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AI-Based Recommendation System, FOMO, and Online Impulse Buying Behavior: An S-O-R Perspective

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Abstract

This study examines how AI-based recommendation system features influence online impulse buying behavior through the mediating role of fear of missing out (FOMO), based on the Stimulus-Organism-Response (S-O-R) framework. Using data from 365 online shoppers analyzed with PLS-SEM, four system attributes: accuracy, diversity, portability, and visual appeal were tested as stimuli affecting consumer responses. The structural and mediation analyses revealed that portability (β = 0.161, p < 0.001) and visual appeal (β = 0.238, p <0.01) significantly enhanced FOMO, which in turn increased impulse buying behavior (β = 0.350, p < 0.001). In contrast, accuracy (β = –0.101, p < 0.05) showed a negative effect, and diversity (β = 0.089, p = 0.051) showed no significant impact. FOMO fully mediated the relationships between portability, visual appeal, and impulse buying, confirming its central emotional role. Theoretically, the findings extend the S-O-R framework to AI-driven shopping environments by emphasizing emotional rather than purely functional system effects. Practically, enhancing visual appeal and portability can effectively boost user engagement, but ethical considerations are crucial to avoid excessive psychological influence.

Keywords: AI-based recommendation system, fear of missing out, mobile shopping application, online impulse buying behavior, stimulus-organism-responses (S-O-R) model.

1. Introduction

The rapid development of technology has significantly transformed shopping habits, with e-commerce showing remarkable growth, especially after the COVID-19 pandemic. According to Statista Market Forecast (2024), global e-commerce revenue surged by 66.5%, from USD 1.93 trillion in 2019 to USD 3.22 trillion in 2021, and is expected to reach USD 5.89 trillion by 2029. Mobile shopping has become a major trend, with mobile e-commerce usage rising from 33.8% in 2017 to a projected 58.7% by 2028 (Statista Market Forecast, 2024). In early 2024, mobile shopping apps in the U.S. generated USD 280.4 billion in sales, 47.7% of total online purchases, while over 76% of smartphone users shopped via mobile apps (Quickway Infosystems, 2025).

Vietnam reflects this global shift, emerging as one of Southeast Asia's most dynamic e-commerce markets. In the first half of 2024, Vietnamese consumers spent approximately 143.9 trillion VND (USD 5.68 billion) on online platforms, representing a 55% increase in transaction value and a 66% rise in purchase volume compared to 2023. Between 2020 and 2024, the country's e-commerce sector achieved an annual growth rate from 16% to 30% (Vu, 2024). Notably, 96% of Vietnamese consumers shop via smartphones, which account for 70% of online purchases (Payment & Commerce Market Intelligent, 2024).

Since OpenAI's release of ChatGPT in 2022 (Wong et al., 2023), artificial intelligence (AI) has become transformative across numerous fields, including education, customer service, and business. In e-commerce, AI is widely used to enhance personalization and user experience through recommendation systems (Yin et al., 2025). The market for AI-based recommender systems reached USD 2.8 billion in 2023 and is projected to grow to USD 34.4 billion by 2033, with a CAGR of 28.5% (Shinde, 2024). Major platforms such as Amazon, Taobao, Shopee, and TikTok Shop invest heavily in AI to analyze user behavior and provide tailored product suggestions. Amazon alone allocates 35% of its sales to recommendation engine development (Market.us, 2024).

From a consumer perspective, personalization strongly influences shopping behavior. Forbes Technology Council (2025) reports that 71% of consumers expect personalized suggestions, while 91% are more likely to engage with brands offering customized recommendations. This personalization trend also affects impulse buying, which has become a major contributor to retail sales. According to Capital One Shopping Research (2025), 89% of U.S. shoppers make impulse purchases, with 54% spending over USD 100 impulsively.

Recent studies have increasingly explained AI-based recommendation systems in e-commerce, making this a new direction of research (Valencia-Arias et al., 2024). Some researchers have focused on expanding recommendation systems with AI techniques (Pujastuti et al., 2022; Tahir et al., 2021; Wang & Qiu, 2021), while others have explored how these systems enhance customer experience and sales (Zhao et al., 2025). However, Valencia-Arias et al. (2024) identified four key research gaps, including the limited investigation of personalized recommendations from a psychological perspective and the modest number of studies on the impact of AI-driven recommendation systems on consumer behavior.

Impulse buying behavior is another well-studied topic that continues to attract global research interest. Redine et al. (2023) reported that scholars from many countries have examined this behavior, mainly in e-commerce and traditional retail contexts. Ampadu et al. (2022), for example, analyzed how recommended product quality affects e-impulse buying, mediated by affective image and satisfaction, and moderated by online reviews. Similarly, Floh and Madlberger (2013) applied the Stimulus-Organism-Response (S-O-R) model to explore how virtual atmospheric cues influence online impulse purchases. Despite these contributions, gaps remain, particularly concerning mobile commerce contexts, time- and quantity-limited deals, and research in developing countries (Redine et al., 2023).

To address these gaps, this study explores the impact of AI-based recommendation systems on consumer behavior, focusing specifically on impulse buying in Vietnam's mobile commerce (m-commerce) context. Employed in the S-O-R framework, the study aims to provide insights into how AI-driven recommendations influence consumer decision-making and emotional responses. The research follows four objectives:

(1) To identify external factors of AI-based recommendation systems affecting consumer decisions in Vietnamese mobile shopping;
(2) To examine the internal psychological state, called fear of missing out, triggered by AI-driven systems;

(3) To analyze the relationship between the internal state and online impulse buying through the S-O-R model;

(4) To offer practical insights for Vietnamese e-commerce platforms to enhance sales through personalized AI strategies.

A quantitative approach was conducted using an online questionnaire survey. Descriptive statistics were analyzed with SPSS 29.0, while Partial Least Squares-Structural Equation Modeling (PLS-SEM) using SmartPLS 4 was employed to test and validate the proposed model, including moderating effects.

