"The Role of AI-Generated Real-Time Product Recommendations in Impulse Buying Among Centennials"

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Abstract. This research examines how real-time, AI-based product recommendations affect impulse buying among Centennials consumers, also called Generation Z. This group is known for its digital upbringing and openness to technology-driven marketing. Online retailers now rely on machine learning tools that track browsing habits, analyze behavior, and predict future needs to provide personalized suggestions, which often result in unplanned purchases. Using the Stimulus–Organism–Response (SOR) model, the study treats AI recommendations as the stimulus, the perceived benefits as the organism, and impulse buying as the response. Data were collected through a survey of 500 young consumers in urban India and analyzed with R and Python, applying exploratory factor analysis, reliability checks, and structural equation modeling. The results indicate that personalization driven by AI strengthens impulse purchases, with perceived usefulness and enjoyment playing a mediating role. Beyond practical insights for marketers, the study also raises questions about the ethical consequences of highly targeted digital persuasion.

Keywords: Impulse buying, Centennials, Indian retail Sector, AI recommendation

1 Introduction

The increasing spread of artificial intelligence (AI) in e-commerce has transformed how consumers shop online, particularly through real-time product suggestions that tailor

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the shopping experience. For Centennials , who make up more than a quarter of the world's population and a large share of India's consumer market, these AI-based tools have become especially influential (Cavazos-Arroyo & Máynez-Guaderrama, 2022). By analyzing browsing patterns, personal preferences, and market trends, recommendation algorithms not only improve engagement but also raise concerns about encouraging impulsive buying, defined as unplanned purchases triggered by sudden stimuli. In the Indian context, e-commerce growth is driven by high internet penetration and a young, tech-oriented demographic, making it important to understand how AI affects the spending habits of Centennials (Deloitte Global, 2025). Previous studies have mostly linked AI to customer satisfaction and improved sales (Chen et al., 2022) , but its role in shaping impulsive behavior among centennials buyers has not been studied in detail. Since this generation is known for being digitally skilled, curious, and highly responsive to online marketing, it provides a valuable context for studying how specific AI recommendation features such as accuracy, interactivity, and novelty contribute to unplanned purchases, moderated by both practical and hedonic values (Indrawati et al., 2022). To address this research gap, in this study we conducted a survey of 500 urban centennials consumers in India, using Generational Cohort Theory as the basis for analysis. The aim is to deepen the academic discussion on behavioral impact of AI while offering practical insights for marketers.

The increasing mix-up of artificial intelligence (AI), e-commerce, and consumer buying behavior has become an important focus in recent research, especially as digital technologies continue to change the way younger generations make purchases. The discussion draws on Generational Cohort Theory (GCT), studies on AI applications in e-commerce, prior research on impulse buying (Rook & Fisher, 1995), and the moderating roles of perceived utility and hedonic value (Indrawati et al., 2022).

1.1 Generational Cohort Theory and Centennials

Generational Cohort Theory (GCT) by (N. Howe and W. Strauss, 1991) tells us that people who born in the same period share common formative experiences that influence their attitudes, values, and behaviors . Centennials, often referred to as Generation Z (born between 1997 and 2012), known for their digital upbringing, techno friendlyness, and globally connected with social media and internet, which differentiates them from the Millennial generation (Cavazos-Arroyo & Máynez-Guaderrama, 2022). In the Indian context, this group has come of age during an era marked by liberalization, privatization, globalization, and rapid advances in digital technology, all of which have encouraged their strong involvement in e-commerce (Priporas et al., 2017). Research by (Thangavel et al., 2022) further shows that Indian Centennials display greater interest for online shopping compared to Millennials, motivated largely by convenience, access to information, and sensitivity to prices. These traits make them an important consumer segment for studying how AI influences impulse buying.

