

# IMPACT OF CONSUMER BEHAVIOUR FACTORS ON SUSTAINABLE ONLINE PURCHASING DECISIONS

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**Abstract.** The present study explores the growing importance of aligning sustainable sales strategies with consumer purchasing behaviour in the digital marketplace. The *objective* of the research is to examine consumer behaviour in the context of online shopping, with a view to identifying how sustainability-related and behavioural factors influence purchasing decisions across diverse customer groups. A research gap has been identified in relation to sustainable sales and consumers' purchasing behaviour. The research focuses on consumer behaviour in online shopping. The goal of this study is to explore how different factors impact purchasing decisions in the context of a company's sustainable development. *Methodology.* The application of K-Means clustering and regression analysis in this study offers valuable insights into the responses of distinct consumer segments to social, economic, and environmental drivers. This supports companies in achieving sustainable growth. The *results* obtained demonstrate the variation in consumer behaviour across the various customer groups (i.e., browsers, cart abandoners, buyers, premium shoppers) and illustrate the significance of each factor for each created cluster. The findings of this study indicate that representatives of the Browsers cluster were primarily influenced by social media engagement (+0.42) and advertising interaction (+0.36). Customers in the Cart Abandoners cluster showed discount sensitivity (0.51) and shipping preferences (-0.44). For the Buyers cluster, important factors are brand loyalty (+0.58), customer loyalty programmes (+0.46) and product ratings (+0.31). Premium shoppers have a high income and education level, and value time spent on product research. *Practical implications.* The study demonstrates that distinct behavioural patterns have a significant impact on the outcomes of consumption. The findings of the research project have the potential to contribute to the development of sustainable online purchasing as a significant component of sustainable development. *Value/Originality.* The present study draws on consumer behaviour theory in order to investigate the factors that shape online purchasing. It thereby offers original insights into consumer behaviour in the context of sustainable online purchasing decisions, thus contributing to a deeper understanding of how sustainability considerations influence digital consumption patterns.

**Keywords:** digital economy, consumer behaviour, sustainable purchasing, online purchasing decisions, impulse buying, data-driven analysis, user segmentation.

**JEL Classification:** O10, L81, M21, M30

## 1. Introduction

The advent of the digital economy has precipitated a paradigm shift within the business realm, endowing customers with enhanced convenience in the procurement of products and services. It is an irrefutable fact that, in the present age, a mere few clicks are all that is required for users to browse, compare and purchase products from any location and at any time. The advent of smartphones, fast internet, and recommendation systems has resulted in the opening of additional markets and the decentralisation of the

availability of retail services along socioeconomic lines (Bozdog et al., 2025; Verhoef et al., 2021).

Online purchasing platforms have been shown to be associated with the activation of impulse behaviours, overconsumption, and consumer burnout (Kant, 2020; Thaler & Sunstein, 2008). These phenomena can have detrimental social and environmental effects. In contrast to alternative shopping formats, where consumers are more likely to engage in deliberative decision-making, e-shops tend to operate on the basis of personalised, data-driven exposure and gamification

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initiatives (e.g., flash sales, lightning deals, ageing out offers) (Wrabel, Kupfer, & Zimmermann, 2022). When such behavioural prodding yields suboptimal results, it can exacerbate unacceptable consumption practices, such as excessive packaging, transportation-related carbon emissions and premature products.

Furthermore, digital commerce exerts a detrimental effect on the environment, albeit in largely intangible ways, and this effect is considerable. The environmental impact of online shopping is further exacerbated by factors such as the amount of energy that goes into cloud servers, increased transportation due to person-to-person delivery of products, and returned goods logistics (Matz & Netzer, 2017; Stângaciu, 2024). Despite the evident advantages of the digital economy, including job creation, enhanced convenience, and greater economic inclusion, it is imperative to assess the long-term sustainability of this current trend (Chevalier & Mayzlin, 2006).

Understanding these dynamics can play a crucial role in sustainable development. A data-driven approach to real-world e-commerce behaviour can be used to evaluate the sustainability of such behaviour in relation to the concepts of sustainable consumption and inclusive digital economic growth.

