

Internal and External Drivers of Compulsive Buying in Digital Consumption Contexts and the Mediating Role of Contextual Factors: A Study of Consumer Behavior in Beijing

Yuhan Hou

School of Business Administration, Capital University of Economics and Business, Beijing 100070, China

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Abstract: Digital consumption platforms reduce the friction of purchase decision-making through algorithmic recommendations, scarcity cues, payment convenience, and fragmented usage patterns, and also make some consumers more prone to uncontrolled purchasing under negative emotional states and specific contexts. This study takes 621 consumers with independent consumption capacity in Beijing as the research object and establishes a research and analysis framework of “internal susceptibility factors and the external consumption environment interact with contextual triggers, thereby contributing to compulsive buying behavior. It comprehensively uses reliability and factorability tests, the Kruskal-Wallis test, XGBoost regression and SHAP interpretation, Bootstrap mediation analysis, and context sensitivity grouping comparison. The results showed that the average total score of the sample compulsive buying was 49.995 (SD = 9.693), and 66.5% of the internal stratification of the study was in the middle group and 22.9% was in the high group; The nine internal factors showed significant differences between groups, and the shopping addiction model has the greatest effect ($\epsilon^2 = 0.104$); Except for the non-significant difference in the atmosphere of live-streaming e-commerce, all other factors were significant, and the effect of fragmented leisure and consumption habits is the greatest ($\epsilon^2 = 0.096$). The XGBoost model achieved an R^2 of 0.78 on the test set. Emotional dysregulation and impulse control, emotion regulation needs, advanced consumption and debt sensitivity, perfectionism and hoarding tendencies, and contextual triggers made substantial contributions to the model’s predictions. The three contextual triggers, browsing shopping apps when lonely or bored, frequently placing orders under stress, and making compensatory purchases after setbacks, formed strong indirect associations between most internal and external factors and compulsive buying. High-context-sensitivity people will be activated by the live atmosphere and algorithm recommendations, and low-context-sensitivity people rely more on the endogenous action of emotion regulation. Judging from the conclusion of the study, compulsive buying is not the product of a single personality factor or marketing factor, but the joint effect of internal susceptibility and external scenarios in concrete life scenarios.

Keywords: Compulsive buying; Digital consumption; Emotion regulation; Contextual triggers; SHAP

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1. Introduction

Mobile payment, one-click ordering, personalized recommendations, and live e-commerce make consumption more convenient. Low-friction transactions improve efficiency for most consumers, but for those with poor emotion regulation, insufficient impulse control, or formed shopping habits, facilitation may shorten the decision-making process of “desire formation–need evaluation–payment completion,” contributing to the transformation from satisfying functional needs to relieving stress, avoiding negative emotions, or obtaining instant rewards.

Compulsive buying generally refers to persistent, repetitive, and difficult-to-control purchasing behavior that continues despite financial problems, guilt, anxiety, or interpersonal conflict. Not only has the study identified internal reasons such as emotional difficulties, impulsiveness, low self-esteem, compensatory motives, and addictive tendencies, but it has also discussed the reasons outside the platform environment, such as materialism, fear of missing out, scarcity cues, personalized recommendations, and smooth payment. However, many studies distinguish between individual and platform environmental factors, and lack attention to “at what time these factors are converted into actual orders.”

In the digital consumption environment, loneliness, work pressure, and self-reward after setbacks are not common background variables, but may also be key scenarios that drive long-term susceptibility and instant purchases. The same algorithm recommendation may produce different results for different consumers: For context-sensitive consumers, the same algorithmic recommendation may function as a direct external stimulus. For those who are not sensitive to the context, shopping may have more emotional repair function. Therefore, it is difficult to explain how compulsive buying occurs by reporting variable correlation or average effect alone.

