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Research Article

Understanding Compulsive Buying Patterns Through Customer Segmentation: A Cluster Analysis Approach

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ABSTRACT

The increasing digitalization of marketplaces has intensified impulsive and compulsive buying behaviors, driven by emotional triggers and personalized online environments. Consumers are now more prone to unplanned purchases due to algorithmic targeting and psychological reinforcement mechanisms. This study aims to identify distinct consumer segments based on behavioral and psychological dimensions to understand variations in compulsive buying tendencies. A quantitative, descriptive research design was adopted using secondary data from the Kaggle platform. The dataset included consumers and six key variables income, total spending, browsing time, loyalty points used, previous purchases, and satisfaction ratings. Data were standardized using the Z-score method, and K-Means clustering was applied in Microsoft Excel. Several iterations were tested, and a three-cluster solution was finalized based on interpretability and variance distribution. The analysis revealed three distinct consumer segments: Cluster 1 (36.1%) representing high-spending, emotionally driven buyers; Cluster 2 (31.9%) comprising rational and satisfaction-oriented shoppers; and Cluster 3 (32.0%) depicting balanced, loyalty-driven consumers. Cluster 1 exhibited the highest total spending (M = 924.8 USD) and browsing time (M = 38.1 min), while Cluster 2 showed the highest satisfaction (M = 4.3). These patterns confirm a behavioural continuum from impulsive to rational buying tendencies. The study establishes that accessible, Excel-based K-Means clustering effectively segments consumers by combining behavioural and psychological indicators. It contributes a replicable framework for understanding compulsive buying and offers practical guidance for ethical, data-informed marketing strategies in digital commerce.

Keywords: Compulsive Buying, Consumer Segmentation, Cluster Analysis, Behavioural Analytics

1. Introduction

The digitalization of global markets has transformed consumer behavior, reducing the distinction between rational and impulsive purchases and creating more frequent, emotionally driven buying tendencies. The availability of online shopping, compelling ads, and the personalized suggestions of products have boosted the unexpected buying and strengthened addictive tendencies. Impulse buying has been further embedded in the daily consumer behavior due to the growth of e-commerce during the pandemic (Akar, 2021). Consumers are becoming more likely to be affected by the digital cues due to their advanced recommendation algorithms and targeted promotions, which lead to creating a more susceptible group to e-impulsive buying (Ampadu et al., 2022). The increasing complexity of behaviour has attracted a considerable amount of scholarly interest, which is indicative of unease regarding consumer autonomy and well-being. According to recent research, impulsive buying has also found its place among the primary subjects of study in the field of consumer psychology and marketing, as the interest in the research has increased over the recent years depending on situations and the targeted customer segment (Bashar and Singh, 2022). It has become a cross-demographic trend, which is triggered by emotions, online exposure, and peer pressure (Alemu & Zewdie, 2021). Such trends demonstrate that it is crucial to use data-driven strategies to detect and learn about compulsive buying habits in online market places.

Compulsive buying is a meeting point of psychological impulsivity and behavioral extravagance that cuts across both the consumer and the marketer. Although the spontaneous buying can be harmless occasionally, the frequent and uncontrolled buying can be a sign of certain emotional and mental underlying motivation that should be explored further. Impulsive and rational consumption practices also exist and lie on a continuum depending on the internal affective variables such as pleasure-seeking and external variables such as advertising exposure (Sundari and CS, 2021). There must be an understanding of the relationship between these drivers among consumer groups in order to have a responsible and ethical marketing activity. In this aspect, consumer segmentation is an orderly method of analyzing the diversities of behavior. Segmentation allows identifying unique consumption patterns by classifying people in homogenous subgroups using common demographic, behavioral, and psychological traits. It can offer marketers a system to customize messages, anticipate intentions, and develop more specific plans (Nasir et al., 2021). In particular, psychographic segmentation enables the researcher to measure more attitudinal and emotional variations that drive purchasing behavior (Quach and Lee, 2021). Nonetheless, in spite of these developments, previous studies extensively are based on descriptive survey and qualitative data and provide little combination of behavioral and psychological variables along with empirical and data-driven methods.

