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Ai-Driven Personalization Cues: Unraveling Consumer Impulsive Buying in E-Commerce

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ABSTRACT

In the era of AI-powered online retail, personalization cues play a central role in influencing consumer behavior. Drawing upon the Stimulus–Organism–Response (S–O–R) framework, this study examines how these dimensions of accuracy, relevance, timeliness, and diversity impact e-impulsive buying, defined as spontaneous online purchases triggered by digital stimuli. A quantitative approach was employed using a structured questionnaire, and responses from 475 participants were analyzed in SPSS 25. The model's validity was established through reliability testing, KMO, and exploratory factor analysis. Further, mediation analysis using PROCESS Macro (Model 4) was applied to test the effect of personalization cues on impulsive buying through the urge to buy. Findings reveal that accuracy, relevant experiences, and timeliness significantly influence e-impulsive buying, while diversity does not show a notable effect. The results highlight the uneven influence of different personalization cues and provide valuable insights for optimizing AI-driven recommendation systems to stimulate impulse purchases. The study also outlines implications and encourages future research that incorporates psychological and contextual factors.

Keywords-Cues; *Impulsive buying; Personalization cues; Relevant experiences; Urge to buy*

1. INTRODUCTION

Brick-and-mortar stores have long served as the cornerstone of retail, offering consumers tactile experiences, personal interaction, and the immediacy of in-store purchasing. However, with the digital transformation of commerce, there has been a notable shift in consumer behavior—one increasingly defined by convenience, speed, and personalization (Yan, 2024). The rise of e-commerce has not only restructured how consumers shop but also redefined how brands engage with them in real time. Traditional in-store experiences are now being replicated—and in many ways, enhanced—through digital platforms that dynamically respond to individual consumer needs.

This evolution in digital retail is largely driven by technological advancements, particularly in artificial intelligence (AI), which has enabled brands to provide tailored online environments that feel intuitive, responsive, and individualized. Within this context, personalization has emerged as one of the most influential strategies in shaping online experiences. Instead of offering static, one-size-fits-all interactions, e-commerce platforms increasingly integrate content and design elements that adapt to user behavior, preferences, and contextual data (Benlian, 2015).

These personalized elements—ranging from curated product suggestions and limited-time offers to visually highlighted sections and interactive features—support consumers in locating relevant products quickly and efficiently (Gkikas & Theodoridis, 2022). By doing so, they transform the online journey from passive browsing into active engagement, offering users a sense of convenience, relevance, and alignment with their needs. Unlike static web content, such elements are dynamic and adaptive, leveraging behavioral data to guide consumers' decision-making and enhance their overall shopping experience.

One important outcome of this growing personalization is impulsive buying,(Amin,2025) a phenomenon that has gained increasing relevance in the context of AI-powered retail. Impulse buying

refers to a consumer's tendency to make purchases without preplanning, typically triggered by environmental or situational cues. Research shows that personalized suggestions—particularly those that are highly accurate, diverse, timely, and contextually relevant—can significantly enhance the likelihood of impulsive purchases (Chen et al., 2019). As personalization technologies become more sophisticated, the line between product discovery and purchase decision continues to blur, making impulsive buying a strategic focus for online retailers.

Platforms such as Amazon and Flipkart exemplify this shift by integrating real-time, AI-generated elements like "Frequently Bought Together" or "Customers Also Viewed" to engage users at critical decision points. These cues are not only persuasive in design but also engineered to trigger immediate responses aligned with the user's implicit preferences. Despite the growing integration of such strategies, there remains a gap in understanding how different dimensions of personalization—such as accuracy, diversity, relevance, and timeliness—affect impulsive buying behavior. While personalization is generally acknowledged as beneficial, not all cues function identically. This study aims to investigate these dimensions to develop a more nuanced understanding of AI-driven personalization in shaping online consumer behavior.

2. LITERATURE REVIEW

2.1 THEORETICAL BACKGROUND

The Stimulus–Organism–Response (S-O-R) framework, initially introduced by (Mehrabian and Russell 1974) and later expanded within consumer behavior research (Bigne et al., 2020), provides a systematic approach to understanding how individuals respond to their environment. According to this model, external environmental factors (stimuli) influence a person's internal emotional and cognitive conditions (organism), which subsequently shape their behavioral outcomes (response) (Duong et al., 2024). The theory is often applied to assess how individuals interpret and react to both external and internal stimuli through a sequence of psychological processing stages (Sampat & Raj, 2022).

