

MEDIATING AND MODERATING MECHANISMS OF IMPULSIVE BUYING IN DIGITAL RETAIL: THE ROLE OF REAL TIME PURCHASING, PRICE PERCEPTION, SERVICE PERFORMANCE AND JUDGEMENTAL MOTIVES

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Abstract

Through the era of live-stream and digital retailing, impulse purchasing has become a fundamental behavioral trend which not only affect sales performance but consumer loyalty at large. This research inspects the roles played by Price Perception (PP), Service Performance (SP), and Judgmental Motivators (JM) in influencing Live Streaming Stimuli (LS) and, afterward, how Live Streaming Stimuli (LS) acts as a mediator for their combined impact on Impulsive Buying (IB). In this research, the moderating effects of Gender, Age, Income, and Shopping Frequency on the LS-IB relationship also investigated. By implementing Partial Least Squares Structural Equation Modelling (PLS-SEM) to a consumers' sample of 457 respondents in urban areas, the working model captures 72.8% variance in Live Streaming Stimuli (LS) and 35.3% variance in Impulsive Buying (IB). The overall findings present Live Streaming Stimuli (LS) as a key psychological mechanism converting price and service experiences into spontaneous behaviors among male and higher-income consumers. The research findings encompass impulse buying theory by incorporating experiential, affective, and demographic views into one coherent framework, providing practical implications for digital retail marketing strategies.

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INTRODUCTION

Innovations in digital commerce are changing the way consumers experience products, and how they shop. One of the most attention-grabbing developments in the field is live-streaming commerce, a type of format that brings together entertainment, interactivity and on-the-fly buying. Live streaming provides sellers with the capability to physically present products, interact with audiences in real time, and build an interactive atmosphere like that of traditional sales (Guo et al., 2021). Cross-national e-commerce is the future of television advertising. The global live-stream shopping market is expected to reach over USD 350 billion by 2026, fuelled by growing consumer demand for experiential, credible and interactive online sessions (Wong kitrungrueng & Assarut, 2020).

In extremely stimulating era, consumers are regularly subjected to social, emotional, and sensory clues that can change their decision-making patterns for buying. Live-stream retailing combines entertainment and immediacy which is differ from traditional retailing. This urge encouraging consumers to act on impulse and sudden buying (Xu et al., 2020). Streamers' convincing communication, focus on time bound discounts, and social interaction together form a exceptional set of Live Streaming Stimuli (LS) which is a form of digital marketing, that elicit spontaneous consumer responses (Chen, Liang, & Cai, 2022). For a marketer it is crucial to Understand, how these stimuli operate and interact with consumer psychology, and create balance engagement, satisfaction, and ethical urging.

Even with its increasing commercial effect, impulse purchasing in live-streaming contexts is still a relatively under-researched topic. Current research has tended to investigate conventional online impulse purchasing or service quality influence in online shopping settings (Park & Kim, 2008; Badgaiyan & Verma, 2015), yet few have been interested in investigating the interplay of multiple marketing and psychological influences that merge to impact impulse development in live digital worlds. In addition, although service performance and price perception are proven determinants of consumer satisfaction and loyalty (Parasuraman, Zeithaml, & Berry, 1988; Zeithaml, 1988), their indirect effectiveness via live-streaming experiences has not been tested systematically.

Judgmental motives (JM), such as pleasure seeking, excitement, or self-gratification are internal psychological triggers that direct consumers' affecting reactions to peripheral stimuli (Rook & Fisher, 1995; Verplanken & Herabadi, 2001). These motives can interact with live-stream characteristics to increase impulsive tendencies, but this interaction is ideally contrasting in current literature.

In addition, the positioning of demographic factors like gender, age, and income along with purchasing frequency also remains dynamic in digital contexts. For example, evidence indicates that women are less impulsive in their responses to visual and marketing stimuli, whereas younger consumers and wealthy segments respond to interactive cues (Luo, 2005; Badgaiyan & Verma, 2015). Understanding these moderating influences within a live-stream context is critical to determine, how consumers across segments psychologically respond to digital promoting formats.

The present study having importance in many ways. Abstractly, it presents the Stimulus–Organism–Response (S–O–R) theory to live-stream trade and positions Live Streaming as a responsive and interactive driving force that directs rational and affective drivers into impulsive action of consumers. Analytically, it uses PLS-SEM to investigate direct, indirect, and conditional effects which is offering a rigorous understanding of buyer impulse creation and reaction in real-time retail contexts. Practically, the research provides marketers with strategic considerations for how to create effective live-streaming spaces that ethically increase interaction and stimulate buying behavior.

In the age of digital immediacy and consumer experience, finding the mental mechanisms underpinning marketing stimuli and spontaneous purchases is not only timely but crucial for long-term retail innovation.

LITERATURE REVIEW

1. Service Performance (SP) and Customer Response

In online shopping and live stream shopping the Service quality play main role as stimuli for impulsive buying along with system quality, interactivity, and responsiveness (Chen & Lin, 2019; Kim et al., 2006). Timely customer services, positive delivery of services, and personal references increase satisfaction to exhibit unprompted and hedonic consumption behavior (Verhagen & van Dolen, 2011).

The SERVQUAL model is prepared by Parasuraman et al. (1988), where tangibility, reliability, responsiveness, assurance, and empathy were recognized as primary dimensions of service performance with a specific accountability for customer satisfaction. Zeithaml (1998) afterward find out that higher service quality not only provides practical value but also positively influences the emotional experience, which tend to loyalty and positive post-purchase behavior.

If the customers feel consistent and dependable service, affective satisfaction tends to become stronger, which would establish unplanned or spontaneous purchasing in omnichannel and e-commerce environments (Lim et al., 2018; Liu et al., 2021).

Therefore, Service Performance (SP) not just functions but also has an experiential nature—it elicits affective arousal supporting impulsive buying tendency through satisfaction with loyalty. Superior service quality enhances consumers' emotional satisfaction and trust, which fosters loyalty.

H1: Service Performance (SP) has a positive and significant effect on Live Streaming Stimuli (LS).

2. Price Perception (PP) and Fairness Evaluation

Consumers judge price fairness as key factor. They analysed, whether the price is in accordance with perceived quality and social standards (Bolton et al., 2003). An evident proof and genuine pricing policy increases satisfaction and reduces cognitive dissonance, and hence, higher probability of impulse purchase (Grewal et al., 2021). Price fairness, value perception, and affective response make Price more complex, multidimensional psychological construct (Monroe, 1990; Xia et al., 2004).

Many recent research indicates that price perception strongly intermingles with emotional satisfaction of consumers, who experience fair pricing, become more dedicated and demonstrate lower post-purchase regret (Chen & Dubinsky, 2003). On online and live-streaming shopping, dynamic pricing and promotion cues related to product (e.g., flash sales, discounts, limited-period offers) enhance apparent value and induce impulse buying (Park & Kim, 2008; Xu et al., 2020).