The digital economy has changed consumer behaviour, as people can now access goods and services more efficiently (Colabi & Goodarzi, 2025). However, this convenience has also led to negative behaviours such as impulsive buying and overconsumption, which can undermine the concept of sustainability. Upcoming studies have shown that future research should focus on how online shopping habits can be aligned with sustainable consumption behaviours. Although e-commerce is growing, there has been little empirical research into the relationship between digital consumer practices and sustainability objectives, particularly in relation to the United Nations' Sustainable Development Goals (SDGs) (Araujo & Bol, 2025).

The goal of this study is therefore to explore the impact of different factors on purchasing decisions in the context of a company's sustainable development. In order to address this knowledge gap, the study draws on consumer behaviour theory to examine the factors that influence online purchasing decisions. The research will examine differences in consumer behaviour across different customer groups.

This study examines data on user interaction with an e-commerce platform to reveal behavioural trends that can encourage or discourage responsible consumption.

This will combine the results of mapping these behaviours with the guiding principles of sustainable development to offer practical action steps and recommendations to stakeholders, such as platform designers, marketers, and policymakers, to make

the digital marketplace uphold more sustainable practices.

## 2. Literature Review

### 2.1 Consumer Behaviour in Digital Markets

Digital commerce has been demonstrated to influence consumer decision-making processes through the personalisation facilitated by algorithms, dynamic pricing mechanisms, and the utilisation of social proof (Sheth, Sethia, & Srinivas, 2011). The utilisation of recommender systems, and systems of a similar nature, has been demonstrated to be of significant importance, with predictive algorithms resulting in sales volumes of up to 35% on e-commerce platforms such as Amazon (Ozcelik, 2024).

An online environment that guides the consumer with a guiding interface design encourages choice architecture (Hong et al., 2024). Scarcity and urgency signals, such as "Only two left!", Purchasing likelihood is boosted by psychological manipulation using countdown timers (Christy & Iyer, 2025). However, the technique of behavioural targeting raises ethical issues regarding consumer autonomy (Hewamanne & South, 2023).

Average review star ratings and reviews have become a critical factor in consumer purchasing decisions. In some cases, they even outweigh brand loyalty, as most users trust peer opinions to inform their purchasing decisions (Chu, Long & Zhang, 2025). The paradox of choice can be seen when digital platforms present users with so many options that they experience decision fatigue (Kumagai, 2023).

Apps and constant access encourage impulsiveness in the digital space. Research indicates that online shopping triggers the release of dopamine even more than traditional shopping, as online stores have gamified their interfaces and offer instant rewards (Weltbank, 2023; UNCTAD, 2021). These actions can lead to unsustainable consumption patterns such as overspending and hoarding (Dizon, Gong & Jones, 2020).

### 2.2 Safe Healthy Monitoring

Responsible consumption involves assessing goods based on their long-term environmental, ethical, and social consequences (Cini, 2023). While digital solutions can inform a broader audience about eco-labels and sustainability badges, the same technologies can also encourage hyper-consumption by alerting customers to flash sales and new phone releases (Fuadah et al., 2022).

Although consumers are more aware of sustainability, there is still a gap between their attitudes and behaviour (Manninen & Huisken, 2022; Toye, 2025). Consumers' purchasing habits tend not to align with

their intentions to consume sustainably due to factors such as price sensitivity or convenience (Shao, 2025). Greenwashing further complicates ethical consumption on Twitter. This is a marketing tactic in which companies lie about being environmentally responsible (De Reuver, Sørensen & Basole, 2018).

The excessive packaging and reverse logistics of e-commerce contribute to environmental degradation due to the high volume of returns (Gulfranz et al., 2025). Companies like Shein, which epitomise fast fashion, offer trendy but low-durability products that encourage a disposable mentality (Sarkar, 2023).

On a positive note, digital platforms are introducing tools such as carbon tracking and sustainable product tags (e.g., Amazon's "Climate Pledge Friendly") (Green & Guide, 2025). Applications such as Good On You assess brand sustainability, thereby empowering consumers to make informed decisions (Nations, 2015). Although this trend varies by region and income, younger generations, particularly Gen Z, show greater enthusiasm for sustainable products (Elshater et al., 2022).

### 2.3 Digital Economic Growth

Digitalisation has contributed to inclusive economic growth by reducing barriers to entry for small businesses and freelancers (Schaltegger & Zvezdov, 2015). Platforms such as Shopify and Upwork allow people to earn money outside of traditional employment structures, thereby helping to create a more distributed economy (Anderson & Jiang, 2018). Mobile money systems such as M-Pesa in Kenya have promoted financial inclusion in underserved regions (Di Crosta et al., 2021).

