

IMPACT OF ARTIFICIAL INTELLIGENCE APPLICATIONS ON PERSONALIZED COSMETIC SHOPPING EXPERIENCE ON SHOPEE E-COMMERCE PLATFORM IN VIETNAM

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Received: 05/02/2026. Revised: 06/08/2026. Accepted: 24/08/2026

DOI: 10.59266/houjs.2026.1450

Abstract: *The authors investigated the impact of Artificial Intelligence on the personalized cosmetic shopping experience on the Shopee e-commerce platform in Viet Nam. The team proposed seven hypotheses examining how AI-related factors influence user satisfaction. A quantitative approach was used, with survey data collected from 229 respondents and analyzed via SPSS 22. Results indicate that five factors - Personalization Risk Management, Perceived Usefulness, Trust Level, Customer Behavior Recognition, and User Data Quality- have significant positive effects on user satisfaction. At the same time, the quality of Machine Learning Algorithms, when applied mechanically without domain-specific calibration, has a statistically significant negative effect. These findings contribute a novel empirical perspective on AI adoption in a high-involvement product category to offer practical recommendations for platform developers, cosmetic sellers, and regulatory authorities.*

Keywords: *artificial intelligence, cosmetics, e-commerce, personalization, user satisfaction*

I. Introduction

The rapid growth of Viet Nam's e-commerce, dominated by Shopee, is increasingly driven by Artificial Intelligence (AI). By shifting platforms from reactive displays to proactive recommendations, AI is particularly transformative for cosmetics, where purchasing decisions rely heavily on unique physiological traits.

Despite this, empirical research on AI-driven cosmetic shopping within specific platform contexts remains scarce. Prior studies typically isolate

functional technology acceptance from emotional responses and overlook the cosmetic "privacy paradox"-the inherent tension between surrendering sensitive biometric data and receiving accurate AI recommendations.

To address these gaps, this study integrates the S-O-R paradigm with UTAUT2 to capture both cognitive and emotional dimensions. Specifically, it offers critical theoretical contributions by empirically validating the "personalization-privacy coupling" in high-involvement products and identifying an "algorithmic

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misfit effect,” in which mechanically applied, uncalibrated algorithms actively diminish user satisfaction.

II. Theoretical background

2.1. Integrated Theoretical Framework: S-O-R and UTAUT2

Instead of treating functional technology acceptance and emotional responses in isolation, this study adopts an integrated framework combining the S-O-R (Stimulus-Organism-Response) paradigm and UTAUT2. The core logic of this integration lies in complementing S-O-R's affective dimensions with UTAUT2's cognitive focus. Specifically, the framework positions the actual AI technological features on Shopee (e.g., virtual try-on, predictive recommendations, biometric data collection) as external environmental Stimulus (S). These technical stimuli subsequently trigger complex internal Organism (O) states, conceptualized through a dual lens: the *cognitive evaluations* drawn from UTAUT2 (perceived usefulness/performance expectancy) and the *emotional/risk evaluations* (trust and personalization risk perception). Ultimately, this combined cognitive-affective processing dictates the behavioral Response (R), quantified in this study as user satisfaction. This synthesis resolves a key limitation in the prior literature by effectively capturing the intricate psychological dynamics in which functional utility and privacy concerns coexist in high-involvement cosmetic shopping.

2.2. AI personalization in e-commerce

Akter et al. (2021) demonstrated that AI fundamentally shifts e-commerce from a reactive to a predictive paradigm. By encoding behavioral data points into

user profiles, machine learning algorithms can anticipate consumer needs before explicit search queries are formulated. Putha et al. (2021) further elaborated that recommendation engines employing collaborative and content-based filtering achieve progressively higher personalization accuracy as training data volumes increase.

Kumaret al. (2023), using A/B testing on deep learning-integrated platforms, confirmed that AI recommendation systems significantly improve conversion rates and can elicit latent demand through cross-category suggestions. Wang et al. (2024) showed through Structural Equation Modeling (SEM) that natural language processing-enabled chatbots reduce cognitive load (effort expectancy), facilitating technology adoption.

Ngo et al. (2025), applying the S-O-R framework to Vietnamese consumers in Da Nang, found that AI-generated suggestions shorten decision-making time and activate positive emotional responses. However, avoidance behaviors emerge when algorithmic outputs lack relevance or transparency. A Vietnam-specific study on Shopee.vn likewise frames AI adoption in e-commerce in terms of opportunities, challenges, and business solutions (Chu & Nguyen, 2025).