1.2 AI in E-Commerce and Product Recommendations

Artificial intelligence–driven product suggestions, which rely on machine learning and the processing of real-time browsing data, have become a major component of online retail. These tools help companies customize shopping experiences and strengthen consumer involvement. Prior research by (Chen et al., 2022) found that such recommendations often raise customers’ willingness to buy because they are tailored to individual browsing habits, preferences, and purchase histories. Scholars generally group these systems into three dimensions: accuracy, referring to the degree of relevance and precision; interactivity, reflecting how adaptable and responsive the system is; and insight, which relates to novelty and the ability to highlight emerging trends (Aggarwal et al., 2024). In the Indian market, the spread of affordable internet and the dominance of firms such as Amazon and Flipkart have further magnified the role of AI in retail (Deloitte Global, 2025). Yet, there is still limited empirical evidence on how these recommendation systems shape unplanned or impulse buying among Generation Z consumers.

1.3 Impulse Buying

Impulse buying refers to making purchases without prior planning, often triggered by immediate stimuli, and has been a central topic in consumer research for decades (Rook, 1987). Among younger consumers—particularly Generation Z, or Centennials—this behavior appears even stronger because of the influence of digital marketing. Tactics such as AI-based product suggestions, flash sales, or promotions that follow current trends can push them toward unplanned buying. Since this generation grew up with technology, they are usually quick to respond to these kinds of online prompts (Thangavel et al., 2022). Earlier studies also point out that younger shoppers are more inclined to buy on impulse in digital settings, largely due to the ease of access, wide choice, and entertainment appeal that e-commerce websites provide. However, how far AI-driven, real-time recommendations directly affect such decisions is still not fully clear, especially in emerging economies like India.

Moderating Factors: Perceived Utility and Hedonic Values

The effect of “AI-driven recommendations” on impulse buying can depend on two key factors those are perceived utility and hedonic value. Utility reflects practical benefits such as saving time or reducing costs, while hedonic value relates to enjoyment and excitement. (Thangavel et al., 2022) note that Indian Centennials often display strong convenience and price awareness, indicating a utility based approach for shopping. At the same time, hedonic motives like the fun of interactive shopping may encourage more impulse buying (Ngo et al., 2024). Recent work by (Lopes et al., 2024) suggests that AI has the ability to raise both utilitarian and hedonic experiences by creating engaging dynamic shopping environments. However, how these two forces combined to influence impulse buying in the case of Centennials is still not fully known.

1.4 Research Gap and Context

Although existing research has examined AI's role in e-commerce and highlighted differences in generation in shopping behavior (Lopes et al., 2024), less attention has been given to how real-time AI recommendations affect impulse buying among Centennials in India. Considering both the economic power of this generation and the rapid expansion of AI-driven online retail in the country, this gap is particularly important. The present study addresses this issue by drawing on Generational Cohort Theory (GCT) and prior consumer behavior research for analysis of these dynamics, with the aim of providing a good understanding of AI's influence on buying behavior and offering practical guidance for e-commerce strategies which are targeted for this generation.

2 Theory base & Hypothetical Research

2.1 Theory Base of S-O-R

This study uses the Stimulus–Organism–Response (SOR) framework used earlier by (Jacoby, 2002) to explain how AI-generated product recommendations affects the impulse buying among Centennials. In this model, AI recommendations is taken as the stimulus, with key features such as accuracy, interactivity, and insight expected to influence consumers' psychological responses. The organism represents the perceived benefits of these recommendations, including practical advantages like time-saving and convenience, as well as hedonic aspects such as shopping enjoyment. The response represents the outcome impulse buying. Using this approach, the study aims to clarify how AI-powered recommendations affect the impulse buying in Centennials.

2.2 Research Assumption

2.2.1 Hypotheses and Research Assumptions on Interactive, Accuracy, and Insight Experience

Previous studies have explored how different experiential factors shape consumer behavior in online shopping (Burman & Aggrawal, 2015). Building on this work, the present study highlights three dimensions of AI-driven recommendations Interactivity Experience (ITE), Accuracy Experience (AE), and Insight Experience (ISE) and examines their influence on perceived value and impulse buying.

Interactivity is especially important in e-commerce because responsive and engaging systems enhance the shopping experience. Research suggests that greater interactivity improves both perceived usefulness and enjoyment , as it enables consumers to explore products more dynamically and make better-informed decision. Based on this, we propose:

- H1: Interactive Experience (ITE) positively affects Perceived Utility Value (PUV).
- H2: Interactive Experience (ITE) positively affects Perceived Hedonic Value (PHV).