2. Literature Review

2.1 The Stimulus-Organism-Response Model

The Stimulus-Organism-Response (S-O-R) model, developed by Mehrabian and Russell (1974), explains how external stimuli influence individuals' internal states and, consequently, their behaviors (Zhu et al., 2023). It includes three components: Stimulus (external factors), Organism (cognitive and emotional reactions), and Response (observable behaviors), with the Organism mediating between Stimulus and Response (Erensoy et al., 2024). This study adopts the S-O-R framework for two main reasons: (1) it is a well-established model widely applied in impulse buying research, and (2) it provides a psychological approach to address existing gaps in studies on AI-based recommendation systems (Valencia-Arias et al., 2024).

The S-O-R model has been extensively used to examine impulse buying in both online and offline contexts. For example, Floh and Madlberger (2013) investigated the effect of online atmospheric cues, while Xu et al. (2020) studied social interactions and self-control in social commerce. Djafarova and Bowes (2021) found that Instagram stimuli like ads and influencer content trigger unplanned purchases, and Erensoy et al. (2024) applied the model in virtual reality retail. In this study, AI-based recommendation systems act as external stimuli influencing shoppers' psychological state, ultimately leading to impulse buying behavior in the online environment.

2.2 AI-based recommendation systems in m-commerce

2.2.1. The concept of AI-based recommendation system in m-commerce

Mobile commerce (m-commerce) is a subcategory of e-commerce involving transactions via mobile devices (Ngai & Gunasekaran, 2007). It enables consumers to search for product information, make purchases, and complete payments anytime and anywhere through smartphones or tablets. Common examples of m-commerce include mobile shopping platforms such as Amazon, Shopee, and Lazada, where users can browse and buy products, as well as mobile payment and financial services like Apple Pay, KakaoPay, and PayPal, which facilitate secure and convenient transactions. The widespread use of these mobile applications has significantly transformed consumer shopping behavior by enhancing accessibility, personalization, and real-time engagement (Li et al., 2021).

With the rise of big data and complex consumer behavior, artificial intelligence (AI) has been integrated into these systems to enhance accuracy and overcome issues like missing data (Valencia-Arias et al., 2024). AI-based recommendation systems autonomously generate ranked, personalized product suggestions using advanced algorithms (Wien & Peluso, 2021). For instance, Amazon's AI engine recommends relevant products and uses voice assistants like Amazon Echo for personalized shopping (Zhu et al., 2023). Similarly, platforms such as Shopee, Lazada, and TikTok Shop provide tailored product suggestions and voucher ads based on user interactions, supporting both sales growth and the "long-tail effect" by promoting niche products (Necula & Păvăloaia, 2023).

Research on AI-based recommendation systems continues to expand. Wien and Peluso (2021) compared trust in AI versus human recommendations, while Ampadu et al. (2022) found that perceived product quality and satisfaction mediate e-impulse buying behavior. Zhao et al. (2025) revealed that personalized recommendations influence purchase intentions through psychological needs like competence and relatedness. Finally, Zhang et al. (2021) and Valencia-Arias et al. (2024) reviewed existing studies, identifying major gaps and directions for future research in AI-driven recommender systems.

2.2.2. Dimensions of the AI-based Recommendation System

Recommendation systems are evaluated using various metrics; however, accuracy and diversity are regarded as two of the most essential dimensions defining the quality of AI-driven recommendation systems (Kunaver & Požrl, 2017; Valencia-Arias et al., 2024; Zhao et al., 2025). In addition, compared with other shopping platforms such as websites or physical stores, mobile commerce (m-commerce) possesses unique characteristics, particularly portability and visual appeal (Yang et al., 2021). Therefore, this study considers these four factors, including accuracy, diversity, portability, and visual appeal, as environmental stimuli (S) in the S-O-R model.

Accuracy refers to how precisely the recommended products align with users' actual needs and preferences (Zhao et al., 2025). The integration of artificial intelligence (AI) into recommendation systems has significantly improved this dimension by enabling more personalized and data-driven predictions (Valencia-Arias et al., 2024). Diversity, on the other hand, represents the variation among the recommended items. Rather than compromising between accuracy and diversity, modern AI algorithms can enhance both simultaneously, providing users with a broader and more engaging shopping experience (Kunaver & Požrl, 2017).

Portability is a defining feature of m-commerce, allowing consumers to shop anytime and anywhere using mobile devices. Unlike desktop-based e-commerce or physical retail, m-commerce enables real-time interactions and instant personalized recommendations, regardless of the user's location (Yang et al., 2021). Finally, visual appeal involves the use of rich visual and aesthetic elements, such as color, layout, animation, and imagery, to create engaging, emotionally appealing product presentations (Chen et al., 2019). Because mobile screens are smaller than desktop displays, optimizing design for clarity and enjoyment is crucial.

Collectively, accuracy, diversity, portability, and visual appeal represent the core environmental factors influencing user perception and impulse buying behavior in AI-based mobile commerce environments.

2.3. Fear of Missing Out (FOMO)

2.3.1. The concepts of Fear of Missing Out

As social media platforms and apps like WeChat, Twitter, and TikTok continue to develop rapidly, many individuals have grown increasingly dependent on them. This growing dependence has introduced a new concept, called "fear of missing out" (FOMO), which describes the persistent concern that others might be experiencing enjoyable or rewarding moments without one's involvement (Li et al., 2021). According to Good and Hyman (2021), FOMO has been associated with various personality characteristics, levels of social connectedness, and excessive or problematic use of the internet, social media, and mobile applications.

The concept of FOMO has become deeply ingrained in popular culture and youth psychology, as evidenced by the widespread presence of FOMO-related content and advertising campaigns across digital platforms. Marketers frequently use FOMO appeals, particularly in travel promotions and youth-oriented products, to stimulate consumer demand and engagement (Hodkinson, 2019).

