Impulsive purchase behavior analysis

Modeling Impulsive Buying through Lifestyle Factors and In-Store Stimuli

IN A PARK

1.Introduction

Understanding impulsive purchasing behavior has become increasingly crucial in modern data-driven retail analytics. Impulsive buying–defined as unplanned, emotionally driven purchasing–constitutes a significant portion of consumer expenditure, particularly in environments designed to elicit sensory engagement.

In the era of big data and behavioral analytics, understanding impulsive purchase behavior offers a bridge between psychological insight and data science application. Retailers now collect vast streams of consumer data–from browsing logs to in-store sensor data–making it essential to identify latent behavioral patterns that can inform predictive models of purchasing behavior.

This study employs quantitative methods, including Exploratory Factor Analysis (EFA) and Multiple Regression Modeling, to investigate how consumers with distinct lifestyle orientations respond to in-store stimuli such as atmosphere, packaging, and point-of-purchase (POP) advertising. While the analysis was performed using SPSS, the framework is designed to be generalizable for data science workflows involving segmentation and predictive modeling.

Ultimately, the study illustrates how integrating psychographic constructs with measurable environmental variables can advance data-informed retail personalization and strategic decision-making.

2. Theoretical Background

Impulsive purchase behavior has long been examined in consumer psychology; however, recent data-driven approaches enable quantification of its underlying determinants. This research conceptualizes in-store stimuli (store layout, product arrangement, POP advertising, packaging, and atmosphere) as predictive variables influencing impulsive buying tendencies.

Furthermore, lifestyle orientation is treated as a latent independent construct that drives consumers' responses to purchasing stimuli such as store atmosphere, packaging, and point-of-purchase advertising. From a data science perspective, this framework represents a multi-factor behavioral model, in which individual lifestyle values serve as key predictors explaining variance in impulsive purchasing behavior.

By operationalizing these constructs through Likert-scale measurements, this study provides structured data suitable for statistical modeling, feature extraction, and potential machine learning applications.

Construct	Definition	Scale
Lifestyle	A pattern of living that reflects individuals' values, activities, and self-expression tendencies, shaping how they perceive and react to marketing stimuli.	5-point Likert scale
Store Layout	Store layout refers to the strategic design of store space intended to encourage customers to stay longer and explore more areas of the store.	5-point Likert scale
Product Arrangement	Organization of items on shelves to enhance visual attention and facilitate search behavior.	5-point Likert scale

POP Advertising	Point-of-purchase visual or promotional displays that evoke immediate affective responses and encourage unplanned purchases.	5-point Likert scale
Packaging	Visual and structural design elements of a product's container that communicate value, quality, or novelty.	5-point Likert scale
Atmosphere	The holistic sensory environment—lighting, music, scent, and color—that shapes emotional states and shopping motivation.	5-point Likert scale
Impulsive Purchasing	The tendency to make unplanned, emotion-driven buying decisions with limited cognitive deliberation.	5-point Likert scale

Table 1. Definitions and Measurement Scales for Model Constructs

3. Research Model

The research model examines how distinct lifestyle factors influence impulsive purchase behavior under varying in-store conditions. Specifically, atmosphere, packaging, and POP advertising serve as stimuli variables, while impulsive purchasing acts as the dependent outcome. Methodologically, this framework aligns with the predictive modeling process in data analytics–identifying key predictors, testing their statistical significance, and validating behavioral hypotheses. The study follows a two-stage analytical pipeline.

1) Exploratory Factor Analysis (EFA) identifies latent lifestyle dimensions from survey data.
2) Multiple Regression Analysis evaluates how each factor predicts impulsive purchase tendencies under distinct stimuli conditions.

This structured pipeline reflects a feature extraction → model fitting → interpretation approach, central to data science reasoning.