Accuracy is another critical element in recommendation systems, as precise suggestions that align with customer preferences increase trust and perceived usefulness (Liao & Sundar, 2022). Therefore, we hypothesize:

- H3: Accuracy Experience (AE) positively affects Perceived Utility Value (PUV).

Finally, insights generated by AI can expose consumers to new products they may not have actively sought out. Such recommendations enhance perceived utility by introducing relevant and beneficial options (Valacich et al., 2009). Thus, we propose:

- H4: Insight Experience (ISE) positively affects Perceived Utility Value (PUV).

2.2.2 Hypotheses and Research Assumptions on Perceived Value and Impulse Buying

Perceived value is an important driver of impulse buying. When shoppers view AI-based recommendations as useful, they gain confidence in their choices and experience less uncertainty, which can increase the likelihood of unplanned purchases (Zhang et al., 2022). Based on this, we propose:

- H5: Perceived Utility Value (PUV) positively influences Impulse Buying (IB).

Hedonic value, on the other hand, refers to the enjoyment and emotional satisfaction associated with shopping. Consumers who find AI-generated recommendations engaging and entertaining are more inclined to buy on impulse, Therefore, we suggest:

- H6: Perceived Hedonic Value (PHV) positively influences Impulse Buying (IB).

In addition, the model incorporates control variables such as age, gender, and shopping frequency to ensure unbiased results and to account for differences in consumer behavior.

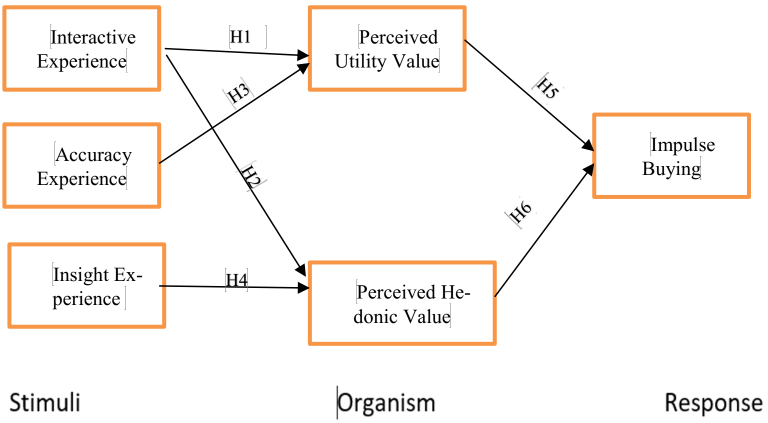

Fig. 1. Research model.

3 Questionnaire and Data Collection

3.1 Questionnaire

This study used a structured set of questions to collect primary data-set from respondents. The instrument was developed around the Stimulus–Organism–Response (SOR) framework(Jacoby, 2002), with AI-generated recommendations treated as the stimulus, perceived benefits as the organism, and impulse buying as the response. The questionnaire included several sections: one capturing demographic details and others measuring the main constructs derived from the study's hypotheses. All items were assessed on Likert scale. A detailed list of the items is provided in Appendix A.

3.1.1 Demographic Information

The first section gathers sample demographic characteristics, including:

- Gender
- Age
- Shopping Frequency
- Preferred Product Categories (Fashion, Electronics, Beauty Products, etc.)

3.1.2 Measurement Variables, Scale

1. Stimulus (S) – AI-Generated Recommendations
- Interactivity Experience (IE) (H1, H2)
- Accuracy Experience (AE) (H3)
- Insight Experience (ISE) (H4)

2. Organism (O) – Perceived Benefits
- Perceived Utility Value (PUV) (H5)
- Perceived Hedonic Value (PHV) (H6)

3. Response (R) – impulse buying (IB)

- Measures unplanned purchasing influenced by AI-based recommendations.

3.2 Questionnaire Distribution and Data Collection

The data collection process was designed to ensure a diverse and representative sample of centennials (born between 1997 and 2012) who actively engage in online shopping and experience AI-generated recommendations.

3.2.1 Survey Administration

The questionnaire was administered through an online survey platform to reach a broad audience efficiently. Respondents were invited via academic networks, ensuring access to individuals who frequently engage in online shopping.