2.3. AI in cosmetics: Opportunities and the Privacy Paradox

Cosmetics represent a high-involvement, high-risk product category in which mismatched recommendations can have real physiological consequences (skin irritation, allergic reactions). Luong et al. (2017) identified the absence of expert consultation as the primary barrier to online cosmetic purchase. AI addresses this through virtual dermatology advisors and ingredient-matching algorithms.

Dassouli et al. (2024) found that the usefulness of cosmetic chatbots is evaluated not by response speed but by the system's capacity to function as a virtual skincare consultant. Yin et al. (2025) demonstrated that high personalization accuracy in AI product recommendations significantly enhances consumer trust, effectively transferring trust from the brand to the algorithmic platform itself.

However, the privacy paradox presents a structural challenge: accurate AI recommendations require the collection of deep personal data (e.g., skin biometrics, purchase history), yet this collection triggers user anxiety. Park and Lee (2023) found that when the perceived risk of data leakage exceeds a safety threshold, it completely neutralizes performance expectancy. Truong (2025) confirmed this in the Vietnamese market, showing that transparency deficits in data handling produce avoidance behaviors even when recommendation accuracy is high.

Li et al. (2024) identified a behavioral reversal: when hedonic motivation and perceived usefulness jointly surpass a threshold, consumers willingly trade privacy for personalization quality - particularly in the context of augmented reality (AR) try-on features.

2.4. Hypothesis development and research model

This study identifies User Satisfaction as the dependent variable (Response - R). Within the integrated S-O-R/UTAUT2 framework, the seven independent variables (Stimuli - S and Organism - O) and their corresponding hypotheses are developed as follows:

User Data & Algorithms (S): High-quality behavioral data and sophisticated machine learning algorithms enable

platforms to predict latent demand and fulfill users' performance expectancy accurately (Akter et al., 2021; Putha et al., 2021). *H1: User data quality positively impacts cosmetic shopping satisfaction. H2: Machine learning algorithms positively impact cosmetic shopping satisfaction.*

Personalization & Behavior Recognition (S): Capturing real-time consumer behaviors allows the AI to act as a virtual consultant, dynamically adapting the interface and reducing cognitive overload (Kumar et al., 2024; Mehrabian & Russell, 1974). *H3: A personalized shopping experience positively impacts satisfaction with cosmetic shopping. H4: Customer behavior recognition positively impacts cosmetic shopping satisfaction.*

Trust Level & Perceived Usefulness (O): Trust effectively transfers from cosmetic brands to the algorithms, mitigating uncertainty (Yin et al., 2025), while perceived usefulness reflects the rational value of AI tools (Davis, 1989; Venkatesh et al., 2012). *H5: Trust level positively impacts cosmetic shopping satisfaction. H6: Perceived usefulness positively impacts cosmetic shopping satisfaction.*

Privacy Anxiety (O): The invasive collection of sensitive biometric and behavioral data triggers a negative psychological state that can neutralize the benefits of personalization (Park & Lee, 2023; Truong, 2025). *H7: Privacy anxiety negatively impacts cosmetic shopping satisfaction.*

III. Research methodology

This study adopts a quantitative design using a 5-point Likert-scale questionnaire, adapted from established TAM, S-O-R, and AI personalization

literature. Data were collected via a non-probability convenience online survey (June 2025 - March 2026) targeting Vietnamese consumers who had engaged in AI-driven cosmetic shopping on Shopee. The final sample of 229 valid respondents satisfies the strict requirements for data analysis.

Data analysis was performed using SPSS 22.0 through a sequential analytical procedure: (1) Reliability analysis using Cronbach's Alpha (threshold: $\alpha \geq 0.7$;

item-total correlation ≥ 0.3) to assess internal consistency. (2) Exploratory Factor Analysis (EFA) with Principal Component Analysis extraction and Varimax rotation ($KMO \geq 0.6$; Bartlett's test $p < 0.05$; factor loading ≥ 0.5) to assess construct validity. (3) Pearson correlation analysis to assess inter-factor relationships and multicollinearity risk. (4) OLS multiple regression to test the proposed hypotheses and estimate factor impacts on the dependent variable.