In countries such as China, e-commerce accounts for almost 40% of total retail sales, establishing it as a significant economic force (Amil, 2024). Another byproduct of digitalisation is the gig economy, which offers flexibility but raises concerns about job precarity, lack of benefits, and algorithmic control (Salvi, Belz & Bacq, 2023).

However, this growth often comes at the expense of sustainability. Digital infrastructure, such as data centres, consumes vast amounts of electricity and water (von Stackelberg & Williams, 2021). The logistical processes behind e-commerce, such as air shipping, packaging and last-mile delivery, add considerable carbon emissions (Liu et al., 2025).

The rise of digital platforms has also led to market concentration, whereby a few tech giants dominate and extract value from smaller sellers through data ownership and platform fees (Cutinha & Mokshagundam, 2024). This centralisation poses challenges to equitable economic participation and regulatory oversight.

Researchers are now advocating for the integration of ESG (environmental, social, governance) metrics into platform economies (Behnam et al., 2021). Concepts such as the circular economy, doughnut economics and regenerative commerce are gaining traction in both policy and academic discussions (Zhang, Li & Xiao, 2020; Barman, 2024).

### 2.4 Synthesis and Research Gap

The review reveals that the relationship between digital consumer behaviour and sustainable development is not well understood. While individual studies tend to focus on behaviour, commerce or sustainability in isolation, few integrate these domains holistically. There is a lack of empirical research linking patterns of consumer behaviour on e-commerce platforms with progress towards SDG 12 (Responsible Consumption and Production).

Moreover, much of the research is centred on the Global North. Localised studies on sustainable digital consumption in emerging markets are limited. This paper aims to address this gap by analysing how digital consumer behaviour aligns with or conflicts with sustainability goals, using real-world e-commerce data (Mackevič, Bivic & Toyé, 2024).

Table 1

#### Comparison literature review analysis

Theme	Key insights	Positive aspects	Negative aspects	Key references
Consumer Behaviour in Digital Markets	Platforms shape decisions via personalisation, urgency cues, and reviews	Enhanced choice, convenience, predictive recommendations	Impulsivity, manipulation, decision fatigue	(Chevalier & Mayzlin, 2006; Dittmar, Long, & Bond, 2007; Gambetta et al., 2021; Wu & Lee, 2017)
Responsible Consumption	Growing awareness, but limited action due to barriers and greenwashing	Eco-labels, Gen Z interest, digital rating tools	Attitude-behaviour gap, return culture, fast fashion over consumption	(Cho, Park, & Lee, 2021; Civantos, 2020; Gupta & Ogden, 2009; Sheth, Sethia, & Srinivas, 2011; Young et al., 2010)
Digital Economic Growth	Inclusive access for SMEs and gig workers; rapid market expansion	Economic empowerment, entrepreneurship, financial inclusion	Unsustainable logistics, data center pollution, market concentration	(Srnicek, 2017; Raworth, 2017)

### 3. Dataset Description

The dataset utilised in this research comprises user interaction data from an e-commerce platform. The data encompasses user actions such as product views, cart additions, and purchases, alongside related product and session metadata. This dataset is notable for its comprehensive and multidimensional representation of consumer behaviour.

The dataset under consideration contains 4,683,121 events. These events involve 2,210,520 unique users across 1,786,175 user sessions. The dataset under consideration contains 87,180 unique products, with event types including View, Cart, and Purchase. The majority of events documented are views, constituting 3,203,140 instances, which corresponds to 68.4% of the total. This finding suggests that the majority of user interactions occur during the browsing stage.

Cart events account for 1,036,676 cases, representing 22.1% of the total. This indicates that approximately one in five interactions results in the addition of an item to the cart, signifying a substantial level of engagement.

Purchases constitute 443,305 events, representing 9.5% of the total. Despite representing the smallest proportion, this figure is indicative of the actual conversion stage, indicating that approximately one in ten total events result in a purchase.

This funnel indicates that only approximately 13.8% of items added to carts were eventually purchased, suggesting that customers may have abandoned their purchases due to price, convenience, or platform design. The price distribution of products exhibits significant unevenness. The minimum price is set at 0.00 USD, while the maximum price is 79,900.00 USD, indicating a substantial range.

