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Online shopping intent on ai-integrated e commerce platforms among students in Ho Chi Minh City: The role of attitudes and trust toward AI

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Abstract Artificial Intelligence (AI) is revolutionizing the digital landscape, driving transformative changes in consumer behavior, particularly online shopping on e-commerce platforms integrated with AI technologies. By utilizing machine learning, predictive analytics, and personalized recommendations, these platforms create enhanced user experiences, appealing especially to tech-savvy younger generations. In Ho Chi Minh City, where digital adoption accelerates, this study explores how students' attitudes and trust in AI influence their online shopping intentions. Key factors such as personalization, perceived risk, ease of use, usefulness, attitudes, and trust in AI are analyzed to understand their impact on online shopping behavior. Data from 335 students were collected through a structured survey and analyzed using SmartPLS 3 software to ensure robust quantitative insights. The findings emphasize the critical roles of trust and positive attitudes toward AI, with personalization and ease of use are significant mediators in fostering shopping intentions. This study provides timely recommendations for e-commerce platforms and policymakers to strategically leverage AI technologies, aligning with consumer expectations and optimizing online shopping experiences for university students in a rapidly evolving digital economy.

Keywords: consumer behavior, ai-enhanced shopping, digital trust, personalized marketing, user experience optimization

1. Introduction

With the rapid advancement of technology and increasing demand for convenient shopping, online shopping has emerged as a dominant trend. Ease of access to products, time-saving benefits, and attractive promotions offered by e-commerce platforms have significantly contributed to their widespread adoption. Simultaneously, advancements in information technology, particularly artificial intelligence (AI), have transformed the online shopping experience. AI is extensively applied in e-commerce platforms, enabling personalized product recommendations, enhancing customer support, and optimizing the user experience.

According to a report by Kirin, e-commerce in Vietnam has grown substantially. The data reveal that 50% of consumers prefer shopping online, whereas only 30% prefer traditional retail stores, highlighting the shift toward digital marketplaces. Notably, mobile phones have become the primary tool for online shopping, with 91% of consumers using them for purchases, whereas desktop and laptop usage has declined from 18% in 2023 to 46% in 2022. These data underscore the increasing dominance of mobile shopping applications (Anh, 2024).

AI plays a crucial role in enhancing the efficiency of e-commerce. This enables sellers to personalize the shopping experience, increasing order conversion rates by up to 20% while automating product categorization, which significantly reduces processing time. Consequently, businesses achieve greater operational efficiency and customer satisfaction (Vu, 2024).

The rapid expansion of e-commerce in Vietnam has contributed significantly to its economic growth. Recent statistics indicate that the combined revenue of the top five e-commerce platforms—Shopee, Lazada, Tiki, Sendo, and TikTok—reached 156 trillion VND in the first half of the year, reflecting a remarkable 78% increase compared with the previous year. Shopee dominates the market with a 67.9% share, followed by TikTok Shop at 23.2%. This impressive growth highlights the immense potential of Vietnam's e-commerce sector (Hoa, 2024).

AI is a transformative force in e-commerce, reshaping business operations and improving the consumer shopping journey. By integrating AI with advanced technologies, businesses can increase their operational efficiency, reduce costs, and optimize warehouses and supply chain management. AI-driven innovations streamline e-commerce operations, making online shopping more efficient, user friendly, and aligned with consumers' expectations (Duc, 2024).

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Recent studies have examined the impact of AI on consumer purchase intentions in e-commerce. Sudarti & Sari (2020) emphasized that trust and enjoyment in online shopping platforms significantly influence perceived usefulness and customer satisfaction. Similarly, AI-driven technologies, such as image and voice recognition, as well as machine learning, have enhanced personalization in e-commerce, making the shopping experience more engaging and effective. AI not only optimizes business operations but also aids in analyzing consumer behavior, refining marketing strategies, and improving product recommendations, ultimately fostering stronger customer engagement and increasing sales (Bag et al., 2022).

Furthermore, studies have explored the key factors that influence online shopping intent on AI-integrated e-commerce platforms. Research by Chi & Anh (2024) highlights the significance of usefulness and personalization in shaping consumer purchasing behavior, even when perceived risks exist. Additionally, Marjerison et al. (2025) reported that perceived usefulness plays a pivotal role in determining consumer adoption of AI-driven online shopping.

However, previous studies have largely overlooked the influence of attitudes and beliefs toward AI on shaping consumer behavior. Therefore, this study aims to bridge this gap by investigating "Online Shopping Intent on AI-Integrated E Commerce Platforms Among Students in Ho Chi Minh City: The Role of Attitudes and Trust Toward AI". By exploring consumer concerns and expectations regarding AI, this research seeks to optimize AI functionalities to increase customer satisfaction and trust in online shopping. The findings provide valuable insights for e-commerce managers to better understand Gen Z students' shopping behaviors, ultimately benefiting businesses and fostering the growth of Vietnam's digital economy.