In the context of the present study, personalization cue dimensions—namely accuracy, relevant experiences, timeliness, and diversity—serve as the stimuli. These cues trigger the consumer's internal state of urge to buy impulsively, representing the organism reaction, which then leads to impulsive buying as the behavioral response. The framework allows for a structured exploration of how multidimensional personalization features influence consumer's behavior. Unlike prior studies that treated personalization as a one-dimensional construct, this study adopts a more nuanced approach, thereby highlighting the complex and sometimes contradictory influence of personalization cues in digital retail environments.

2.2 PERSONALIZATION CUES AS STIMULUS

Artificial intelligence (AI) has become central to modern marketing, evolving from initial skepticism to widespread adoption (Sharma & Paço, 2024). As consumers increasingly engage with AI-powered services, marketers leverage these technologies to enhance user interfaces and experiences (Roslan & Ahmad, 2023), leading to improved efficiency, time savings, and interactivity (Puntoni et al., 2021). A key application of AI in this context is the integration of personalization cues that directly shape users' online interactions.

Personalization cues are visible stimuli embedded within digital platforms that adapt in real time to user behavior, preferences, and contextual data (Benlian, 2015). They may appear as recommended items, content suggestions, filters, ratings, or time-sensitive offers, all strategically designed to align digital content with individual needs. These cues can be broadly divided into two categories: content-based (e.g., "You may also like" sections, recommendations, reviews) and design-based (e.g., layout, interactivity, animations, visual highlighting) (Kwon & Kim, 2012).

Drawing from Similarity-Attraction Theory (Ellen Berscheid & Elaine Hatfield), individuals are naturally drawn to content that mirrors their preferences and behaviors. AI-powered recommendation systems operationalize this by curating suggestions based on browsing history, past

purchases, and engagement patterns, thereby enhancing perceived relevance and accuracy.

In essence, personalization cues serve as adaptive digital stimuli that distinguish modern e-commerce platforms from traditional static websites. By integrating these cues, service providers create environments that are not only more efficient but also tailored to reflect user-specific goals and preferences, thereby shaping the overall quality of the online shopping experience.

2.3 URGE TO BUY IMPULSIVELY AS MEDIATOR

Impulsive buying refers to the sudden, unplanned desire to purchase. The urge to buy impulsively is a feeling that arises when encountering a specific product, model, or brand while shopping (Rook, 1987; Dholakia, 2000; Beatty & Ferrell, 1998; Mohan et al., 2013). According to (Zheng et al. 2019), this urge results from exposure to external stimuli prior to the purchase. Impulse buying represents the actual behavior exhibited after being persuaded to buy (Beatty & Ferrell, 1998; Bao & Yang, 2022) and is consistently spontaneous and sudden.

2.4 ONLINE IMPULSIVE BUYING AS RESPONSE

Impulsive buying refers to spontaneous and unplanned purchases made without prior intention or extensive deliberation (Rook, 1987). It is typically driven by sudden urges and immediate desires rather than rational or premeditated decision-making, making it distinct from planned consumption. As a behavioral tendency, impulsive buying reflects the powerful role of situational and psychological stimuli in shaping consumer choices.

In online contexts, impulsive buying preserves these characteristics but occurs within digital environments. Unlike traditional retail, where physical interactions with products and store atmospheres may stimulate impulses, online impulsivity arises from digital exposure. The convenience of browsing, instant access to a wide assortment of products, and continuous product visibility contribute to the frequency of such purchases (Wells et al., 2011; Eroglu et al., 2001).

With the rise of e-commerce, impulsive buying has become increasingly prevalent. Studies indicate that it is approximately 5% more common online than in brick-and-mortar retail (Nielsen, 2017), largely due to the speed and efficiency of digital transactions (Zhao et al., 2022). Consumers can explore multiple platforms in seconds, encouraging quick, unplanned decisions (Ngo et al., 2024). Moreover, the absence of traditional shopping constraints—such as store hours, physical possession, or sensory interactions—has reshaped consumer impulsivity in digital commerce (Sun et al., 2023).

Overall, impulsive buying remains a fundamental aspect of consumer behavior. Whether in physical or online settings, it reflects the intersection of emotional urges and situational triggers, underscoring its importance in understanding modern consumption patterns.