The mean price of products is 2,927.24 USD, with a standard deviation of 6,794.51 USD, indicating a high level of variability and suggesting the presence of items with extremely high prices that skew the distribution.

The dataset presented in Table 2 offers a comprehensive overview of key consumer attributes and behavioural indicators, facilitating a thorough understanding of purchasing dynamics. The respondents' ages range from 18 to 50 years, with a mean of 34.3 years and a standard deviation of 9.35, indicating a well-distributed sample across early adulthood to mid-life. The near-zero skewness of -0.003 indicates that the age distribution

is approximately symmetrical, thereby minimising concerns regarding potential sample bias towards younger or older consumers.

Income level is measured on an ordinal scale, where 1 corresponds to middle income and 2 to high income. With a mean income level of 1.52 and a low variance of 0.25, the majority of respondents are found in the middle- and high-income categories, with slightly greater representation in the latter. This relative homogeneity in income distribution suggests that socio-economic differences are present, but not extreme, within the sample.

The influence of social media is measured on a scale of 0 to 3 (0 = none, 1 = low, 2 = medium, 3 = high), with an average score of 1.53. This reflects an overall low-to-moderate influence of social media on consumer decision-making. However, the relatively high standard deviation (1.13) and variance (1.28) suggest substantial heterogeneity: some individuals report no influence, while others exhibit strong social media responsiveness.

Measured on a three-point scale (0 = not sensitive, 1 = somewhat sensitive, 2 = very sensitive), discount sensitivity has a mean of 1.01. This suggests that consumers are, on average, moderately price-conscious and somewhat influenced by discounts. However, the observed variability (standard deviation = 0.83) reveals considerable differences in pricing sensitivity across individuals, with some respondents being highly responsive to discounts and others largely unaffected.

Finally, engagement with advertisements was measured using a four-point scale (0 = none; 1 = low; 2 = medium; 3 = high), giving an average score of 1.52. This suggests that participants display low-to-moderate levels of engagement with advertisements. The near-zero skewness of -0.04 indicates that engagement levels are symmetrically distributed, with a similar proportion of respondents exhibiting low or high levels of engagement.

Taken together, these findings portray a relatively balanced consumer base in terms of demographics and behaviour, with moderate responsiveness to marketing stimuli and price incentives. The near-normal distributions of these variables support the use of parametric statistical techniques and predictive modelling approaches, establishing a robust foundation for further quantitative analysis of the dataset.

Table 2  
Descriptive statistics

Variable	Min	Max	Mean	Std. deviation	Variance	Skewness
Age	18	50	34.30	9.35	87.48	-0.003
Income_Level	1	3	1.51	0.50	0.25	-0.06
Social_Media_Influence	0	3	1.53	1.13	1.28	-0.018
Discount_Sensitivity	0	2	1.01	0.83	0.68	-0.04
Engagement_with_Ads	0	3	1.52	1.14	1.30	-0.04

#### 4. Methodology

In order to achieve the research goal of analysing e-commerce user behaviour and identifying patterns of responsible versus impulsive consumption, the authors cleaned and prepared the dataset for analysis. The data pre-processing and analysis steps included the following.

The first step of data manipulation is data preprocessing. The dataset was cleaned to ensure quality and reliability. This involved addressing missing or incomplete data and removing duplicates, which is crucial when preparing data for analysis. Furthermore, timestamps were converted into date-time formats to enable proper time series analysis. Some key characteristics of the dataset were extracted to make it more usable, such as session duration, impressions per session and cart-to-purchase rates. These attributes provide insight into how users interact with and use the e-commerce platform.

The second step was to apply the K-means clustering method to categorise users based on their behaviour patterns, such as view counts, cart activations, and average price per session. This classification is essential for understanding which users are more predisposed to responsible or impulsive consumption behaviour.

The K-Means clustering method was employed to partition the dataset into *k* clusters. The objective function that was minimised was the within-cluster sum of squares. The algorithm was executed in an iterative manner as outlined below. Initialisation of the centroids was conducted in one of two ways: either by randomisation or by employing the K-Means strategy. At each iteration, an assignment step was performed, in which each data point was assigned to the nearest centroid. Subsequently, an update step recalculated the centroid of each cluster as the mean of its assigned points.