To achieve these research objectives, the subsequent sections of this paper introduce the theoretical framework and construct hypotheses for the research model. Additionally, data analysis methods were employed to derive empirical insights into the factors driving AI-powered online shopping behavior.

2. Research Methodology

Qualitative methods: This study employed qualitative methods through group discussions and a comprehensive review of relevant literature, including journals, articles, and scientific research from both domestic and international sources. These materials help refine the observation variables, develop measurement scales, and establish a theoretical foundation for this study. Additionally, a pilot interview questionnaire was administered to consumers in Ho Chi Minh City to gather insights, which were then used to calibrate the final questionnaire before proceeding with the formal research.

Quantitative methods: A structured survey was conducted via a predeveloped questionnaire. The survey targeted students in Ho Chi Minh City and collected 350 responses, of which 335 were valid for analysis. The final sample size was determined to be 335. Data analysis was performed via SPSS and SmartPLS. The Cronbach's alpha coefficient was employed to assess and refine the reliability of the measurement scales by identifying and eliminating nonconforming indicators. Exploratory factor analysis (EFA), Pearson correlation analysis, and structural equation modeling (SEM) were used to examine the relationships between variables. SmartPLS was used for structural equation modeling, whereas Excel facilitated additional calculations and data processing.

Quantitative Analysis Techniques: The study utilized various quantitative analysis techniques, including descriptive statistics, measurement model evaluation, structural model testing, and hypothesis testing, to ensure robust and reliable results.

3. Results

3.1. Descriptive statistics

After the questionnaires were collected and cleaned, data analysis was conducted. Table 1 presents preliminary statistics categorized by gender, academic year, income, and shopping frequency. Among the 335 valid responses, 34.6% were from females, and 65.2% were from males. The highest proportion of respondents were third- and fourth-year students, at 35.4% and 35.7%, respectively, whereas first- and second-year students accounted for 11.9% and 17.0%, respectively.

The income distribution showed a minimal difference between the groups earning less than 2 million VND (33.9%) and those earning between 2–5 million VND (35.4%). Students with incomes exceeding 5 million VND formed a relatively small proportion. Consistent with expectations, online shopping was highly prevalent among students, with 43.5% shopping frequently, whereas occasional and infrequent shoppers accounted for 36.3% and 20.2%, respectively.

3.2. Evaluation of the measurement model

This study employed a quantitative research approach via structural equation modeling (SEM) via SmartPLS software. The model was designed to assess the impact of AI-driven factors on online shopping behavior among students in Ho Chi Minh City by incorporating seven key constructs: (1) trust (TR), (2) attitude toward AI (ATT), (3) personalization (PCST), (4) usefulness (PU), (5) risk calculation (PR), (6) ease of use (PEOU), and (7) online shopping intention (OPI). These factors were systematically examined via 46 measurement items derived from preliminary qualitative research.

Table 2 presents the outer loading coefficients of the observed variables, which range from 0.706--0.892. The measurement model was rigorously assessed via composite reliability (CR), average variance extracted (AVE), and outer loading factors to ensure construct validity and reliability. The findings in Table 2 indicate that all the metrics for composite reliability, AVE, and outer loadings met the required validity and reliability criteria.

Table 1 Description of the study sample.

Personal Information	Standard	Frequency	Percent (%)
Gender	Male	116	34.6
	Female	219	65.2
School Year	Year 1	40	11.9
	Year 2	57	17.0
	Year 3	119	35.4
	Year 4	119	35.7
Income	Less than 2 million	113	33.9
	From 2-5 million	119	35.4
	Over 5 million	98	29.2
Level of procurement	Very often	146	43.5
	Occasionally	121	36.3
	Seldom	68	20.2
	Never	0	0

Furthermore, Table 2 also reports Cronbach's alpha values for each construct, all of which exceed the 0.6 threshold (Hair et al., 2014). Specifically, the Cronbach's alpha values for personalization (0.795), risk calculation (0.791), usefulness (0.853), ease of use (0.908), trust (0.867), attitudes toward AI (0.705), and online shopping intentions (0.919) demonstrated strong internal consistency. Given that all the Cronbach's alpha coefficients were greater than 0.6 and that the total correlation coefficient exceeded 0.3, the measurement scales used in this study were deemed reliable.

Table 2 Reliability and convergence value results of the scale.