3. RESEARCH MODEL AND DEVELOPMENT OF HYPOTHESIS

3.1 ACCURACY

Accuracy in personalization cues refers to how precisely recommendation systems align with a user's preferences, behavior, and contextual needs (Sharma et al., 2023). AI algorithms use inputs such as search keywords, browsing history, and voice commands to interpret consumer intent, enhancing recommendation precision (Zhang, 2019; Wu et al., 2023). Accurate cues capture emotional triggers and latent preferences, increasing engagement and drawing users deeper into the shopping experience (Guowei et al., 2021; Guo et al., 2017). They also stimulate curiosity through immersive, graph-based marketing elements (Zheng & Ding, 2022).

Several studies emphasize that accuracy significantly influences consumers' buying decisions. For instance, when a recommendation aligns with a consumer's shopping goal, satisfaction and likelihood of purchase increase (He et al., 2024; Cremonesi et al., 2012). Additionally, (Song 2023) found that algorithmic recommendation accuracy can directly encourage impulsive buying behavior by making product suggestions feel more relevant and reliable.

Based on this, the following hypothesis is proposed:

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H1a: Accuracy positively influences impulsive buying behavior.

Beyond this direct effect, accuracy also shapes psychological processes that trigger impulse responses. Accurate, appropriate, and relevant recommendations foster both cognitive and emotional trust in the system (Chen et al., 2020). Perceived similarity with the recommender further strengthens this trust, evoking emotional responses that stimulate the urge to buy impulsively (Chen et al., 2019;2020). This urge is expected to mediate the relationship between accuracy and impulsive buying.

Thus, the following hypothesis is proposed:

H1b: The urge to buy impulsively mediates the relationship between accuracy and impulsive buying behavior

3.2 RELEVANT EXPERIENCES

Relevant experiences in personalized systems refer to cues aligned with users' past behavior, including previous purchases, browsing patterns, and preferences. These cues reduce search effort and cognitive load by presenting familiar, tailored suggestions, simplifying decision-making (Mantha et al., 2019; Xiao & Benbasat, 2007). When recommendations resonate with consumers' needs, they enhance emotional engagement and a sense of being understood, increasing the likelihood of spontaneous purchases (Yum & Kim, 2024; Yin et al., 2025).
Thus, based on this we hypothesize:

H2a: Relevant experiences positively influence impulsive buying behavior.

Relevance also generates the psychological urge to purchase. For instance, (Taneja 2024) explained how relevance in recommendations impacts urge, while (Parboteeah et al. 2009) referred to such signals as task- and mood-relevant cues that positively affect the urge to buy. Similarly, (Eroglu et al. 2001) emphasized the influence of task-relevant cues on impulse buying behavior. This urge is expected to mediate the relationship between relevant experiences and impulsive buying.

Thus, the following hypothesis is proposed:

H2b: The urge to buy impulsively mediates the relationship between relevant experiences and impulsive buying behavior.

3.3 TIMELINESS

Timeliness in personalization cues refers to delivering suggestions at the most appropriate moment, matching the user's context and behavior. Timely updates enhance trust, credibility, and responsiveness, supporting user satisfaction (Meng et al., 2023). Chen et al. (2019) defined timeliness as the degree to which content is up to date, reinforcing its role in information quality. Time-based algorithms, such as forgetting curves, adjust cues in real time to reflect shifts in interest and behavior (Qin & Zhang, 2021). Users trust platforms that show up-to-date content, perceiving it as more relevant and accurate (Doll & Torkzadeh, 1988; Liu & Arnett, 2000).
(Ariff et al. 2013) found that delivery timelines positively affect consumers' online purchase inclination, while (Khokhar et al. 2019) noted that timely suggestions within categories or price ranges can enhance impulsivity. Similarly, (Temel 2024) observed that well-timed app notifications influence purchase decisions and may lead to impulse-driven behavior.

Thus, the following hypothesis is proposed:

H3a: Timeliness positively influences impulsive buying behavior.

Real-time, context-sensitive recommendations create urgency, encouraging emotional responses and spontaneous purchases. Timely exposure increases the urge to buy impulsively, especially when aligned with current needs or moods (Priyadarshini et al., 2017; Yun et al., 2024). This urge is expected to mediate the relationship between timeliness and impulsive buying.

So, we hypothesize:

H3b: The urge to buy impulsively mediates the relationship between timeliness and impulsive buying behavior.