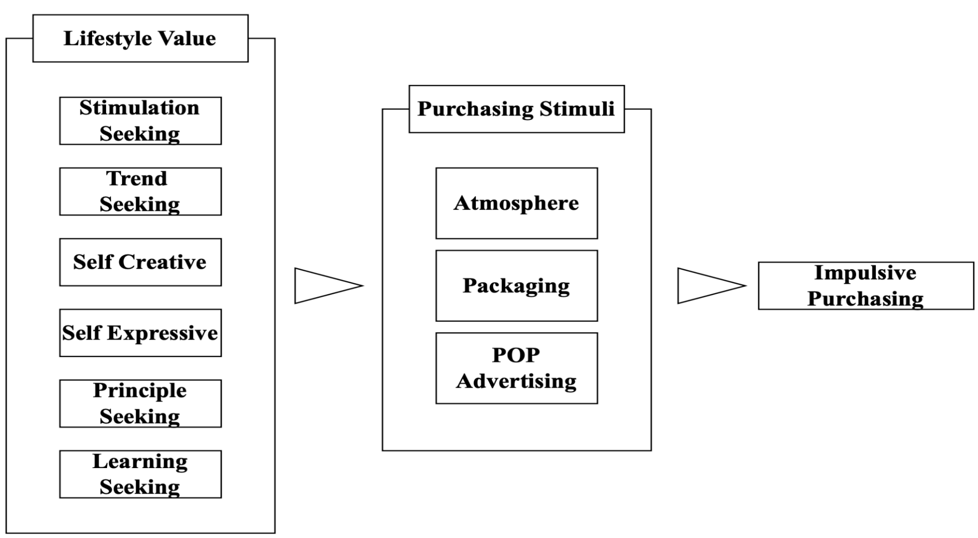

Figure 1. Conceptual model linking lifestyle dimensions, in-store stimuli, and impulsive purchase behavior.

4. Research Method

4.1 Analytical Overview

Data were collected using a structured questionnaire with all constructs measured on a 5-point Likert scale. Analyses were conducted using SPSS, following a standard two-stage process:

1) EFA for dimensionality reduction.
2) Multiple Regression for hypothesis testing.

4.2. Exploratory Factor Analysis

Lifestyle Type	Explained Variance (%)	Cronbach's α
Stimulation-Seeking	11.333	0.791
Trend-Seeking	9.244	0.846
Self-Creative	8.880	0.852
Self-Expressive	8.838	0.723
Principle-Exploring	8.724	0.771
Learning-Seeking	7.229	0.554

Table 2. Results of Exploratory Factor Analysis and Reliability Coefficients

The EFA identified six latent lifestyle dimensions-Stimulation-Seeking, Trend-Seeking, Self-Creative, Self-Expressive, Principle-Exploring, and Learning-Seeking-explaining a cumulative variance exceeding 50%. Although one factor (Learning-Seeking) had a slightly lower reliability (Cronbach's $\alpha = 0.554$), it was retained for theoretical completeness. Such dimensionality reduction reflects the data science concept of feature extraction, isolating latent variables that best capture variance across consumer behaviors.

4.3. Multiple Regression Analysis

Regression models were estimated under three conditions–Atmosphere, Packaging, and POP Advertising–to test the predictive influence of each lifestyle factor on impulsive purchasing. For clarity and interpretability, standardized β coefficients are reported to assess relative importance. In a data science framework, these results parallel feature importance estimation in predictive modeling.

(a) Atmosphere

Predictor	Unstandardized B	Standardized β	t-value
Stimulation-Seeking	0.312	0.218	3.043
Trend-Seeking	0.018	0.018	0.264
Self-Creative	0.083	0.087	1.221
Self-Expressive	0.173	0.122	1.715
Principle-Exploring	-0.01	-0.114	-1.649
Learning-Seeking	-0.033	-0.03	-0.445

Table 3. The results of the multiple regression analysis examining the influence of different lifestyle dimensions on impulsive purchasing under the store atmosphere condition.

The stimulation-seeking lifestyle had a significant positive effect on impulsive purchasing ($\beta = 0.218$, $t = 3.043$, $p < .05$), indicating that consumers who are highly responsive to external sensory cues tend to engage in more spontaneous buying behaviors. Self-expressive consumers also showed a marginally significant positive relationship ($\beta = 0.122$, $t = 1.715$, $p < .01$). In contrast, principle-exploring consumers exhibited a negative but non-significant association, suggesting that rational and analytical shoppers are less affected by atmospheric stimuli.

These results imply that creating sensory and experience-oriented store environments can effectively attract stimulation-seeking consumers, who are driven by emotional and environmental cues. However, for principle-exploring consumers, transparent product information, rational justifications, and price clarity remain more influential in shaping purchasing decisions.