Construct	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Outer Loading
ATT	0.705	0.835	0.628	0.781 - 0.811
OPI	0.919	0.939	0.756	0.831 - 0.892
PCST	0.795	0.880	0.709	0.830 - 0.855
PEOU	0.908	0.929	0.685	0.789 - 0.873
PR	0.791	0.865	0.616	0.706 - 0.816
PU	0.853	0.895	0.631	0.716 - 0.850
TR	0.867	0.909	0.715	0.802 - 0.891

Extensive testing was conducted to evaluate the reliability and validity of the measurement models. This was achieved by examining the relationships between variables via average variance extracted (AVE). The assessment was based on the Fornell–Larcker criterion, as presented in Table 3, which demonstrates that the square root of the AVE for each construct exceeded the correlation between conceptual pairs.

AVE values ranging from 0.7 to 0.9 are considered statistically significant, confirming the robustness of the measurement model. These values indicate a high level of reliability compared with the recommended threshold of 0.5 (Fornell & Larcker, 1981). These findings support the appropriateness of the model and ensure its validity for further analysis.

Table 3 Results of the Fornell–Lacker differential value analysis.

	ATT	OPI	PCST	PEOU	PR	PU	TR
ATT	0.793						
OPI	0.558	0.870					
PCST	0.585	0.614	0.842				
PEOU	0.252	0.476	0.364	0.828			
PR	0.361	0.400	0.374	0.201	0.785		
PU	0.540	0.571	0.570	0.359	0.268	0.795	
TR	0.335	0.611	0.456	0.416	0.367	0.427	0.845

To assess the heterotrait–monotrait (HTMT) ratio (Clark & Watson, 2016; Kline, 2016), an HTMT value of ≤ 0.85 indicates adequate discriminant validity between the constructs in the model. If the HTMT value exceeds 0.85, this suggests a lack of differentiation among the variables. As shown in Table 4, all the HTMT values were below the threshold of 0.85, confirming that the constructs in the model achieved discriminant validity.

3.3. Structural model evaluation

To assess multicollinearity and ensure no strong correlation between independent observed variables, the variance inflation factor (VIF) was used. According to Hair et al. (2019), a model does not exhibit multicollinearity if the variance inflation factor (VIF) value remains below 5. As Table 5 shows, all the constructs met this criterion, with the highest recorded VIF value of 3.088. This result confirms that multicollinearity was not present in the model, thereby ensuring the reliability of the structural model.

Table 4 HTMT.

	ATT	OPI	PCST	PEOU	PR	PU	TR
ATT							
OPI	0.687						
PCST	0.778	0.717					
PEOU	0.311	0.518	0.426				
PR	0.482	0.468	0.437	0.239			
PU	0.690	0.640	0.688	0.402	0.326		
TR	0.427	0.681	0.548	0.469	0.444	0.492	

Table 5 VIF.

	VIF		VIF		VIF
ATT1	1.367	PCST3	1.689	PR4	1.695
ATT2	1.425	PEOU1	2.085	PU1	1.596
ATT3	1.346	PEOU2	2.230	PU2	1.862
OPI1	2.757	PEOU3	2.380	PU3	2.332
OPI2	2.844	PEOU4	3.081	PU4	2.376
OPI3	3.088	PEOU5	3.029	PU5	1.903
OPI4	3.053	PEOU6	2.006	TR1	2.132
OPI5	2.388	PR1	1.333	TR2	2.097
PCST1	1.720	PR2	1.721	TR3	2.623
PCST2	1.654	PR3	1.760	TR4	1.888

Table 6 presents the R-squared values for the key dependent variables in the model. The R-squared value for ATT is 0.427, indicating that the independent variables PCST, PR, and PU collectively explain 42.7% of the variation in ATT. Similarly, the R-squared value for OPI is 0.598, meaning that ATT, PCST, PEOU, PR, PU, and TR together account for 59.8% of the variance in OPI. Finally, the R-squared value for TR is 0.562, showing that PU and PEOU contribute to explaining 56.2% of the variation in TR.

Table 6 Coefficient of determination R squared (R Square).

	R Square	R Square Adjusted
ATT	0.427	0.442
OPI	0.598	0.492
TR	0.562	0.457

To assess the structural model, we used the f-effect size index, which evaluates the influence of the independent variables on the dependent variable within the SEM. The f-squared values for each independent variable are presented in Table 7, reflecting their respective effect sizes (Cohen, 1988).

The results indicate that the f-square values ranged from 0.030 to 0.173, indicating effects ranging from low to high impact. Among these, the strongest effect was observed in the relationship between TR and OPI, with an f-squared value of 0.173. Additionally, PCST, PEOU, and PR exhibited moderate impact levels, with PR showing a notable effect on the OPI at 0.037.