3.4 DIVERSITY

Consumer preferences continuously evolve in dynamic online environments, making choices difficult to predict (Wang et al., 2020). Presenting a

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diverse set of personalized cues gives users broader options, reduces uncertainty, and improves decision-making (Li et al., 2020). Diversity enhances perception that the platform understands unique and changing needs, strengthening perceived control and autonomy (Xu et al., 2020). This sense of autonomy often promotes spontaneous buying, especially in immersive digital environments (Liu & He, 2022). Diverse options increase satisfaction and speed decision-making by reducing perceived limitations (Ratner & Kahn, 2002; Broniarczyk et al., 1998). Song (2023) found that algorithmic recommendation diversity encourages impulsive purchases. (Zhao et al. 2025) showed that diversity predicts perceived autonomy, boosting purchase intention. (Safitri & Arifin 2024) and (Costa Pacheco et al. 2021) confirmed a direct positive relationship between product diversity and impulse buying, with (Nasution et al., 2025) validating this in the Indonesian context.

Thus, the following hypothesis is proposed:

H4a: Diversity positively influences impulsive buying behavior.

Research further suggests that diversity provokes exploration and emotional engagement, which stimulate the urge to buy impulsively. This urge is expected to mediate the effect of diversity on spontaneous purchases. Based on this we propose:

H4b: The urge to buy impulsively mediates the relationship between diversity and impulsive buying behavior.

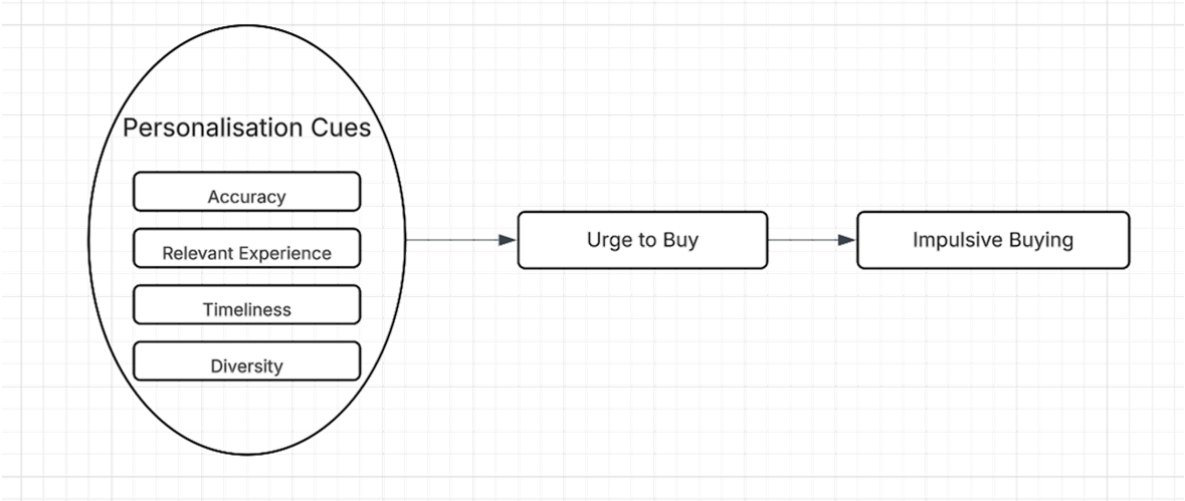

Fig.1 Research Framework

4. RESEARCH METHODOLOGY

4.1 SAMPLE

A total of 483 responses were collected using the snowball sampling (Goodman, 1961) technique, from Northern India specifically Punjab, Haryana, Delhi NCR, Chandigarh and Uttar Pradesh, which allowed for the recruitment of participants through referrals and personal networks. This non-probability sampling method was suitable for reaching a broad audience of online shoppers who have experienced personalization cues while shopping digitally.

After screening for completeness and consistency, 475 valid responses were retained for analysis. This sample size was adequate for conducting robust statistical procedures such as regression analysis and factor analysis, ensuring the reliability of findings related to the impact of personalized cues on impulsive buying behavior.

4.2 MEASUREMENT SCALE

The study employs a structured questionnaire to measure constructs related to AI-driven recommendation systems and their impact on impulsive buying behavior. Developed through a thorough literature review, the questionnaire

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includes items for four independent variables, one mediating variable (urge to buy), and one dependent variable (impulsive buying), adapted from previously validated scales in online consumer behavior research. All items are rated on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), ensuring consistency in data collection and facilitating robust statistical analysis. (Likert, 1932). Likert scales are a popular rating format for surveys that use five or seven levels to rank quality from best to worst or high to low (Allen & Seaman, 2007).