2.3.2 AI-Based Recommendation System and FOMO

The accuracy of an AI recommender enhances users' perception of product value and reliability, leading them to believe that they might miss out on highly suitable deals or items if they delay their purchase decisions. According to the S–O–R framework, this heightened perception of relevance can evoke psychological arousal, such as FOMO, which motivates users to engage immediately (Mehrabian & Russell, 1974). Therefore, accurate and tailored recommendations are likely to intensify FOMO during online shopping.

H1. Accuracy of AI recommendations positively influences fear of missing out (FOMO).

Diversity in recommendation systems broadens the customer-perceived choice. Exposure to diverse product options can simultaneously increase excitement and uncertainty, leading users to fear missing potentially better alternatives (Good & Hyman, 2021). From the perspective of the S-O-R model, this abundance of choices acts as an external stimulus that triggers internal psychological tension and amplifies FOMO.

H2. Diversity of AI recommendations positively influences fear of missing out (FOMO).

Mobile accessibility promotes constant connection and instant notifications, which may create a sense of urgency and enhance users' awareness of limited-time offers or social updates (Okazaki & Mendez, 2013). This "always-on" environment intensifies the perception that one might miss out on opportunities, thus stimulating FOMO.

H3. Portability of AI recommendation systems positively influences fear of missing out (FOMO).

Attractive visuals can capture users' attention and generate emotional arousal, encouraging spontaneous responses (Childers et al., 2001). When visually appealing product recommendations are combined with cues like popularity indicators or limited-time offers, they can trigger FOMO by making users feel they may lose an appealing opportunity.

H4. Visual appeal of AI recommendation interfaces positively influences fear of missing out (FOMO).

2.4. Impulse Buying Behavior

Impulse buying behavior is a well-established topic in consumer psychology. Since the 1940s, researchers have examined this phenomenon, as unplanned purchases account for 40-80% of total consumer spending (Rodrigues et al., 2021). Impulse buying behavior refers to spontaneous, irresistible urges to purchase immediately (Chen et al., 2019), while online impulse buying (or e-impulse buying) describes similar unplanned purchases made through digital platforms (Ampadu et al., 2022). Psychologically, impulse buying is driven by strong emotional arousal and minimal rational evaluation; consumers often act on immediate desires despite potential negative consequences (Rodrigues et al., 2021). This behavior has long contributed significantly to retail sales and was further amplified during the COVID-19 pandemic (Redine et al., 2023).

Technological developments and new marketing practices have renewed interest in impulse buying research. In physical retail settings, Bellini and Aiolfi (2019) found that mobile phone use enhances consumers' tendency to buy impulsively, while Chen et al. (2019) demonstrated that emotional trust toward the recommender and positive affect toward recommended products strongly influence impulse purchases. In the digital environment, Chen et al. (2019) used Signaling Theory to explain how product suggestions in WeChat commerce stimulate impulse buying. Similarly, Vazquez et al. (2020) revealed that parasocial interactions with influencers on social media can trigger impulsive purchases. Redine et al. (2023) synthesized global research on impulse buying, emphasizing the shift from traditional to online contexts. Their conceptual framework outlined major antecedents, mediators, and research gaps, offering a foundation for future studies on impulsive consumer behavior in digital environments.

When investigating the relationship between FOMO and Impulse buying behavior, Çelik et al. (2019) found that FOMO toward sales promotions increases impulse purchasing behavior, which in turn leads to post-purchase regret. Similarly, Saleh (2012) reported that FOMO stimulates impulsive buying as consumers fear missing out on special offers or products. Therefore, FOMO acts as a strong psychological driver of online impulse buying, especially in digital environments where time-limited promotions and persuasive marketing messages amplify consumers' sense of urgency. Hypothesis 5 was proposed:

H5. Fear of missing out (FOMO) positively influences online impulse buying behavior (IBB).

3. Methodology

3.1 Research Framework

This study seeks to examine how external stimuli, specifically the characteristics of AI-based recommendation systems, affect online impulse buying behavior, with FOMO acting as a

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mediating variable. The research is structured around the Stimulus-Organism-Response (S-O-R) framework, as proposed in Figure 1.

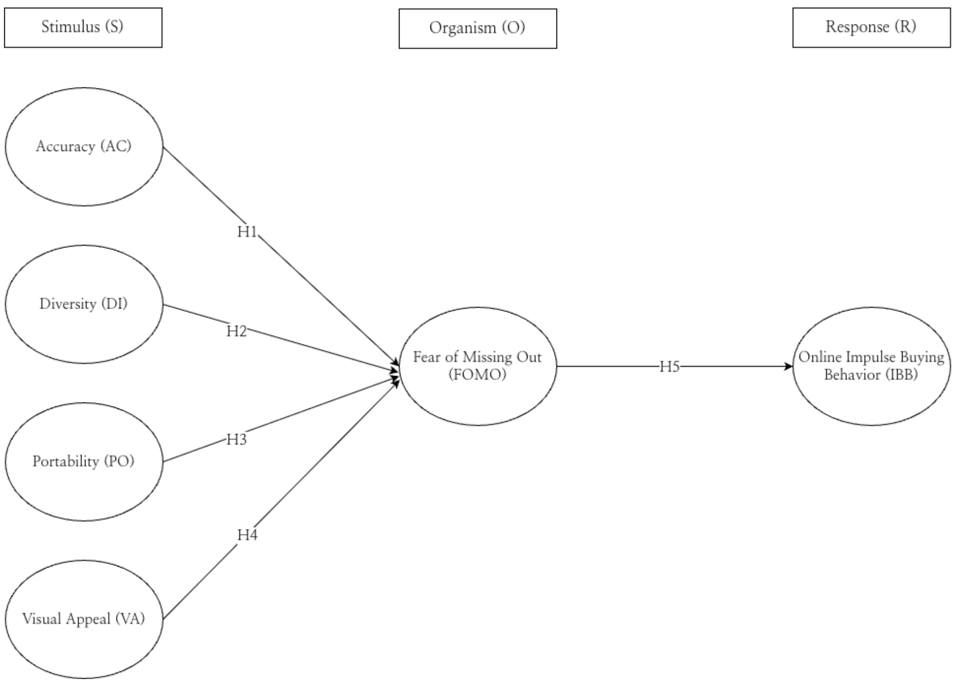

Figure 1. Research Framework

2.2 Construction of the questionnaire and data collection

This study targets individuals with prior mobile shopping experience. The questionnaire first verifies participants' use of mobile shopping apps; only those with experience continue to the main section, which includes measurement items and demographic questions. Six constructs, accuracy, diversity, portability, visual appeal, fear of missing out, and online impulse buying behavior, are evaluated using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), as detailed in Table 1.

