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The Impact Of AI Application On Generation Z's Online Fashion Purchase Intention

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Abstract—This study investigates the impact of artificial intelligence (AI) applications on Generation Z's online fashion purchase intention by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). It examines how perceived ease of use, perceived personalization, perceived quality, and perceived risk influence attitudes toward AI, perceived usefulness, and purchase intention. Data were collected from 308 Generation Z respondents in Vietnam through a structured questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that perceived ease of use and perceived personalization have significant positive effects on attitudes toward AI, while perceived quality and perceived risk do not show significant relationships. Attitude toward AI is identified as a key determinant, strongly influencing perceived usefulness and moderately affecting purchase intention. Furthermore, perceived usefulness emerges as the strongest predictor of purchase intention. The model demonstrates satisfactory explanatory and predictive power. This study contributes to the literature by clarifying the role of AI in shaping consumer behavior in e-commerce. Practically, it suggests that businesses should enhance usability, strengthen personalization strategies, and emphasize the functional benefits of AI to improve customer engagement and purchase intention among Generation Z.

Keywords— artificial intelligence; generation Z; online shopping; purchase intention; personalization.

1. Introduction

In today's economy, when digital transformation is taking place rapidly worldwide, e-commerce and online retailing have become one of the fastest-growing sectors. The development of online shopping platforms offers numerous benefits to consumers, such as time savings, diversified product choices, and more opportunities for price comparisons. However, online shopping also creates more challenges for businesses, particularly more difficulties in enhancing the shopping experience or attracting more customers in an increasingly competitive shopping environment as it is now. One of the remarkable drawbacks of online shopping is that consumers cannot directly experience products as they would in a traditional shopping environment, increasing uncertainty in the purchasing decision-making process (Mooy & Robben, 2002). Therefore, businesses are now becoming more interested in applying advanced technologies to support consumers in product selection as well as to improve the online shopping experience.

In recent years, Artificial Intelligence (AI) has emerged as one of the most useful technological devices widely applied in marketing. AI enables businesses to automate many marketing activities, including analyzing customer data, finding out consumer behaviors, personalizing advertising content, or supporting customer interaction through the tools such as chatbots or product recommendation systems (Baig & Yadegaridehkordi, 2024; Subbaiah et al., 2024). Thanks to its ability to process and

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analyze large volumes of data, AI helps businesses better understand the needs, preferences, and behavior of individual customer, thereby building more personalized and effective marketing strategies (Hicham et al., 2023). Furthermore, AI applications in marketing contribute to enhancing user experience by providing relevant information, supporting decision-making processes, and optimizing online shopping experiences (Huang & Liao, 2015).

Past research has built up a pretty clear picture of how AI shapes the way people shop. Febriani et al. (2022) found that AI nudges purchase intentions upward, and that perceived value is a big part of what actually moves someone toward buying. That tracks. Beyari (2024) went further, pointing to specific tools such as machine learning, product recommendation systems, behavioral analytics, as real drivers of how consumers make decisions online. And honestly, anyone who's noticed Amazon's "you might also like" sidebar knows what that looks like in practice. Yin and Qiu (2021) argued that AI on e-commerce platforms lifts perceived value by improving both the practical and emotional sides of shopping — which is an interesting way to frame it, or — more accurately — a useful reminder that shopping isn't purely rational. Other studies round this out, with Liang et al. (2020) and Ruiz-Viñals et al. (2024) both linking perceived usefulness, ease of use, and general attitudes toward AI to stronger purchase intentions.

Vietnam's e-commerce scene has moved fast, honestly faster than most people outside the region realize. Platforms like Shopee aren't just selling products anymore; they're building experiences around them. The SkinCam feature Shopee rolled out during its "3.3 Super Sale" in 2023 is a decent example of that shift: users take a selfie, an AI reads their skin condition, and suddenly they're getting skincare recommendations that actually feel relevant (Can Y, 2023). Does it always work perfectly? Probably not. But the direction is clear. What's kind of interesting is how this extends into fashion specifically. According to Ruiz-Viñals et al. (2024), AI is touching pretty much every stage of the fashion supply chain such as design, logistics, marketing and the speed and cost improvements are real. Or they're becoming real, because a lot of this is still playing out. The potential is there, though, and Vietnam's market seems genuinely eager to test it.

Although AI offers many potential benefits, its practical application has not yet met expectations and remains largely undiminished (Yim & Park, 2019). The majority of the previous studies on AI in marketing have focused primarily on the intention to use the technology (Huang & Liao, 2015), while the impact of AI on user experience and online shopping behavior has not been fully clarified. Meanwhile, consumers believe that AI can improve service quality and reduce uncertainty in the purchasing decision-making process (Dako et al., 2020). Simultaneously, researchers emphasize the importance of effectively managing customer experience in the context of multi-channel marketing (Lemon & Verhoef, 2016). Therefore, further empirical research is needed to clarify the role of AI in improving user experience and promoting online consumer shopping behaviors.