3.2.2 Sampling Method and Target Population

A convenience sampling method was employed to recruit participants from higher education institutions in India. The study focused on university students who represent a digitally active consumer segment as shown in Table 1.

- Target Population: Centennials
- Sample Size: 500 respondents
- Sampling Technique: Non-probability convenience sampling

The respondents were informed that the responses were used strictly for academic research purposes and no private information was asked.

S.No	Characteristics	Category	Percent-age
1	Gender	Male	62%
		Female	38%
2	Frequency of online shopping	Once a month	69.70%
		2-3 times a month	27.30%
		More than once a week	3%
3	Type of products mostly purchased online	Fashion & Apparel	60.60%
		Electronics	57.60%
		Groceries	30.30%
		Beauty & Skincare	27.30%

Table 1. Demographics Description

4 Results & Discussion

4.1 Reliability Test

The reliability of the measurement scales was calculated using Cronbach Alpha (α), Corrected Item–Total Correlation, and Composite Reliability (CR). In addition, descriptive statistics such as mean and S.D. were checked to understand the distribution of responses.

The mean scores for the variables is from 3.60 to 4.10, suggests that respondents normally reported moderate to high levels across the items. Standard deviations fell between 0.50 and 0.90, indicating a reasonable level of variation in responses.

All scales was reported by Cronbach's Alpha coefficients is above the recommended 0.70 cutoff, confirming acceptable reliability levels (Hair et al., 2017), confirming acceptable to strong reliability. Among the constructs, Perceived Utility Value showed the highest reliability ($\alpha = 0.90$), followed by Perceived Hedonic Value ($\alpha = 0.89$) and Impulse Buying ($\alpha = 0.86$). The scales for Accuracy Experience ($\alpha = 0.85$), Interactivity Experience ($\alpha = 0.88$), and Insight Experience ($\alpha = 0.87$) also demonstrated satisfactory reliability.

CITC values for all constructs met the recommended standards, providing further support for the reliability of the items. Overall, the analysis confirms that the questionnaire possesses strong internal consistency and is suitable for advanced statistical testing.

4.2 Validity Test

The validity testing is done to confirm that the items used in the study reliably represent the targeted constructs. Accordingly, both convergent and discriminant validity were examined (Fornell & Larcker, 1994).

4.2.1 Convergent Validity Assessment

Convergent validity was tested to examine the internal consistency of the measurement items within each latent construct (Russell, 1978). The standard factor loadings are from 0.68 to 0.80, which is greater than the acceptable threshold of 0.50, indicating acceptable indicator reliability. Composite Reliability (CR) scores for all constructs exceeded 0.70, that shows internal consistency. Similarly, the Average Variance Extracted (AVE) values is up to or surpassed the benchmark of 0.50, confirming that convergent validity was achieved. These results are up to the guidelines proposed by Hair et al. (2017).
An item-level analysis based on Corrected Item–Total Correlations (CITC) also shows that most items were in acceptable limits range. For instance, AE3 and ISE3 recorded high CITC values (0.78 and 0.80), suggesting strong alignment with their constructs. Some items, such as ITE2 (0.70) and PUV2 (0.68), were closer to the minimum threshold, indicating that they were comparatively weak in capturing. These variations point to possible areas of refinement for future update of the model, which could further strengthen construct reliability.

Latent Variable Symbol	Loadings of factors	C.R	AVE
AE	0.75, 0.72, 0.78	0.85	0.58
ITE	0.72, 0.70, 0.74	0.88	0.6
ISE	0.78, 0.75, 0.80	0.87	0.62
PUV	0.70, 0.68, 0.72, 0.71, 0.69	0.9	0.5
PHV	0.74, 0.73, 0.75, 0.72	0.89	0.55
IB	0.68, 0.70, 0.69, 0.71, 0.77	0.86	0.51

