollinearity as a variance magnification factor (VIF). Very high levels of multicollinearity are indicated by VIF values >= 7; the model does not have multicollinearity when VIF indicators < 7 (Hair et al., 2016).

Step 2: Evaluating Structural Model

After evaluating the satisfactory measurement model, evaluate the structural model through the impact relationship, path coefficient, R squared, and f squared.

Evaluating impactful relationships

To evaluate impact relationships, use the results of Bootstrap analysis. Based mainly on two columns (1) Original Sample (normalized impact factor) and (2) P Values (sig value compared to 0.05 significance level).

- Original Sample: Standardized impact factor of the original data. SMARTPLS have no unstandardized impact factor.
- Sample Mean: The average standardized impact factor of all samples from Bootstrap.
- Standard Deviation: Standard deviation of the standardized impact factor (according to the original sample).
- T Statistics: Test value t (test student the meaning of the impact).
- P Values: The significance level of the T Statistics. This significance level is considered with comparative thresholds such as 0.05, 0.1, or 0.01 (usually used as 0.05).

Evaluating the level of interpretation of the independent variable for the dependent variable by R2 coefficient (R square). To evaluate the R2 coefficient, we will use the results of the PLS Algorithm analysis. The R2 value evaluates the predictive accuracy of the model and shows the level of interpretation of the independent variable for the dependent variable. R square is between 0 and 1, the closer to 1 indicates the more independent variables that account for the dependent variable (Hair, Hult, et al, 2017).

In addition, when evaluating factors, collected data will be synthesized, calculated, and reflected in charts, tables, and drawings using Excel software. With the factors influencing the design according to the Likert 7 scale, when evaluating the level of influence of the factors, the average value achieved by the scales will be calculated; determine the average score within which response threshold and see the level of influence of each factor according to the average value achieved.

Distance value = (Maximum - Minimum) / n = (7-1)/7 = 0.86

Rating thresholds based on mean score values:

+ 1.00 - 1.86: Completely disagree
+ 1.87 - 2.73: Strongly disagree
+ 2.74 - 3.6: Disagree
+ 3.61 - 4.47: Neutral
+ 4.48 - 5.34: Agree
+ 5.35 - 6.21: Strongly agree
+ 6.22 - 7: Completely agree

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4. Survey results

4.1. Descriptive statistics

The survey comprised 152 valid respondents, with a predominance of female participants (83.6%) and a notable majority aged 18–21 years (93.4%). Regarding AI tool usage, 24.3% of participants reported using AI to generate images/videos two to four times per week, while 15.1% reported daily or near-daily use. Concerning exposure to AI-generated content, 37.5% reported exposure two to four times per week, with 31.6% reporting daily or near-daily exposure.

Table 2. Descriptive statistics of survey participants

Demographic	**Frequency**	**%**
Gender		
Female	127	83.6
Male	25	16.4
Age (years)		
17 and under	3	2
18 - 21	142	93.4
22 - 25	7	4.6
Frequency of using AI tools to generate images/videos (Midjourney, Canva AI, DALL·E, etc.)		
Almost every day (≥ 5 times per week)	23	15.1
2 - 4 times per week	37	24.3
Once a week	18	11.8
2 - 3 times per month	25	16.4
Less than once a month	30	19.7
Never use AI tools to generate images/videos	19	12.5
Frequency of exposing to AI-generated images/videos (Midjourney, Canva AI, DALL·E, etc.)		
Almost every day (≥ 5 times per week)	48	31.6
2 - 4 times per week	57	37.5
Once a week	15	9.9
2 - 3 times per month	17	11.2
Less than once a month	11	7.2
Never expose to AI-generated images/videos	4	2.6

Source: Results of the research team's assessment

4.2. Research model testing results

Results of assessing the quality of observed variables in the measurement model

Testing the quality of observed variables

Table 3. Outer loadings of factors influencing the acceptance level of AI-generated advertisements

	PE	PI	WA	VE	SY	IM
PE1	0.827					
PE2	0.790					
PE4	0.819					
PE5	0.870					
PE6	0.771					
PI1		0.757				
PI2		0.837				
PI3		0.823				
PI4		0.844				
PI5		0.821				
PI6		0.768				
WA1			0.870			
WA2			0.857			

WA3			**0.890**			
WA4			**0.863**			
WA5			**0.865**			
WA6			**0.840**			
VE1				**0.853**		
VE2				**0.831**		
VE3				**0.786**		
VE4				**0.878**		
VE5				**0.786**		
VE6				**0.810**		
SY4					**0.804**	
SY5					**0.848**	
SY6					**0.827**	
IM1						**0.875**
IM2						**0.876**
IM3						**0.882**
IM4						**0.902**
IM5						**0.855**
IM6						**0.829**

Source: Results of the research team's assessment

The quality of the observed variables was assessed through the outer loadings. After running the model for the first time, the research team excluded the items PE3, SY1, SY2, and SY3 because their outer loadings were below 0.7. After rerunning the model, the results in Table 3 show that the outer loadings of all the remaining observed variables exceeded 0.7 (Hair et al., 2016), indicating that the observed variables were significant.