4.3 TOOLS

SPSS 25 was used to analyze the data, beginning with a reliability test to ensure internal consistency. The Cronbach's alpha (Cronbach, 1951) for the overall dataset was calculated as 0.877, indicating a high level of reliability, which is above the acceptable threshold of 0.7 (Forero, 2014). Kaiser-Meyer-Olkin (KMO) (Kaiser, 1974) and Bartlett's test of sphericity (Bartlett, 1950) were tested, which are prerequisites for exploratory factor analysis (EFA) (Williams et al., 2010). EFA (Spearman, 1904) is a statistical technique used to identify the underlying structure of a set of observed variables by grouping them into factors based on their correlations (Watkins, 2018). Since the values exceeded the minimum threshold (KMO = 0.876, Bartlett's Test of Sphericity = 0.000, 0.000 < 0.005), the data were deemed suitable for EFA (Hair et al., 2014; Tabachnick & Fidell, 2013).

The study examined four independent variables—accuracy, diversity, relevant experiences, and timeliness—one mediating variable, urge to buy, along with impulsive buying as the dependent variable. To identify underlying factor structures, principal component analysis (PCA) was performed using varimax rotation to achieve a more interpretable factor solution. PCA (Pearson, 1901) is a statistical technique used to eliminate data with little or no relevance for target prediction while preserving data that exhibit greater variation (Ahmad & Benjamin, 2023). Varimax rotation is considered the most effective and widely used orthogonal rotation method, as it enhances interpretability by maximizing the variance of factor loadings within each factor (Fabrigar et al., 1999).

Factors with eigenvalues greater than 1 were retained, ensuring that only meaningful constructs were considered (Kaiser Criterion). Items with factor loadings above 0.50 were accepted as valid indicators of their respective constructs. However, one item from diversity showed a factor loading below 0.50. To maintain the robustness of the factor structure, necessary modifications were made by dropping the item. After these adjustments, no further cross-loadings were observed, confirming a stable factor structure.

Following EFA, the reliability was reassessed using Cronbach's alpha, which came at 0.884.

Construct	Item Code	Measurement Item	EFA Loading
Accuracy	AC1	The AI recommendation system helps me find products accurately.	0.779
	AC2	The system understands my shopping habits and suggests relevant items.	0.764
	AC3	The recommended product categories align with my interests.	0.787
	AC4	The system considers personal traits (e.g., gender, age, style).	0.834
	AC5	It helps me find high-quality products with better features.	0.779
Relevant Experience	RE1	Recommended items match those I searched for before.	0.799
	RE2	Recommended items are consistent with my past purchases.	0.703
	RE3	The system personalizes based on browsing, registration, and shopping history.	0.844
	RE4	Items appear in "bought together," "you may also like," or similar sections.	0.651
Timeliness	TL1	Recommendations are fast and without delay.	0.740
	TL2	The system provides the most up-to-date product options.	0.682

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	TL3	I receive recommendations exactly when I need them.	0.731
	TL4	Recommendations are provided at the right moment.	0.773
Diversity	DV1	Recommended items cover a wide range of brands and types.	0.714
	DV2	The system caters to multiple aspects of my interests.	0.806
	DV3	Recommendations introduce new and unique products.	0.711
	DV4	Recommended items are diverse and distinct from each other.	0.362*
Urge	UB1	I have the urge to purchase items other than or in addition to my specific shopping goal while browsing the app.	.977
	UB2	I feel the desire to buy items that do not pertain to my specific shopping goal while browsing the app.	.911
	UB3	I have the inclination to purchase items outside my specific shopping goal while browsing the app.	.832
Impulsive Buying	IB1	When I go shopping, personalised suggestions often make me buy things I had not intended to purchase.	.791
	IB2	I tend to buy spontaneously when I come across relevant personalised recommendations.	.807
	IB3	I often buy items suggested by the app without considering the consequences.	.729
	IB4	I sometimes cannot resist purchasing products recommended to me on the app.	.877

*Item dropped

Table 1- Factor Loadings

5. RESULTS

5.1 DEMOGRAPHIC CHARACTERISTIC

Demographic Variable	Category	Frequency	Percentage (%)
Age	Below 18	20	4.2%
	18–24	90	18.9%
	25–34	235	49.5%
	35–45	70	14.7%
	Above 45	60	12.6%
Gender	Male	235	49.5%
	Female	240	50.5%
Income Group (per month)	Below ₹25,000	80	16.8%
	₹25,000–₹50,000	120	25.3%
	₹50,000–₹1,00,000	140	29.5%
	Above ₹1,00,000	135	28.4%
Frequency of Online Shopping	Never	10	2.1%
	Occasionally	100	21.1%
	Sometimes	140	29.5%
	Often	170	35.8%
	Always	55	11.6%