Based on this, this study raises four research questions. First, whether internal psychological factors, external consumption environment, and demographic statistical variables have different explanatory effects on compulsive buying; Second, after multiple factors enter the model together, whether the variables affecting compulsive buying have different predictive contributions; Third, whether loneliness, stress, and frustration scenarios are the indirect paths through which internal and external factors affect compulsive buying; Fourth, whether the sensitive groups of high and low contexts present different driving structures.

The contribution of this research is: First, integrating internal susceptibility, external consumption environment, and contextual triggering into the same framework, and emphasizing the continuity of “trait-situation-behavior.” Second, combining XGBoost and SHAP with traditional non-parametric tests used in the past to identify nonlinear relationships and relative importance. Third, through Bootstrap mediation analysis and context grouping comparison, we can distinguish between externally activated and internally driven mechanisms, and provide a more targeted basis for stratified intervention.

2. Literature review and research hypotheses

2.1. Compulsive buying and its measurement

Faber and O’Guinn^[1] conceptualized compulsive buying as persistent, repetitive, and difficult-to-control behavior and developed a screening scale for compulsive buying. Factors such as post-purchase guilt, compensatory consumption, addiction, and concealment of problems^[2] were also added in the follow-up study. These studies basically point out that, in nature, compulsive buying is not a one-time buying behavior^[3], but a continuous pattern that includes a single trigger, short-term emotional gains, and long-term negative consequences.

This study treats compulsive buying performance in four aspects: irrational repeated purchase, post-purchase emotional contrast, addiction and concealment, and compensatory consumption. This includes not only behavioral performance, but also post-purchase emotion and behavioral solidification, which is conducive to distinguishing individuals with different degrees of compulsive buying tendencies in non-clinical samples.

2.2. Internal susceptibility factors

According to emotion regulation theory ^[4], when individuals are unable to effectively identify and accept their emotions or adopt appropriate strategies to regulate negative emotions, they may engage in immediately gratifying behaviors to alleviate negative affect. Shopping can provide temporary excitement, a sense of control, and self-reward, and may therefore serve as a low-cost means of emotional repair. At the same time, insufficient impulse control will reduce individuals' ability to weigh financial consequences ^[5], and instant rewards are given greater weight in the decision-making process.

Compensatory consumption research found ^[6] that individuals will try to make up for the lack of self-worth, security, sense of gain, and other aspects through commodity and consumption experiences. Once shopping is repeatedly used for emotional relief, it may become habitual and even develop into addictive patterns ^[7]. Inadequate budget planning blurs people's boundaries, and emotional drives are more likely to result in overspending ^[8]. Therefore, it is proposed:

H1: Difficulty in emotional regulation, insufficient impulse control, compensatory motives, shopping addiction pattern, and insufficient budget planning are significantly positively related to compulsive purchasing.

2.3. External consumption environment

Digital consumption platforms have changed consumers' information environment ^[9] and choice architecture through personalized recommendations, scarcity cues, social displays, and instant payments. Consumers' fear of missing out will widen the gap between themselves and social groups ^[10], and short-term opportunities are easy to lose ^[11], and other scarce information frames the decision-making time. Personalized recommendations improve the product-preference matching. Scarcity information such as "limited inventory" and "limited-time discounts" ^[12] will compress consumers' decision-making time, while buy now, pay later and mobile payment will dull the pain of paying.

These factors may not have the same effect on everyone. The effect of the external environment may depend on people's high susceptibility to boredom, stress, frustration, etc. at that time, but in general, they reduce the time and cognitive cost required for people to restrain purchases. From this, it is proposed that:

H2: Fear of missing out and social comparison, perceived scarcity, payment convenience, advance consumption, life stress, and fragmented consumption habits are significantly positively associated with compulsive buying.

2.4. Mediating and heterogeneous effects of contextual triggers

Emotional and environmental factors often need to be triggered at a certain moment ^[13] before they can be transformed into purchases. Loneliness and boredom will prompt more aimless browsing ^[14], stress will stimulate higher immediate comfort needs, and setbacks will activate the compensatory motivation of "treating oneself." Contextual triggers provide a proximal mechanism between long-term susceptibility and actual purchasing behavior.