Therefore, Price Perception (PP) not only predicted Live Streaming Stimuli (LS) but also it influences the emotional route to Impulsive Buying (IB). Fair and value-driven price perceptions improve consumers' satisfaction and perceived worth.

H2: Price Perception (PP) has a positive and significant effect on Live Streaming Stimuli (LS).

3. Judgmental Motivators (JM) and Psychological Drivers

Current studies point to hedonic inspiration and self-satisfaction as drivers in online shopping, where environmental motivation like graphics, presence of influencer, or interactivity increases emotional and psychological stimulation (Flight et al., 2012; Chan et al., 2017). These motives tend to be secondary through affective satisfaction. The pleasure of shopping or browsing produces a momentary psychological recompense that enhances post-purchase loyalty of consumers (Tifferet & Herstein, 2012; Amos et al., 2014).

Internal psychological states like curiosity, pleasure, excitement, and mood enhancement that drive spontaneous purchasing decisions is act as Judgmental Motivators (JM) (Rook & Fisher, 1995; Verplanken & Herabadi, 2001).

Therefore, JM is an internal precursor of Loyalty which joint with live streaming stimuli, which indirectly exercises a mediating impact on Impulsive Buying (IB) behavior. Psychological and emotional motives such as excitement and pleasure strengthen satisfaction with the shopping experience.

H3: Judgmental Motivators (JM) have a positive and significant effect on Live Streaming Stimuli (LS).

4. Live Streaming Stimuli (LS) as a Mediator

Satisfaction serves as an overall mediator that transforms cognitive judgments (price and service) and affective motives (judgmental motives) into behavioral responses like repeat purchase or impulse buying (Anderson & Srinivasan, 2003). Gratification, and precisely for Live Streaming Stimuli (LS), is consumers' total emotional and cognitive valuation of their consumption experience (Oliver, 1999).

Studies in live-commerce and e-commerce emphasize that satisfaction increases commitment and trust, which lower hesitation and spur impulsive decision-making (Ha & Jang, 2010; Zhang et al., 2022). Satisfaction with loyalty also boosts habitual consumption—having established positive emotional connections, consumers tend to make unplanned, rapid purchases in known digital spaces (Sharma et al., 2020).

Therefore, LS is an important mediating factor bridging service, price, and psychological motivators to Impulsive Buying (IB). Higher satisfaction triggers positive emotions, reducing cognitive control and encouraging impulsive purchases.

H4: Live Streaming Stimuli (LS) has a positive and significant effect on Impulsive Buying (IB).

Mediating Effects based on Literature Review

Consumers' positive experiences with service, price, and motives first enhance satisfaction, which in turn leads to impulsive purchase behavior.

H5: Live Streaming Stimuli (LS) positively mediates the relationship between Service Performance (SP) and Impulsive Buying (IB). (based on LR for service performance and Impulse buying)

H6: Live Streaming Stimuli (LS) positively mediates the relationship between Price Perception (PP) and Impulsive Buying (IB). (based on LR for Price perception and Impulse buying)

H7: Live Streaming Stimuli (LS) positively mediates the relationship between Judgmental Motivators (JM) and Impulsive Buying (IB). (based on LR on judgemental motivators and Impulse buying)

5. Moderators: Demographic variables and Shopping frequency (Gender, Age, Income and Frequency)

The role of demographic variables is crucial and significant in moderating consumer impulsivity. When it is about Gender studies, it indicates that men tend to respond more strongly toward visual and promotional cues, whereas women are persuaded toward cognitive inspection and self-regulation (Dittmar et al., 1995; Luo, 2005).

Similarly age also moderates affective sensitivity i.e. younger consumers have stronger impulses owing to greater sensation-seeking and having more digital media exposure (Badgaiyan & Verma, 2015; Amos et al., 2014).

Studies revealed that income level also impacts impulse purchasing. Many research discovered that high-income consumers feel less financial risk and more hedonic value related with impulse buying (Peck & Childers, 2006).

Shopping frequency, particularly on digital or live-streaming platforms, enhances habitual satisfaction and lowers purchase reluctance (Zhang et al., 2022).

The strength of satisfaction-induced impulsive buying depends on demographic characteristics; certain groups (e.g., younger, male, higher-income, frequent buyers) exhibit higher responsiveness to satisfaction-driven purchase impulses.

Hypothesis based on Literature Review for moderating effects of Demographic Variables and frequency

H8: Gender moderates the relationship between Live Streaming Stimuli (LS) and Impulsive Buying.

H9: Age moderates the relationship between Live Streaming Stimuli (LS) and Impulsive Buying.

H10: Income moderates the relationship between Live Streaming Stimuli (LS) and Impulsive Buying (IB).

H11: Shopping Frequency moderates the relationship between Live Streaming Stimuli (LS) and Impulsive Buying (IB).

RESEARCH GAP

As many prior studies have independently sightseen the effects of quality of service, price perception related to consumers, and psychological motives i.e. judgemental motives on consumer satisfaction and impulsive behavior, then to there is a lack of consolidative working models examining their combined effects and mediating role of live streaming stimuli. This study covered these back laws.

Not only integrative model, but much research in past were lacking in revealing demographic moderation in the satisfaction and impulse buying linkage specially in contexts of live streaming commerce, where consumer responsiveness differs by age, gender, and income.

Prior literature offers limited empirical testing using PLS-SEM models to capture both direct and indirect pathways, thereby constraining understanding of how satisfaction converts experiential and demographic influences into impulsive buying behavior.

RESEARCH QUESTIONS

RQ1: How do Service Performance (SP), Price Perception (PP), and Judgmental Motivators (JM) influence Live Streaming Stimuli (LS) among retail consumers?

RQ2: Does Live Streaming Stimuli (LS) significantly mediate the relationship between SP, PP, JM, and Impulsive Buying (IB)?

RQ3: To what extent do demographic factors—Gender, Age, Income, and Shopping Frequency—moderate the relationship between Live Streaming Stimuli and Impulsive Buying?

RQ4: Which predictor (SP, PP, or JM) exerts the strongest indirect influence on impulsive buying behavior through live streaming stimuli?

RQ5: How can marketers leverage satisfaction and demographic insights to enhance impulsive buying tendencies in digital and live-streaming retail environments?