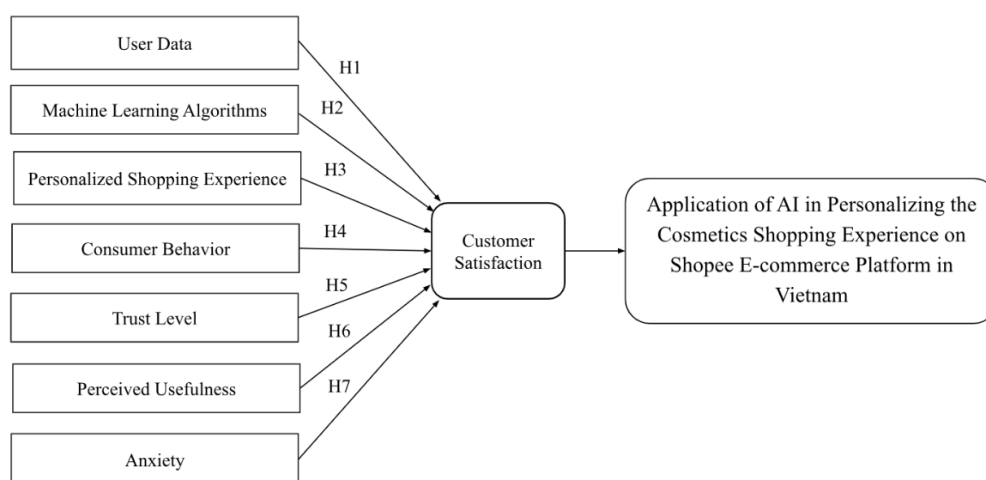


Figure 1. Proposed Research Model

IV. Research results and discussion

The measurement model was comprehensively evaluated in two consecutive stages: internal consistency reliability (Cronbach's Alpha) and construct validity (Exploratory Factor Analysis - EFA).

4.1. Reliability analysis

As presented in Table 1, the internal consistency of the measurement scales was

evaluated using Cronbach's Alpha. The values for all constructs ranged from 0.850 to 0.906, significantly exceeding the 0.70 recommended threshold. Furthermore, corrected item-total correlations for all 39 items were well above the 0.30 minimum requirement (lowest: 0.545). This confirms excellent reliability, justifying the retention of all items for subsequent analysis.

Table 1. Results of Cronbach's Alpha test

Observed Variable (Item)	Corrected Item-Total Correlation
User Data (DL)	Cronbach's Alpha = 0,870, N of Items = 6
Machine Learning Algorithms (TT)	Cronbach's Alpha = 0,867, N of Items = 6
Personalized Shopping Experience (TN)	Cronbach's Alpha = 0,893, N of Items = 6
Consumer Behavior (HV)	Cronbach's Alpha = 0,866, N of Items = 5
Trust Level (TC)	Cronbach's Alpha = 0,892, N of Items = 5

Observed Variable (Item)	Corrected Item-Total Correlation
Perceived Usefulness (HI)	Cronbach's Alpha = 0,906, N of Items = 4
Anxiety (LL)	Cronbach's Alpha = 0,871, N of Items = 4
User Satisfaction (HL) - Dependent	Cronbach's Alpha = 0,850, N of Items = 3

(Source: Compiled by the authors from SPSS 22)

4.2. Exploratory Factor Analysis (EFA) for independent variables

Principal Component Analysis (PCA) and Varimax rotation.

Construct validity was tested using Exploratory Factor Analysis (EFA) with

Table 2. KMO coefficients and Bartlett's test for independent variables.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.808
Bartlett's Test of Sphericity	Approx. Chi-Square	3513.17
	df	5
	Sig.	0.000

(Source: Data from SPSS 22)

Table 3. Results of total variance analysis extracted for the independent variables.

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Curmulative %	Total	% of Variance	Curmulative %
1	6.837	18.992	18.992	6.837	18.992	18.992
2	4.312	11.979	30.971	4.312	11.979	30.971
3	3.752	10.422	41.393	3.752	10.422	41.393
4	3.486	9.684	51.077	3.486	9.684	51.077
5	3.101	8.613	59.690	3.101	8.613	59.690
6	2.656	7.378	67.069	2.656	7.378	67.069
7	.894	2.483	69.552			
...	...	...	...	...	...	...
36	-3.985E-17	-1.107E-16	100.000			

Extraction Method: Principal Component Analysis.