The same context may also produce different paths ^[15]. Consumers with high context sensitivity are more likely to respond to live atmosphere, algorithm recommendations, and scarcity reminders; while consumers with low context sensitivity, even without any external stimulation, may enter the shopping process because of their own emotional needs. Resulting from this:

H3: Contextual triggers form a significant indirect association between internal factors, external factors, and compulsive buying.

H4: High-context-sensitivity groups are more affected by external marketing factors, and low-context-sensitivity groups are more affected by internal factors such as emotional regulation and impulse control.

3. Research design

3.1. Sample and data collection

The research subjects are consumers who live or work in Beijing, are over 18 years old, and have independent or partially disposable income. A total of 32 valid questionnaires were collected in the preliminary survey to check the understandability and internal consistency of the questions. The official survey was conducted online in late February 2026. Quota controls were applied with reference to the administrative region, gender, and age structure of Beijing, and respondents were recruited through WeChat communities, college alumni groups, and relevant online communities. Since actual recruitment relied on online channels, the sampling method in this article is defined as “stratified quota sampling combined with convenience recruitment,” and the sample is not regarded as a strict probability sample.

A total of 631 questionnaires were collected from the official survey. The team reviewed the questionnaires according to the rules of repeated filling, abnormal response patterns, extreme times, and logical consistency, eliminated 10 questionnaires, and obtained 621 valid questionnaires, yielding a valid response rate of 98.41%. The questionnaires are all mandatory, so there are no missing items in the final data.

3.2. Variable measurement

See Table 1.

Table 1. Variable composition and measurement sources

Variable	No. of items	Main dimensions	Source
Compulsive Buying	14	Irrational repetitive buying, post-purchase emotional contrast, addiction and concealment, compensatory consumption	Adapted from the CBS, ECBS, RCBS, and BSAS
Internal Factors	29	Emotion regulation, impulse control, compensatory motives, perfectionism/hoarding, low self-esteem, hedonism, delayed gratification, shopping addiction, budgeting	DERS, BIS-11, and other established scales
External Factors	32	Materialism, fear of missing out, algorithmic recommendations, scarcity, livestreaming atmosphere, payment convenience, advance consumption, life stress, fragmented consumption habits	MVS, FoMOs, PSS, and related studies
Contextual Triggers	3	Three contexts: loneliness/boredom, stress, and frustration	Adapted to digital consumption contexts
Demographic Variables	6	Gender, age, education, occupation, marital/relationship status, monthly disposable income	Self-reported

All core items were rated on a 5-point Likert scale. The higher the score, the more obvious the corresponding characteristics. The total score range of compulsive buying is 14–70. For the convenience of description, this study divides 14–41, 42–55 and 56–70 into low, medium and high groups; Stratification is only used for internal comparison in this study and does not represent the clinical diagnostic thresholds.

3.3. Research methods

First, Cronbach's alpha was used to assess internal consistency, while the KMO test and Bartlett's test of sphericity were employed to determine the suitability of the data for factor analysis. Second, the Kruskal–Wallis test was used to compare compulsive buying scores across factor-level groups, with ε^2 reported as the effect size.

Next, an XGBoost regression model was constructed with the continuous total score of compulsive buying as the dependent variable.

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (1)$$

The samples were divided into training and test sets at a ratio of 80% and 20%, respectively. The prediction results were evaluated using the R^2 of the test set.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (2)$$

Mean |SHAP| values are used to represent the average predictive contribution of the variables. The SHAP results are used solely to interpret model predictions and not for causal inference.

Finally, using the three context categories—loneliness/boredom, stress, and frustration—as mediators, indirect effects and 95% confidence intervals were estimated via 2,000 Bootstrap iterations.

Additionally, the median context-trigger score of 3.67 served as the cutoff to classify participants into high and low context-sensitivity groups, allowing for a comparison of the Mean |SHAP| values of key variables between the two groups. Given that the data are cross-sectional and self-reported, this paper interprets the mediation results as indirect associations consistent with the hypothesized theoretical sequence, rather than as strict causal effects. See **Figure 1**.