All the tables and figures referenced in this section have been cited appropriately before their appearance, ensuring clarity and coherence within the discussion.

To further emphasize the reliability of the study, the authors used the bootstrapping analysis technique with a resampling scale of 5000 observations to test the research hypotheses. Table 8 presents the results.

First, hypotheses H1a and H1b consider the impact of the Personalization Variable (PCST) on two variables, namely, online shopping intent (OPI) and attitude toward AI (ATT), respectively. The results in Table 8 show that the P values of PCST on OPI and ATT are both 0.000; therefore, these two effects are statistically significant. The normalized impact coefficients of PCST on OPI and ATT were 0.202 and 0.365, respectively, indicating that personalization significantly impacts shopping intent and attitudes toward AI. Therefore, H1a and H1b were accepted. This conclusion is consistent with that of previous research (AlGerafi et al., 2023).

Table 7 F-Square index results.

	ATT	OPI	PCST	PEOU	PR	PU	TR
ATT		0.068					
OPI							
PCST	0.148	0.053					
PEOU		0.052					0.107
PR	0.037						
PU	0.098	0.030					0.120
TR		0.173					

Hypothesis H2: The results in Table 8 for the risk calculation (PR) affecting attitudes toward AI (ATT) show that the P value of PR on ATT is 0.000; therefore, these two effects are statistically significant. The normalized impact coefficient of PR on ATT (0.156) indicates that PR significantly impacts attitudes toward AI. Therefore, H2 was accepted. This conclusion is consistent with that of previous research (AlGerafi et al., 2023).

H3a: H3a, H3b, and H3c consider the impact of the usefulness variable (PU) on three variables, namely, attitudes toward AI (ATT), trust (TR), and online shopping intention (OPI), respectively. The results in Table 8 show that the P values of PU on ATT and TR are both 0.000; therefore, these two effects are statistically significant. The normalized impact coefficients of PU on ATT and TR were 0.290 and 0.319, respectively, indicating that usefulness had a significant positive effect on attitudes toward AI and trust. Therefore, H3a and H3b were accepted. This conclusion is consistent with that of previous research (AlGerafi et al., 2023). In addition, the results in Table 8 show that usefulness (PU) has an effect on online shopping intention (OPI), with a normalized coefficient of 0.146, and is statistically significant at the 5% level (P = 0.003). Therefore, H3c was accepted. This conclusion was consistent with the findings of AlGerafi et al. (2023).

Hypothesis H4: This study confirms that ease of use (PEOU) has a significant positive effect on trust (TR) and online shopping intent (OPI). The results in Table 8 show that the P values of the PEOU on TR and OPI are both 0.000; therefore, these two effects are statistically significant. The normalization coefficients were 0.301 and 0.165, respectively. Therefore, H4 is accepted. This conclusion was consistent with the findings of AlGerafi et al. (2023).

Hypothesis H5: The results in Table 8 show that attitude toward AI (ATT) influences online shopping intent (OPI), with a normalization coefficient of 0.214, and is statistically significant at the 5% level (P = 0.002). Therefore, H5 is accepted. This conclusion was consistent with the findings of AlGerafi et al. (2023).

Hypothesis H6: The results in Table 8 for confidence (TR) affecting online shopping intention (OPI) show that the P values of TR affect the OPI by 0.000; therefore, these two effects are statistically significant. The normalized impact coefficient of TR on OPIs of 0.316 suggests that TR significantly impacts attitudes toward OPIs. Therefore, H6 was accepted. This conclusion is consistent with that of previous research (AlGerafi et al., 2023).

Table 8 Results of the direct impact of relationships.

Relationship	Original Sample (O)	Sample Mean (M)	T Statistics (|O/STDEV|)	P Values
Personalization -> Online Purchase Intention	0.202	0.201	4.341	0.000
Personalization -> Attitudes toward AI	0.365	0.364	7.685	0.000
Risk -> Attitudes toward AI	0.156	0.160	3.783	0.000
Usefulness -> Attitudes toward AI	0.290	0.291	6.138	0.000
Usefulness -> Trust AI	0.319	0.320	6.611	0.000
Usefulness -> Online Purchase Intention	0.146	0.146	3.025	0.002
Ease Of Use -> Trust AI	0.301	0.303	6.304	0.000
Ease Of Use -> Online Purchase Intention	0.165	0.165	3.682	0.000
Attitudes toward AI -> Online Purchase Intention	0.214	0.215	4.542	0.000
Trust AI -> Online Purchase Intention	0.316	0.316	7.551	0.000

When ATT is considered an intermediate variable, factors such as PCST, PR, and PU positively impact the OPI, with beta coefficients of 0.021, 0.039, and 0.027, respectively. Moreover, when TR is considered an intermediate variable, factors such as PEOU or PU also positively impact OPI, with beta coefficients of 0.079, 0, and 100, respectively. In addition, all p-factors are less than 0.05, indicating that the PCST, PR, PU, and PEOU factors impact the OPI. The results presented in Table 9 indicate that personalization, risk, usefulness, and ease of use impact students' online shopping intentions by increasing their trust in AI technology and attitudes toward the value that AI brings.