In order to address the research gap found from the previous studies, this study carried out aims to analyze and evaluate the impact of artificial intelligence applications in marketing on user experience and online consumer purchasing behaviors with the expectation to contribute to the academic literature in two ways. First, it expands understanding of AI role in digital marketing by examining the relationship between AI applications, user experience, and online purchasing behaviors. Second, the research findings provide important managerial implications for e-commerce businesses in developing and implementing AI strategies to enhance customer experience and market competitiveness.

2. Theoretical Background and Proposed Research Model

2.1 Theoretical background

This study is built on an integrated theoretical framework, combining two major theoretical approaches: the Theory of Planned Behavior - TPB (Ajzen, 1991) and the Technology Acceptance Model TAM (Davis, 1989).

In the TPB theory, this behavioral tendency is defined as the degree of effort people put into performing that behavior (Ajzen, 1991). Instead of assuming that human behavior is entirely rational, TPB focuses on analyzing an individual's intention when they perform a particular behavior. This intention is influenced by three main factors: attitude toward the behaviors, perceived behavioral control, and subjective norms, and these factors interact with each other (Ajzen, 1991). In addition, the TPB model has been expanded by adding the element of perceived behavioral control to the model. This factor measures the ease or difficulty of performing a behavior, depending on available resources and opportunities and directly influences the intention to perform the behavior. If participants have an accurate perception of their level of control, this factor can predict behavior (Ajzen, 1991).

Furthermore, the TAM model (Davis, 1989) states that the use of an information system is determined by behavioral intention. Conversely, behavioral intention is determined by the user's attitude towards using the system and also by their perception of its utility (Davis, 1989). According to the Technology Acceptance Model, user behavior in using technology is based on two main factors: perceived usefulness and perceived ease of use. The TAM model also indicates that external factors influence user behaviors in using technology. These factors may include prior knowledge, support from colleagues, personal psychology, experience, and personal characteristics, which can positively or negatively impact a user's confidence and willingness to use new technology.

2.2 Hypothesis Development and Research Model Proposal

Perceived Quality (PQ)

Perceived quality is understood as the overall assessment of consumers of a product (Sun et al., 2022), and reflects their perception of the product's characteristics and functions (Ruiz-Viñals et al., 2024). According to Sun et al. (2022), perceived quality can influence customer purchase intentions by reinforcing brand trust. Furthermore, Ruiz-Viñals et al. (2024) emphasize that perceived quality is an important factor impacting purchase intentions through consumer attitudes towards artificial intelligence (AI). Specifically, consumers tend to highly value the quality of AI-integrated products, thereby increasing their willingness to purchase.

In the fashion industry, perceived product quality plays a crucial role in shaping positive attitudes toward brands and influencing consumer purchasing decisions (Alharthi, 2025; Ruiz-Viñals et al., 2024). Consumers with positive attitudes toward technology tend to be more inclined to choose and purchase AI-powered fashion products (Alharthi, 2025). In the highly competitive fashion industry, where consumers seek not only aesthetics but also quality, perceived quality becomes a key factor influencing product acceptance and preference, including AI-integrated products (Ruiz-Viñals et al., 2024). Therefore, the following research hypothesis is proposed:

H_1: Perceived quality positively influences attitudes toward AI.

Perceived Ease of Use (PEU)

Perceived ease of use is a key factor in determining the use of technology or systems (Davis, 1989, 1993; Davis, Bagozzi, & Warshaw, 1992; Mathieson, 1991). In the TAM, perceived ease of use is defined as "the degree to which an individual believes that using a particular system will not require much effort" (Davis, 1989). Previous studies have confirmed a positive relationship between perceived ease of use and consumer attitudes toward technology. Kim et al. (2017) argue that perceived ease of use is a key factor in deciding to adopt smart retail technologies, while Lunney et al. (2016) point out that perceived ease of use positively influences consumer attitudes toward wearable health tracking technology. For AI products, ease of use means the product is easy to operate and easy to interact with the program. Brill (2018) suggests that consumer satisfaction will improve if digital assistants like Alexa meet their expectations. Therefore, if consumers perceive that the product is easy to operate and interact with, they will tend to form a positive attitude. Thus, the study suggests:

H_2: Perceived ease of use will positively influence attitudes toward AI.

Perceived Risk (PR)

Consumer risk perception includes financial risk, product risk and security risk, time risk, and psychological risk (Kamalul Ariffin et al., 2018). A study by Hansen et al., (2018) confirmed that increased perceived risk leads to increased attitudes toward technology. In the fashion technology industry, perceived risk when consumers shopping online can influence their trust and attitudes toward technology applications that support sales (Liang et al., 2020). Therefore, the hypothesis is:

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https://ijpsat.org/
Vol. 59 No. 1 September 2026, pp. 258-271

H_3: Perceived Risk positively influences attitudes toward AI

Perceived Personalized (PP)