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Table 1. Measurement Items for Constructs in the Research Model

Constructs			Items	References
Stimuli (S)	Accuracy (AC)	AC1	The products recommended in mobile shopping apps are of interest to me.	Zhao et al. (2025)
		AC2	Mobile shopping apps understand my needs and preferences for products.	
		AC3	The recommended products in mobile shopping apps match my interests.	
	Diversity (DI)	DI1	Mobile shopping apps recommend a wide of goods.	Zhao et al. (2025)
		DI2	Mobile shopping apps recommend products that satisfy different aspects of my interests.	
		DI3	The recommended items include multiple brands or types.	
	Portability (PO)	PO1	These services are practical because I can use them easily wherever I am.	Okazaki and Mendez (2013)
		PO2	Using these services outside my home or workplace is convenient for me.	
		PO3	I find these services convenient because they do not depend on any fixed location.	
	Visual	VA1	The graphics in the	Chen et al.

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	appeal (VA)		recommendation posts are attractive.	(2019)
		VA2	The product recommendation posts are visually pleasing.	
		VA3	The product recommendation posts look lively and engaging.	
		VA4	The product recommendation posts capture my visual interest.	
Organism (O)	Fear of missing out (FOMO)	FOMO1	I often open shopping apps because I fear missing out on recommended products or promotions.	(Good & Hyman, 2021; Li et al., 2021)
		FOMO2	I feel uneasy thinking that others might buy better products recommended by AI that I have not seen.	
		FOMO3	I worry about being left behind if I do not follow the trending products recommended to me.	
		FOMO4	I feel regretful when I miss a discounted or recommended product that my friends have already purchased.	
Response (R)	Online impulse buying behavior (IBB)	IBB1	I often buy things impulsively.	Ampadu et al. (2022)
		IBB2	If I see something I like and have the money, I buy it.	
		IBB3	I sometimes buy things without	

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	much thought.
IBB4	I occasionally "treat myself" with unplanned purchases.
IBB5	My mood at a particular moment can drive me to buy things.

This study used a modified S-O-R model to examine FOMO's mediation in online impulse buying, surveying 359 Vietnamese users of AI-based mobile shopping apps from July 15 to August 15, 2025 via Google Form. Data were analyzed with SPSS and SmartPLS 4, and hypotheses were tested using PLS-SEM, ensuring reliability, validity, and statistical robustness.

4. Results

4.1 Demographic information

Among the 359 valid respondents, 222 were female (61.8%) and 137 were male (38.2%), indicating a higher proportion of female participants. Most were in their 30s (60.2%), followed by those in their 20s (28.4%), with smaller proportions in their 40s (11.1%) and one respondent in their 50s. Regarding education, the majority held an undergraduate degree (67.7%), while postgraduate and vocational school graduates accounted for 11.7% and 11.1%, respectively; 9.5% had completed high school or below.

In terms of marital status, 76% were single and 24% married. Geographically, 44% resided in Northern Vietnam, 40.1% in the South, and 15.9% in the Central region. For monthly income, most respondents (67.1%) earned from 10 to 20 million VND, while approximately 15% earned less than 10 million VND or between 20 and 30 million VND.

4.2 Reliability and validity test

The measurement model was assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate reliability and validity. Reliability and validity were tested through outer loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance

Extracted (AVE). All outer loadings exceeded the recommended threshold of 0.708, except HM5 (0.707), which was retained due to its theoretical contribution. Cronbach's alpha values ranged from 0.718 to 0.888, and CR values ranged from 0.837 to 0.913, indicating strong internal consistency and reliability across all constructs. Convergent validity was confirmed through AVE values above the acceptable threshold, ensuring that the indicators adequately reflected their respective constructs. Convergent validity was assessed using Average Variance Extracted (AVE), with values above 0.50 indicating adequacy (Hair et al., 2019). As shown in Table 2, all constructs exceeded this threshold, confirming satisfactory convergent validity.

Table 2. Reliability and Validity Test Results

Constructs	Items	Loadings	Cronbach's alpha	CR	AVE
Accuracy	AC1	0.767	0.718	0.837	0.632
	AC2	0.792			
	AC3	0.824			
Diversity	DI1	0.885	0.787	0.872	0.696
	DI2	0.889			
	DI3	0.716			
Portability	PO1	0.765	0.815	0.888	0.726
	PO2	0.862			
	PO3	0.922			
Visual appeal	VA1	0.735	0.796	0.868	0.624
	VA2	0.887			
	VA3	0.833			
	VA4	0.688			
Fear of missing out	FOMO1	0.838	0.872	0.912	0.723
	FOMO2	0.885			
	FOMO3	0.834			
	FOMO4	0.842			

Online impulse buying behavior	IBB1	0.785	0.881	0.913	0.678
	IBB2	0.770			
	IBB3	0.821			
	IBB4	0.902			
	IBB5	0.834			

Note. CR: Composite Reliability, AVE: Average Variance Extracted

To assess discriminant validity, three commonly applied methods are used, including: cross-loadings, the Fornell–Larcker criterion, and the Heterotrait–Monotrait ratio (HTMT).

In the cross-loading assessment, each indicator is expected to load more strongly on its associated construct than on any other construct (Hair et al., 2019). The results showed that all items in this study exhibited higher loadings on their respective constructs than on others, indicating an acceptable level of discriminant validity.