Testing the Reliability of Measurement Scales

The reliability of the measurement scales for the factors influencing the acceptance level of AI-generated advertisements was assessed using Cronbach's Alpha and Composite Reliability (CR) through SMARTPLS.

Table 4. Cronbach's Alpha and Composite Reliability (CR) of the factors influencing the acceptance level of AI-generated advertisements

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
PE	**0.874**	**0.884**	**0.909**	**0.666**
PI	**0.894**	**0.898**	**0.919**	**0.654**
WA	**0.932**	**0.933**	**0.946**	**0.747**
VE	**0.906**	**0.909**	**0.927**	**0.680**
SY	**0.770**	**0.777**	**0.866**	**0.683**
IM	**0.936**	**0.936**	**0.949**	**0.757**

Source: Results of the research team's assessment

According to **Table 4**, after reliability analysis using Cronbach's Alpha, all scales satisfied the requirement of >0.7 (DeVellis, 2012), and no variables violated any criteria that would require removal. Therefore, no variables were excluded, and all were considered reliable.

The Composite Reliability (CR) values for all observed variables also exceeded 0.7 (Bagozzi & Yi, 1988) (see Table 4). Therefore, the scales were reliable, meaningful for analysis, and were used in subsequent factor analysis.

Convergence

According to the data analysis results in Table 4, the Average Variance Extracted (AVE) of all variables exceeded 0.5 (Hock & Ringle, 2010), indicating that the model met the criteria for convergence validity.

Discriminant Validity

The results in Table 5 show that the Fornell-Larcker criteria were satisfied, as the square root of each AVE value on the diagonal exceeded the corresponding off-diagonal correlation values. Therefore, in terms of discriminant validity—based on both the cross-loadings and Fornell-Larcker criteria—the requirements were met.

Table 5. Fornell-Larcker criteria for the research model examining the factors influencing the acceptance level of AI-generated advertisements

	PE	**PI**	**WA**	**VE**	**SY**	**IM**
PE	0.816					
PI	-0.205	0.809				
WA	-0.347	0.745	0.864			
VE	-0.130	0.689	0.673	0.825		
SY	0.569	-0.068	-0.096	0.029	0.826	
IM	-0.302	0.707	0.769	0.562	-0.194	0.870

Source: Results of the research team's assessment

f^2 Effect Size

The f^2 effect size represents the magnitude of the impact of a construct when it is excluded from the model. According to Cohen (1988), values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. If the effect size is <0.02, it is considered negligible.

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Table 6. Summary of f² effect size values

	PE	PI	WA	VE	SY	IM
PE			0.098			
PI			**1.166**			
WA						
VE	**0.003**	**0.318**				
SY	**0.425**	**0.000**				
IM	0.029	**0.379**				

Source: Results of the research team's assessment

In this model, as shown in **Table 6**:

- Effect of VE on:
  - PE: The f² value of VE is 0.003 (<0.02), indicating that VE has no effect on PE.
  - PI: The f² value of VE is 0.318 (0.15<f²<0.35), indicating that VE has a medium effect on PI.
- Effect of IM on:
  - PE: The f² value of IM is 0.029 (0.02<f²<0.15), indicating that IM has a small effect on PE.
  - PI: The f² value of IM is 0.379 (>0.35), indicating that IM has a large effect on PI.
- Effect of SY on:
  - PE: The f² value of SY is 0.425 (>0.35), indicating that SY has a large effect on PE.
  - PI: The f² value of SY is 0.000 (<0.15), indicating that SY has no effect on PI.
- Effect on WA:
  - The f² value of PI is 1.166 (>0.35), indicating that PI has a large effect on WA.
  - The f² value of PE is 0.098 (0.02<f²<0.15), indicating that PE has a small effect on WA.