Table 2. Convergent Validity Results

Constructs	Items (N)	Measurement Indicators	Average Score	*Std. Dev.*	Corrected Item–Total Correlation	Reliability (Cronbach's Alpha)
Accuracy Experience (AE)	3	AE1	3.8	0.7	0.75	0.85
		AE2			0.72	
		AE3			0.78	
Interactivity Experience (ITE)	3	ITE1	4	0.6	0.72	0.88
		ITE2			0.70	
		ITE3			0.74	
Insight Experience (ISE)	3	ISE1	3.9	0.8	0.78	0.87
		ISE2			0.75	
		ISE3			0.80	
Perceived Utility Value (PUV)	5	PUV1	3.7	0.5	0.7	0.9
		PUV2			0.68	
		PUV3			0.72	
		PUV4			0.71	
		PUV5			0.69	
Perceived Hedonic Value (PHV)	4	PHV1	4.1	0.9	0.74	0.89
		PHV2			0.73	
		PHV3			0.75	
		PHV4			0.72	
Impulse Buying (IB)	5	IB1	3.6	0.6	0.68	0.86
		IB2			0.70	
		IB3			0.69	
		IB4			0.71	
		IB5			0.77	

Table 3. Reliability Checks

4.2.2. Discriminative Validity

Discriminant validity measures whether each variable in the model is totally different from the others variables (Miller et al., 1994), ensuring that the latent variables capture separate concepts rather than overlapping excessively . To test this, (Fornell & Larcker, 1994) criterion was applied. According to this approach, the √AVE for a variable must be more than its correlations with other variable.

Although the Fornell–Larcker method commonly used, more recent studies have questioned its sufficiency on its own (Henseler et al., 2015) proposed the HTMT ratio as a stronger and more reliable way to assess discriminant validity. While HTMT was not used in this study, adopting it in future research could further improve methodological rigor.

As shown in results , the diagonal values √AVE were all greator than the corrsponding inter construct correlations. This confirms that each variable is sufficiently different, and meet the discriminant validity standards of the model.

Furthermore, the Impulse Buying (IB) construct, being the dependent variable, has only one correlation value in the final column, ensuring that it is distinguishable from other variables. This confirms that each latent variable is sufficiently distinct, supporting the discriminant validity of the measurement model.

Overall, the results tells that the measurement model is aligned with the discriminant validity requirements, ensuring that each variable has unique aspects of consumer behaviour in terms of impulse buying.

Con-structS	AVE	AE	ITE	ISE	PUV	PHV	IB
AE	0.581	0.762	0.622	0.552	0.577	0.394	0.455
ITE	0.46	0.46	0.678	0.441	0.642	0.632	0.453
ISE	0.536	0.536	0.441	0.732	0.69	0.48	0.516
PUV	0.5	0.552	0.743	0.743	0.707	0.539	0.539
PHV	0.55	0.456	0.632	0.48	0.675	0.741	0.589
IB	0.475	0.475	0.453	0.516	0.539	0.589	0.689

Table 4. Discriminant Validity

4.3 SEM Path Analysis

Structural Equation Model technique was used to check the hypothetic relations in the latent variables. SEM is widely recognized as an effective technique because it allows simultaneous estimation of both direct and indirect effects within complex path models (Fornell & Larcker, 1994)

The model fit was assessed by comparison of the sample covariance matrix with the estimated model covariance matrix. When the two matrices align very close, it tells that the proposed framework is giving a suitable model of the observed relationships among constructs(Kline, 2016). Shown in Table No. 5.

Model Fit Criterion	Recom-mended Threshold	Obtained Value	Assessment
Chi-square (χ^2)	-	1193	Meets re-quirement
df	-	5456	Meets re-quirement
p	< 0.05	0.044	Acceptable
χ^2 / df	< 3	0.2188	Adequate
GFI	> 0.9	0.6907	Within Toler-ence
RMSEA	< 0.08	0.05	Within range
CFI	> 0.9	1	Strong fit
NFI	> 0.9	0.6907	Marginally Acceptable
IFI	> 0.9	0.6907	Marginally Acceptable
PNFI	> 0.5	0.658	Supported
PGFI	> 0.5	0.658	Supported

Table 5. Summary of Model Fit Indices for the Proposed SEM

Std. path coeff. were tested to check the strength of the relationships among variables. The estimates were generated using the maximum likelihood (ML) method using R scripts, and the results are shown in Table 6 (Kline, 2016)