Table 2- Demographic characteristics of respondents

The demographic profile of the study, based on 475 responses, from northern India reveals a diverse and balanced sample suitable for analyzing the impact of personalized cues on impulsive buying behavior. The majority of respondents fall within the 25–34 age group (49.5%), followed by 18–24 (18.9%) and 35–45 (14.7%), indicating strong representation from young and mid-career adults who are typically more active in online shopping. Gender distribution is nearly equal, with 49.5% males and 50.5% females, ensuring gender balance. In terms of

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income, a significant portion of the respondents earn between ₹50,000–₹1,00,000 (29.5%) and above ₹1,00,000 (28.4%), indicating a concentration of middle to upper-income consumers with greater online purchasing power. Regarding online shopping behavior, the majority shops often (35.8%) or sometimes (29.5%), with only 2.1% indicating they never shop online. This suggests the sample is well-aligned with the study's objective, as most participants are experienced online shoppers capable of meaningfully evaluating AI-driven personalized recommendations and their influence on impulsive buying.

5.2 HYPOTHESIS TESTING

This section reports the results of hypothesis testing based on regression and mediation analyses. The findings highlight the direct and indirect effects of personalization dimensions on impulsive buying, with a particular focus on the mediating role of urge to buy. The results are summarized in Table 3 and 4 and are discussed in detail below.

Outcome	Predictors	B	SE	p	LLCI	ULCI
Urge	Constant	2.41	0.04	0.000	2.32	2.49
	Accuracy	0.41	0.01	0.000	0.38	0.43
	$R^2 = 0.741$, $F = 1358.17$, $p < 0.05$					
Impulsive Buying	Constant	0.47	0.06	0.000	0.34	0.59
	Accuracy	0.16	0.01	0.000	0.14	0.18
	Urge	0.69	0.02	0.000	0.64	0.74
	$R^2 = 0.929$, $F = 3072.60$, $p < 0.05$					
Urge	Constant	3.21	0.05	0.000	3.10	3.32
	Relevant Experiences	0.22	0.01	0.000	0.19	0.25
	$R^2 = 0.296$, $F = 198.76$, $p < 0.05$					
Impulsive Buying	Constant	-0.03	0.06	0.667	-0.15	0.09
	Relevant Experiences	0.03	0.01	0.000	0.01	0.04
	Urge	0.95	0.01	0.000	0.91	0.98
	$R^2 = 0.904$, $F = 2233.19$, $p < 0.05$					
Urge	Constant	2.70	0.05	0.000	2.59	2.82
	Timeliness	0.34	0.01	0.000	0.31	0.37
	$R^2 = 0.505$, $F = 482.25$, $p < 0.05$					
Impulsive Buying	Constant	0.11	0.05	0.067	-0.01	0.22
	Timeliness	0.09	0.01	0.000	0.07	0.11
	Urge	0.86	0.01	0.000	0.82	0.89
	$R^2 = 0.916$, $F = 2584.17$, $p < 0.05$					
Urge	Constant	4.09	0.07	0.000	3.95	4.23
	Diversity	-0.04	0.01	0.036	-0.07	-0.00
	$R^2 = 0.009$, $F = 4.41$, $p = 0.036$					
Impulsive Buying	Constant	-0.08	0.07	0.217	-0.21	0.04
	Diversity	-0.00	0.01	0.852	-0.01	0.01
	Urge	0.99	0.01	0.000	0.96	1.02
	$R^2 = 0.901$, $F = 2136.30$, $p < 0.05$					

Table 3 – Hypothesis Testing

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IV (X)	Direct Effect (B)	95% CI (LL–UL)	Indirect Effect (B)	95% BootCI (LL–UL)	Mediation Type
Accuracy	0.16	0.141 – 0.189	0.28	0.26 – 0.31	Partial (Indirect > Direct)
Relevant Experiences	0.03	0.01 – 0.04	0.21	0.19 – 0.24	Partial (Indirect > Direct)
Timeliness	0.09	0.07 – 0.11	0.29	0.27 – 0.33	Partial (Indirect > Direct)
Diversity	0.00	-0.01 – 0.011	-0.04	-0.07 – -0.004	Full mediation (only indirect, negative)