At the construct level, discriminant validity was further examined using the Fornell–Larcker criterion (Fornell & Larcker, 1981). This approach stipulates that the square root of the Average Variance Extracted (AVE) for each construct should exceed its highest correlation with any other construct. The results shown in Table 3 confirmed that each construct captures a unique conceptual domain rather than reflecting overlap with other latent variables.

Table 3. Discriminant Validity Results (Fornell-Lacker Criterion)

	AC	DI	FOMO	IBB	PO	VA
AC	**0.795**					
DI	-0.069	**0.834**				
FOMO	-0.127	0.143	**0.850**			
IBB	-0.056	0.149	0.347	**0.824**		
PO	-0.034	0.075	0.261	0.165	**0.852**	
VA	-0.058	0.171	0.317	0.186	0.377	**0.790**

Note. Values in bold represent the square root of the variance extracted (AVE), and the values outside the diagonal represent the correlations between the constructs. AC: Accuracy, DI: Diversity, PO: Portability, VA: Visual Appeal, FOMO: Fear of Missing Out, IBB: Impulse Buying Behavior

To strengthen these assessments, a more rigorous test of discriminant validity was performed using the Heterotrait-Monotrait (HTMT) ratio proposed by Henseler et al. (2015). According to the recommended threshold of 0.90 (Franke & Sarstedt, 2019; Hair et al., 2019), values below this level indicate satisfactory discriminant validity. As presented in Table 4, all HTMT values fell below the threshold, thereby confirming the distinctiveness of the constructs and the robustness of the measurement model.

Table 4. Discriminant Validity Results (Heterotrait-Monotrait ratio (HTMT))

	AC	DI	FOMO	IBB	PO	VA
AC						
DI	0.103					
FOMO	0.156	0.159				
IBB	0.073	0.176	0.383			
PO	0.063	0.092	0.299	0.180		
VA	0.118	0.203	0.372	0.227	0.478	

Note. AC: Accuracy, DI: Diversity, PO: Portability, VA: Visual Appeal, FOMO: Fear of Missing Out, IBB: Impulse Buying Behavior

4.3 Hypothesis testing

The structural model was evaluated using standardized path coefficients (β), t-statistics, and p-values to test the hypothesized relationships among constructs. As shown in Table 5, the results indicate that the path from accuracy to FOMO had a significant impact (p = 0.034) but opposite direction to the hypothesis positive relationship (*β=-0.101)*, therefore H1 was not supported. Similarly, diversity did not significantly influence FOMO (β = 0.089, t = 1.948, p = 0.051), thus H2 was not supported.

In contrast, portability exhibited a significant positive effect on FOMO (β = 0.161, t = 2.714, p < 0.001), providing support for H3. Likewise, visual appeal had a strong positive influence on FOMO (β = 0.238, t = 4.579, p = 0.007), supporting H4. Finally, FOMO showed a significant positive effect on impulse buying behavior (β = 0.350, t = 7.419, p < 0.001), confirming H5.

Overall, these findings highlight that while accuracy and diversity did not significantly predict FOMO, portability and visual appeal were important antecedents of FOMO. Furthermore, FOMO served as a key driver of impulse buying behavior, emphasizing its mediating role in the model.

Table 5. Hypothesis Testing Results

	Paths	Path Coefficient (β)	Standard Deviation	*t* statistics	*p*-values	Results
H1	AC->FOMO	-0.101	0.048	2.125	**0.034**	**Not Supported**
H2	DI->FOMO	0.089	0.046	1.948	**0.051**	**Not Supported**
H3	PO-> FOMO	0.161	0.059	2.714	<0.001	Supported
H4	VA -> FOMO	0.238	0.053	4.579	0.007	Supported
H5	FOMO -> IBB	0.350	0.047	7.419	<0.001	Supported

Note. AC: Accuracy, DI: Diversity, PO: Portability, VA: Visual Appeal, FOMO: Fear of Missing Out, IBB: Impulse Buying Behavior

4.4 Mediation Effect Results

Table 6 presents the results of the mediation analysis using the percentile bootstrapping method with a 95% confidence interval. The table summarizes the direct, indirect, and total effects of the independent variables, accuracy (AC), diversity (DI), portability (PO), and visual appeal (VA), on impulse buying behavior (IBB), along with their corresponding significance levels.

For accuracy (AC), both direct and indirect effects on impulse buying through FOMO are insignificant ($p > 0.05$), indicating that recommendation accuracy does not evoke FOMO or impulsive behavior. Similarly, for diversity (DI), neither direct nor indirect effects are significant, with only a marginal total effect ($p < 0.05$), suggesting a weak or indirect association with impulse buying not mediated by FOMO. In contrast, portability (PO) shows a significant indirect effect through FOMO, supporting full mediation: when platforms are accessible and convenient, FOMO increases, driving impulsive purchases. Visual appeal (VA) also exhibits full mediation, with a significant indirect effect via FOMO but a non-significant direct effect. Overall, these results highlight that emotional arousal from FOMO mediates the influence of experiential features, like portability and visual appeal, on online impulse buying, while informational features such as accuracy and diversity play minimal psychological roles.