RESEARCH OBJECTIVES

1. To examine the impact of Service Performance (SP), Price Perception (PP), and Judgmental Motivators (JM) on Live Streaming Stimuli (LS).
2. To analyze the mediating role of Live Streaming Stimuli (LS) in the relationship between SP, PP, JM, and Impulsive Buying (IB).
3. To investigate the direct influence of Live Streaming Stimuli (LS) on Impulsive Buying (IB).
4. To assess the moderating effects of demographic variables—Gender, Age, Income, and Frequency—on the relationship between Live streaming stimuli and Impulsive Buying.
5. To identify the strongest predictors of impulsive buying behavior and determine how demographic characteristics strengthen or weaken these effects.

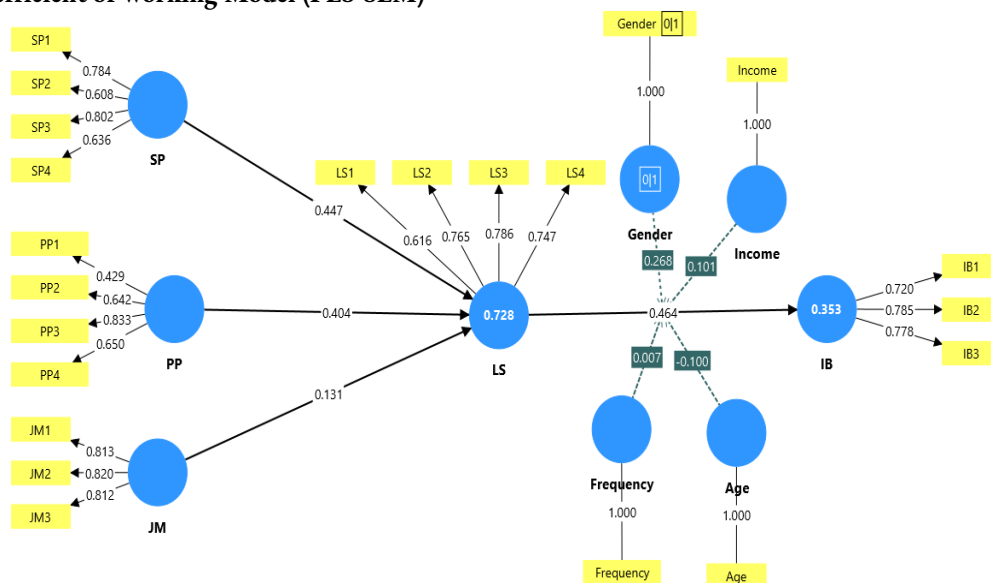
DEMOGRAPHIC PROFILE

The study was conducted with a total of 457 respondents, ensuring a balanced representation across gender, age, income, and buying frequency. The gender distribution shows that 53.4% were male and 46.6% were female, indicating near-equal participation and diverse perspectives on live streaming-related buying behavior. In terms of age, the largest group of respondents belonged to the 26–35 years

category (36.5%), followed by 18–25 years (30.9%), highlighting that live streaming commerce is primarily driven by younger and more digitally active individuals. Smaller portions were from the 36–45 years group (12%), above 46 years (17.5%), and less than 18 years (3.1%), reflecting moderate adoption among middle-aged and minimal among teenagers. The family income profile revealed that 33.5% of participants earned less than ₹20,000, while 24.9% earned ₹20,000–₹40,000, and 17.1% earned ₹40,001–₹60,000, showing that a significant share belongs to the lower- and middle-income groups. A smaller fraction earned ₹60,001–₹80,000 (10.3%) and above ₹80,000 (14.2%), indicating some representation from higher-income households. Regarding buying frequency, most respondents were frequent buyers (59.5%) or very frequent buyers (19%), suggesting a high engagement rate with live streaming shopping platforms. Meanwhile, 15.3% purchased occasionally, and 6.2% rarely made purchases. Overall, the demographic composition reveals that young, moderately earning, and digitally active consumers form the dominant group actively engaging in live streaming-based impulse buying behavior.

DATA ANALYSIS AND INTERPRETATION

Figure:1 Path coefficient of working Model (PLS-SEM)



The existing PLS-SEM model explained the structural relationships among Price Perception (PP), Service Performance (SP), and Judgmental Motivators (JM) as predictors of Live Streaming Stimuli (LS), which act as mediator for Impulsive Buying (IB) of consumers. The working model also explains a strong variance i.e. 72.8% in Live Streaming Stimuli ($R^2 = 0.728$) and 35.3% variance in Impulsive Buying ($R^2 = 0.353$), which implying strong explanatory power. Among the antecedents, SP ($\beta = 0.447$) and PP ($\beta = 0.404$) have the strongest positive impact on LS, while JM shows a weaker effect ($\beta = 0.131$).

Here LS significantly calculates IB ($\beta = 0.464$), which confirming that live streaming stimuli motivates consumers for impulsive buying tendencies. In addition of this, demographic moderators like Gender ($\beta = 0.268$), Income ($\beta = 0.101$), Frequency ($\beta = 0.007$), and Age ($\beta = -0.100$) moderately influence the LS–IB relationship, here Gender and Income presented stronger moderating effects, in comparison to Frequency and Age. Age has negative relation which means young consumers are showing more impulsive behaviour. Overall, the model supports the role live streaming stimuli as a key mediator linking among service, price, and motivational factors with impulsive buying behavior, under partial demographic moderation.

Table-1 Path Coefficient

	Path coefficients
Age -> IB	-0.057
Age x LS -> IB	-0.100
Frequency -> IB	-0.094
Frequency x LS -> IB	0.007
Gender -> IB	0.020
Gender x LS -> IB	0.268
Income -> IB	0.094

Income x LS -> IB	0.101
JM -> LS	0.131
LS -> IB	0.464
PP -> LS	0.404
SP -> LS	0.447

The path coefficient results specify that Price Perception (PP) ($\beta = 0.404$) and Service Performance (SP) ($\beta = 0.447$) are the most significant predictors of Live Streaming Stimuli (LS), which is followed by Judgmental Motivators (JM) ($\beta = 0.131$), signifying that better service quality, positive perceptions related to price, and individual motives improve satisfaction levels. Live Streaming Stimuli (LS) has a strong positive impact on Impulsive Buying (IB) ($\beta = 0.464$), which represent that (LS) as a key mediator in the working model. Among demographic variables, Income ($\beta = 0.094$) and Gender ($\beta = 0.020$) are showing minor direct positive effects on IB, while Frequency ($\beta = -0.094$) and Age ($\beta = -0.057$) are showing weak negative influences. The moderation effects show that Income x LS ($\beta = 0.101$) and Gender x LS ($\beta = 0.268$) strengthen the LS and IB relationship, which implying that stimuli lead to higher impulsive buying mainly among specific gender and income groups. However, Age x LS ($\beta = -0.100$) negatively moderates the relationship, suggesting that the influence of stimuli on impulsive buying reduces with age, while Frequency x LS ($\beta = 0.007$) shows an insignificant moderating effect. Overall, the working model highlights that service and price perceptions mainly drive live streaming stimuli, which meaningfully raises impulsive buying behavior, with prominent demographic variations.