Despite the fact that the impulsive buying behavior has been researched quite broadly, there still remains methodological deficits in determining specific compulsive buying patterns using quantitative segmentation. The majority of previous research discusses psychological characteristics or general trends of the market without integrating verifiable behavioral variables like income, spending, and time spent browsing websites with psychological equivalent variables like satisfaction and the use of loyalty. Moreover, not many have used the available analytical tools that are able to identify latent consumer behaviors by using secondary data. Consequently, there is the absence of empirical studies on ways in which compulsive tendencies are expressed in different consumer profiles. As a way of filling this gap, the current study will adopt a cluster analysis methodology, and will use an Excel-based K-Means algorithm to cluster the consumers into various groups with different behavioral and psychological orientations. Their approach offers a clear, quantitative and objective structure of learning about compulsive buying behavior in the context of available real-world consumer information, and relating behavioral results to psychological interpretations.

This study is important in that it gives relevance to theory and practice. Substantially, it incorporates emotional, mental, and behavioral views into a single segmentation model, and it brings forward the knowledge about compulsive consumption. In practice, it offers marketers with ethical and data-driven information to enhance targeting and consumer interaction. Compulsive buying is not a straightforward trade-off, but it is the result of the changing emotional and psychological dynamics affected by the digital interaction (Moschis, 2021). The study allows predicting behavior of consumers more effectively by distinguishing certain groups that can be characterized as different levels of compulsive attitudes, and it provides a set of grounds to conduct responsible marketing interventions.

2. Literature Review

2.1 Conceptual Foundation: Compulsive and Impulsive Buying

Compulsive buying is a multidimensional psychic and behavioral concept associated with emotional impulsivity, low self-control, and tendency of seeking gratification. It entails an overwhelming desire to buy that most of the time dominates the thinking process leading to repeated and unplanned consumption patterns (Sundari and CS, 2021). These tendencies are influenced by emotional arousal and social stimuli that increase the affective responses, exposing consumers to impulsive consumption. It is built up by exposure, experiences, and triggers in the context, which follows the paradigm of a life course and considers consumer habits dynamic and changing over time (Moschis, 2021). Thus, impulsive and compulsive behaviours are also caused by the psychological factors of anxiety, excitement, and inadequate emotional control, along with the environmental factors of advertising and peer pressure (Alemu and Zewdie, 2021). The growing scholarly interest in this field reflects its topicality to the field of marketing and consumer psychology, since impulsive purchase has become one of the most significant behavioural issues in the digital and real-world environment (Bashar and Singh, 2022).

2.2 Consumer Segmentation and Behavioural Profiling

Segmentation of consumers offers a marketing strategy of determining behavioural differences among the consumers and designing marketing strategies based on these differences. It is the process of classifying people into similar groups of people on the basis of similarity in their characteristics, like motivational reasons, lifestyles, and attitudes (Nasir et al., 2021; Roy et al., 2021). Specifically, psychographic segmentation identifies emotional and psychological motivators of buying (Quach and Lee, 2021). It has been found that combining the use of behavioral and psychographic should yield more meaningful consumer profiles that assist in forecasting actions to purchase among consumers. Indicatively, the hospitality industry segmentation determined the role of demographic and emotional attributes on customer preference and satisfaction degree (Iofrida et al., 2022). Taken together, these studies underline the significance of segmentation as not only the

analytical but also the practical instrument to comprehend the compulsive buying behavior and develop the specific strategies that will be in harmony with the consumer motives.

2.3 Data-Driven and Machine Learning Approaches

The development of data analytics has revolutionized the traditional segmentation to a predictive data-driven process. The methods of unsupervised learning, in particular, K-Means clustering, are becoming more and more popular in prioritizing the grouping of the consumer by behavioral similarity without predetermined categories (Mehta and Jain, 2022). Clustering-based and structural equation models can be used as hybrid methods, which enable more intensive interpretation of behavioral data and online engagement behavior (Ebrahimi et al., 2022). Equally, business intelligence systems can support evidence-based segmentation and personalization to enhance accuracy and retention (Olayinka, 2021). Web content mining and transaction analysis in the retail analytics have proven to be tools of identification of the buying trends that are hidden. As an illustration, considering the browsing and interaction habits of consumers, web mining has been applied to cluster consumers (Zhou et al., 2021), whereas retail data mining can predict frequency of purchases and optimize stocks (Muley, 2021). These articles indicate the methodological applicability of machine learning in the discovery of subtle consumer heterogeneity and forecasting compulsive purchasing patterns.