Perceived personalized refers to the extent to which consumers feel that marketing programs are tailored to their individual preferences, interests, and needs (An and Ngo, 2025). According to Babatunde et al. (2024), thanks to the support of artificial intelligence (AI), personalized advertising has become more sophisticated, allowing brands to deliver highly targeted messages that resonate with consumers. Personaliz signals to consumers that the brand understands them, respects their preferences, and is committed to providing relevant content, which builds a stronger foundation of trust (An and Ngo, 2025). Personalized advertising can be seen as both positive and negative for customers (De Groot, 2022). When consumers feel that advertisements are carefully designed to suit their individual preferences and needs, they are more likely to develop trust in both the brand and its promotional messages (Rahmawaty et al., 2024). Therefore, the hypothesis is:

H_4: Perceived Personalized positively influences attitudes toward AI

Attitudes Towards AI (AAI)

Attitude is understood as the general and lasting evaluation of an individual toward people, things, or issues (Baron & Byrne, 1987). Ajzen and Fishbein (1980) defined attitude as "an individual's positive or negative evaluation of the performance of a behavior." Previous studies have confirmed that consumer attitudes influence purchase intentions (Pradhanawati & Pinem, 2025), particularly in the fashion industry (Liang et al., 2020; Alharthi, 2025). Furthermore, the use of AI makes tasks easier, thus it is considered very useful (Geddam et al., 2024). Several studies have also shown that consumer attitudes strongly influence perceived usefulness (Williams et al., 2014; Khan & Emon, 2024). Therefore, this study proposes:

H_5: Consumer attitudes towards AI will positively influence the intention to purchase fashion products.

H_6: Consumer attitudes towards AI will positively influence Perceived Usefulness

Purchase Intention (PI)

Purchase intention is the probability that a consumer will purchase a product or service in the future (Liang et al., 2020). This is an important measure of consumer behavior, reflecting not only the level of interest but also the willingness to make an actual purchase (Alharthi, 2025). Previous studies have shown that perceived usefulness strongly impacts the intention to purchase products with AI integration in marketing (Khan & Emon, 2024; An & Ngo, 2025). In the fashion industry, purchase intention is strongly influenced by factors such as brand awareness, perceived quality, and current trends (Liang et al., 2020). Therefore, the hypothesis is:

H_7: The intention to purchase a product is positively influenced by the consumer's perception of its usefulness.

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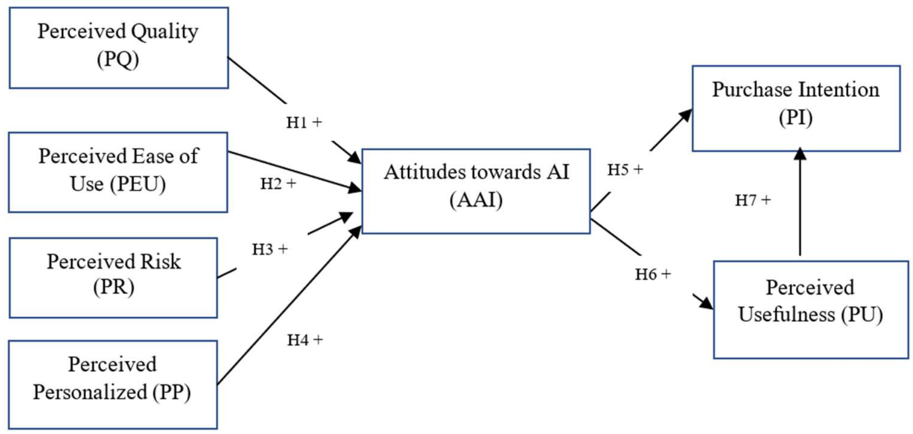

Fig. 1. Proposed research model. *(Source: The authors)*

3. Research Methods

3.1 Sample Selection and Data Collection

The researchers of this study collected their data from Generation Z individuals who were born between 1997 and 2012. The researchers conducted data collection between May 1st and September 30th 2025 through online survey links which used Google Forms. The questionnaire used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Researchers distributed 325 questionnaires and received 308 responses which resulted in a response rate of 94.8%. The research team discarded 17 questionnaires during data screening because they contained insufficient variability while 308 valid observations remained in the study. The study developed an anonymous and secure data collection method which required minimal effort and time from participants in order to improve respondent participation. The researchers assessed Common Method Bias (CMB) through Harman's one-factor test and complete multicollinearity assessment which revealed that CMB did not present a major issue for this research (Harman, 1976; Kock & Lynn, 2012; Podsakoff et al., 2003). The final sample size met the criteria for Structural Equation Modeling (SEM) analysis according to Hair et al. (2012) which validated the statistical reliability of the analysis outcomes.

3.2 Measurement Instruments

The study's questionnaire is structured into two primary sections. The first part of the study gathers demographic data from participants, which includes their gender and birth year and job title. The second part of the study contains all research variables that make up the proposed model. The study used a standard 5-point Likert scale to assess all variables between two extreme points which ranged from 1 to 5. The Perceived Quality (PQ) and Purchase Intention scales are inherited from Ruiz-Viñals et al. (2024), while Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Attitude Towards AI (AAI) are developed based on Liang et al. (2020). The study used the Perceived Personalized (PP) variable from An and Ngo (2025) and adopted Perceived Risk (PR) measurement through questionnaires which were modified from Yeo et al. (2022). The research team selected all measurement items from validated studies to establish content validity and conceptual alignment with their research framework.