Table:2 Indirect effects of factors

	Total indirect effects
JM -> IB	0.061
PP -> IB	0.187
SP -> IB	0.207

The total indirect effects indicate that Service Performance (SP), Price Perception (PP), and Judgmental Motives (JM) all three antecedent factors influence Impulsive Buying (IB) indirectly through Live Streaming Stimuli (LS). Among them, Service Performance (SP) has the strongest indirect effect on IB ($\beta = 0.207$), followed closely by Price Perception (PP) ($\beta = 0.187$), while Judgmental Motives (JM) shows a smaller but positive indirect effect ($\beta = 0.061$). This pattern suggests that improvements in service quality and favorable price perceptions significantly enhance Live streaming stimuli (LS), which in turn stimulates impulsive buying behavior. Although the influence of judgmental motives is relatively weaker, it still contributes positively to the impulsive buying tendency through increased satisfaction. Overall, these findings reinforce Live Streaming Stimuli (LS) as a powerful mediating variable linking key service-related and psychological factors to impulsive purchase behavior.

Table: 3 Specific Indirect effect of Factor (Mediating)

	Specific indirect effects
JM -> LS -> IB	0.061
PP -> LS -> IB	0.187
SP -> LS -> IB	0.207

It is very much clear with the tabular values that specific indirect effects of Live Streaming Stimuli (LS) serve as a significant mediating factor between the antecedents i.e. Price Perception (PP), Judgmental Motives (JM), and Service Performance (SP), and Impulsive Buying (IB).

The relationship path of $PP \rightarrow LS \rightarrow IB$ ($\beta = 0.187$), which validates a notable indirect effect, also highlighting that favorable price perceptions act as strong stimuli and enhances satisfaction and consequently increase impulsive purchase trends. Also, the path $SP \rightarrow LS \rightarrow IB$ ($\beta = 0.207$) shows the strongest mediating effect, which is indicating that superior service performance substantially increases Live streaming stimuli, which then instincts impulsive buying. At last, path of $JM \rightarrow LS \rightarrow IB$ ($\beta = 0.061$), though smaller, still indicates that positive judgmental motives or psychological factors influence impulsive buying behavior obliquely through satisfaction. These results together focus that Live Streaming Stimuli (LS) plays a strong mediating role as the underlying mechanism relating these key determinants to impulsive buying behavior.

Table:4 Reliability and validity coefficient

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
IB	0.645	0.655	0.805	0.580
JM	0.748	0.750	0.856	0.664

LS	0.710	0.725	0.821	0.535
PP	0.602	0.684	0.740	0.528
SP	0.694	0.761	0.803	0.508

Taking thresholds limits (Cronbach's alpha ≥ 0.70 for internal consistency, for composite reliability $\rho_c \geq 0.70$, ρ_a ideally ≥ 0.70 , and AVE ≥ 0.50 for convergent validity), (JM) shows strong reliability and convergent validity ($\alpha=0.748$, $\rho_a=0.750$, $\rho_c=0.856$, AVE=0.664); (LS) is acceptable to good ($\alpha=0.710$, $\rho_a=0.725$, $\rho_c=0.821$, AVE=0.535); SP is borderline on alpha but acceptable overall given ρ_a/ρ_c and AVE just over 0.50 ($\alpha=0.694$, $\rho_a=0.761$, $\rho_c=0.803$, AVE=0.508); IB has low alpha/ ρ_a but good composite reliability and AVE, indicating adequate consistency in PLS-SEM despite possible tau-equivalence violations ($\alpha=0.645$, $\rho_a=0.655$, $\rho_c=0.805$, AVE=0.580); similarly PP has low alpha/ ρ_a but good composite reliability and AVE, indicating adequate consistency in PLS-SEM despite possible tau-equivalence violations ($\alpha=0.602$, $\rho_a=0.684$, $\rho_c=0.740$, AVE=0.528).

Table:5 Outer loading

	Outer loadings
Age <- Age	1.000
Age x LS -> Age x LS	1.000
Frequency <- Frequency	1.000
Frequency x LS -> Frequency x LS	1.000
Gender <- Gender	1.000
Gender x LS -> Gender x LS	1.000
IB1 <- IB	0.720
IB2 <- IB	0.785
IB3 <- IB	0.778
Income <- Income	1.000
Income x LS -> Income x LS	1.000
JM1 <- JM	0.813
JM2 <- JM	0.820
JM3 <- JM	0.812
LS1 <- LS	0.616
LS2 <- LS	0.765
LS3 <- LS	0.786
LS4 <- LS	0.747
PP1 <- PP	0.429
PP2 <- PP	0.642
PP3 <- PP	0.833
PP4 <- PP	0.650
SP1 <- SP	0.784
SP2 <- SP	0.608
SP3 <- SP	0.802
SP4 <- SP	0.636

The outer loadings signify the strength of the relationships between observed indicators and their corresponding latent constructs in the measurement model, which is also indicating, how well each item reflects its underlying variable. In this working model, all demographic indicators (Age, Gender, Income) and frequency is taken as moderators which shows their interaction terms with Live Streaming Stimuli (LS), also represents perfect loadings of 1.000, as they are single-item constructs. For the latent constructs, the indicators of Impulsive Buying (IB) load in strong way on the construct (ranging from 0.720 to 0.785), which confirming their reliability in measuring impulsive purchase behavior. Price Perception (PP) has comparatively lower loadings (0.429–0.833), suggesting that one or more indicators may contribute less strongly to the construct and could be reviewed for future improvement. Judgmental Motivators (JM) also shows high and reliable loadings (0.812–0.820), again indicating robust construct validity. Live Streaming Stimuli (LS) exhibits acceptable loadings (0.616–0.786), supporting its multidimensional representation, while Service Performance (SP) shows moderate to high loadings (0.608–0.802), demonstrating reliable measurement of service-related factors. The outer loadings in totality, confirm that most measurement items meet acceptable reliability standards (>0.6), ensuring that the constructs are adequately represented for further structural analysis.