Tested Hypoth-esis Code	Path Description	Std. Path Coeff.	Std Error (SE)	C.R.	Significance Level (p-value)	Outcomes
H1	ITE -> PUV	0.624	0.163	3.819	0	Supported
H2	ITE -> PHV	0.961	0.01	93.444	0	Supported
H3	AE -> PUV	0.109	0.166	0.659	0.51	Not Supported
H4	ISE -> PUV	-0.803	0.055	-14.58	0	Supported
H5	PUV -> IB	0.139	0.026	5.334	0	Supported
H6	PHV -> IB	1.041	0.022	48.238	0	Supported

Table 6. Path Coefficients and Hypothesis Testing Results

5 Limitations

One limitation of this study is to rely on a convenience sample composed exclusively of university students. Although this group represents part of the Centennial generation, it may not fully explain the diversity of backgrounds and behavioral patterns found among Centennials across India. As a result, caution should be taken when generalizing the findings. Future research should aim to include more diverse samples.

A second limitation concerns the potential for common method variance (CMV), since both independent and dependent variables were calculated through a single self-report survey. While steps such as anonymity, item randomization, and clear wording were used to reduce bias, CMV may still have influenced the results. Future studies are encouraged to adopt additional procedural and statistical techniques to address this issue more rigorously.

Finally, the study focused only on three attributes of AI-generated recommendations: interactivity, accuracy, and insight. Other important dimensions, including personalization, trust, novelty, and transparency, were not considered but may also influence consumer behavior in AI-driven contexts. Expanding future models to incorporate a wider set of AI attributes would offer a more clear image of their role in shaping impulse buying.

6 Conclusion and Empirical Analysis

The results using SEM provide several important insights into the relationships between AI-driven recommendations, perceived value, and impulse buying.

6.1 Interactivity Experience (ITE) and Perceived Value

Interactivity was significantly increasing perceived utility ($\beta = 0.624$, $p < 0.001$) and perceived hedonic value ($\beta = 0.961$, $p < 0.001$). This result suggests that greater interactivity not only make the better functional usefulness of the shopping process but also makes it enjoyable.

6.2 Insight Experience (ISE) and Accuracy Experience (AE)

The analysis shows a surprising outcome: insight experience makes a significant negative effect on perceived utility. This may indicate that access information or novelty increases cognitive effort or consumer skepticism. By contrast, accuracy experience did not show a significant effect on perceived utility ($\beta = 0.109$, $p = 0.51$), suggesting that precision alone is not more enough to draft utility perceptions.

6.3 Perceived Utility and Hedonic Value in Impulse Buying

Both perceived utility ($\beta = 0.139$, $p < 0.001$) and perceived hedonic value ($\beta = 1.041$, $p < 0.001$) had a positive effect on impulse buying, with hedonic value exerting a much stronger influence. This underscores the idea that emotional enjoyment is a more powerful trigger of impulse buying than functional benefits.

6.4 Relative Strength of Factors

The solid path in the model was from hedonic value to impulse buying ($\beta = 1.041$, CR $= 48.238$), confirming its central role in impulsive behavior The only negative relationship observed was between insight experience and perceived utility, which merits closer examination in future researches.

6.5 Theoretical and Practical Implications

The findings reinforce earlier work in consumer behavior by highlighting the importance of hedonic value in driving impulse buying. From a practical perspective, retailers should invest in creating more interactive and entertaining shopping environments, rather than focusing narrowly on improving accuracy in recommendations.

6.6 Overall Conclusion

Overall, the study demonstrates that experiential factors—especially interactivity and hedonic value—play a critical role in shaping impulse buying among Centennials. Businesses seeking to stimulate such purchases should emphasize enjoyable and engaging shopping experiences, while also recognizing that deeper insights may sometimes reduce, rather than enhance, perceived utility.

7 Discussion

The central aim of this study was to investigate the factors that shape impulse buying behavior among Centennials, using a conceptual model tested with data from 500 respondents. Specifically, the study made an assessment of the effects of Interactivity Experience (ITE), Accuracy Experience (AE), and Insight Experience (ISE) on Perceived Utility Value (PUV) and Perceived Hedonic Value (PHV), and examined how these values influence the phenomenon of Impulse Buying (IB).