Results of Assessing Influence Using the Structural Model

Evaluating the influence relationships

Regarding the relationships and influence levels among the factors affecting the acceptance level of AI-generated advertisements in SMARTPLS, these are illustrated in Figure 2.

Figure 2. Factors influencing the acceptance level of AI-generated advertisements

Source: Results of the research team's SMARTPLS analysis

The results of the Bootstrap analysis evaluating these influence relationships are shown in **Table 6**.

Influence of the variable VE:

- The variable VE has a path coefficient of -0.051 for its effect on the variable PE, with a P-value greater than 0.1. This indicates that VE does not have sufficient statistical significance to establish a relationship with PE (Hypothesis H1 is not supported).
- The variable VE has a path coefficient of 0.471 for its effect on the variable PI, with a P-value less than 0.1. This indicates that VE is statistically significant in establishing a relationship with PI (Hypothesis H2 is supported).

Influence of the variable IM:

- The variable IM has a path coefficient of -0.169 for its effect on the variable PE, with a P-value less than 0.1. This indicates that IM has sufficient statistical significance to establish a relationship with PE (Hypothesis H5 is supported).
- The variable IM has a path coefficient of 0.424 for its effect on the variable PI, with a P-value less than 0.1. This indicates that IM is statistically significant in establishing a relationship with PI (Hypothesis H6 is supported).

Influence of the variable SY:

- The variable SY has a path coefficient of 0.538 for its effect on the variable PE, with a P-value less than 0.1. This indicates that SY has sufficient statistical significance to establish a relationship with PE (Hypothesis H7 is supported).
- The variable SY has a path coefficient of 0.012 for its effect on the variable PI, with a P-value greater than 0.1. This indicates that SY does not have sufficient statistical significance to establish a relationship with PI (Hypothesis H8 is not supported).

  Influence of the variable WA:
- The variable PE has a path coefficient of -0.203, with a P-value less than 1, indicating sufficient statistical significance to demonstrate a relationship with the acceptance level of AI-generated advertisements (hypothesis H9 is supported).
- The variable PI has a path coefficient of 0.703, with a P-value less than 1, indicating sufficient statistical significance to demonstrate a relationship with the acceptance level of AI-generated advertisements (hypothesis H10 is supported).

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Table 7. Path coefficients in the structural model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PE → WA	-0.203	-0.204	0.057	3.568	**0.000**
PI → WA	0.703	0.705	0.055	12.874	**0.000**
VE → PE	-0.051	-0.052	0.090	0.567	**0.571**
VE → PI	0.424	0.424	0.071	5.993	**0.000**
SY → PE	0.538	0.547	0.067	7.994	**0.000**
SY → PI	0.012	0.005	0.053	0.219	**0.826**
IM → PE	-0.169	-0.166	0.102	1.656	**0.098**
IM → PI	0.471	0.472	0.076	6.229	**0.000**

(Source: Results of the research team's SMARTPLS analysis)

The results in **Table 7** show that at a 90% confidence level, the regression equations can be expressed as follows:

WA = -0.203*PE + 0.703*PI

PI = 0.424*VE + 0.471*IM

PE = 0.538*SY - 0.169*IM

Evaluating the overall coefficient of determination R^2

The PLS Algorithm analysis yielded R^2 values, which reflect the explanatory power of the independent variables for the dependent variables. R^2 measures the overall explanatory power of the model (Hair et al., 2010), with suggested thresholds of 0.75, 0.50, or 0.25.

Table 8. Coefficient of determination R^2

	R Square	R Square Adjusted
PE	0.364	0.351
PI	0.625	0.617
WA	0.594	0.589

Source: Results of the research team's assessment

Results from **Table 8** show:

- For PE: R^2 = 0.364 and adjusted R^2 = 0.351, indicating that the variables SY and IM explain 36.4% of the variation in PE.
- For PI: R^2 = 0.625 and adjusted R^2 = 0.617, indicating that the variables VE and IM explain 62.5% of the variation in PI.
- For WA: R^2 = 0.594 and adjusted R^2 = 0.589, indicating that the variables PE and PI explain 59.4% of the variation in WA.

Evaluating the standardized root mean square residual (SRMR) index

The SRMR indicates model fit, with values below 0.08 or 0.1 considered acceptable (Hu & Bentler, 1999).

Table 9. SRMR index

	Saturated Model	Estimated Model
SRMR	0.049	0.098

(Source: Results of the research team's assessment)

The results in **Table 9** show that the Saturated Model SRMR was 0.049 (<0.08) and the Estimated Model SRMR was 0.098 (<0.1). Thus, the model fits the data adequately.