Table 9 Results: specific indirect effects.

Relationship	Original Sample (O)	Sample Mean (M)	T Statistics (|O/STDEV|)	P Values
Personality -> Attitudes toward AI -> Online Purchase Intention	0.021	0.021	2.373	0.018
Risk -> Attitudes toward AI -> Online Purchase Intention	0.039	0.039	3.071	0.002
Usefulness -> Attitudes toward AI -> Online Purchase Intention	0.027	0.028	2.421	0.016
Ease Of Use -> Trust AI -> Online Purchase Intention	0.079	0.080	3.824	0.000
Usefulness -> Trust AI -> Online Purchase Intention	0.100	0.100	4.666	0.000

Figure 1 illustrates the PLS–SEM measurement model results that evaluate the reliability and validity of the research constructs. The model assesses key indicators, such as factor loadings, composite reliability (CR), and average variance extracted (AVE), to ensure construct validity. High factor loadings (> 0.7) indicated strong relationships between the observed variables and their latent constructs. Additionally, the model verified discriminant validity via the Fornell–Larcker criterion, ensuring that each construct was distinct from the others. These results confirm the robustness of the measurement model and support the reliability of the constructs for further structural model analysis.

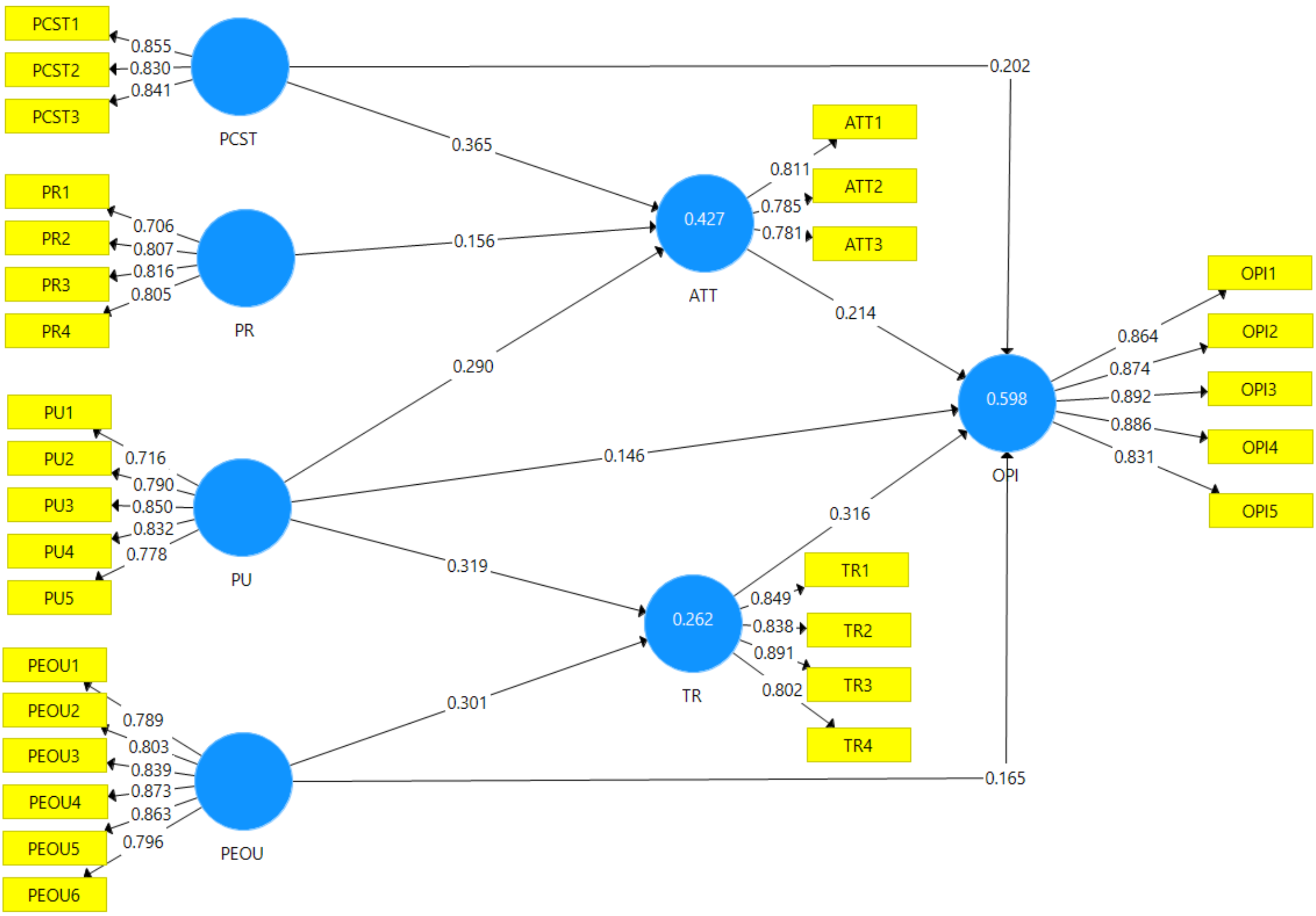

Figure 1 PLS-SEM measurement model results.

4. Discussion

This study explores the role of artificial intelligence (AI) in shaping consumer behavior and online shopping intentions within AI-integrated e-commerce platforms. AI has significantly transformed the e-commerce landscape by enhancing personalization, predictive analytics, supply chain management, and customer service. Through AI-driven algorithms, businesses can analyze consumer data, predict demand, and improve customer experience via chatbots and virtual assistants that provide real-time assistance. However, AI adoption in e-commerce raises concerns related to trust, perceived usefulness, ease of use, and risk perception, all of which influence consumer attitudes and purchase intentions.

Personalization plays a critical role in shaping online shopping intentions by providing consumers with customized recommendations on the basis of browsing behavior and purchase history. Previous studies (Raji et al., 2024; Wang et al., 2023) have highlighted that AI-powered personalization increases customer satisfaction and loyalty, fostering a stronger intent to purchase. The results of this study indicate that personalization (β = 0.157) has a positive effect on online shopping intent, which is consistent with prior research (Choi et al., 2011) that revealed a similar correlation (β = 0.118). Additionally, personalization influences attitudes toward AI as users develop greater familiarity and comfort with AI-powered recommendations (Singh et al., 2024). This finding reinforces the hypothesis that personalization positively affects consumers' attitudes toward AI and their shopping intentions (H1a, H1b).