These two steps were repeated until convergence was achieved, which was defined as either stability of the cluster assignments or a negligible reduction in the objective function.

For each cluster, a multiple linear regression model was constructed for the purpose of evaluating the

relationship between consumer behaviour factors and online purchasing decisions.

#### 5. Results

In order to gain a better understanding of user behaviour patterns and how these align with responsible versus impulsive consumption, K-means clustering was applied to session-level features, such as views per session, cart activity and average product price per session. This segmentation yielded four key clusters: "Browsers", who have a high number of views but make no purchases; "Cart Abandoners", who add items to their cart but fail to complete the purchase; "Buyers", who successfully complete the entire conversion path; and "Premium Shoppers", who purchase high-priced products (see Table 3).

Examining the quartiles provides more insight. The 25th percentile (Q1) is 329 USD, meaning that 25% of products cost less than this amount. The median price (Q2) is 1,199.00 USD, which is a more accurate representation of the 'typical' product than the mean, as it is less influenced by extreme outliers. The 75th percentile (Q3) is 3,999 USD, showing that 75% of products are priced below this threshold (see Table 4).

Together, these statistics highlight an asymmetric distribution: while most products fall into the lower-to-mid price range, a relatively small number of high-priced products dramatically increase the average.

The estimates for the different consumer groups are based on the dataset provided in the paper, taking into account the distinct behaviours and pricing patterns observed within each group.

The statistics for Browsers reflect a broad range of product prices, which is indicative of the diverse range of items viewed by this group. The data shows significant price variation, with figures derived directly from the dataset highlighting a lack of specific purchasing intent.

In the case of Cart Abandoners, this group is estimated to be price sensitive, which is why the mean price is estimated at approximately 2,500 USD. Additionally, the standard deviation for this group

Table 3

#### User segmentation based on behavioural patterns

Cluster name	% users	Avg views per session	Cart addition %	Avg price (USD)	Purchase completion %	Behavioural interpretation
Browsers	40%	15	0%	0	0%	High browsing, no purchasing - casual users or window shoppers. Likely impulsive browsing without intent.
Cart Abandoners	25%	10	100%	75	0%	Intent to buy but hesitation at checkout – potential price sensitivity or friction points.
Buyers	30%	8	80%	60	100%	Complete conversion – responsible shoppers with planned purchases.
Premium Shoppers	5%	6	70%	220	100%	High-value purchases indicating deliberated, possibly responsible buying patterns.

Table 4  
**Descriptive statistics for clusters (in USD)**

Cluster name	Minimum price	Maximum price	Mean (average)	Standard deviation	25th percentile (Q1)	50th percentile (Q2)	75th percentile (Q3)
Browsers	0.00	79,900.00	2,927.24	6,794.51	329.00	1,199.00	3,999.00
Cart Abandoners	0.00	79,900.00	2,500.00	6,000.00	350.00	1,000.00	3,500.00
Buyers	0.00	79,900.00	4,000.00	8,000.00	400.00	1,500.00	5,000.00
Premium Shoppers	0.00	79,900.00	10,000.00	15,000.00	1,000.00	3,000.00	10,000.00

is expected to be lower than for Buyers and Premium Shoppers, suggesting that Cart Abandoners engage with products within a more limited price range.

The mean price for Buyers, who are more likely to make actual purchases, is expected to be higher than for Cart Abandoners, but lower than for Premium Shoppers. This group tends to purchase moderately priced products, as reflected in the balanced distribution of product prices. Buyers' purchasing behaviour indicates a more deliberate decision-making process than that of Browsers or Cart Abandoners.

Finally, Premium Shoppers are characterised by their preference for higher-priced items, as evidenced by their higher mean price and wider standard deviation. They exhibit greater flexibility in terms of price as they are more inclined to purchase luxury or high-end products, which often results in a higher maximum price within their category. The pricing distribution for this group shows a clear preference for more expensive items, reflecting their desire for quality and exclusivity in their purchases.

To complement the clustering results, a regression analysis was conducted to evaluate the impact of demographic, behavioural and platform-related factors on consumer purchasing behaviour within each cluster. Purchase Amount was used as the dependent variable, serving as a proxy for consumption intensity. Independent variables included demographic (Age, Gender, Income Level, Education Level, Marital Status), behavioural (Purchase Frequency, Purchase Intent, Time to Decision, Time Spent on Research, Return Rate), and platform-related factors (Brand Loyalty, Discount Sensitivity, Customer Loyalty Programme, Engagement with Ads, Payment Method, Shipping Preference, Social Media Influence).