3.3 Pilot Testing of the Research Instrument

The researchers conducted a pilot study with 50 students to test questionnaire reliability before they started their main research analysis. The researchers used Cronbach's alpha to evaluate data internal consistency because previous studies recommended this method, with an acceptable threshold of 0.7 (Hair et al., 2017). The research findings demonstrated that all scales achieved

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Vol. 59 No. 1 September 2026, pp. 258-271

Cronbach's alpha values which met the required threshold, thus establishing data reliability and its readiness for Structural Equation Modeling (SEM) analysis.

3.4 Research findings

Demographic analysis

The online survey conducted through Google Forms received a total of 325 responses. After completing data screening procedures, 308 valid questionnaires remained for analysis, which exceeded the required sample size needed for quantitative research that requires 155 participants. The sample displayed demographic distribution with 74.35% female respondents and 25.65% male respondents. Students made up the highest percentage of the sample at 52.5%, followed by office employees who constituted 25% of the sample, while all other occupations made up the remaining workforce. The sample distribution demonstrates sufficient representativeness to conduct research on AI tool usage during online fashion shopping.

Measurement model

Reliability and convergent validity:

The results of the first reliability assessment indicated that one observed variables (PEU1) were removed due to outer loading coefficients lower than 0.7. After eliminating these indicators, the results of the second analysis demonstrated that all remaining indicators achieved satisfactory reliability, with outer loadings exceeding 0.7. The Average Variance Extracted (AVE) values of all latent constructs were greater than 0.5, meeting the criterion for convergent validity. Furthermore, all outer loadings of the observed variables were above 0.7, confirming that the indicators adequately represent their corresponding latent constructs (Table 1). Overall, the measurement model satisfies the requirements for reliability and convergent validity (Table 1).

TABLE I. CONSTRUCTS' PROPERTIES AND ITEMS' LOADINGS

Constructs	Outer Loading		CR		AVE	
	1st	2nd	1st	2nd	1st	2nd
Perceived Quality (PQ)			0.761	0.761	0.550	0.550
PQ1	0.738	0.738				
PQ2	0.803	0.803				
PQ3	0.742	0.742				
PQ4	0.705	0.705				
Perceived Ease of Use (PEU)			0.875	0.864	0.595	0.646
PEU1	0.623	Removed				
PEU2	0.803	0.783				
PEU3	0.791	0.794				
PEU4	0.795	0.815				
PEU5	0.808	0.824				
PEU6	0.791	0.803				
Perceived Risk (PR)			0.731	0.731	0.644	0.644
PR1	0.725	0.725				

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Vol. 59 No. 1 September 2026, pp. 258-271

Constructs	Outer Loading		CR		AVE	
	1st	2nd	1st	2nd	1st	2nd
PR2	0.865	0.865				
PR3	0.811	0.811				
Perceived Personalized (PP)			0.775	0.775	0.593	0.593
PP1	0.728	0.728				
PP2	0.786	0.786				
PP3	0.762	0.762				
PP4	0.803	0.803				
Attitude towads AI (AAI)			0.890	0.890	0.688	0.688
AAI1	0.728	0.728				
AAI2	0.786	0.786				
AAI3	0.762	0.762				
AAI4	0.803	0.803				
AAI5	0.728	0.728				
Perceived Usefulness (PU)			0.912	0.912	0.694	0.694
PU1	0.820	0.820				
PU2	0.852	0.852				
PU3	0.815	0.815				
PU4	0.846	0.846				
PU5	0.822	0.822				
PU6	0.841	0.841				
Purchase Intention (PI)			0.851	0.851	0.767	0.767
PI1	0.900	0.900				
PI2	0.855	0.855				
PI3	0.872	0.872				

(Source: Data analysis result of the research)

Structural model assessment

The assessment of discriminant validity is based on the Heterotrait–Monotrait (HTMT) ratio of correlations, as proposed by Henseler et al. (2015). The evaluation results are presented in Table 2. The results of the discriminant validity assessment using the HTMT criterion, based on the bootstrapping procedure, indicate that all construct pairs meet the required threshold. Specifically, the HTMT values range from 0.311 to 0.876, all of which are below the recommended threshold of 0.90 suggested by Hair et al. (2021) for bootstrapping-based analysis. These findings confirm that there is no issue of conceptual overlap among the latent constructs in the model. Therefore, it can be concluded that the measurement scales employed in this study satisfy the discriminant validity criterion based on the HTMT approach. In other words, the constructs are empirically distinct and capture different conceptual domains, thereby justifying the continuation of further analyses in the structural model (see Table 2).