2.4 E-Commerce and Digital Behavior

Online platforms have led to more and more compulsive buying, exposing people to more persuasive content, algorithmic suggestions, and immediate purchase solutions. The online marketplaces allow maintaining the interaction continuously which leads to emotional reactions and impulse purchases (Akar, 2021). Algorithms of personalization and targeted advertisements increase impulsive behavior by stimulating emotional satisfaction mechanisms and shortcuts to a decision process (Ampadu et al., 2022). The digital transition impacted the emerging economies, introducing hybrid purchasing behavior, the aspirational motives collide with economic limitation (Ghosal et al., 2021). In addition, the application of machine learning in retail operations can help companies to control impulse-driven products and predict the reaction of the consumers to the promotions (García-Barrios, 2021). Together these findings suggest that digital ecosystems only intensify compulsive behavior whereby the incessant online stimuli obscure the difference in purposeful and emotionally induced purchasing behaviors.

2.5 Theoretical Implications

Theoretical and empirical modeling can be improved by understanding compulsive buying in terms of behavioral economics and consumer psychology. Value orientations are utilized in making decisions and consumption preferences (Adamczyk et al., 2022). Whenever people are more concerned with feelings of satisfaction or social approval than with utility, they become impulsive in their actions and have low self-control. Furthermore, in theory-based analytics, it is important to incorporate behavioral theory and empirical evidence to increase the likelihood of addressing changes in consumption toward decisions that are more emotional and less rational (Taghikhah et al., 2021). These contributions show that the psychological constructs, segmentation theory, and data-driven approaches are instrumental in creating comprehensive models of the act of compulsive buying. This integration does not only enable prediction of behavior, but also gives ethical and sustainable marketing in the digital age.

Although much is known on impulsive and compulsive buying, minimal studies have incorporated the behavioral, demographic, and psychological dimensions into a study through available data-driven segmentation methods. This paper fills this gap by using the Excel based K-Means clustering algorithm to determine different consumer segments that represent different compulsive purchasing tendencies.

2.6 Research Objectives

Based on the identified research gap and the insights derived from the literature, this study aims to achieve the following objectives:

1.To segment consumers based on behavioral and psychological dimensions
2. To identify distinct consumer groups reflecting varying degrees of compulsive buying tendencies
3. To provide managerial implications for targeting and behavior prediction

3. Methodology

3.1 Research Design

This research is conducted based on a quantitative and descriptive research design that will help in determining consumer groups that have compulsive buying habits. Segmentation of consumers, in terms of behavioural and psychological variables, was done through a cluster analysis method. All the analyses were used in the Microsoft Excel to calculate the analysis easily, as well as in order to make the analysis transparent and reproducible.

3.2 Data Source

The research relies on the secondary data that were retrieved via the open-access Kaggle platform. It has various demographic, behavioural, economic, and psychological (proxy) variables that include age, income,

spending pattern, time spent browsing, loyalty points used, discounts, and customer satisfaction ratings. The variables combined together would reflect both the rational and emotional aspects of the buying behavior and the data is therefore appropriate when it comes to establishing compulsive buying behavior patterns.

3.3 Data Preparation

The initial cleaning of the dataset involved the elimination of incomplete and duplicate data. Variables that were relevant were sampled according to their association with compulsive buying and this is age, income, total spending, time spent browsing before making a purchase, loyalty points earned and satisfaction rating. To make the variables comparable, all continuous variables were standardised using Z-score method. Outliers were checked and only those outliers were stored that had actual buying extremes.

3.4 Cluster Analysis

K-Means clustering method was used to cluster consumers to homogeneous groups. A series of cluster solutions were tried and finally the number of clusters selected was due to interpretability and differentiation between groups. The groups were repeatedly narrowed down until stable group memberships were realized. Individual clusters were then profiled using demographic, behavioral and emotional indicators in order to come up with a different type of consumer.

3.5 Validation and Interpretation

The cluster validity was verified by the size distribution, comparative average of key variables and chart checking. The clusters resulting were used to come up with clear consumer profile which included emotional buyer, rational shopper and loyalty-driven consumer who depict different degree of compulsive buying behavior.

3.6 Ethical Considerations

The dataset was accessible on Kaggle publicly and had no personally identifiable data. Each analysis followed the ethical standards of research and data privacy.