Table 6. Mediation Effect Results

Paths	95% CI of percentile method: Lower	Upper	Two-tailed test *p*-value	Mediation Result
AC ->FOMO ->IBB				
Direct effect	-0.120	0.115	>0.05	No mediation
Indirect effect	-0.066	-0.001	>0.05	
Total effect	-0.148	0.094	>0.05	
DI ->FOMO ->IBB				
Direct effect	-0.006	0.198	>0.05	No mediation
Indirect effect	-0.002	0.062	>0.05	
Total effect	0.022	0.225	<0.05	
PO ->FOMO ->IBB				
Direct effect	-0.056	0.178	>0.05	Full mediation
Indirect effect	0.014	0.094	<0.05	
Total effect	-0.011	0.231	<0.01	
VA ->FOMO ->IBB				
Direct effect	-0.065	0.165	>0.05	Full mediation
Indirect effect	0.031	0.126	<0.01	
Total effect	0.012	0.237	<0.05	

Note. AC: Accuracy, DI: Diversity, PO: Portability, VA: Visual Appeal, FOMO: Fear of Missing Out, IBB: Impulse Buying Behavior

5. Discussion

The findings of this study provide several insights into how AI-based recommendation system attributes influence FOMO and online impulse buying behavior, viewed through the lens of the Stimulus-Organism-Response (S-O-R) framework. The results suggest that users are more likely to experience FOMO when AI recommendations are easily accessible across platforms and presented with appealing visual cues. These results align with prior research emphasizing the importance of convenience and sensory appeal in stimulating emotional responses in digital environments (Chen et al., 2019; Okazaki & Mendez, 2013).

The findings of this study offer valuable insights into the mechanisms through which mobile media characteristics shape consumers' impulse buying behavior (IBB) through the mediating role of fear of missing out (FOMO). Consistent with the results of the structural model, accuracy (AC) had a negative effect and diversity (DI) was found to have no significant impact on FOMO, suggesting that the precision and variety of recommended products may not be strong triggers of psychological arousal leading to impulsive tendencies. This implies that users may already perceive recommended products as generally accurate and diverse, making these attributes less influential in stimulating FOMO. This result contrasts with the findings of Good and Hyman (2021), who identified accuracy and diversity as factors creating fear of missing out. An explanation for this inconsistency could be the contextual variations across studies, including differences in consumer behavior, cultural background, or the characteristics of the shopping environment investigated in the present research.

Highly accurate AI-based product recommendations enhance users' sense of personalization and control, reducing uncertainty and the need to explore other options, which lowers fear of missing out (FOMO). In Vietnam, many consumers value convenience and trust in mobile shopping apps, so precise recommendations make them feel confident they are not missing better products. In contrast, diversity of recommendations does not significantly influence FOMO. Vietnamese users are accustomed to seeing a wide range of products on platforms like Shopee and Lazada, and excessive variety may even cause decision fatigue, especially for low-involvement goods. Consequently, users respond more to recommendation accuracy than diversity when forming emotional reactions such as FOMO, highlighting the importance of personalization over variety in m-commerce.

In contrast, portability (PO) and visual appeal (VA) significantly influenced FOMO, underscoring the importance of media accessibility and aesthetic design in driving emotional engagement. The positive effect of PO indicates that mobile-friendly platforms and easy access to content enhance users' connectivity and the immediacy of social comparison, which in turn intensifies FOMO. Likewise, the strong influence of VA on FOMO highlights that visually engaging interfaces can capture users' attention and evoke emotional responses that contribute to impulsive consumption behaviors. The results were supported by Childers et al. (2001) and Okazaki & Mendez (2013).

Furthermore, FOMO exhibited a significant positive effect on impulse buying behavior, reaffirming its role as a key psychological driver in digital consumer contexts. This aligns with prior studies suggesting that heightened FOMO leads individuals to make spontaneous purchases to avoid social exclusion or missed opportunities, supported by Çelik et al., (2019) and Saleh (2012).

The mediation analysis further supports these interpretations and underscores the relevance of the S-O-R framework for this study, as the direct effects of mobile platform features on online impulsive buying behavior (IBB) were not significant. FOMO fully mediates the relationships between portability (PO) and IBB, and between visual appeal (VA) and IBB, indicating that these features influence unplanned purchases entirely through consumers' emotional responses. In other words, when mobile platforms are accessible and visually attractive, they trigger FOMO, which in turn prompts impulsive buying. Overall, these findings highlight FOMO as a central emotional mechanism linking technological affordances and consumer impulsivity, supporting the theoretical applicability of S-O-R in explaining how mobile platform characteristics drive online impulse purchases and offering practical guidance for digital marketing strategies.

6. Implications

The findings of this study contribute both theoretically and practically to the understanding of how AI-based recommendation system attributes shape online impulse buying behavior through the mediating role of FOMO, framed within the Stimulus-Organism-Response (S-O-R) paradigm.

From a theoretical perspective, this study enriches the literature on digital consumer psychology by identifying FOMO as a key emotional mechanism linking technological stimuli (portability and visual appeal) with impulsive behavioral responses. While previous research has mainly emphasized the cognitive aspects of recommendation systems (Chen et al., 2019; Park & Han, 2013; Zhu et al., 2023), this study highlights that emotional and sensory factors, like portability and visual appeal, strongly drive impulsive buying, extending the S-O-R framework to AI-driven mobile experiences.

From a practical perspective, the results provide insights for digital marketers, platform designers, and e-commerce practitioners. The significant influence of portability suggests that improving cross-platform accessibility and mobile responsiveness can enhance users' sense of immediacy and engagement, thereby amplifying their susceptibility to FOMO-driven purchases. Similarly, enhancing the visual appeal of online interfaces, through aesthetic layouts, high-quality imagery, or interactive displays, can evoke emotional excitement and increase impulse buying tendencies. Conversely, the non-significant effects of accuracy and diversity imply that users may already perceive these features as baseline expectations rather than differentiating stimuli. Therefore, marketers should prioritize experiential and emotional design strategies rather than focusing solely on informational accuracy or content variety to stimulate consumer responses.

Nevertheless, to promote ethical and responsible m-commerce practices, platforms should limit the frequency of urgency banners to reduce impulsive pressure, introduce cool-off reminders before one-click purchases, and provide a transparency checklist to clearly distinguish advertisements from AI-based recommendations. These measures help users make more informed and deliberate purchasing decisions.

7. Limitations and Future Research

Despite its valuable contributions, this study is not without limitations. First, the research employed a cross-sectional design, which limits causal inference. Future studies could adopt longitudinal or experimental methods to validate the temporal effects of AI-driven stimuli on FOMO and impulsive behavior.