TABLE II. HTMT VALUE

	PP	**PQ**	**PEU**	**PR**	**AAI**	**PU**	**PI**
PP							
PQ	0.491						
PEU	0.741	0.452					
PR	0.53	0.578	0.517				
AAI	0.843	0.399	0.766	0.453			
PU	0.773	0.446	0.649	0.408	0.85		
PI	0.676	0.311	0.572	0.402	0.80	0.876	

(Source: Data analysis result of the research)

Structural model assessment

The evaluation of the structural model includes the following components: (1) assessment of multicollinearity; (2) assessment of path relationships; (3) evaluation of the coefficient of determination (R^2); (4) assessment of effect size (f^2); and (5) evaluation of predictive relevance (Q^2). The study used Variance Inflation Factor (VIF) values to identify possible multicollinearity problems. The VIF values in Table 3 show a range between 1.000 and 2.430. Since all VIF values are below the conservative threshold of 3, the results confirm that multicollinearity is not a concern in the model. The estimation of structural path coefficients remains unaffected by collinearity, which allows the model to effectively test research hypotheses.

TABLE III. INNER VIF VALUE

	VIF
PP -> AAI	1.721
PQ -> AAI	1.306
PEU -> AAI	1.728
PR -> AAI	1.357
AAI -> PU	1.000
AAI -> PI	2.430
PU -> PI	2.430

(Source: Data analysis result of the research)

The results of hypothesis testing using the bootstrapping method indicate that 5 out of 7 hypotheses are supported. Specifically, the relationships PEU → AAI ($\beta = 0.390$; $p < 0.001$), PP → AAI ($\beta = 0.446$; $p < 0.001$), AAI → PI ($\beta = 0.243$; $p = 0.001$), AAI → PU ($\beta = 0.767$; $p < 0.001$), and PU → PI ($\beta = 0.588$; $p < 0.001$) are all statistically significant. In contrast, the

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hypotheses PQ → AAI ($p = 0.729$) and PR → AAI ($p = 0.660$) are not statistically significant and are therefore rejected. These findings suggest that not all proposed factors exert a significant influence on AAI as initially expected (Table 4).

TABLE IV. BOOTSTRAPPING RESULTS

Hypothesis	Beta	P values	f^2 values	Decision
H1: PQ -> AAI	0.014	0.729	0.000	Rejected
H2: PEU -> AAI	0.390	0.000	0.214	Supported
H3: PR -> AAI	0.023	0.660	0.001	Rejected
H4: PP -> AAI	0.446	0.000	0.281	Supported
H5: AAI -> PI	0.243	0.001	0.064	Supported
H6: AAI -> PU	0.767	0.000	1.430	Supported
H7: PU -> PI	0.588	0.000	0.377	Supported

(Source: Data analysis result of the research)

The model demonstrates high explanatory abilities through its R^2 value which Table 5 presents as its coefficient of determination for its internal variables. AAI produces a value of 0.593 which leads to an adjusted R^2 of 0.588 because exogenous factors explain 59.3% of AAI's total variation. PU shows an R^2 value of 0.588 together with an adjusted R^2 value of 0.587 which together prove that the system explains 58.8% of its output. The model shows R^2 and adjusted R^2 results of 0.623 and 0.621 respectively which demonstrate that it explains 62.3% of the construct variance shown in Table 5. The Q^2 statistic measurement of the model's predictive ability shows that all endogenous variables exist between 0.25 and 0.50. AAI shows a Q^2 value of 0.397 while PU achieves 0.399 and PI reaches 0.469. The extracted data from Table 5 proves that the model shows moderate predictive ability for its internal variables.

TABLE V. RESULTS OF R^2 AND Q^2 COEFFICIENTS IN THE MODEL

Variable	R-square	R-square adjusted	Q^2 (=1-SSE/SSO)
AAI	0.593	0.588	0.397
PU	0.588	0.587	0.399
PI	0.623	0.621	0.469

(Source: Data analysis result of the research)

In terms of effect size (f^2) for the supported hypotheses, the results reveal notable differences in the magnitude of influence among the relationships. Specifically, AAI → PU ($f^2 = 1.430$) and PU → PI ($f^2 = 0.377$) demonstrate substantial explanatory power, indicating strong effects of AAI on PU and PU on PI. The relationships PP → AAI ($f^2 = 0.281$) and PEU → AAI ($f^2 = 0.214$) exhibit moderate effect sizes. In contrast, AAI → PI ($f^2 = 0.064$) shows only a small effect on the dependent variable. These findings suggest that the roles of the constructs in the model are uneven, with AAI and PU playing more prominent roles in explaining the endogenous variables.