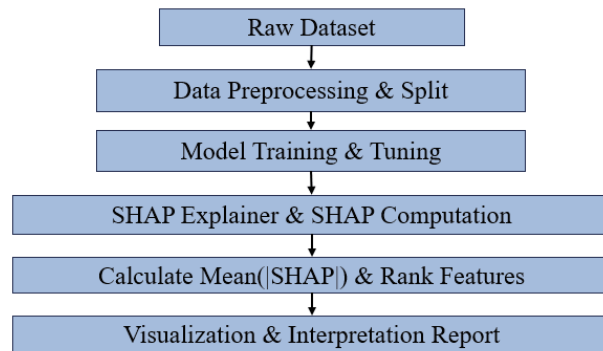


Figure 1. SHAP flowchart

4. Empirical results

4.1. Measurement quality and compulsive buying patterns

The Cronbach's α of the overall scale is 0.971, and the α of the three parts of performance and context, internal factors, and external factors are 0.897, 0.932, and 0.923, respectively. The Cronbach's alpha for the 14-item Compulsive Buying Scale was 0.877, indicating good internal consistency for the scale. The KMO value was 0.981, and Bartlett's test of sphericity yielded $\chi^2 = 18729.743$ ($df = 2775$, $P < 0.001$), indicating that the data were suitable for factor analysis; however, the construct validity requires further examination in subsequent studies. See **Table 2**.

Table 2. Descriptive statistics for compulsive buying

Indicator	Result
Valid Sample Size	621
Mean Compulsive Buying Score	49.995
Standard Deviation	9.693
Median	53
Low-Score Group (14–41)	10.6%
Moderate-Score Group (42–55)	66.5%
High-Score Group (56–70)	22.9%
Mean Scores for the Four Dimensions	3.55–3.61

The overall score of compulsive buying in the sample is high, and the average values of the four dimensions of irrational repeated purchase, post-purchase emotional contrast, addiction and concealment, and compensatory consumption are comparable, which shows that behavior, emotional consequences, compensation mechanisms, etc. are enhanced synchronously in the sample. However, because the sample is not a strict probability sample, and the stratified threshold is set internally by the study, the overall incidence of Beijing cannot be inferred from this.

4.2. Group differences in internal and external factors and demographic variables

The results support the overall direction of H1 and H2: there are stable differences in internal psychological and behavioral characteristics, and most external environmental factors are also associated with higher levels of compulsive purchasing. The role of demographic characteristics is relatively weak, and only age and occupation show significant differences. This means that priority should be given to emotions, self-control, habits, and the consumption environment when identifying risks, rather than simple classifications by gender or income. See **Table 3**.

Table 3. Summary of Kruskal–Wallis test results

Variable group	Significance	Main results
Internal Factors	All 9 dimensions were significant ($P < 0.05$)	Shopping addiction patterns had the largest effect size ($\epsilon^2 = 0.104$), followed by inadequate budget planning and compensatory motives
External Factors	8 of 9 dimensions were significant ($P < 0.05$)	Fragmented leisure and consumption habits had the largest effect size ($\epsilon^2 = 0.096$), followed by perceived scarcity and urgency
Livestream Shopping Atmosphere	Not significant ($P > 0.05$)	Limited average direct differences; context-dependent effects may exist
Age	Significant ($P < 0.001$)	$\epsilon^2 = 0.077$

Occupation	Significant ($P < 0.001$)	$\epsilon^2 = 0.065$
Gender, Education, Marital/ Relationship Status, and Disposable Income	Not significant ($P > 0.05$)	Demographic characteristics generally had limited explanatory power

4.3. XGBoost prediction and SHAP interpretation

The R^2 of the XGBoost regression model is 0.78, indicating that 19 internal, external, and context variables can explain a large proportion of the variation in the compulsive buying score. SHAP shows that “emotional dysregulation and impulse control” have the highest average prediction contribution. The demand for emotional regulation, advance consumption and debt sensitivity, perfectionism and hoarding tendency, low self-esteem and sense of security, and contextual triggers are of high importance.