Second, the sample may not fully represent all online consumers, as behavioral responses could vary across cultures, age groups, or product categories. Comparative studies across different cultural contexts or AI recommendation types (e.g., personalized vs. algorithmic-based) could offer broader generalizability.

Third, the study focused on four AI system attributes; other factors, such as personalization, trust, or perceived intrusiveness, may also shape FOMO and impulse buying. Future research should incorporate these variables to develop a more comprehensive understanding of consumer responses to AI-based systems.

Finally, while this study emphasized the psychological benefits of AI recommendations, ethical aspects, such as privacy concerns and algorithmic transparency, remain underexplored. Investigating these dimensions could help balance the commercial utility of AI with responsible technology design.

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References

Ampadu, S., Jiang, Y., Debrah, E., Antwi, C. O., Amankwa, E., Gyamfi, S. A., & Amoako, R. (2022). Online personalized recommended product quality and e-impulse buying: A conditional mediation analysis. *Journal of Retailing and Consumer Services*, *64*, 1–11. https://doi.org/10.1016/j.jretconser.2021.102789

Batra, R., & Ahtola, O. T. (1991). Measuring the hedonic and utilitarian sources of consumer attitudes. *Marketing Letters*, *2*(2), 159–170. https://doi.org/10.1007/BF00436035

Bellini, S., & Aiolfi, S. (2019). Impulse buying behavior: The mobile revolution. *International Journal of Retail & Distribution Management*, *48*(1), 1–17. https://doi.org/10.1108/ijrdm-12-2018-0280

Capital One Shopping Research. (2025, May 5). *Impulse Buying Statistics (2024): Consumer Spending Habits*. Capital One Shopping Research. https://capitaloneshopping.com/research/impulse-buying-statistics/

Çelik, I. K., Eru, O., & Cop, R. (2019). The Effects of Consumers' FoMo Tendencies On Impulse Buying and The Effects of Impulse Buying on Post- Purchase Regret: An Investigation on Retail

Stores*. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, *10*(3), 124–138. https://doi.org/10.70594/brain/v10.i3/13

Chen, M. C., Chan, T.-W., & Chen, Y. H. (2024). How to encourage students continue learning English on podcast? The perspectives of stimulus-organism-response and interest driven creator theory. *Interactive Technology and Smart Education*, *21*(1), 131–148. https://doi.org/10.1108/ITSE-06-2022-0076

Chen, Y., Lu, Y., Wang, B., & Pan, Z. (2019). How do product recommendations affect impulse buying? An empirical study on WeChat social commerce. *Information & Management*, *56*(2), 236–248. https://doi.org/10.1016/j.im.2018.09.002

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing*, *77*(4), 511–535. https://doi.org/10.1016/S0022-4359(01)00056-2

Djafarova, E., & Bowes, T. (2021). 'Instagram made Me buy it': Generation Z impulse purchases in fashion industry. *Journal of Retailing and Consumer Services*, *59*, 1–19. https://doi.org/10.1016/j.jretconser.2020.102345

Erensoy, A., Mathrani, A., Schnack, A., Elms, J., & Baghaei, N. (2024). Consumer behavior in immersive virtual reality retail environments: A systematic literature review using the Stimuli-Organisms-Responses (S-O-R) model. *Journal of Consumer Behaviour*, *23*(6), 2781–2811. https://doi.org/10.1002/cb.2374

Floh, A., & Madlberger, M. (2013). The role of atmospheric cues in online impulse-buying behavior. *Electronic Commerce Research and Applications*, *12*(6), 425–439. https://doi.org/10.1016/j.elerap.2013.06.001

Forbes Technology Council. (2025). *How personalization is reshaping customer journeys in e-commerce*. https://councils.forbes.com/blog/personalization-reshaping-ecommerce-customer-journeys

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382–388. https://doi.org/10.1177/002224378101800313

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research*, *29*(3), 430–447. https://doi.org/10.1108/IntR-12-2017-0515

Good, M. C., & Hyman, M. R. (2021). Direct and indirect effects of fear-of-missing-out appeals on purchase likelihood. *Journal of Consumer Behaviour*, *20*(3), 564–576. https://doi.org/10.1002/cb.1885

Hair, J. F., William C. Black, Barry J. Babin, & Rolph E. Anderson. (2019). *Multivariate data analysis* (Eighth edition). Cengage.

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. https://doi.org/10.1007/s11747-014-0403-8

Hodkinson, C. (2019). 'Fear of Missing Out' (FOMO) marketing appeals: A conceptual model. *Journal of Marketing Communications*, *25*(1), 65–88. https://doi.org/10.1080/13527266.2016.1234504

Kunaver, M., & Požrl, T. (2017). Diversity in recommender systems – A survey. *Knowledge-Based Systems*, *123*, 154–162. https://doi.org/10.1016/j.knosys.2017.02.009

Li, J., Qi, J., Wu, L., Shi, N., Li, X., Zhang, Y., & Zheng, Y. (2021). The Continued Use of Social Commerce Platforms and Psychological Anxiety—The Roles of Influencers, Informational Incentives and FoMO. *International Journal of Environmental Research and Public Health*, *18*(22), 12254. https://doi.org/10.3390/ijerph182212254

Lo, L. Y.-S., Lin, S.-W., & Hsu, L.-Y. (2016). Motivation for online impulse buying: A two-factor theory perspective. *International Journal of Information Management*, *36*(5), 759–772. https://doi.org/10.1016/j.ijinfomgt.2016.04.012

Market.us. (2024). *AI-Based recommendation system market*. Market.Us. https://market.us/report/ai-based-recommendation-system-market/

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology* (pp. xii, 266). The MIT Press.