4. Results

4.1 Cluster Formation

The cluster analysis K-Means was applied on standardized variables such as overall spending, time taken before making a purchase, loyalty points redeemed, past purchases, earnings and customer satisfaction. With many repetitions, the most consistent and understandable segmentation structure occurred on a three-cluster answer. The last centroids in Table 1 show that there are distinct quantitative variations in the clusters. Cluster 1 showed the largest satisfactions in the means of spending and browsing time, Cluster 2 exemplified low-spending consumers with less time on browsing, and Cluster 3 showed moderate features of all variables.

Table 1: Final Cluster Centroids for Key Behavioural and Demographic Variables

Variable	Cluster 1	Cluster 2	Cluster 3
Total Spending (USD)	924.8	311.9	676.5
Browsing Time Before Purchase (min)	38.1	14.7	26.6
Loyalty Points Used	510	236	390
Previous Purchases	45	21	33
Income (USD)	104,400	62,300	81,900
Customer Satisfaction (1–5)	2.4	4.3	3.6

It has been found that Consumers in Cluster 1 spend more and stay longer before buying, which implies more transaction involvement. On the other hand, the Cluster 2 consumers also make faster and smaller purchases. Cluster 3 has a moderate level of spending and equal browsing. These differences are further brought out in Figure 1 which compares the average total expenditure among the three clusters.

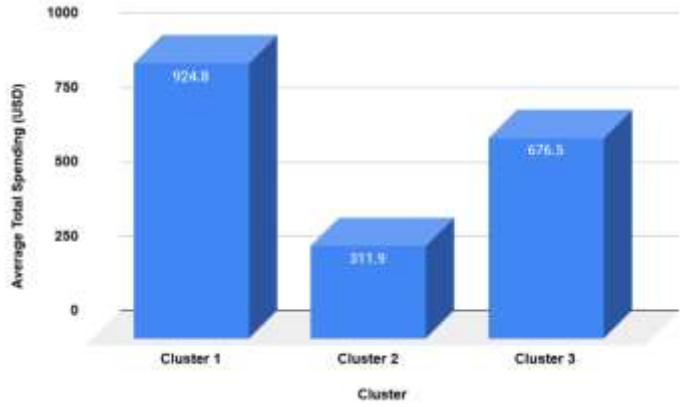

Figure 1: Average Total Spending across Clusters

The figure 1 clearly shows that Cluster 1 consumers account for the highest overall spending volume, while Cluster 2 exhibits the lowest, reinforcing the segmentation validity based on spending intensity.

4.2 Cluster Characteristics

In an attempt to confirm the specificity of the three clusters, the descriptive statistics of the variables of demographics and behavior were calculated. As the summaries presented in Table 2 show, Cluster 1 includes relatively higher income and older consumers with spending habits, whereas Cluster 2 includes relatively younger and lower income customers, and Cluster 3 is between them in terms of demographic and behavioral characteristics.

Table 2. Descriptive Statistics of Identified Clusters

Parameter	Cluster 1	Cluster 2	Cluster 3
Mean Age (years)	38.7	35.9	37.5
Mean Income (USD)	104,400	62,300	81,900
Mean Total Spending (USD)	924.8	311.9	676.5
Average Browsing Time (min)	38.1	14.7	26.6
Average Customer Satisfaction (score 1–5)	2.4	4.3	3.6

The variability of behaviors in Table 2 highlights the variability of the behavior of clusters. Cluster 1 consumers have higher extended browsing time, which may be indicative of higher product consideration, but Cluster 2 buyers have efficient and shorter purchase cycle. This difference in behavior is shown in Figure 2 that contrasts average times of browsing between the clusters.