Among them, when $SHAP > 0$, this feature increases the model’s predicted compulsive buying score relative to the baseline prediction, whereas a negative SHAP value indicates that it decreases the predicted score. When $SHAP < 0$, the predicted compulsive buying score is reduced; that is, it has a negative impact. When the absolute value of SHAP is smaller, it may have a non-monotonic or mixed impact.

The results of machine learning complement the Kruskal–Wallis test. The former shows that impulse control and emotional mechanisms are still core predictors in the case of multiple variables, while the latter shows that shopping addiction and budget planning seem to have a strong impact on the intergroup effect. The relationship of some variables in SHAP analysis shows a non-monotonic pattern, indicating that the impact of these variables may depend on the variable interval and other variable combinations. Therefore, the article does not judge the causal direction of the stable positive and negative nature shown by the predictor based on the simple SHAP bar chart, but uses Mean $|SHAP|$ to compare the importance of prediction. See **Figure 2**.

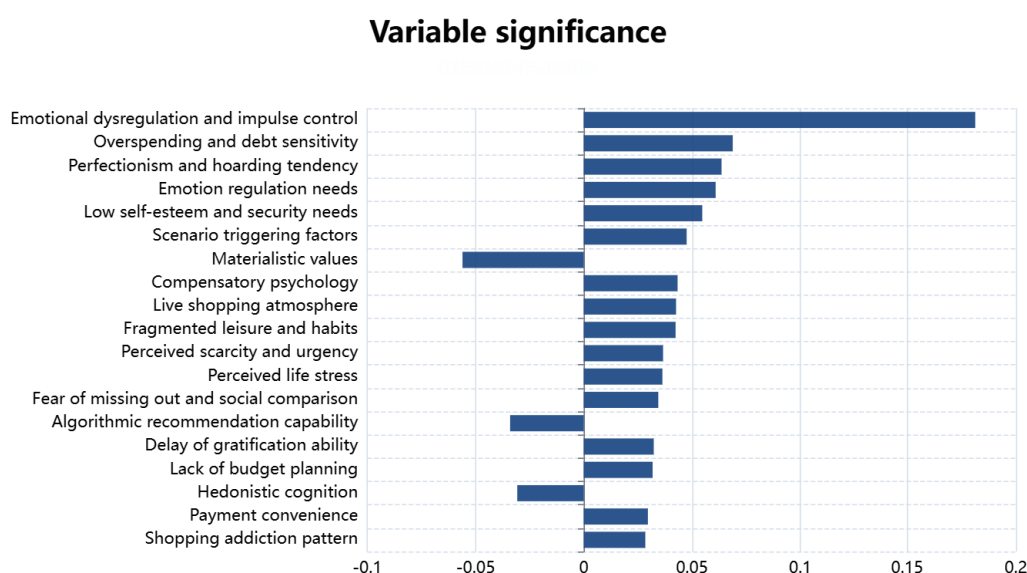


Figure 2. Direction and magnitude of the influence of each factor on compulsive buying

4.4. Indirect effects of contextual triggers

Bootstrap analysis showed that the three contextual triggers—browsing shopping apps when lonely or bored,

frequently placing orders for comfort under stress, and making compensatory purchases after frustration—produced stable positive indirect effects between all nine internal factors and compulsive buying, with the 95% confidence intervals excluding 0. Emotional regulation needs and emotional dysregulation and impulse control both form strong and relatively balanced indirect effects in the three types of scenarios, which belong to the core mechanism across contexts.

Low self-esteem has a strong indirect effect on one of the specific paths. The pathway of “compensatory purchases after setbacks” may involve multiple reflexive interpretations.. Perfectionism and hoarding tendencies appear more in stressful and frustrated scenarios. The effect of hedonism and delay of gratification is concentrated in lonely and boring contexts, and its effect value is slightly higher. The effect value of the shopping addiction pattern and lack of budget planning is relatively stable in the three scenarios. It shows that they are more like a persistent behavioral basis.