Trust is a fundamental factor in AI-integrated e-commerce platforms. Consumer confidence in AI technology influences their willingness to engage in online shopping, particularly with respect to data security, product reliability, and AI-driven decision-making. The findings show that trust (β = 0.326) is the strongest predictor of online shopping intent, a result that is consistent with those of Sharma et al. (2024) and Wistedt (2024). Customers tend to trust AI-powered platforms when they perceive them to be secure and reliable, particularly in ensuring product quality (TR1), technology reliability (TR2), and data protection (TR3). Previous studies (Singh et al., 2024; Xing et al., 2024) further confirm that trust significantly affects consumer satisfaction and the intent to purchase, emphasizing the need for businesses to implement robust security measures and transparent AI algorithms to build consumer confidence (H6).

Perceived usefulness (PU) is another key factor that influences online shopping intentions. AI technologies enhance e-commerce efficiency by streamlining purchasing processes, improving search accuracy, and reducing decision-making effort. The results indicate that perceived usefulness (β = 0.125) positively influences online shopping intent, although to a lesser extent than does trust and ease of use. This finding is consistent with previous research (Chi et al., 2024) (β = 0.292), which also revealed a significant impact of usefulness on shopping intentions. Additionally, usefulness influences trust in AI-based shopping platforms, as consumers tend to trust technologies that they find effective and efficient (Singh et al., 2024). The mediating effect of trust between perceived usefulness and online shopping intent has also been confirmed (Marjerison et al., 2025), reinforcing the importance of developing AI features that increase user convenience and efficiency (H3a, H3b, H3c).

Ease of use (PEOU) plays a crucial role in encouraging consumers to adopt AI-powered shopping platforms. When AI systems are user friendly and require minimal effort, consumers are more likely to trust and engage with them. The study shows that ease of use (β = 0.275) has a strong positive effect on online shopping intent, which aligns with the findings of Alnaim (2022) and Teo et al. (2024), who reported that ease of use significantly enhances consumers' perception of AI. Moreover, ease of use directly contributes to trust in AI (H4a), as intuitive AI interfaces reduce skepticism and encourage adoption (Adawiyah et al., 2024). Previous research (Lopes et al., 2024) further supports the idea that a well-designed AI interface fosters both trust and shopping intentions, making it easier to use a critical element in AI-driven e-commerce.