Table 4- Direct and indirect effect

Accuracy had a significant positive effect on Impulsive Buying (B = 0.16, SE = 0.01, $p < 0.05$), supporting H1a. Also, it had a significant positive effect on Urge to Buy (B = 0.41, SE = 0.01, $p < 0.05$). In turn, Urge to Buy had a significant positive effect on Impulsive Buying (B = 0.69, SE = 0.02, $p < 0.05$). The indirect effect through Urge to Buy was significant (B = 0.28, SE = 0.01, 95% CI = 0.26–0.31), indicating that a substantial portion of Accuracy's influence on Impulsive Buying operates through Urge to Buy, confirming the mediating role proposed in H1b. Consistent with Table 4, Accuracy showed partial mediation, where the indirect effect (B = 0.28) was stronger than the direct effect (B = 0.16), highlighting the dominance of the mediated pathway. The model explained 74.2% of the variance in Urge to Buy ($R^2 = 0.742$, F = 1358.17, $p < 0.05$) and 92.9% of the variance in Impulsive Buying ($R^2 = 0.929$, F = 3072.60, $p < 0.05$).

Relevant Experiences had a significant positive effect on Impulsive Buying (B = 0.03, SE = 0.01, $p < 0.05$), supporting H2a. Also, it had a significant positive effect on Urge to Buy (B = 0.22, SE = 0.01, $p < 0.05$). Urge to Buy subsequently had a significant positive effect on Impulsive Buying (B = 0.95, SE = 0.02, $p < 0.05$). The indirect effect through Urge to Buy was significant (B = 0.21, SE = 0.01, 95% CI = 0.19–0.24), indicating that much of the effect of Relevant Experiences is transmitted via Urge to Buy, confirming the mediating role proposed in H2b. As shown in Table 4, the indirect effect (B = 0.21) was considerably larger than the direct effect (B = 0.03), indicating partial mediation dominated by the mediated pathway. The model explained 29.6% of the variance in Urge to Buy ($R^2 = 0.296$, F = 198.76, $p < 0.05$) and 90.4% of the variance in Impulsive Buying ($R^2 = 0.904$, F = 2233.19, $p < 0.05$).

Timeliness had a significant positive effect on Impulsive Buying (B = 0.09, SE = 0.01, $p < 0.05$), supporting H3a. It also had a significant positive effect on Urge to Buy (B = 0.34, SE = 0.01, $p < 0.05$). Urge to Buy subsequently had a significant positive effect on Impulsive Buying (B = 0.86, SE = 0.01, $p < 0.05$). The indirect effect through Urge to Buy was significant (B = 0.29, SE = 0.01, 95% CI = 0.27–0.33), confirming that Timeliness primarily influences Impulsive Buying via Urge to Buy, confirming the mediating role proposed in H3b. This aligns with Table 4, where the indirect effect (B = 0.29) outweighed the direct effect (B = 0.09), demonstrating partial mediation with stronger indirect influence. The model explained 50.5% of the variance in Urge to Buy ($R^2 = 0.505$, F = 482.25, $p < 0.05$) and 91.6% of the variance in Impulsive Buying ($R^2 = 0.916$, F = 2584.17, $p < 0.05$).

Diversity had no significant direct effect on Impulsive Buying (B = 0.00, SE = 0.01, $p = 0.852$), indicating that H4a is not supported. Diversity, reflecting the variety in personalized recommendations, had a small but significant negative effect on Urge to Buy (B = –0.04, SE = 0.01, $p = 0.036$). Urge to Buy, in turn, had a strong positive effect on Impulsive Buying (B = 0.99, SE = 0.02, $p < 0.05$). The indirect effect through Urge to Buy was significant (B = –0.04, SE = 0.02, 95% CI

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= –0.07 to –0.004), indicating that Diversity's influence on Impulsive Buying occurs entirely through Urge to Buy, confirming the mediating role proposed in H4b. Table 4 further supports this by showing a non significant direct effect (B = 0.00) and a significant negative indirect effect (B = –0.04), confirming full mediation through the urge pathway**.** The model explained 0.9% of the variance in Urge to Buy ($R^2 = 0.009$, $F = 4.41$, $p = 0.036$) and 90.1% of the variance in Impulsive Buying ($R^2 = 0.901$, $F = 2136.30$, $p < 0.05$).