(b) Packaging

Predictor	Unstandardized B	Standardized β	t-value
Stimulation-Seeking	0.271	0.158	2.207
Trend-Seeking	0.095	0.079	1.177
Self-Creative	0.035	0.031	0.432
Self-Expressive	0.302	0.176	2.493
Principle-Exploring	-0.047	-0.044	-0.641
Learning-Seeking	-0.028	-0.021	-0.311

Table 4. The results of the multiple regression analysis examining the influence of different lifestyle dimensions on impulsive purchasing under the store Packaging condition.

Table 4 presents the results of the multiple regression analysis for the packaging stimulus. Stimulation-seeking consumers showed a significant positive effect on impulsive purchasing ($\beta = 0.158$, $t = 2.207$, $p < .05$), while self-expressive consumers also exhibited a significant positive association ($\beta = 0.176$, $t = 2.493$, $p < .05$). These results indicate that consumers with high sensitivity to visual and aesthetic cues are more likely to make spontaneous purchase decisions when exposed to visually engaging packaging.

These findings suggest that packaging designs emphasizing novelty, bold colors, or creative forms effectively attract stimulation-seeking consumers, who are motivated by sensory arousal and curiosity. Meanwhile, self-expressive consumers tend to favor luxurious or unique packaging that reinforces their sense of individuality and self-image. Conversely, principle-oriented or image-conscious consumers are less influenced by visual appeal and may instead prioritize credibility, product information, or social value communicated through the packaging.

(c) POP Advertising

Predictor	Unstandardized B	Standardized β	t-value
Stimulation-Seeking	0.267	0.201	2.968
Trend-Seeking	0.146	0.157	2.473
Self-Creative	0.236	0.266	3.941
Self-Expressive	0.150	0.114	1.692
Principle-Exploring	-0.084	-0.103	-1.568
Learning-Seeking	-0.127	-0.122	-1.936

Table 5. The results of the multiple regression analysis examining the influence of different lifestyle dimensions on impulsive purchasing under the store POP Advertising condition.

Table 5 summarizes the regression results for POP advertising stimuli. Stimulation-seeking ($\beta = 0.201$, $t = 2.968$, $p < .01$), trend-seeking ($\beta = 0.157$, $t = 2.473$, $p < .05$), and self-creative ($\beta = 0.266$, $t = 3.941$, $p < .001$) consumers exhibited significant positive effects on impulsive purchasing. In contrast, principle-exploring ($\beta = -0.103$, $t = -1.568$) and learning-seeking ($\beta = -0.122$, $t = -1.936$) groups showed negative, statistically insignificant effects.

These results indicate that stimulation-seeking and trend-seeking consumers are more responsive to sensory-rich and emotionally engaging POP advertisements. Self-creative consumers, in particular, demonstrate heightened responsiveness to novel and imaginative ad designs that emphasize originality and self-expression. Conversely, principle-exploring and learning-oriented consumers respond less favorably to emotionally driven messages, preferring informational advertisements grounded in logic and detail. From a managerial standpoint, combining sensory stimulation with creative and participatory ad formats may be the most effective strategy for engaging stimulation-seeking, trend-seeking, and self-creative consumers. Given their emphasis on self-expression and creativity, these groups are likely to respond positively to co-creation or interactive advertising campaigns.

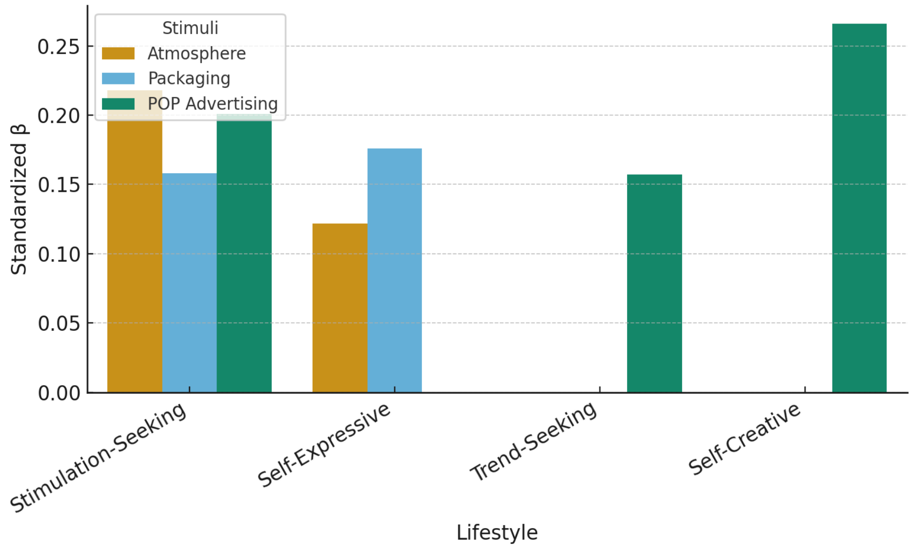

Figure 2. The standardized regression coefficients across lifestyle types and stimuli conditions.