Consumers' attitudes toward AI significantly influence their willingness to engage with AI-integrated platforms. The study revealed that attitudes toward AI (β = 0.122) positively impact online shopping intent, which aligns with the findings of Singh et al. (2024) and Adawiyah et al. (2024). Positive attitudes toward AI develop when consumers recognize their efficiency, accuracy, and ability to enhance their shopping experiences. Furthermore, AI-powered tools, such as voice commerce and AI chatbots (Calahorra-Candao & Martín-de Hoyos, 2024), have been found to enhance consumer attitudes toward AI, ultimately influencing their intent to purchase (H5).

Although AI offers numerous benefits, concerns about privacy, security, and product reliability persist. The study revealed that risk perception (β = 0.039) has the least impact on online shopping intent, suggesting that, while consumers acknowledge risk, their willingness to adopt AI-driven shopping platforms remains largely unaffected. These results are consistent with those of previous research (Kronemann et al., 2023), which revealed that consumers increasingly trust AI's ability to protect personal information and enhance their shopping experiences. Interestingly, the study highlights that risk perception influences attitudes toward AI, which in turn affects shopping intent (H2). This finding is partially aligned with that of Mogaji & Jain (2024), who suggest that consumers' concerns about AI risks impact their shopping behaviors. As AI continues to evolve, enhancing security protocols and transparency is essential for mitigating risks and fostering consumer trust.

The findings highlight that trust, ease of use, and personalization are the most influential factors shaping online shopping intentions on AI-powered e-commerce platforms. While usefulness and attitudes toward AI also contribute to purchase intent, their impact is comparatively lower. Risk perception does not significantly deter consumers from engaging in AI-driven shopping. These insights suggest that businesses should focus on enhancing trust through secure AI systems, ensuring user-friendly interfaces, and leveraging personalization strategies to improve customer engagement.

Furthermore, the mediating role of trust between perceived usefulness and ease of use highlights the importance of building consumer confidence in AI technology. As AI adoption in e-commerce continues to grow, future research should explore how emerging AI advancements, such as generative AI and augmented reality (AR), further shape consumer behavior. By addressing consumer concerns and continuously improving AI-driven personalization and security features, businesses can maximize AI's potential to drive e-commerce growth and customer satisfaction.

5. Managerial Implications

This study aimed to evaluate the factors influencing the intention to use AI technology in online shopping among Ho Chi Minh City students. These factors included trust, attitude, personalization, risk, usefulness, and ease of use. This study utilizes the TAM model to explain the impact of AI on online shopping intentions. The findings reveal that "Personalization," Risk, "Ease of Use," and "Usefulness" positively influence "online shopping intentions." Moreover, "trust" and "attitudes" toward AI are crucial in shaping students' online shopping intent in Ho Chi Minh City.

On the basis of the analysis, the following conclusions are drawn:

First, the relationship between trust (TR) and online shopping intent (OPI) is the most significant. This finding indicates that Ho Chi Minh City students perceived trust in AI-integrated e-commerce platforms as crucial to their online shopping decisions. The managerial implication is that developers of AI-powered e-commerce systems should focus on building trust and emphasizing quality. By improving their perceptions of AI technology, businesses can increase the effectiveness of online shopping.

Second, attitudes toward AI (ATT) are a critical factor influencing online shopping intent (OPI). This suggests that a favorable attitude toward using AI technology on e-commerce platforms positively affects students' shopping decisions in Ho Chi Minh City.

Third, personalization (PCST) is a key factor affecting online shopping intent (OPI). This highlights that student consumers prioritize personalized online shopping experiences. Businesses should optimize data collection and analysis by gathering data from various sources and leveraging algorithms to understand customer habits, preferences, and behaviors. Simultaneously, privacy rights must be respected to build customer trust. These efforts not only enhance customer trust but also differentiate businesses from competitors.

Fourth, perceived risk (PR) poses a significant barrier to online shopping intent (OPI), particularly in AI-integrated e-commerce environments. These risks are often associated with product quality, security, and privacy. Managerial implications for businesses include minimizing product risk through transparent return policies, realistic product descriptions, and quality commitments. They should also ensure customer data privacy and security, provide certifications, and communicate compliance with data-protection standards to reassure customers.