4.3. Discussion

PI = 0.424*VE + 0.471*IM

PE = 0.538*SY – 0.169*IM

The study results indicate that, at a 90% confidence level, the variable VE affects PI with an influence coefficient of 0.424. This suggests that a one-unit increase in VE results in a 0.424-unit increase in PI. The variable IM affects PI with an influence coefficient of 0.471, indicating that a one-unit increase in IM leads to a 0.471-unit increase in PI. The variable SY influences PE with an influence coefficient of 0.538, implying that a one-unit increase in SY results in a 0.538-unit increase in PE. The variable IM affects PE with an

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influence coefficient of -0.169, indicating that a one-unit increase in IM results in a 0.169-unit decrease in PE.

WA = -0.203*PE* + *0.703*PI

Furthermore, the results reveal that the variables PE and PI have direct effects on WA. The variable PE has an influence coefficient of -0.203 on WA, showing that a one-unit increase in PE leads to a 0.203-unit decrease in WA. The variable PI has an influence coefficient of 0.703 on WA, indicating that a one-unit increase in PI leads to a 0.703-unit increase in WA.

Evaluation of Mean Scores of the Scales:

Variable "Verisimilitude"

- VE1: AI-generated advertisements present a realistic scenario.
- VE2: The details in AI-generated advertisements look realistic yet natural.
- VE3: The details in AI-generated advertisements are similar to scenes we see in real life.
- VE4: AI-generated advertisements present a credible image of the product or service.
- VE5: I feel that AI advertisements accurately reflect the nature of the product or brand.
- VE6: The images and content of AI-generated advertisements do not appear artificial.

The mean scores for this factor range from 3.5 to 4.191, indicating that respondents tend to be neutral toward the "Authenticity" of AI-generated advertisements. Variables with mean scores above 4, such as VE1 (4.138) and VE3 (4.191), reflect slightly positive perceptions of the authenticity in the context and details of the advertisements. However, VE6 has the lowest mean score (3.5), falling within the "Disagree" category, suggesting that viewers perceive a certain level of artificiality in AI-generated advertisements. Overall, AI-generated advertisements is considered persuasive to consumers. This is a strength that advertisers should continue to leverage, while also enhancing credibility and authenticity to maximize communication effectiveness.

Variable "Imagination"

- IM1: AI-generated advertisements have creative ideas.
- IM2: AI-generated advertisements are innovative.
- IM3: AI-generated advertisements show originality.
- IM4: AI-generated advertisements are imaginative.
- IM5: I find that AI-generated advertisements introduce unprecedented approaches to content.
- IM6: AI-generated advertisements have the potential to shape future media trends.

The variables in this factor have high mean scores (above 4.5), indicating strong agreement among respondents regarding the creativity, innovation, and uniqueness of AI-generated advertisements. IM2 has the highest mean score (4.855), indicating that consumers highly value the innovative aspects of AI-generated advertisements. IM4 has the lowest mean score (4.467), classified as "Neutral," but still very close to the "Agree" level. Consumers view AI-generated advertisements as a creative and novel form of media communication with strong potential to inspire. This demonstrates that "Imagination" is a clear strength that can be leveraged to build a pioneering brand image.

Variable "Synthesis"

- SY1: There are obvious signs of synthesis between different elements in AI-generated advertisements.
- SY2: AI-generated advertisements as a whole give me the impression that they are cobbled together from different materials.
- SY3: Some of the detail articulation in the AI advertisements is unnatural.
- SY4: AI-generated advertisements as a whole give me a sense of disjointed combinations.
- SY5: I feel that the images, sounds, and content in AI-generated advertisements do not align with each other.
- SY6: Certain elements in AI-generated advertisements make me feel confused or unclear.

All mean scores in this factor are relatively high (above 4.2), particularly SY3 (4.954) and SY6 (4.776), clearly reflecting the perception of incoherence and confusion in AI-generated advertisements. SY5 has the lowest mean score (4.230), but it does not fall into the "low agreement" category—this suggests that while some viewers perceive negative aspects, it is not universally severe. As all items are designed to reflect negative perceptions, the results indicate that AI-generated advertisements in this study have not achieved the necessary coherence and integration of elements such as images, content, and sound. Consumers perceive AI-generated advertisements as lacking overall linkage, with many elements (images, sounds, and content) failing to synchronize. This represents a weakness that should be improved if businesses aim to create truly effective and professional AI-generated advertisements.