6. DISCUSSION

The study examined how four personalization cue dimensions—Accuracy, Relevant Experiences, Timeliness, and Diversity—affect impulsive buying behavior both directly and through the mediating role of the urge to buy impulsively. Accuracy directly promotes impulsive buying and positively influences the urge to buy, which partially mediates its effect, showing that precise and relevant recommendations stimulate cognitive and emotional responses that encourage spontaneous purchases (Song, 2023; Chen et al., 2020). Relevant Experiences, reflecting the system's alignment with users' past behavior, also directly influence impulsive buying and enhance the urge to buy, indicating that tailored suggestions reduce cognitive load, increase engagement, and strengthen the psychological drive for spontaneous purchases (Mantha et al., 2019; Yum & Kim, 2024). Timeliness, or delivering recommendations at contextually appropriate moments, directly increases impulsive buying and heightens the urge to buy, reinforcing emotional and cognitive triggers for unplanned purchases (Meng et al., 2023; Priyadarshini et al., 2017). In contrast, Diversity did not have a direct effect on impulsive buying and had a small negative effect on the urge to buy, suggesting that while offering diverse options can enhance perceived autonomy and encourage exploration, it may suppress impulsive tendencies (Wu et al., 2019). Overall, the results indicate that personalization cues operate in nuanced ways, with some dimensions stimulating impulsive behavior directly and indirectly through the urge to buy, while others, like Diversity, may counteract impulsive tendencies despite promoting engagement and autonomy.

7.1 THEORETICAL IMPLICATIONS

This study offers several important theoretical contributions. First, it extends the Stimulus–Organism–Response (S-O-R) framework by positioning personalization cue dimensions—accuracy, relevant experiences, timeliness, and diversity—as stimuli, with the urge to buy impulsively as the mediating organism state, leading to impulsive buying as the response. This multi-dimensional conceptualization challenges prior models that treated personalization as a singular construct, enhancing theoretical precision. Second, the study confirms the mediating role of urge, highlighting its importance as an affective trigger that explains how personalization cues convert into behavioral outcomes. Third, the findings reveal that not all cues are equally effective—while accuracy, relevance, and timeliness positively influence urge and impulsive buying, diversity shows a suppressing effect, introducing a boundary condition in personalization theory. Lastly, by integrating insights from AI-driven personalization and impulse buying literature, the study bridges two important streams of consumer research, offering a richer understanding of how digital stimuli influence spontaneous consumer behavior.

7.2 PRACTICAL IMPLICATIONS

This study provides several practical implications for marketers, e-commerce managers, and digital platform designers. First, by identifying accuracy, relevant experiences, and timeliness as strong drivers of impulsive buying via the urge to buy, platforms can prioritize refining AI algorithms to deliver highly precise and contextually relevant product suggestions in real time. Second, marketers should design interfaces and recommendation strategies that tap into users' past behaviors and emotional preferences to stimulate immediate engagement and purchasing decisions. Third, findings suggest that simply increasing the diversity of cues may not always enhance impulsive buying; excessive or poorly contextualized options can overwhelm users and reduce their sense of urgency. Personalization efforts should aim for curated variety rather than indiscriminate breadth. Finally,

understanding that the urge to buy is a key mediating factor allows platforms to craft persuasive messages, limited-time offers, or dynamic visual cues that evoke immediate emotional responses, effectively nudging consumers toward spontaneous purchases. These insights can help brands optimize recommendation systems not only for relevance but also for emotional and behavioral impact.

8. CONCLUSION

This study deepens the understanding of how distinct personalization cue dimensions—accuracy, relevant experiences, timeliness, and diversity—shape impulsive buying behavior in online environments. By applying the S-O-R framework, the research demonstrates that accuracy, relevance, and timeliness exert significant direct and indirect effects on impulsive buying through the mediating role of the urge to buy, whereas diversity exhibits a unique suppressing effect via a negative influence on urge. These results highlight that personalization is not a uniformly positive driver of spontaneous purchases; its impact depends on the specific nature of the cues employed. Theoretical contributions include refining the conceptualization of personalization as a multi-dimensional construct and establishing urge as a critical affective mechanism linking digital stimuli to impulsive responses. Practically, the findings guide e-commerce practitioners toward prioritizing precision, contextual relevance, and timely recommendations, while exercising caution with diversity to avoid cognitive overload. Overall, the study bridges personalization and impulse buying literature, offering nuanced insights into how digital platforms can strategically leverage AI-driven personalization to influence consumer behavior.

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