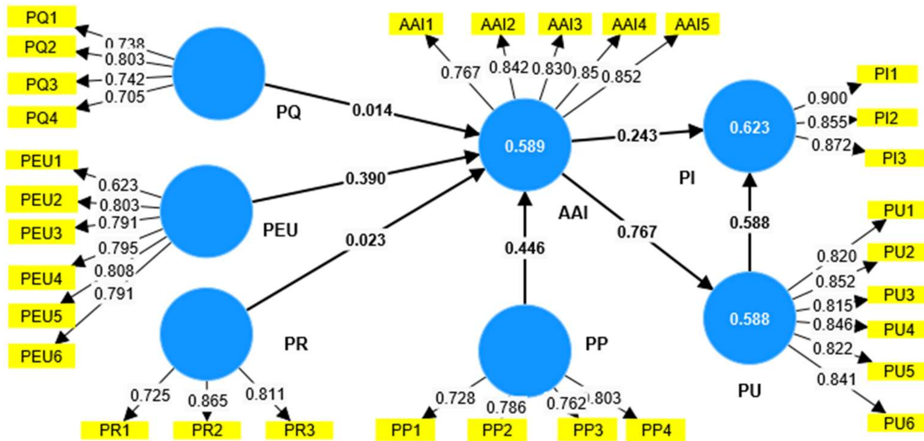

Fig. 2. Structural model of the study. *(Source: The authors)*

4. Conclusion and managerial implications

The study aims to examine the impact of artificial intelligence (AI) applications on the online fashion shopping intentions of Generation Z by combining the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). The research results based on data from 308 participants who were examined through PLS-SEM analysis provide multiple important theoretical and practical outcomes. The model identified Attitude towards AI (AAI) as its primary variable which demonstrated strong statistical relevance toward Perceived Usefulness (PU) ($\beta = 0.767$, $p < 0.001$) with a very huge effect ($f^2 = 1.430$). This finding is consistent with previous empirical studies (Khan & Emon, 2024). The AAI variable positively influenced Purchase Intention (PI) ($\beta = 0.243$, $p = 0.001$) whereas the resulting effect size remained small ($f^2 = 0.064$). The finding contradicts the findings obtained by Liang et al. (2020) and Alharthi (2025). The results demonstrated that attitude holds a vital position in determining how customers view products and their subsequent actions which matches the theoretical models of TAM and TPB. Perceived Usefulness (PU) emerged as the strongest predictor of Purchase Intention (PI) ($\beta = 0.588$, $p < 0.001$) which showed a medium to large effect ($f^2 = 0.377$). The study found that consumers raise their purchase intention when they see AI as delivering actual benefits and efficient help during their buying journey. This result matches the findings of An and Ngo (2025) who studied AI applications in personalized advertising.

Secondly, both Perceived Personalized (PP) ($\beta = 0.446$, $p < 0.001$, $f^2 = 0.281$) and Perceived Ease of Use (PEU) ($\beta = 0.390$, $p < 0.001$, $f^2 = 0.214$) had a positive and statistically significant influence on Attitudes Towards AI (AAI). These findings suggest that Perceived Personalized (PP) and Ease of Use (PEU) play important roles in shaping positive consumer attitudes toward AI applications in online fashion shopping. This result further reinforces previous studies, particularly the research by An and Ngo (2025) in the field of AI-based advertising, as well as the research by Lunney et al. (2016) in the context of wearable health tracking technology or Ruiz-Viñals et al. (2024) on the application of AI in the fashion industry.

Conversely, Perceived Quality (PQ) ($\beta = 0.014$, $p = 0.729$) and Perceived Risk (PR) ($\beta = 0.023$, $p = 0.660$) did not show a statistically significant impact on AAI. This result implies that in the research context, Gen Z consumers are less influenced by traditional factors such as perceived quality or risk, and instead focus more on technological experience and level of personalization. This finding contradicts previous studies in the technology industry (Hansen et al., 2018) as well as the fashion industry (Liang et al., 2020).

Overall, the structural model shows relatively good explanatory power for endogenous variables. Specifically, the model explains 59.3% of the variance of Attitude towards AI (AAI), 58.8% of Perceived Usefulness (PU), and 62.3% of Purchase

Intention (PI), reflecting a medium to high level of explanation. At the same time, the Q^2 values (AAI = 0.397; PU = 0.399; PI = 0.469) are all greater than 0.25, thus confirming the model's moderate predictive power.

4.1 Practical implications

The research presents key managerial recommendations which e-commerce platforms and digital marketers and fashion companies can use to implement artificial intelligence technology in their operations. The first requirement for organizations involves them to enhance the user experience of their AI applications through better design of their chatbot systems and virtual fitting technology and product recommendation tools. Businesses should develop AI systems which designers built to enable users to navigate through their functions without encountering difficulties because perceived ease of use directly affects how consumers view products. The user experience improves through better navigation methods which create more natural ways for users to connect with AI systems that lead to favorable outcomes for users. The effectiveness of personalized experiences through AI technology indicates that organizations should dedicate resources towards developing AI-driven personalized solutions. Through data analysis businesses can provide customers with personalized shopping experiences which include tailored product recommendations and individualized content. Businesses use personalization to create more relevant experiences which lead to stronger brand connections with their customers. Organizations must demonstrate to customers how their AI programs deliver practical advantages because perceived usefulness serves as the primary driver for technology adoption. AI technology enables customers to enhance their decision-making abilities while decreasing their shopping time and boosting their overall shopping results. The AI recommendation system needs to deliver actual advantages which users will experience through its intelligent suggestions and virtual assistant functions and AI style recommendation features. The study results show that perceived risk did not reach statistical significance yet companies must recognize that privacy protection and data security issues require their full attention. The establishment of clear data handling procedures together with robust security mechanisms stands as essential requirement for organizations to achieve enduring consumer confidence. Marketers who want to reach Generation Z should create shopping experiences which combine interactive elements with advanced technology because this customer segment prefers innovative and convenient yet customized solutions over standard product features.