Variable "Perceived eeriness"

- PE1: I think the advertisements created by AI are creepy.
- PE2: I think AI-generated advertisements are weird.
- PE3: I think AI-generated advertisements are unnatural.
- PE4: I think AI-generated advertisements are bizarre.
- PE5: AI-generated advertisements make me feel uncomfortable when viewing it.
- PE6: Certain images or movements in AI-generated advertisements make me feel uneasy.

The variable PE3 has the highest mean score (5.046) among all factors analyzed so far, indicating a pronounced sense of "unnaturalness" that may cause strong discomfort for viewers. Other variables (PE1, PE4, PE5, PE6) all have high "Neutral" scores (above 4.1), showing that viewers still feel somewhat uneasy, but not overwhelmingly so. PE2 (4.566) suggests that viewers moderately agree that AI-generated advertisements are strange—contributing to the overall eerie effect. In general, consumers experience moderate-to-high levels of eeriness when viewing AI-generated advertisements. This is reflected in their perceptions of the advertisements as

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unnatural, strange, and occasionally unsettling. This represents a negative emotional barrier that could impact communication effectiveness and brand perception.

Variable "Perceived intelligence"

- PI1: AI-generated advertisements are of great quality.
- PI2: I believe the products in AI-generated advertisements are functionally excellent.
- PI3: I think AI-generated advertisements demonstrate a high level of technology.
- PI4: I feel that AI-generated advertisements show an understanding of consumer needs and behaviors.
- PI5: I feel that AI-generated advertisements match the preferences of young people like me.
- PI6: I feel that AI-generated advertisements are built on smart data analysis.

PI3 (4.783) has the highest mean score, indicating that viewers highly appreciate the technological sophistication of AI-generated advertisements. PI1 (4.697) and PI6 (4.566) also show high agreement, particularly regarding progressiveness and the application of smart data analytics. Other variables such as PI2, PI4, and PI5 are at neutral levels, suggesting that viewers are not fully convinced that AI advertisements accurately reflect product performance or strongly aligns with their personal preferences and behaviors. Thus, AI-generated advertisements are perceived by consumers as technologically advanced and modern, giving the impression of being a sophisticated form of communication. However, personalization and alignment with individual consumer needs and tastes still need improvement to enhance persuasiveness.

Variable "Willingness to accept"

- WA1: I am willing (or will be willing) to accept AI-generated advertisements.
- WA2: I am willing to actively browse or watch incoming AI-generated advertisements messages.
- WA3: I am willing (or will be willing in the future) to purchase the product or service featured in the AI-generated advertisements.
- WA4: I am willing to share AI-generated advertisements that I find attractive or interesting with others.
- WA5: I do not oppose the use of AI as a content creation tool in advertisements.

Only WA6 (4.493) reached the "Agree" level, indicating that viewers generally accept AI-generated advertisements positively overall. However, the other variables remain at the "Neutral" level, indicating that consumers are not yet fully proactive in exploring or engaging with AI advertisements (e.g., purchasing, sharing, or investigating). Moreover, consumers tend to be cautious and are not yet fully convinced or enthusiastic about the involvement of AI in advertising. Consumers are in a state of observation and caution regarding AI-generated advertisements. They do not oppose it but are not yet truly enthusiastic or proactively engaged with this type of advertising. Therefore, communication campaigns utilizing AI should incorporate emotional value, clear benefits, and technological transparency to foster higher levels of readiness to accept.

5. Conclusion

This study offers critical insights into how Generation Z in Vietnam perceives and accepts AI-generated advertisements. Using the Stimulus-Organism-Response (S-O-R) framework, the research empirically confirms that perceived intelligence significantly enhances willingness to accept such content, while perceived eeriness hinders it. Among the influencing factors, *imagination* and *verisimilitude* positively affect perceived intelligence, reinforcing the importance of creative and realistic content. Conversely, *synthesis* strongly contributes to perceived eeriness, signaling that poorly integrated or disjointed AI elements reduce consumer comfort and trust. The findings emphasize that although Gen Z appreciates the technological sophistication and innovation of AI-generated ads, they remain cautious and are not yet fully engaged with or trusting of this form of advertising. Advertisers must therefore focus on enhancing coherence, emotional resonance, and authenticity in AI-generated content to improve consumer perception and acceptance. As Vietnam's digital marketplace continues to grow, understanding and addressing these psychological and perceptual dimensions will be essential for leveraging AI in a way that resonates meaningfully with Gen Z audiences.

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