Fifth, ease of use (PEOU) is another essential factor, as consumers are becoming increasingly demanding and selective owing to the growing number of e-commerce platforms. Consumers prefer platforms with user-friendly interfaces, excellent buyer support, secure policies, and efficient issue resolution processes. These features save time, reduce inconvenience, and enhance the shopping experience. To achieve this, businesses should invest in a simple and intuitive interface design, improve search functionalities, and incorporate intelligent product suggestions. They should also optimize the page loading speeds and provide 24/7 customer support services. Ease of use improves online shopping intentions and enhances customer satisfaction and loyalty.

Finally, the usefulness (PU) of AI-integrated e-commerce platforms significantly increases online shopping intent by making the process more convenient and efficient. AI's timely, accurate, and professional support increases customer satisfaction and trust in the platform. To maximize the usefulness of AI, businesses can invest in personalized AI experiences, optimize chatbots and virtual assistants, and integrate image and voice search technologies to facilitate product discovery. Simplifying the payment process and offering multiple payment options further enhances convenience. By effectively leveraging usefulness, businesses can increase customers' online shopping intentions and establish a sustainable competitive advantage in AI-integrated e-commerce environments.

In conclusion, this study identified the relationships among personalization, risk, usefulness, ease of use, and the roles of trust and attitudes in influencing online shopping intentions among students in Ho Chi Minh City on AI-integrated e-commerce platforms. Students should cultivate a positive mindset toward using AI on these platforms. Businesses should focus on integrating AI into e-commerce to enhance brand recognition and increase revenue. Additionally, companies should create opportunities for students to engage more with AI-integrated e-commerce platforms, enabling them to understand AI technology better.

6. Limitations of the Study

In future studies, this research has the potential to serve as a reference for assessing students' attitudes toward AI technology during online shopping. However, this study has certain limitations.

First, the research content has not been fully explored owing to the short implementation time. Second, the data were only collected from undergraduate students; therefore, expanding the research audience to include graduate students or distance learning students could yield richer findings. Additionally, the study was only conducted at select universities in Ho Chi Minh City, meaning that the results represent a specific group of subjects and may not be generalizable to a broader population.

Moreover, the responses from the survey participants were primarily subjective, which can affect the accuracy of the data. Future studies should adopt other data collection methods to enhance reliability. In addition to the factors examined in this study, numerous other variables may influence online shopping intentions, which remain unexplored. Finally, the contributions and evaluations of the research team are based on their perspectives, which may not fully reflect the broader context of AI adoption in online shopping at other universities.

This team hopes that the limitations of this study will serve as a foundation for future research, leading to a deeper understanding of the impact of AI on students' online shopping intentions. Therefore, future studies should consider incorporating new independent variables that influence students' online shopping behavior, particularly within Ho Chi Minh City.

7. Suggestions for Future Research

This study has several limitations that may affect the comprehensiveness of its findings. These include a primary focus on attitudes and trust in AI, whereas other potential factors, such as familiarity with AI technology, hands-on experience with AI-integrated e-commerce platforms, and customization capabilities of AI, were not considered. Furthermore, the research scope was limited to Ho Chi Minh City students, which reduced objectivity and failed to represent the broader intent to use AI-integrated e-commerce platforms for online shopping. Additionally, reliance on online surveys through Google Forms may compromise data accuracy and reliability because of respondent honesty, engagement, and motivation.

To address these limitations and broaden the research scope, future studies could incorporate additional factors, such as user experience with AI, the level of AI personalization, and perceived risks associated with AI-integrated platforms. Expanding the survey to include diverse demographic groups in terms of age, occupation, and geographical location would enhance the representativeness of the results. Combining online surveys with in-depth interviews or face-to-face surveys can improve the reliability and depth of the data. Comparative studies between consumer groups (e.g., students versus working professionals) or between AI-integrated and non-AI e-commerce platforms could provide valuable insights into different online shopping intentions. Finally, conducting longitudinal studies to track changes in consumer attitudes and trust in AI over time would offer a more accurate understanding of AI's impact on online shopping behavior.

8. Conclusions

The researchers presented their final thoughts and insights based on the analysis and interpretation of the data. This section addresses the research objectives and hypotheses and determines whether they are supported or contradicted by the findings. The conclusions are supported by evidence from the results and discussion sections, which emphasize the significance and novelty of the research outcomes. This section also discusses the limitations of the study and suggests potential areas for future research. Ultimately, this section ties together all the research findings, providing a clear and coherent summary that contributes to a broader understanding of AI-driven e-commerce and its impact on consumer behavior.

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Ethical considerations

This study was carried out in compliance with ethical guidelines. Informed consent was obtained from all participants, guaranteeing voluntary participation and the confidentiality of their responses.

Conflict of interest

The authors affirm that this research was conducted independently, with no commercial or financial connections that might be viewed as potential conflicts of interest.

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