4.2 Limitations and future research

The research exhibits major contributions to knowledge but its existing constraints require additional research work for future studies. The research investigates Generation Z in Vietnam through its study which excludes other demographic and cultural groups. Future studies should expand their sample size to include different age groups while testing the model through cross-cultural research to establish its strength. The study depends on cross-sectional data which prevents scientists from observing how consumer views and behaviors develop across different time periods. The researchers should use longitudinal methods in their upcoming research to track how AI adoption affects consumer behavior over time. The model can explain a large part of customer purchase intention but it needs to study additional variables which include customer beliefs, their feelings of enjoyment, social pressures, and their brand dedication. The inclusion of these variables would enable the study results to present a complete picture of consumer behavior. The study uses self-reported data which leads to methodological and social biases despite the researchers performing required statistical tests. Future research should merge survey findings with real-world behavior tracking which includes purchase records to enhance result authenticity and accuracy. The study will investigate how different AI technology applications including virtual try-on tools and AI fashion assistants and AI generative tools affect customer behavior and their decision-making process to purchase products.

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Declaration of Interest Statement

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References

[1] Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

[2] Alharthi, S. (2025). From Browsing to Decision: How Artificial Intelligence Systems Influence the Modern Fashion Consumer Journey. *Systems*, 14(1), 31.

[3] An, G. K., & Ngo, T. T. A. (2025). AI-powered personalized advertising and purchase intention in Vietnam's digital landscape: The role of trust, relevance, and usefulness. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(3), 100580.

[4] Babatunde, S. O., Odejide, O. A., Edunjobi, T. E., & Ogundipe, D. O. (2024). The role of AI in marketing personalization: A theoretical exploration of consumer engagement strategies. *International Journal of Management & Entrepreneurship Research*, 6(3), 936-949.

[5] Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in the higher education: A systematic literature review and research challenges. *International Journal of Educational Research*, 127(March), 102411. https://doi.org/10.1016/j.ijer.2024.102411

[6] Baron, R. A., & Byrne, D. (1987). *Social psychology: Understanding human interaction* (630 p.). Needham Heights, MA.

[7] Beyari, H. (2024). The effect of AI on pink marketing: the case of women's purchasing behavior using mobile applications. *Frontiers in Artificial Intelligence*, 7, 1502580.

[8] Brill, T. M. (2018). Siri, Alexa, and Other Digital Assistants: A Study of Customer Satisfaction With Artificial Intelligence (Doctoral dissertation, Ph. D. thesis, University of Dallas).

[9] Cẩn Y(2023, March 2) *Shopee ứng dụng AI đẩy mạnh tương tác với khách hàng*. VnExpress. https://vnexpress.net/shopee-ung-dung-ai-day-manh-tuong-tac-voi-khach-hang-4576758.html

[10] Dako, O. F., Onalaja, T. A., Nwachukwu, P. S., Bankole, F. A., & Lateefat, T. (2020). Big data analytics improving audit quality, providing deeper financial insights, and strengthening compliance reliability. *Journal of Frontiers in Multidisciplinary Research*, 1(2), 64-80.

[11] Davis, F. D. (1989). Technology acceptance model: TAM. Al-Suqri, MN, Al-Aufi, AS: Information seeking behavior and technology adoption, 205(219), 5.

[12] Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts*. International journal of man-machine studies*, 38(3), 475-487.

[13] Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of applied social psychology*, 22(14), 1111-1132.

[14] De Groot, J. I. M. (2022). The personalization paradox in Facebook advertising: The mediating effect of relevance on the personalization–brand attitude relationship and the moderating effect of intrusiveness. *Journal of Interactive Advertising*, 22(1), 57-74.

[15] Dimock, M. (2019). Defining generations: Where Millennials end and Generation Z begins. *Pew research center*, 17(1), 1-7.

[16] Febriani, R. A., Sholahuddin, M., & Kuswati, R. (2022). Do artificial intelligence and digital marketing impact purchase intention mediated by perceived value?. *Journal of Business and Management Studies*, 4(4), 184-196.

[17] Fishbein, M., & Ajzen, I. (1980). Predicting and understanding consumer behavior: Attitude-behavior correspondence. *Understanding attitudes and predicting social behavior*, *1*(1), 148-172.

[18] Geddam, S. M., Nethravathi, N., & Hussian, A. A. (2024). Understanding AI adoption: The mediating role of attitude in user acceptance. *Journal of Informatics Education and Research*, 4(2)

[19] Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of multivariate data analysis*, 1(2), 107-123.

[20] Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer international publishing.