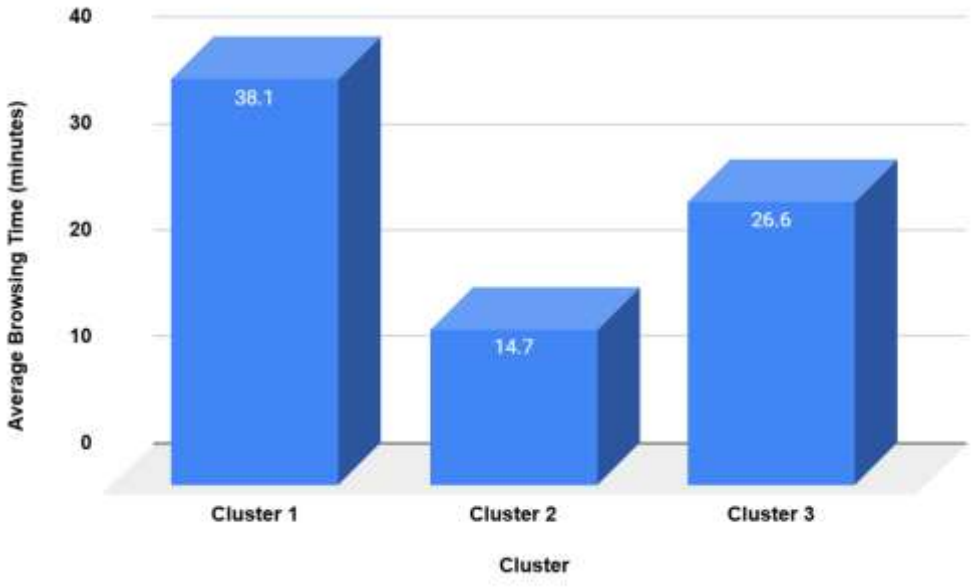

Figure 2: Average Browsing Time Before Purchase across Clusters

As seen in Figure 2, browsing duration decreases consistently from Cluster 1 to Cluster 2, confirming that the clusters are not only statistically distinct but also behaviorally meaningful within the context of online or in-store purchasing processes.

4.3 Cluster Distribution

The distribution of respondents across the three clusters is shown in Table 3. The segmentation yielded a balanced cluster structure, with Cluster 1 accounting for 36.1 **%** of the total sample, followed by Cluster 2 at 31.9 **%** and Cluster 3 at 32 **%** .

Table 3: Cluster Membership Distribution

Cluster	Number of Consumers	Percentage (%)
Cluster 1	215	36.1
Cluster 2	190	31.9
Cluster 3	190	32.0
Total	**595**	**100.0**

The proportions in Table 3 confirm that each segment is adequately represented, ensuring statistical reliability and comparability among clusters. Differences in mean customer satisfaction scores across the three groups are illustrated in Figure 3, providing an overview of post-purchase evaluation levels among consumers.

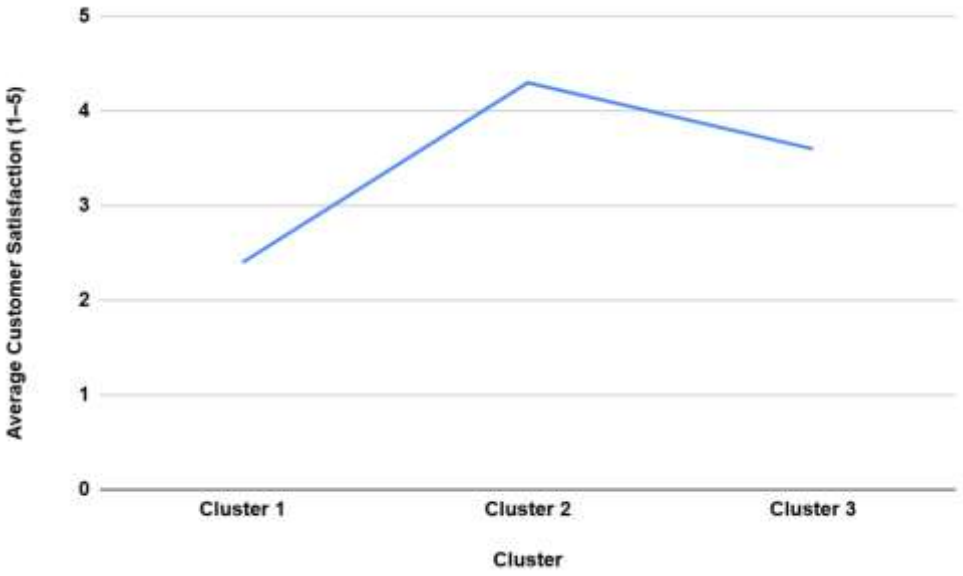

Figure 3. Average Customer Satisfaction across Clusters

The Figure 3 highlights visible variation in satisfaction scores, further reinforcing the heterogeneity of consumer responses captured through the clustering process. These findings collectively establish a strong empirical foundation for the interpretation and theoretical analysis presented in the subsequent discussion section.