Most external factors also form significant positive and indirect effects through three types of scenarios, namely materialism, fear of missing out and social comparison, algorithm recommendation, scarcity and urgency, payment convenience, advance consumption, life pressure, and fragmented consumption habits. The indirect effect of demographic variables is more selective, mainly forming significant positive indirect effects in age, education, occupation, and disposable income. The overall result supports H3.

4.5. Comparison between groups with high and low context sensitivity

H4 is relatively supported between groups. The compulsive buying of high-context-sensitivity groups is more likely to be directly activated by the live atmosphere and algorithm recommendations. The contribution of emotional regulation needs in low-context-sensitivity groups reaches 0.2527, which is higher than other factors, indicating that shopping is more like an internally driven emotion-regulation strategy for this group. Livestream shopping atmosphere was not significant for the Kruskal–Wallis test of the whole sample, and it has a high contribution in the high-context group, suggesting that the average effect may obscure the conditional impact. See **Figure 3** and **Table 4**.

Key SHAP Contributions of High- vs. Low-Scenario-Sensitivity Groups

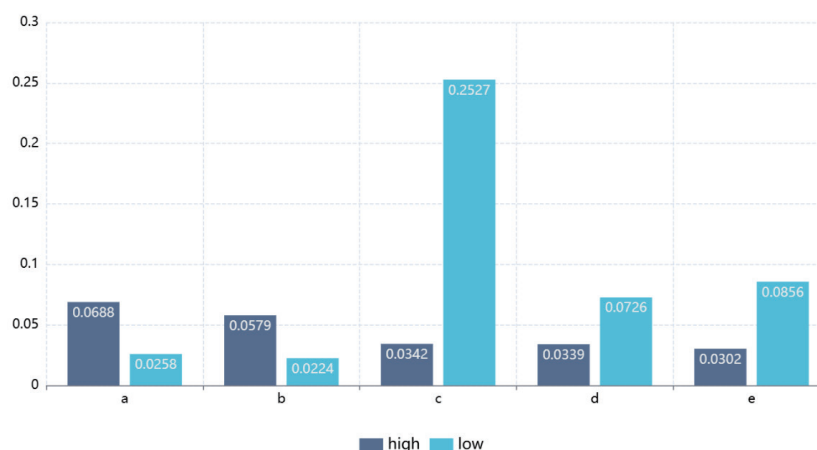


Figure 3. Comparison of key SHAP contributions between high- and low-context-sensitivity groups (a = Live-streaming shopping atmosphere, b = Algorithmic accurate recommendation, c = Emotion regulation needs, d = Emotional dysregulation and impulse control, e = FoMO and social comparison.)

Table 4. Comparison of key SHAP contributions between the high- and low-context-sensitivity groups

Factor	High-context-sensitivity group mean SHAP	Low-context-sensitivity group mean SHAP	Interpretation
Livestream Shopping Atmosphere	0.0688	0.0258	Stronger in the high-context-sensitivity group; externally activated
Algorithmic Personalized Recommendations	0.0579	0.0224	Stronger in the high-context-sensitivity group; externally activated
Emotion Regulation Needs	0.0342	0.2527	Substantially stronger in the low-context-sensitivity group; internally driven
Emotional Dysregulation and Impulse Control	0.0339	0.0726	Stronger in the low-context-sensitivity group; underlying susceptibility
Fear of Missing Out and Social Comparison	0.0302	0.0856	Stronger in the low-context-sensitivity group; cognitively entrenched

5. Discussion

5.1. Main findings

Based on 621 valid questionnaires, a study was conducted on the factors affecting compulsive buying, which were divided into internal susceptibility factors and external consumption environment factors, and included contextual triggers as mediators. It was found that:

First, the core of compulsive buying may not be “like shopping,” but the internal susceptibility structure of emotional regulation, impulse control, addiction habits, and budget boundaries. Whether it is based on non-parametric testing or explanatory machine learning, emotional and self-control variables have strong explanatory power, indicating that shopping may be used as a shortcut for emotional rescue by some consumers.