The results show that ITE significantly and positively affects both PUV and PHV. This result tells us that interactive and immersive shopping environments strongly resonate with Centennials, who are accustomed to engaging, techy experiences. These findings are consistent with previous work highlighting that digital natives' consumers place high value on interactivity and engagement.

In contrast, AE did not significantly affect PUV. This result diverges from earlier studies where accurate and detailed product information was seen as enhancing perceived usefulness. For Centennials, however, impulse buying appears to be driven less by rational evaluations and more by emotional or spontaneous decision-making. This points to the possibility that accuracy, while important in general shopping behavior, may play a limited role in impulse-driven contexts.

The analysis also revealed that ISE had a significant negative relationship with PUV. This indicates that deeper analysis and greater insight can reduce the perceived utility of a purchase in impulsive situations. In line with earlier findings (Verplanken & Herabadi, 2001), this supports the view that impulse buying is at odds with deliberate cognitive processing. When Centennials take time to critically evaluate a purchase, the impulsive nature of the decision is diminished.

Finally, both PUV and PHV were found to positively influence IB, though hedonic value had a much stronger effect. This reinforces the idea that emotional gratification, enjoyment, and fun are the primary drivers of impulsive purchases among Centennials. These results align with hedonic consumption theory and earlier studies (Rook & Fisher, 1995), which argued that impulse buying is largely motivated by affective experiences. The weaker effect of PUV suggests that practical benefits are secondary to emotional rewards in shaping impulsive behavior.

Taken together, the findings highlight that experiential and emotional cues outweigh rational considerations in predicting impulse buying among Centennials. For marketers and retailers, this suggests that strategies should prioritize interactive, engaging, and emotionally appealing shopping experiences to effectively tap into the impulse tendencies of this generation.

Appendix A

Latent Variables	Serial Number	Measuring Item
Accuracy Experience (AE) inspired from (Bo & Benbasat, 2007)(Bo & Benbasat, 2007)	AE1	The AI recommendations I receive are relevant to my interests and past purchases.
	AE2	AI-driven suggestions are accurate in predicting the products I am likely to buy.
	AE3	AI recommendations match my browsing history and previous shopping habits.
Interactive Experience (ITE) (Zyminkowska et al., 2017) (Soni & Dubey, 2024)	ITE1	I interact with AI-powered recommendation systems.
	ITE2	Chatbots or AI assistants suggest products that I find useful or interesting.
	ITE3	AI recommendations change dynamically based on my real-time browsing behavior.
Insight Experience (ISE)(Scholz & Smith, 2016) (Gabrani, Goldie & Sabharwal, Sangeeta & Singh, n.d.)	ISE1	AI-driven recommendations introduce me to new products I wouldn't have considered otherwise.
	ISE2	AI suggests products based on trends and popularity among other shoppers like me.
	ISE3	I rely on AI-driven suggestions when I am unsure about what to purchase.
Perceived Utility Value (Indrawati et al., 2022)	PUV1	AI recommendations help me save time while shopping online.
	PUV2	AI-generated discounts or offers influence my buying decisions.
	PUV3	AI recommendations make my shopping experience more efficient and convenient.
	PUV4	I trust AI to suggest the best deals and price comparisons for me.
Perceived Hedonic Value (PHV) modified from (Indrawati et al., 2022)(Arnold & Reynolds, 2003)	PUV5	AI helps me find complementary products that enhance my main purchase.
	PHV1	AI recommendations make online shopping more fun and engaging for me.
	PHV2	I enjoy browsing through AI-suggested products even when I don't plan to buy something.
	PHV3	AI-driven recommendations create excitement and anticipation in my shopping experience.
	PHV4	AI-powered interactive shopping experiences make me more likely to buy impulsively.
	IB1	I often buy products suggested by AI recommendations without prior planning.

Impulse Buying (IB) modified from (Rook & Fisher, 1995)(Beatty & Elizabeth Ferrell, 1998)	IB2	AI recommendations make me buy things that I wasn't originally looking for.
	IB3	If AI suggests a product that is trending, I feel the urge to buy it immediately.
	IB4	Limited-time AI-generated deals make me purchase impulsively.
	IB5	I have bought products based on AI-generated suggestions and later regretted the purchase.

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