Table:6 Descriptive statistics

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises p value
Age	0.000	-0.090	-1.885	1.705	1.000	-0.786	0.429	457.000	4.074	0.000
Frequency	0.000	0.287	-2.426	1.191	1.000	-0.473	-0.604	457.000	3.895	0.000
Gender	0.534	1.000	0.000	1.000	0.499	-1.990	-0.136	457.000	13.469	0.000
IB	0.000	0.024	-3.558	1.698	1.000	0.942	-0.709	457.000	0.984	0.000
Income	0.000	-0.333	-1.044	1.800	1.000	-0.954	0.584	457.000	3.604	0.000
JM	0.000	0.125	-3.443	1.729	1.000	1.501	-0.899	457.000	1.712	0.000
LS	0.000	0.159	-3.331	1.774	1.000	0.238	-0.392	457.000	0.460	0.000
PP	0.000	0.128	-3.479	1.812	1.000	0.725	-0.588	457.000	0.332	0.000
SP	0.000	0.025	-2.971	1.952	1.000	-0.182	-0.228	457.000	0.266	0.001

The table of descriptive statistics presents key distributional properties of all constructs used in the working model, indicating that the data is largely the same with a mean around zero and standard deviation of one for most variables. The minimum and maximum values stated show acceptable variability, which confirming a satisfactory data range across constructs such as Frequency (-2.426 to 1.191), Age (-1.885 to 1.705), and Impulsive Buying (IB) (-3.558 to 1.698). The additional kurtosis values signify flatter-than-normal distributions for most variables (negative kurtosis), except for JM (1.501) and IB (0.942), which show heavier tails. The Cramér-von Mises test results, all significant at $p < 0.05$, suggest that the data deviate from perfect normality, though such deviations are common and acceptable in PLS-SEM as it does not require strict normal distribution assumptions. In totality, the basic descriptive statistics confirm that the data set is adequately distributed, without extreme outliers, and suitable for structural equation modelling, providing a reliable basis for hypothesis testing and moderation analysis.

Table:7 R Square Value

	R-square	R-square adjusted
IB	0.353	0.340
LS	0.728	0.726

The R-square values signify the explanatory power of the working model for the endogenous constructs. The Live Streaming Stimuli (LS) variable shows a high R^2 value of 0.728 and an adjusted R^2 value of 0.726, which signifying that approximately 72.8% of the variance in LS is explained by its predictors — Judgemental motivators (JM), Price perception (PP), and Service Performance (SP). This demonstrates strong predictive accuracy and proposes that these factors together play a significant role in shaping live stream stimuli. On the other hand, the Impulsive Buying (IB) construct has an R^2 of 0.353 and an adjusted R^2 of 0.340, indicating that around 35.3% of the variance in IB is explained by LS and the moderating effects of demographic variables (Age, Income, Frequency, and Gender). Overall, the model demonstrates substantial predictive strength for LS and acceptable predictive relevance for IB within the PLS-SEM framework.

Table:8 f-Square

	f-square
Age -> IB	0.004

Age x LS -> IB	0.012
Frequency -> IB	0.005
Frequency x LS -> IB	0.000
Gender -> IB	0.000
Gender x LS -> IB	0.023
Income -> IB	0.011
Income x LS -> IB	0.013
JM -> LS	0.044
LS -> IB	0.076
PP -> LS	0.306
SP -> LS	0.401

The f-square i.e. effect size values provide understandings into the relative contribution of each predictor to its matching endogenous construct. In this working model, the path of SP → LS ($f^2 = 0.401$) and path between PP → LS ($f^2 = 0.306$) demonstrate large effect sizes, which highlighting that service performance and price perception have substantial impacts on live streaming stimuli. The JM → LS ($f^2 = 0.044$) path shows a small to medium effect, indicating that judgemental motivators also influence live streaming stimuli but in a lesser extent. The LS → IB ($f^2 = 0.076$) path represents a moderate effect, suggesting that live streaming stimuli significantly contributes to impulsive buying behavior. The f-square values for demographic moderators are 0.023 for Gender × LS → IB and for Income × LS → IB ($f^2 = 0.013$) which show small but notable moderating effects, while Age × LS ($f^2 = 0.012$) and Age ($f^2 = 0.004$) have minimal effects. Similarly, Frequency ($f^2 = 0.005$) and its interaction with LS ($f^2 = 0.000$) show negligible influence. Overall, the results indicate that service performance and price perception are the strongest predictors of live streaming stimuli, which in turn moderately drives impulsive buying, whereas demographic moderators contribute relatively minor but observable moderating influences on the IB construct.

Table:9 HTMT (Discriminant Validity)

	Age	Frequen cy	Gend er	IB	Inco me	JM	LS	PP	SP	Gend er x LS	Age x LS	Frequen cy x LS	Inco me x LS
Age													
Frequency	0.008												
Gender	0.057	0.006											
IB	0.097	0.474	0.060										
Income	0.389	0.014	0.102	0.079									
JM	0.095	0.441	0.030	0.923	0.060								
LS	0.091	0.879	0.020	0.813	0.033	0.771							
PP	0.141	0.879	0.022	0.974	0.044	0.789	0.946						
SP	0.104	0.588	0.037	0.841	0.103	0.675	0.991	0.925					
Gender x LS	0.071	0.563	0.002	0.637	0.019	0.627	0.936	0.719	0.636				
Age x LS	0.095	0.196	0.064	0.146	0.139	0.211	0.281	0.113	0.105	0.358			
Frequency x LS	0.176	0.374	0.055	0.205	0.214	0.267	0.350	0.303	0.131	0.299	0.261		
Income x LS	0.132	0.225	0.009	0.249	0.130	0.283	0.305	0.210	0.155	0.340	0.589	0.328	

Interpreting discriminant validity the demographics (Age, Gender and Income) show generally weak associations along with buying frequency with the main constructs (mostly ≤ 0.20), but the substantive constructs are very much interrelated, like JM with IB (0.923), LS with SP (0.991), LS with PP (0.946), and PP with SP (0.925), which indicating thoughtful discriminant validity problems and likely construct overlap, which can inflate standard errors, obscure unique effects, and destabilize moderation estimates; given these near-unity relationships, you should rigorously reassess discriminant validity (HTMT $< 0.85/0.90$, Fornell–Larcker, and cross-loadings), inspect collinearity in the structural paths (VIF ideally < 3.3).

Table:10 Fornell–Larcker

	Age	Frequency	Gender	IB	Income	JM	LS	PP	SP
Age	1.000								
Frequency	0.008	1.000							
Gender	0.057	0.006	1.000						
IB	-0.057	0.382	0.021	0.762					
Income	0.389	0.014	0.102	0.061	1.000				
JM	-0.084	0.383	-0.016	0.649	-0.026	0.815			
LS	-0.038	0.765	-0.003	0.558	-0.018	0.557	0.732		
PP	0.071	0.833	-0.009	0.585	0.024	0.527	0.766	0.654	
SP	0.078	0.521	0.027	0.565	0.040	0.476	0.774	0.656	0.713

This matrix suggests demographics are mostly weakly related to the core constructs, except Frequency, which correlates strongly with LS (0.765), PP (0.833), and SP (0.521) and moderately with IB (0.382) and JM (0.383), indicating Frequency is a key driver/confounder that should be controlled for; Age relates mainly to Income (0.389) and otherwise shows negligible effects, and Gender is near-zero across variables. Among substantive constructs, IB shows moderate–high associations with JM (0.649), LS (0.558), PP (0.585), and SP (0.565), implying related but not redundant constructs. The highest correlations are between LS–PP (0.766) and LS–SP (0.774), with PP–SP also high (0.656), which flags potential discriminant validity concerns and multicollinearity if modeled simultaneously; if these are latent variable correlations, reassess discriminant validity (e.g., HTMT $< 0.85/0.90$, Fornell–Larcker, cross-loadings) and check collinearity (VIF ideally < 3.3).