Second, the impact of the external digital environment is significant rather than homogeneous. Fragmented browsing, scarcity cues, payment convenience, and advance consumption were generally associated with higher levels of compulsive buying. But the whole sample average effect of the livestream shopping atmosphere is not significant; The results of context grouping further show that the role of live broadcasts and algorithms is mainly concentrated on high-context-sensitive people. Therefore, the platform factor should not be understood as having the same stimulus for all consumers, but acting together with the susceptibility state.

Third, the context is a proximal mechanism that connects long-term characteristics with instant behavior. Emotional regulation needs caused by loneliness, stress, and frustration, lack of impulse control, and external stimuli are more likely to be converted into orders. This result will connect the relatively separated “individual causes” and “platform causes” in existing studies, resulting in the path of behavioral occurrence.

Fourth, there are certain differences in age and occupation, but the overall differences in gender, education, marital/relationship status, and disposable income were limited. Demographic characteristics are not reliable proxies for compulsive buying risk. Lower-income consumers may still face risks associated with emotion-driven buying and poor budget control, while among higher-income consumers, payment convenience and advance consumption may also increase compulsive buying risk.

5.2. Policy recommendations

For consumers, the focus of intervention should be shifted from simple “buying less” intervention to identifying high-trigger contexts in advance and implementing alternative emotional strategies. It can be adopted: “monthly

total budget + category budget + single upper limit” to include installments and buy now, pay later in the same budget. When loneliness/stress/frustration occurs, adopt a 15–30-minute cooling-down period + build a list or related community forms of emotional repair in addition to shopping, such as exercise, socializing, resting, or asking for help.

For platforms and merchants, necessary decision-making frictions can be added to time-limited discounts, scarcity cues, live broadcast strong stimulation, and installment payment links, such as: second payment confirmation, delayed payment entry, explanation of recommendation reasons, and closure of recommendation entry. For users who frequently return purchases, place orders continuously late at night, and use installment tools frequently in the short term, non-punitive risk reminders can be used instead of continuing to give enhanced stimulation.

For the public sector and the education sector, consumer psychology, digital platform identification, and basic financial planning can be easily incorporated into college and community education programs. Supervision should focus on the use of inducing scarce information, fuzzy installment fees, and uncontrollable recommendation systems, and provide low-threshold additional support for individuals experiencing both emotional distress and impulsive behavior.

5.3. Research limitations and future directions

There are still some limitations in this article, which need to be improved by follow-up research.

First, the sample uses stratified quota sampling and online convenience sampling, and the survey area is limited to Beijing. The results cannot be directly generalized to Beijing as a whole or other cities, and the survey group is limited. Subsequently, probability sampling or cross-city stratified samples can be used for replication, and the results can be generalized to a wider population.

Second, the data were collected using a cross-sectional self-report questionnaire, and there is a possibility of common method bias and reverse causality; the mediation analysis made in this article can only support indirect associations consistent with the theory and cannot establish temporal ordering. In the future, longitudinal tracking, experimental manipulation, and actual transaction or billing data should be supplemented.

Third, some of the scales are localized and adapted. The three types of scenarios use single-item measures. The internally defined stratification thresholds are not clinical diagnostic standards. The follow-up research should carry out confirmatory factor analysis, measurement invariance testing, and develop a multi-item contextual trigger scale.

Fourth, XGBoost results are currently based on a training/test division, and cross-validation, hyperparameter reporting, and external validation are still required. SHAP is used to interpret model predictions rather than to establish causal relationships. Subsequently, it can be combined with GAM or structural equation modeling to verify nonlinearity and mechanism.

Disclosure statement

The author declares no conflict of interest.

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