[21] Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. *Long range planning*, 45(5-6), 320-340.

[22] Hansen, J. M., Saridakis, G., & Benson, V. (2018). Risk, trust, and the interaction of perceived ease of use and behavioral control in predicting consumers' use of social media for transactions. *Computers in human behavior*, 80, 197-206.

[23] Harman, G. (1976). Practical reasoning. *The review of metaphysics*, 431-463. https://www.jstor.org/stable/20126812.

[24] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43(1), 115-135.

[25] Hicham, N., Nassera, H., & Karim, S. (2023). Strategic framework for leveraging artificial intelligence in future marketing decision-making. *Journal of Intelligent Management Decision*, 2(3), 139-150.

[26] Huang, T. L., & Liao, S. (2015). A model of acceptance of augmented-reality interactive technology: the moderating role of cognitive innovativeness. *Electronic Commerce Research*, 15(2), 269-295.

[27] Kamalul Ariffin, S., Mohan, T., & Goh, Y. N. (2018). Influence of consumers' perceived risk on consumers' online purchase intention. *Journal of research in Interactive Marketing*, 12(3), 309-327.

[28] Khan, T., & Emon, M. M. H. (2024, November). Determinants of AI Image Generator Adoption Among Marketing Agencies: The Mediating Effects of Perceived Usefulness. *In 2024 IEEE 3rd International Conference on Robotics, Automation, Artificial-Intelligence and Internet-of-Things (RAAICON)* (pp. 177-182). IEEE.

[29] Khatri, M. (2021). How digital marketing along with artificial intelligence is transforming consumer behaviour. *International Journal for Research in Applied Science and Engineering Technology*, 9(VII), 523-527.

[30] Kim, H. Y., Lee, J. Y., Mun, J. M., & Johnson, K. K. (2017). Consumer adoption of smart in-store technology: assessing the predictive value of attitude versus beliefs in the technology acceptance model. *International Journal of Fashion Design, Technology and Education*, 10(1), 26-36.

[31] Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for information Systems*, 13(7), 2.

[32] Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69-96. doi: 10.1509/jm.15.0420

[33] Liang, Y., Lee, S. H., & Workman, J. E. (2020). Implementation of artificial intelligence in fashion: are consumers ready?. *Clothing and Textiles Research Journal*, 38(1), 3-18.

[34] Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. *Computers in Human Behavior*, 65, 114-120.

[35] Mathieson, K. (1991). Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. *Information systems research*, 2(3), 173-191.

[36] Mooy, S. C., & Robben, H. S. (2002). Managing consumers' product evaluations through direct product experience. *Journal of Product & Brand Management*, 11(7), 432-446.

[37] Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, 88(5), 879.

[38] Pradhanawati, A., & Pinem, R. J. (2025). The Influence of Artificial Intelligence on Consumer Purchasing Decisions in the Digital Era: Case on Generation Z in Emerging Country. *Journal of Cultural Analysis and Social Change*, 1862-1873

[39] Rahmawaty, P., Sunarta, S., & Nuranti, B. R. (2024, December). The impact of personalized advertising on consumer purchase decisions with brand trust as a mediator toward Sustainable Development Goals (SDGs). *In 4th International Conference on Social Sciences and Law (ICSSL 2024) (pp. 426-442*). Atlantis Press.

[40] Ruiz-Viñals, C., Pretel-Jiménez, M., Del Olmo Arriaga, J. L., & Miró Pérez, A. (2024). The influence of artificial intelligence on generation Z's online fashion purchase intention. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(4), 2813-2827.

[41] Subbaiah, P. V., Jyothsna, M., Manjushree, P., & Kondamudi, S. G. (2024). Exploring the Influence of Artificial Intelligence (AI) on Online Purchase Decisions: In Case of Consumer's Prospective. *International Journal of Intelligent Systems and Applications in Engineering*, 12(10s), 13–20

[42] Sun, Y., Huang, Y., Fang, X., & Yan, F. (2022). The purchase intention for agricultural products of regional public brands: examining the influences of awareness, perceived quality, and brand trust. *Mathematical Problems in Engineering*, 2022(1), 4991059.

[43] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, 27(3), 425-478.

[44] Williams, M. D., Slade, E. L., & Dwivedi, Y. K. (2014). Consumers' intentions to use e-readers. *Journal of Computer Information Systems*, 54(2), 66-76.

[45] Yeo, S. F., Tan, C. L., Kumar, A., Tan, K. H., & Wong, J. K. (2022). Investigating the impact of AI-powered technologies on Instagrammers' purchase decisions in digitalization era–A study of the fashion and apparel industry. *Technological Forecasting and Social Change*, *177*, 121551.

[46] Yim, M. Y. C., & Park, S. Y. (2019). "I am not satisfied with my body, so I like augmented reality (AR)": Consumer responses to AR-based product presentations. *Journal of Business Research*, *100*, 581-589.

[47] Yin, J., & Qiu, X. (2021). AI technology and online purchase intention: Structural equation model based on perceived value. *Sustainability*, *13*(10), 5671.