(Source: Data from SPSS 22)

Table 4. EFA Analysis Results - Rotated Matrix Table

Rotated Component Matrix ^a						
	Component					
	1	2	3	4	5	6
LL3	.860					
TN6	.840					
LL1	.840					
TN3	.811					
LL4	.785					
TN4	.783					
TN1	.775					
LL2	.768					
TN5	.762					

Rotated Component Matrix ^a						
	Component					
	1	2	3	4	5	6
TN2	.755					
TT4		.829				
TT2		.815				
TT5		.795				
TT3		.781				
TT1		.758				
TT6		.677				
DL5			.813			
DL6			.806			
DL4			.778			
DL3			.778			
DL1			.762			
DL2			.721			
TC3				.914		
TC4				.868		
TC5				.843		
TC1				.802		
TC2				.729		
HV4					.875	
HV5					.824	
HV1					.817	
HV3					.763	
HV2					.738	
HI4						.886
HI1						.886
HI3						.884
HI2						.857
Extraction Method: Principal Component Analysis.						
Rotation Method: Varimax with Kaiser Normalization. ^a						
a. Rotation converged in 6 iterations.						

(Source: Data from SPSS 22)

Table 2 shows a KMO measure of 0.808 and a highly significant Bartlett's test ($p < 0.001$), confirming the suitability of the data. Table 3 shows that six components were extracted, cumulatively explaining 67.07% of the total variance, well above the 50% benchmark. As detailed in the rotated matrix (Table 4), all items yielded strong factor loadings (0.677 to 0.914). A critical theoretical breakthrough emerged during this stage: items initially measuring "Personalized Shopping Experience" and "Privacy Concern" strongly converged

onto a single factor. This empirical convergence demonstrates that the desire for personalization and privacy anxiety are co-activated dimensions in cosmetic e-commerce, which the authors relabeled as Personalization Risk Management (F1_RR). Consequently, the initial seven independent dimensions were restructured into six distinct factors. All factors satisfy convergent and discriminant validity, making them fully suitable for subsequent Pearson correlation and OLS regression analyses.

4.3. Exploratory Factor Analysis (EFA) for the dependent variable

A separate EFA for the dependent variable, User Satisfaction, also confirmed robust structural validity (Table 5).

The KMO value was 0.732 ($p < 0.001$), and the analysis extracted a single component explaining 77.28% of the total variance, verifying the construct's unidimensionality.

Table 5. Results of total variance analysis extracted for the dependent variable

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.318	77.277	77.277	2.318	77.277	77.277
2	0.361	12.080	89.358			
3	0.319	10.642	100.000			

(Source: Data from SPSS 22)

4.4. Structural model and hypothesis testing

4.4.1. Pearson correlation analysis

Pearson correlation analysis confirmed that all six independent factors positively and significantly correlate with User Satisfaction ($p < 0.01$). Personalization Risk Management (F1_RR) exhibited the strongest relationship ($r = 0.441$), while the Machine Learning

Algorithm (F2_TT) showed the lowest ($r = 0.214$). A moderate inter-correlation between F1_RR and F2_TT ($r = 0.706$) necessitated rigorous VIF diagnostics in the subsequent regression.

4.4.2. Model fit and ANOVA

To test the proposed hypotheses and estimate the causal impact of the AI-related factors, an Ordinary Least Squares (OLS) multiple regression analysis was conducted.

Table 6. Results of reliability and autocorrelation tests

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.788 ^a	.622	.607	.45432	1.990

(Source: Data from SPSS 22)

Table 6 indicates a highly significant model fit ($F = 43.008$, $p < 0.001$). The Adjusted R^2 value is 0.607, indicating that the six independent factors collectively explain 60.7% of the variance in User Satisfaction. Furthermore, the Durbin-Watson statistic is 1.990, which falls perfectly within the acceptable range of 1.5 to 2.5, confirming the absence of first-order autocorrelation in the residuals.

4.4.3. Regression coefficients and hypothesis testing

OLS regression results: Collinearity statistics reveal that the Variance Inflation Factor (VIF) values for all predictors range from 1.022 to 2.101. Since all VIF values are well below the stringent threshold of 3.0 (and the conventional threshold of 10.0), severe multicollinearity does not distort the regression estimates.

Table 7. Results of Convergent Linear Regression Analysis

Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	beta			Tolerance	VIF
1	(Constant)	-1.442	.316		-4.562	.000		
	F1_RR	.617	.082	.531	7.498	.000	.481	2.079
	F2_TT	-.177	.072	-.175	-2.464	.015	.476	2.101
	F3_DL	.166	.036	.230	4.620	.000	.968	1.033
	F4_TC	.238	.037	.317	6.367	.000	.972	1.029
	F5_HV	.287	.046	.311	6.194	.000	.953	1.049
	F6_HI	.237	.032	.371	7.485	.000	.978	1.022

(Source: Data from SPSS 22)

Based on the results of the Exploratory Factor Analysis (EFA), the empirical research model has been modified relative to the initial theoretical model. Specifically, the two constructs “Personalized Shopping Experience” and “Anxiety” converged into a single

factor, which the research team labeled as Personalization Risk (F1_RR).