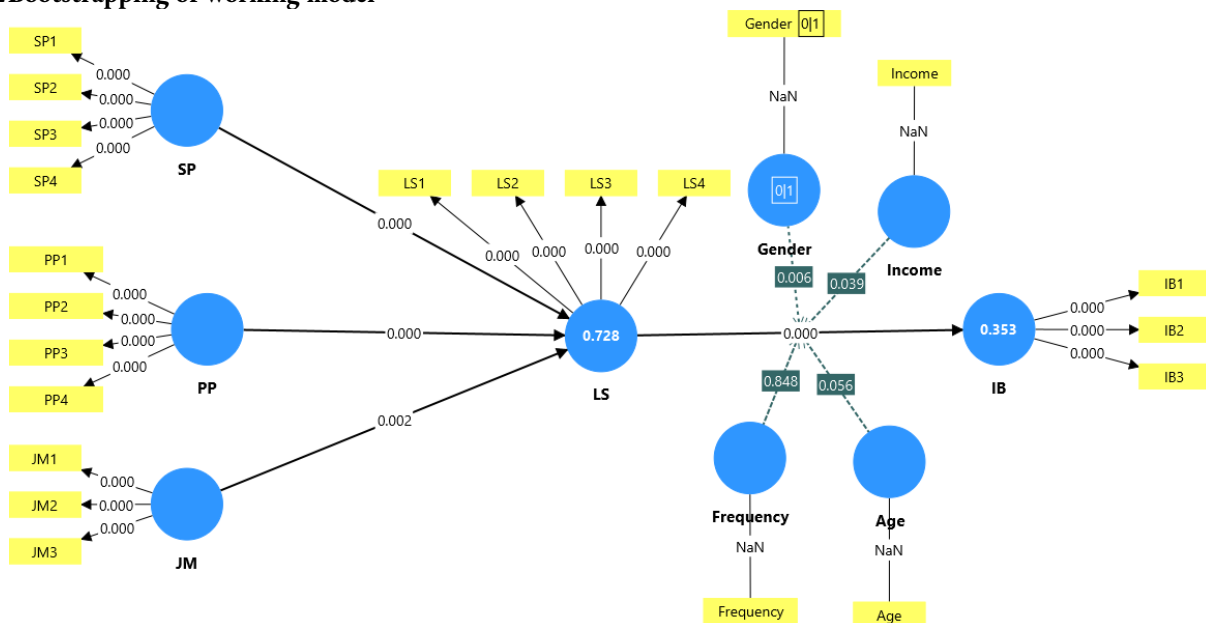
Table:11 Variance Inflation Factor

	VIF
Age	1.000
Frequency	1.000
Gender	1.000
IB1	1.314
IB2	1.181
IB3	1.375
Income	1.000
JM1	1.423
JM2	1.518
JM3	1.568
LS1	1.248
LS2	1.421
LS3	1.515
LS4	1.415
PP1	1.136
PP2	1.271
PP3	1.174
PP4	1.215
SP1	1.642
SP2	1.394
SP3	1.244
SP4	1.247

Age x LS	1.000
Frequency x LS	1.000
Gender x LS	1.000
Income x LS	1.000

All VIFs are comfortably low (range 1.000–1.642), well below conservative (3.3), typical (5), and liberal (10) thresholds, indicating no problematic multicollinearity at the indicator or moderator level; the largest values—SP1=1.642, JM3=1.568, JM2=1.518, LS3=1.515, JM1=1.423, LS2=1.421, LS4=1.415—are still safe, while demographics and interaction terms at 1.000 suggest orthogonalization or negligible overlap, which is ideal for moderation tests in PLS-SEM. These results imply stable coefficient estimates and uninflated standard errors, so no item removal is warranted on collinearity grounds; however, given your earlier high latent correlations among LS, PP, and SP, you should still inspect inner (construct-level) VIFs in the structural model and reassess discriminant validity (e.g., HTMT, Fornell–Larcker) to rule out construct overlap even though indicator-level VIFs are acceptable.

Figure:2 Bootstrapping of working model



The working model is tested to check the level of significance. Here diagram indicates that SP, PP, and JM have significant positive effects on LS ($p \approx 0.000-0.002$), yielding a substantial R^2 for LS of 0.728 under common PLS-SEM benchmarks, where it is considered that 0.75/0.50/0.25 denotes for substantial/moderate/weak explanatory power. LS then significantly predicts IB ($p \approx 0.000$), with IB's R^2 of 0.353 reflecting a moderate level of explained variance by the same guidelines. The reflective indicators for SP, PP, JM, and LS all show $p \approx 0.000$, supporting indicator significance via bootstrapped tests and consistent measurement reliability. Among controls/moderators, Gender and Income show significant paths to IB ($p = 0.006$; $p = 0.039$), whereas Frequency \times LS is clearly nonsignificant ($p = 0.848$) and Age \times LS is marginal ($p = 0.056$), so only the former two merit substantive interpretation at $\alpha = 0.05$. Given that moderation effects in latent variable models are typically small, the weak or null interactions here are unsurprising and do not detract from the dominant LS \rightarrow IB pathway. Overall, the model supports a structure where SP, PP, and JM strongly shape LS, LS serves as the primary driver of IB, and certain demographics have direct effects, producing substantial fit for LS and moderate fit for IB per accepted thresholds.