To provide a holistic comparison across all stimulus conditions, Figure 2 visualizes the standardized β coefficients of key lifestyle factors. This visualization highlights how stimulation-seeking and self-creative lifestyles consistently demonstrate the strongest predictive effects across stimuli types. Such visual comparison facilitates feature importance interpretation—a key step in data-driven behavioral modeling.

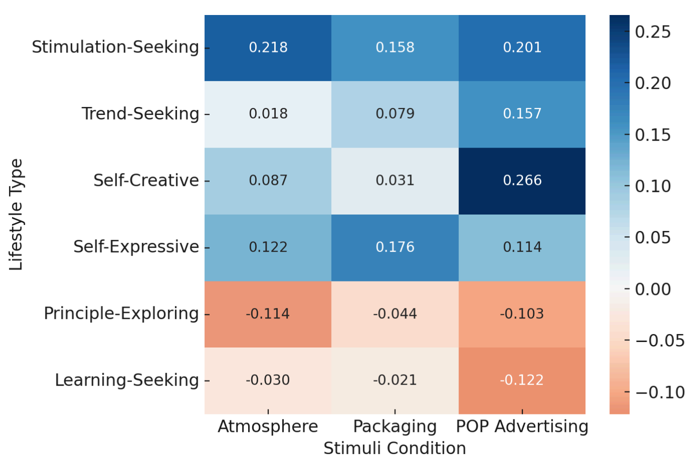

Figure 3. Behavioral Sensitivity Matrix across Lifestyle Types and In-Store Stimuli.

Figure 3 provides a pattern-oriented visualization that integrates the standardized coefficients across all conditions. The heatmap illustrates how each lifestyle type responds differently to the three stimuli-Atmosphere, Packaging, and POP Advertising-revealing distinct clusters of behavioral sensitivity. Compared to other lifestyle groups, stimulation-seeking consumers exhibit the highest overall responsiveness (Atmosphere = 0.218, Packaging = 0.158, POP Advertising = 0.201), indicating that they are particularly sensitive to environmental and promotional cues. Self-creative consumers show relatively elevated sensitivity, especially under POP advertising conditions (0.266), which surpasses the responsiveness of most other groups and suggests that creative self-expression aligns closely with visually stimulating marketing.

In contrast, principle-exploring (−0.114 to −0.103) and learning-seeking (−0.030 to −0.122) consumers consistently exhibit the lowest sensitivity levels across all stimuli, showing notably weaker responsiveness relative to sensation- and creativity-driven groups. Overall, these relative differences indicate that emotionally engaging, visually rich retail cues are most effective for consumer segments driven by stimulation and creativity, while more rational, principle-oriented consumers remain less affected by such stimuli.

5. Conclusion

This study examined how lifestyle orientations shape consumers' impulsive purchase behavior under different in-store stimuli, combining psychological theory with quantitative data analysis. Across three environmental conditions–atmosphere, packaging, and POP advertising–stimulation-seeking and self-creative consumers consistently demonstrated the strongest impulsive tendencies. These findings suggest that emotionally engaging and sensory-rich retail cues are key triggers for unplanned purchasing decisions.

From a data science perspective, the research highlights how psychographic segmentation can enhance predictive modeling of consumer behavior. The integration of latent lifestyle constructs into quantitative models provides a structured pathway for feature extraction and behavioral prediction in retail analytics. Such an approach enables data-driven personalization, allowing marketers to tailor visual and environmental stimuli to distinct consumer segments.

However, this study is limited by its cross-sectional survey design and reliance on self-reported data, which may not fully capture real-time impulsive actions. Future research could apply machine learning techniques to transactional or sensor-based behavioral data to improve predictive accuracy and generalizability.

Overall, the results underscore the value of combining psychological constructs with analytical modeling, bridging behavioral science and data science to better understand and anticipate impulsive consumer decisions.