As a result of this adjustment to the data structure, the original seven hypotheses were revised to six (H1_New to H6_New), corresponding to the six independent variables in the OLS regression model.

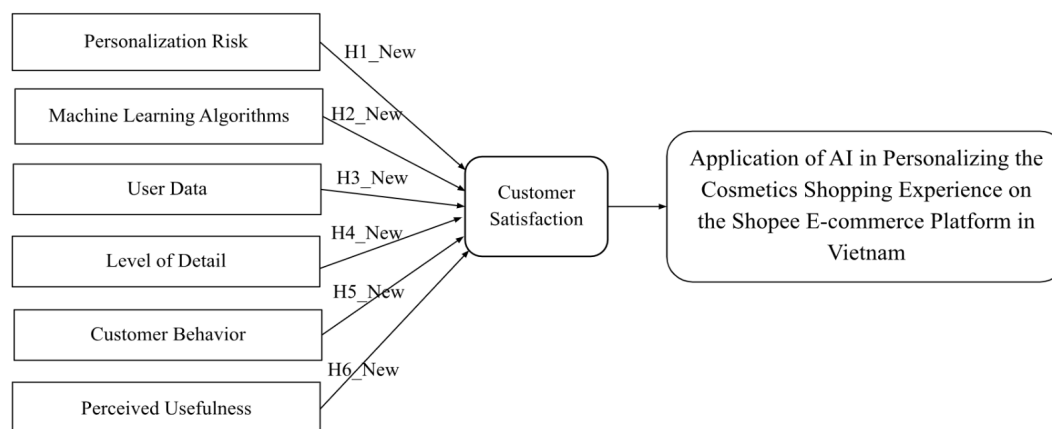


Figure 2. Results of the Model Testing

H1 (Accepted): Personalization Risk Management (F1_RR) exerts the strongest positive effect ($\beta = 0.531$, $p < 0.001$). Effectively managing the dual psychology of personalization desire and privacy anxiety significantly increases satisfaction.

H2 (Rejected): The Machine Learning Algorithm (F2_TT) shows a negative effect ($\beta = -0.175$, $p = 0.015$), implying that mechanical algorithmic

automation without domain-specific calibration actively harms satisfaction.

H3 (Accepted): User Data Quality (F3_DL) positively influences satisfaction ($\beta = 0.230$, $p < 0.001$).

H4 (Accepted): Trust Level (F4_TC) significantly and positively predicts satisfaction ($\beta = 0.317$, $p < 0.001$), confirming its role as a psychological bridge between AI capability and consumer acceptance.

H5 (Accepted): Accurate Customer Behavioral Recognition (F5_HV) positively affects satisfaction ($\beta = 0.311$, $p < 0.001$), supporting the S-O-R proposition that behavioral stimuli shape organism states and subsequent responses.

H6 (Accepted): Perceived Usefulness (F6_HI) is the second strongest positive predictor ($\beta = 0.371$, $p < 0.001$), aligning with UTAUT2 performance expectancy constructs.

4.5. Discussion

4.5.1. Theoretical contributions

This study makes two key theoretical contributions. First, it empirically validates the integration of the S-O-R and UTAUT2 frameworks in the context of AI personalization, showing that consumer responses are influenced by both functional acceptance (e.g., performance and effort expectancy) and emotional factors such as trust and perceived risk. Second, the merging of Personalized Shopping Experience and Privacy Concern into a single Personalization Risk factor extends the privacy paradox theory. In AI-driven cosmetic e-commerce, personalized recommendations require sensitive personal data, increasing concerns about privacy, data misuse, and algorithmic monitoring.

Unlike low-involvement products, cosmetic purchases are closely linked to skin compatibility and personal appearance, making inaccurate AI recommendations more consequential. As a result, the desire for personalization and privacy concerns emerge simultaneously rather than independently, explaining why effective personalization risk management is the strongest determinant of customer satisfaction in AI-based cosmetic shopping.