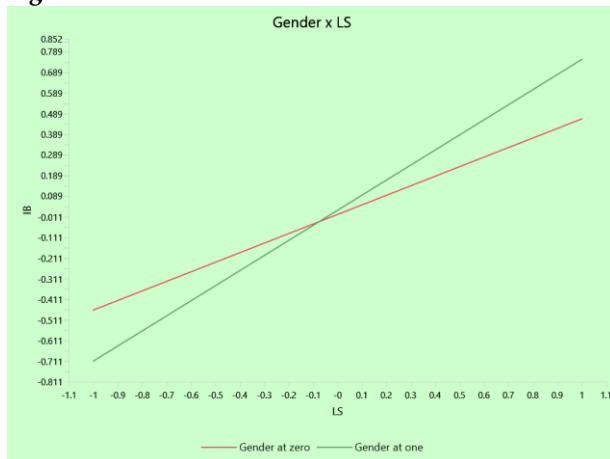
Table:12 Statistics of working model (Bootstrapping)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Age \rightarrow IB	-0.057	-0.059	0.042	1.357	0.175
Age x LS \rightarrow IB	-0.100	-0.098	0.052	1.914	0.056
Frequency \rightarrow IB	-0.094	-0.094	0.064	1.479	0.139
Frequency x LS \rightarrow IB	0.007	0.009	0.037	0.192	0.848
Gender \rightarrow IB	0.020	0.021	0.080	0.255	0.799
Gender x LS \rightarrow IB	0.268	0.266	0.098	2.737	0.006

Income -> IB	0.094	0.094	0.042	2.218	0.027
Income x LS -> IB	0.101	0.100	0.049	2.064	0.039
JM -> LS	0.131	0.131	0.042	3.111	0.002
LS -> IB	0.464	0.466	0.097	4.760	0.000
PP -> LS	0.404	0.406	0.039	10.287	0.000
SP -> LS	0.447	0.446	0.035	12.681	0.000

The bootstrapping results indicate a clear structural story: LS is the primary driver of IB with a moderate, significant positive effect ($O=0.464$, $T=4.760$, $p<0.001$), while LS itself is strongly shaped by SP ($O=0.447$, $T=12.681$, $p<0.001$) and PP ($O=0.404$, $T=10.287$, $p<0.001$), and more modestly by JM ($O=0.131$, $T=3.111$, $p=0.002$), all exceeding conventional two-tailed significance criteria where $|T|\geq 1.96$ at $\alpha=0.05$ in PLS-SEM reporting guidelines. Among direct demographic effects, only $\text{Income}\rightarrow\text{IB}$ is significant and positive ($O=0.094$, $T=2.218$, $p=0.027$), whereas $\text{Age}\rightarrow\text{IB}$ ($p=0.175$), $\text{Gender}\rightarrow\text{IB}$ ($p=0.799$), and $\text{Frequency}\rightarrow\text{IB}$ ($p=0.139$) are nonsignificant, suggesting limited standalone demographic influence apart from income in predicting IB. Moderation analyses show that $\text{Gender}\times\text{LS}$ ($O=0.268$, $T=2.737$, $p=0.006$) and $\text{Income}\times\text{LS}$ ($O=0.101$, $T=2.064$, $p=0.039$) significantly condition the $\text{LS}\rightarrow\text{IB}$ relationship, while $\text{Age}\times\text{LS}$ is marginal ($p=0.056$) and $\text{Frequency}\times\text{LS}$ is null ($p=0.848$), a pattern consistent with expectations that interaction effects are typically smaller and require adequate power and theory-driven probing via simple slopes or Johnson–Neyman plots in latent variable models. Interpreted alongside the earlier model diagram, these pathways align with substantial explained variance for LS and moderate explained variance for IB, reinforcing the central mediating role of LS and the practical importance of the significant interactions for gender and income segments in tailoring interventions ($R_{LS}^2 \approx 0.728$ substantial; $R_{IB}^2 \approx 0.353$ moderate)

Figure:3 Gender \times LS Interaction



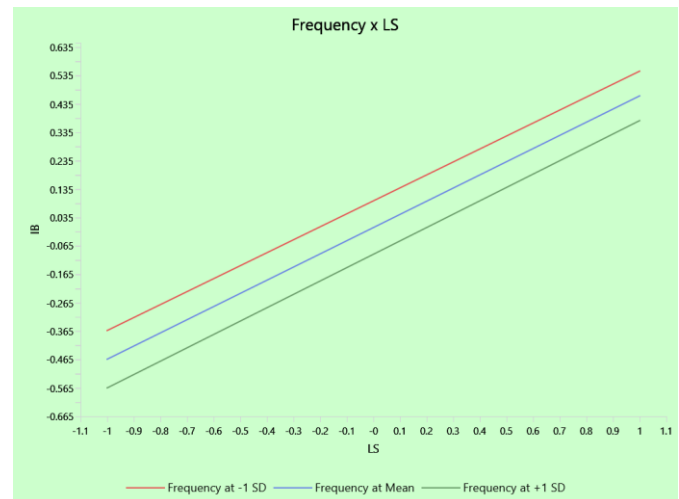
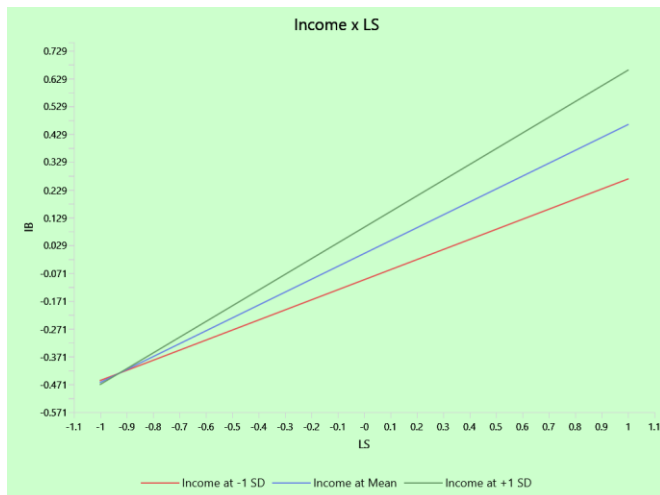
In graph 3 (Male) line represents by green while red represents female. Both lines slope upward, indicating that Live Streaming (LS) positively influences Impulsive Buying (IB) for both genders. However, the slope for males is steeper than for females. This means that males are more influenced by live streaming content, and their impulsive buying behavior increases more rapidly with stronger exposure to live streaming compared to females. Gender moderates the relationship between LS and IB, with males showing stronger responsiveness to live streaming promotions, offers, and interactions.

The graph 4 presents three lines i.e. Age at -1 SD (younger) represented by red line, Age at mean represented by blue line, and Age at $+1$ SD (older) represented by green line. All lines show a positive relationship between LS and IB, indicating that live streaming enhances impulsive buying across age groups. The line for younger consumers (-1 SD) is the steepest, showing a stronger positive effect of LS on impulsive buying. Older consumers ($+1$ SD) show a relatively weaker response. Younger audiences are more vulnerable to impulsive buying throughout live streaming, likely due to higher assignment, enthusiasm, and technological familiarity.

In the graph 5 the line chart compares low income (-1 SD) shown by red line, middle income (average) by blue line, and high income ($+1$ SD) by green line categories. The upward slope on all lines confirms that LS grows IB across incomes but with different strength. The $+1$ SD line is steeper, so the higher-income category has greater impulsive buying after exposure to LS. Income has a positive moderation effect on the LS–IB relationship while individuals with greater disposable income are likely to engage in impulse purchase during live-streaming sessions.