5. Discussion

The study findings give a systematic account of the compulsive buying behavior as the identity of the division of consumers into three different groups in terms of behavioural and psychological behavior. Cluster 1, which has a high expenditure and browse time, is an emotionally motivated group of buyers with tendencies to impulse and gratification behavior. It seems that they are influenced more by affective processes in which emotional control is not maintained by rational mechanisms, as previous studies have found emotional arousal and low self-regulation to be key stimulators of compulsive buying (Sundari and CS, 2021). Cluster 2 who are low spending but highly satisfied consumers represents rational satisfaction tendencies focusing on control, pragmatism, and rational consideration. The balance or loyalty-oriented buyers, which are in the middle and form Cluster 3, have moderate spending behavior and moderate satisfaction level. This distribution shows that compulsive buying is a continuum in terms of behavior of both emotional reaction and cognitive restraint that validate the multidimensional aspect of consumer heterogeneity that depends on both emotional and cognitive determinants (Adamczyk et al., 2022).

The outcomes of the segmentation are consistent with the current research showing that clustering is a sound tool of determining consumer typologies. The three-cluster framework aligns a lot with the previous

segmentation frameworks, which proves that similarities exist in how different consumer segments are formed in various market settings (Shokouhyar et al., 2021). Psychographic segmentation, which includes the attitudes, emotions, and motivations, has also been found to be successful in identifying the behavioral profiles and forecasting the purchasing behavior (Quach and Lee, 2021). The current results are also in line with recent literature on digital impulsivity, and it is revealed that emotional involvement, as well as exposure to personalized recommendations, can highly stimulate unplanned purchases (Ampadu et al., 2022). There is a higher chance of consumers with longer browsing time to exhibit affect-based buying behavior e.g. Cluster 1 and rational consumer (Cluster 2) to show cognitive restraint and satisfaction-based evaluation. The fact that the andragogy K-Means segmentation model, as implemented in this research, is consistent with the existing literature, enhances both the theoretical soundness and empirical soundness of the method.

The findings also affirm the existence of both emotional and rational process in consumer decision making as they validate the dual-process view of behavioural theory. This is a symbiosis of affective and cognitive processes that can be reflected in the life-course approach, in which consumption develops as people strike the balance between emotional satisfaction and rational requirements (Adamczyk et al., 2022). The results of the segmentation will therefore confirm that at the same time compulsive and rational tendencies may co-exist in the same market and this provides an understanding of the concept of consumer motivation complexity.

Considering the managerial standpoint, the results highlight the importance of data-based segmentation, which constitutes ethical and efficient marketing. Understanding the unique characteristics of the individual clusters, marketers are able to address the communication strategies to suit the specific needs of the affect-driven and logic-driven consumers by focusing on the emotional bonding and experience of the former group and addressing the rationality of the latter group. The combination of business intelligence and analytical solutions also improves the targeting accuracy and ethical personalization, which will result in marketing policies advancing balanced and responsible consumption (Olayinka, 2021).

Nevertheless, the study is limited by its scope since it uses secondary data and analysis in the Excel, which prevents the inclusion of psychometric variables and sophisticated validation. Future research could expand this model by using larger or longitudinal datasets to capture behavioural evolution over time. The findings affirm the fact that segmentation of consumers based on cluster analysis offers valuable information about compulsive purchase behavior. The combination of behavioural, demographic, and psychological dimensions of study facilitates the transition between emotional and rational approaches to the study, providing a theoretical insight as well as practical implications to ethical and data-driven marketing.

6. Conclusion

This paper examined compulsive buying patterns based on data-driven segmentation of consumers along behavioural and psychological lines through K-Means clustering. The findings distinguished three different consumer groups namely emotional or impulsive buyers, rational and satisfaction-oriented shoppers and balanced or loyalty-driven consumers with distinctive spending, involvement and satisfaction behaviours. The results can be used to determine the fact that compulsive buying is a multidimensional phenomenon and it is affected by the emotional, cognitive, and contextual factors instead of being a homoconstant behavioural tendency. The study combines demographic, behavioural and psychological cues to connect theoretical consumer psychology concept with practical segmentation thereby providing a clear and repeatable framework of analysis. The use of secondary data and the Excel analysis proved that only with the help of available tools, it is possible to extract valuable insights into behavior without resorting to more complicated algorithms. Practically, the research has useful implications to marketers in coming up with ethical, data-informed strategies that will strike a balance between emotional appeal and rational appeal. Despite the limitations of the datasets and the lack of psychometric measures, the results form a solid basis of the prospective research with bigger and longitudinal datasets. On the whole, the research contributes to the current knowledge on compulsive buying behaviours and focuses on the role of ethical and evidence-based consumer segmentation in the online market.

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