4.5.2. The algorithmic misfit effect in high-involvement categories

The negative impact of the Machine Learning Algorithm factor (H2 rejected) is one of the study's most significant findings, challenging the assumption that greater algorithmic sophistication always enhances consumer experience. In cosmetic shopping, inaccurate recommendations-such as unsuitable foundation shades, incompatible ingredients, or allergen exposure-may have physiological consequences, making users highly sensitive to algorithmic errors. This finding supports the literature on algorithm aversion and highlights the need for domain-specific AI calibration in high-risk product categories.

The negative effect may also result from AI systems relying too heavily on historical behavioral data, such as browsing history and past purchases. Since skincare conditions and beauty needs constantly change due to environmental and physiological factors, poorly calibrated algorithms may generate repetitive, irrelevant, or unsuitable recommendations, thereby reducing trust and overall shopping satisfaction.

4.5.3. Practical implications

These findings provide practical implications for e-commerce stakeholders. Platforms such as Shopee should prioritize transparent data governance, strengthen user privacy protections, and develop skin-type-specific AI systems beyond generic recommendation models. Enhancing explainable AI and calibrating algorithms to the unique characteristics of cosmetic consumer behavior are also essential for improving trust and the effectiveness of personalization. Cosmetic sellers should responsibly use behavioral data to optimize

product listings and integrate post-purchase feedback into recommendation systems. In addition, the findings support policymakers in strengthening personal data protection regulations, such as Vietnam's Decree No. 13/2023/ND-CP, particularly regarding biometric data collected by commercial AI systems.

V. Conclusion and recommendation

This study provides empirical evidence that AI personalization significantly influences customer satisfaction in cosmetic shopping on Shopee. The findings indicate that five AI-related factors positively affect satisfaction, with Personalization Risk Management showing the strongest impact, while poorly calibrated Machine Learning Algorithms negatively influence customer experience. The integrated S-O-R and UTAUT2 framework effectively explains both functional and emotional aspects of AI-driven shopping behavior, contributing to the theoretical understanding of consumer behavior in e-commerce.

Based on the findings, several practical recommendations are proposed. E-commerce platforms should enhance AI transparency, data security, and personalized recommendation systems to predict customer needs better and reduce personalization risks. Cosmetic sellers should standardize product information and combine AI-based recommendations with human consultation. Policymakers are encouraged to strengthen regulations on personal data protection and supervise commercial AI applications.

Despite its contributions, this study has some limitations, including the use of convenience sampling and a relatively small sample size ($n = 229$), which may limit generalizability. Future research

should adopt probability sampling and qualitative methods to explore further the relationship between personalized experiences and users' data anxiety, thereby improving the theoretical model and research reliability.

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TÁC ĐỘNG CỦA ỨNG DỤNG TRÍ TUỆ NHÂN TẠO ĐẾN TRẢI NGHIỆM MUA SẮM MỸ PHẨM CÁ NHÂN TRÊN NỀN TẢNG THƯƠNG MẠI ĐIỆN TỬ SHOPEE TẠI VIỆT NAM

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Tóm tắt: Các tác giả nghiên cứu tác động của ứng dụng trí tuệ nhân tạo (AI) đến trải nghiệm mua sắm mỹ phẩm cá nhân hóa trên nền tảng thương mại điện tử Shopee tại Việt Nam. Nhóm nghiên cứu đề xuất 7 giả thuyết nhằm xem xét cách các yếu tố liên quan đến AI ảnh hưởng đến sự hài lòng của người dùng. Sử dụng phương pháp định tính và định lượng với dữ liệu khảo sát từ 229 người trả lời và được phân tích bằng SPSS 22. Kết quả cho thấy 5 yếu tố gồm: Rủi ro cá nhân hóa, Nhận thức về tính hữu ích, Mức độ tin cậy, Hành vi tiêu dùng khách hàng và Chất lượng dữ liệu người dùng có tác động tích cực có ý nghĩa thống kê đến sự hài lòng của người dùng ảnh hưởng đến ứng dụng AI, trong khi chất lượng thuật toán học máy khi được áp dụng một cách máy móc mà không hiệu chỉnh theo đặc thù lĩnh vực lại có tác động tiêu cực. Những phát hiện này đóng góp góc nhìn thực nghiệm mới về việc ứng dụng AI trong cá nhân hóa nhóm sản phẩm có mức độ tham gia cao, đồng thời đưa ra các khuyến nghị, giải pháp thực tiễn cho nhà phát triển nền tảng, người bán mỹ phẩm và cơ quan quản lý nhà nước

Từ khóa: trí tuệ nhân tạo, mỹ phẩm, thương mại điện tử, cá nhân hóa, sự hài lòng của người dùng

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