Necula, S.-C., & Păvăloaia, V.-D. (2023). AI-Driven recommendations: A systematic review of the state of the art in e-commerce. *Applied Sciences*, *13*(9), 1–22. https://doi.org/10.3390/app13095531

Ngai, E. W. T., & Gunasekaran, A. (2007). A review for mobile commerce research and applications. *Decision Support Systems*, *43*(1), 3–15. https://doi.org/10.1016/j.dss.2005.05.003

Okazaki, S., & Mendez, F. (2013). Perceived Ubiquity in Mobile Services. *Journal of Interactive Marketing*, *27*(2), 98–111. https://doi.org/10.1016/j.intmar.2012.10.001

Park, S.-H., & Han, S. P. (2013). From Accuracy to Diversity in Product Recommendations: Relationship Between Diversity and Customer Retention. *International Journal of Electronic Commerce*, *18*(2), 51–72. https://doi.org/10.2753/JEC1086-4415180202

Payment & Commerce Market Intelligent. (2024). *E-commerce data for 12 key Asia-Pacific (APAC) markets*. https://paymentscmi.com/e-commerce-market-data-asia-pacific/

Pujastuti, E., Arif, L., Richki, H., Rifki, P., & Arief, A. (2022). Handling sparse rating matrix for e-commerce recommender system using hybrid deep learning based on LSTM, SDAE and latent factor. *International Journal of Intelligent Engineering and Systems*, *15*(2), 379–393. https://doi.org/10.22266/ijies2022.0430.35

Quickway Infosystems. (2025). *The rise of mobile shopping: Why e-commerce apps are the future of retail*. Medium. https://mobileappcircular.com/the-rise-of-mobile-shopping-why-e-commerce-apps-are-the-future-of-retail-843130741057

Redine, A., Deshpande, S., Jebarajakirthy, C., & Surachartkumtonkun, J. (2023). Impulse buying: A systematic literature review and future research directions. *International Journal of Consumer Studies*, *47*(1), 3–41. https://doi.org/10.1111/ijcs.12862

Rodrigues, R. I., Lopes, P., & Varela, M. (2021). Factors affecting impulse buying behavior of consumers. *Frontiers in Psychology*, *12*, 1–3. https://doi.org/10.3389/fpsyg.2021.697080

Saleh, M. A. E.-H. (2012). An Investigation of the Relationship between Unplanned Buying and Post-purchase Regret. *International Journal of Marketing Studies*, *4*(4), 106-120. https://doi.org/10.5539/ijms.v4n4p106

Shinde, Y. (2024). AI-based recommendation system market to hit USD 34.4 bn by 2033. *Market.Us Scoop*. https://scoop.market.us/ai-based-recommendation-system-market-news/

Statista Market Forecast. (2024). Statista.Com. https://www.statista.com/outlook/emo/ecommerce/worldwide

Tahir, M., Enam, R. N., & Nabeel Mustafa, S. M. (2021). E-commerce platform based on Machine Learning Recommendation System. *2021 6th International Multi-Topic ICT Conference (IMTIC)*, 1–4. https://doi.org/10.1109/IMTIC53841.2021.9719822

Valencia-Arias, A., Uribe-Bedoya, H., González-Ruiz, J. D., Santos, G. S., Ramírez, E. C., & Rojas, E. M. (2024). Artificial intelligence and recommender systems in e-commerce. Trends and research agenda. *Intelligent Systems with Applications*, *24*, 1–15. https://doi.org/10.1016/j.iswa.2024.200435

Vazquez, D., Wu, X., Nguyen, B., Kent, A., Gutierrez, A., & Chen, T. (2020). Investigating narrative involvement, parasocial interactions, and impulse buying behaviours within a second screen social commerce context. *International Journal of Information Management, 53,* 1–12. https://doi.org/10.1016/j.ijinfomgt.2020.102135

Vu, N. H. (2024, August 20). *Vietnam e-commerce sector outlook: Key growth trends* [News]. Vietnam-Briefing. https://www.vietnam-briefing.com/news/vietnams-e-commerce-sector-outlook-in-2024.html/

Wang, S., & Qiu, J. (2021). A deep neural network model for fashion collocation recommendation using side information in e-commerce. *Applied Soft Computing*, *110*, 1–10. https://doi.org/10.1016/j.asoc.2021.107753

Wien, A. H., & Peluso, A. M. (2021). Influence of human versus AI recommenders: The roles of product type and cognitive processes. *Journal of Business Research*, *137*, 13–27. https://doi.org/10.1016/j.jbusres.2021.08.016

Wong, I. A., Lian, Q. L., & Sun, D. (2023). Autonomous travel decision-making: An early glimpse into ChatGPT and generative AI. *Journal of Hospitality and Tourism Management*, *56*, 253–263. https://doi.org/10.1016/j.jhtm.2023.06.022

Xu, H., Zhang, K. Z. K., & Zhao, S. J. (2020). A dual systems model of online impulse buying. *Industrial Management & Data Systems*, *120*(5), 845–861. https://doi.org/10.1108/IMDS-04-2019-0214

Yang, F., Tang, J., Men, J., & Zheng, X. (2021). Consumer perceived value and impulse buying behavior on mobile commerce: The moderating effect of social influence. *Journal of Retailing and Consumer Services*, *63*, 2–9. https://doi.org/10.1016/j.jretconser.2021.102683

Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI-personalized recommendations on clicking intentions: Evidence from Chinese e-commerce. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(1), 1–40. https://doi.org/10.3390/jtaer20010021

Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. *Complex & Intelligent Systems*, *7*(1), 439–457. https://doi.org/10.1007/s40747-020-00212-w

Zhao, L., Fu, B., & Bai, S. (2025). Understanding the influence of personalized recommendation on purchase intentions from a self-determination perspective: Contingent upon product categories. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(1), 1–24. https://doi.org/10.3390/jtaer20010032

Zhu, Y., Shi, H., Bin Azam Hashmi, H., & Wu, Q. (2023). Bridging artificial intelligence-based services and online impulse buying in E-retailing context. *Electronic Commerce Research and Applications*, *62*, 1–9. https://doi.org/10.1016/j.elerap.2023.101333