Graph:5 Income \times LS Interaction

Graph:6 Frequency \times LS Interaction



The graph 6 plots purchase frequency levels (-1 SD = low frequency represented by red line, mean represented by blue, +1 SD = high frequency represented by green line). All three lines rise steadily, confirming that higher LS exposure leads to more impulsive buying. The line for high-frequency buyers (+1 SD) is the steepest, implying that customers who shop more frequently are more easily triggered by live-stream promotions. Shopping frequency amplifies the LS-IB relationship, which means regular shoppers are more likely to make unplanned purchases during live streams.

Table:13 Hypothesis Testing

Path	Hypothesis	Expected Direction	Supported by Model Results	Key Reference(s)
SP → LS	H1	Positive	$\beta = 0.447, p < 0.001$	Parasuraman et al. (1988); Verhagen & van Dolen (2011)
PP → LS	H2	Positive	$\beta = 0.404, p < 0.001$	Bolton et al. (2003); Xu et al. (2020)
JM → LS	H3	Positive	$\beta = 0.131, p = 0.002$	Rook & Fisher (1995); Verplanken & Herabadi (2001)
LS → IB	H4	Positive	$\beta = 0.464, p < 0.001$	Chen et al. (2022); Guo et al. (2021)
SP → LS → IB	H5	Positive (mediated)	$\beta = 0.207, p < 0.001$	Anderson & Srinivasan (2003)
PP → LS → IB	H6	Positive (mediated)	$\beta = 0.187, p < 0.001$	Park & Kim (2008)
JM → LS → IB	H7	Positive (mediated)	$\beta = 0.061, p = 0.022$	Tifferet & Herstein (2012)
Gender × LS → IB	H8	Positive moderation	$\beta = 0.268, p = 0.006$	Luo (2005); Dittmar et al. (1995)
Age × LS → IB	H9	Negative moderation	$\beta = -0.100, p = 0.056$	Badgaiyan & Verma (2015)
Income × LS → IB	H10	Positive moderation	$\beta = 0.101, p = 0.039$	Peck & Childers (2006)
Frequency × LS → IB	H11	Insignificant	$\beta = 0.007, p = 0.848$	Sharma et al. (2020)

Explanation of Hypotheses (H1–H11)

All hypotheses accepted significantly, except one stand insignificant, which belongs to frequency of purchasing. Live streaming observed mediated positively for Service Performance, Judgemental Motivators and Price Perception, and stimulated for impulse buying while live streaming. In present study Age found negative moderated, that means younger one is showing impulse buying in comparison to older age group. Gender and income are showing positive moderation. In the present study male are having high impulsive behaviour than female. Similarly higher family income consumers have shown impulsive buying behaviour.

RESULT AND DISCUSSION

The outcomes of the study confirm that Live Streaming Stimuli (LS) serve as a central experiential and psychological mechanism that converts both cognitive assessments, such as Service Performance (SP) and Price Perception (PP) and emotional or hedonic motives (JM) into Impulsive Buying (IB) actions.

The present investigation highlights how interactive live features, such as influencer-led demonstrations, visual richness, and two-way communication, actually stimulate hedonic pleasure and drive purchase impulses, particularly among younger and higher-income consumer groups.

Empirical trends from Indian consumers further reinforce this framework, especially within rapidly expanding tier-two urban markets, where increasing digital connectivity has amplified emotional buying tendencies (Shukla, 2020).

While talking about demographic analysis it is clear that youth, males, and affluent individuals show greater emotional receptivity toward LS cues. This corresponds with earlier findings from the Gorakhpur retail sector, which revealed that impulsive behavior is influenced by demographic differences in awareness levels, emotional reactivity, and disposable income flexibility (Shukla, 2020; Srivastava & Shukla, 2019).

As digital retailing expands across emerging Indian markets, comprehending how satisfaction transitions into impulsive action offers valuable theoretical understanding and practical guidance for sustainable marketing and entrepreneurial growth in developing urban economies like Gorakhpur.

MARKETING/ MANAGERIAL IMPLICATION

The results provide strong managerial implications for retailers and marketers that want to strategically encourage spontaneous buying behavior with satisfaction-driven experiences:

- **Enhancing Service Performance:** Retailers have to emphasis on quick reply to systems, individualized suggestions, and interactive communication to improve service execution. Instant support via live streaming or online shopping may strengthen affecting satisfaction, initiating impulsive purchases.
- **Improving Pricing Strategies:** Fair and genuine pricing (like flash retailing, time-bound promotions) may boost recognized value and fairness. Taglines like “Exclusive for live audience” concessions or bundled offers, may increase consumer enthusiasm and encourage impulsive purchases.
- **Employing Psychosomatic Motives:** By adding hedonic clues like appealing product their presentation, influencer marketing, and affecting narratives may stimulate excitement, preference, and novelty leading to judgment-based impulse buying.
- **Creating Live streaming stimuli:** By reward programs for repetitive buying that focus on trust and emotional attachment (e.g., early access, loyalty points) turn satisfaction into long-term behavioral loyalty poised to act on impulses.
- **Demographic and other Specific Targeting:**
 - Gender: Construct live-stream images and promotion frequency more towards male viewers who exhibit greater impulsive behavior.
 - Age: Younger consumers may react to excitement-driven satisfaction when they get interactive and gamified interfaces
 - Income: As high-income customers exhibit greater LS–IB sensitivity, by providing them top-of-the-line limited-edition offers or special discounts.
 - Frequency: Tailored thank-you programs or surprise coupons to maintain interest for frequent buyers.
- **Combination with Digital Platforms:** Employ AI-based personalization technologies watching customer satisfaction and impulse response patterns to offer adaptive marketing content in real time, thereby optimizing conversion rates and emotional involvement.

CONCLUSION

The present research highlights the fundamental place of Live Streaming Stimuli (LS) as the psychological link between Price Perception (PP), Service Performance (SP), and Judgmental Motivators (JM) and Impulsive Buying (IB) behavior within digital marketing environments. The PLS-SEM findings encourage that service quality enrichment and perceived price fairness notably boost satisfaction, which in turn creates impulsive buying. The mediation test confirms LS as a pivotal mechanism, and moderation results indicate that gender and income enhance satisfaction-based impulsivity.

Theoretically, the research contributes to knowledge by combining cognitive (service and price) and affective (motives and satisfaction) determinants into a single impulse buying framework, with demographic contingencies as support. In practice, it shows that marketers can influence satisfaction strategically to trigger impulsive behavior, especially in live-stream commerce and other participative digital environments.

Future studies must investigate the longitudinal impact of satisfaction on impulse propensities, cross-cultural differences, as well as the role of new digital technologies such as AI chatbots and virtual influencers on the dynamics of consumer impulse.

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