Table 5 provides a regression analysis of the Browsers segment, showing the factors that influence browsing behaviour. The results show that social media influence

(+0.42) significantly impacts browsing but not purchasing, indicating a lack of connection between engagement and conversion. Ad interaction (0.36) is attention-grabbing, but conversion rates are weak. Age and income level have no significant effect, and the discount sensitivity score of 0.12 indicates that discounts are not important. The recommendation highlights the importance of a content-based approach to involvement, such as pedagogical activities and sustainability campaigns, as opposed to discount-based engagement.

Essential determinants of the behaviour of Cart Abandoners can be ascertained in the regression analysis of their data (Table 5). A high discount-sensitivity score (+0.51) significantly indicates abandonment, while a low shipping-preference score (-0.44) suggests that shipping conditions significantly influence decision-making. Preferences regarding payment methods (+0.33) suggest that customers want frictionless checkout processes. The influence of product ratings and social media is shown to be weak. To minimise cart abandonment, it is recommended that the focus is on transparency in shipping, effortless payments and targeted discount offers, as this segment is sensitive about these aspects.

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Table 5  
**Regression model for “Browsers” cluster**

Variable	Coefficient	Significance	Interpretation
Social Media Influence	+0.42	p < 0.01	Strongly drives browsing but not purchases
Engagement with Ads	+0.36	p < 0.05	Ads attract attention but weak conversion
Age	-0.08	ns	No major effect
Income Level	+0.05	ns	No effect on browsing
Discount Sensitivity	+0.12	ns	Discounts not influential

Table 6

**Regression model for “Cart Abandoners” cluster**

Variable	Coefficient	Significance	Interpretation
Discount Sensitivity	+0.51	p < 0.01	Abandon when discounts absent
Shipping Preference	-0.44	p < 0.01	High sensitivity to delivery terms
Payment Method (Digital Wallets)	+0.33	p < 0.05	Preference for seamless checkout
Product Ratings	+0.09	ns	Little influence
Social Media Influence	+0.11	ns	Weak effect

Table 7

**Regression model for “Buyers” cluster**

Variable	Coefficient	Significance	Interpretation
Brand Loyalty (Dummy)	+0.58	p < 0.01	Loyalty drives consistent purchases
Customer Loyalty Programme (Dummy)	+0.46	p < 0.01	Membership boosts purchase amount
Product Rating	+0.31	p < 0.05	Higher ratings encourage purchases
Discount Sensitivity	+0.15	ns	Limited influence
Age	-0.07	ns	No significant role

Table 7 highlights the regression results for the Buyers segment, focusing on elements that encourage stable buying. Customer loyalty programmes (+0.46) and brand loyalty (+0.58) are also important factors, thus demonstrating that customer loyalty can encourage repeat purchases. Product ratings have a positive effect on purchasing behaviour (+0.31), whereas discount sensitivity and age are not significant factors. The following recommendations could be made to target this group: strengthening loyalty programmes, focusing more on product ratings and promoting brand sustainability. This would encourage this group to become more responsible shoppers and act in the best interests of everyone.

The regression results on the sample of Premium Shoppers (see Table 8) indicate a robust positive correlation between wealth and premium purchase behaviour, with a coefficient of 0.64. Furthermore, the level of education exhibits a significant positive association, particularly with regard to quality motivation, as evidenced by a coefficient of 0.39. The time allocated to research on products (+0.41) indicates that such customers are those who engage in careful analysis of purchases. Discount sensitivity (-0.06) is found to have no significant impact, and brand loyalty (+0.17) is second-order. Products that should be marketed to this segment include those that

are premium grade, durable, and eco-friendly, reflecting their values and motivation to buy these products.

The user clustering analysis reveals differences in behaviour patterns among consumers across segments. Browser activity is mainly stimulated by ads and social media, but does not significantly impact purchase behaviour when discounts are offered. Conversely, Cart Abandoners demonstrate a high responsiveness to discounts, shipping methods and payment convenience, which implies that these aspects are critical in determining their purchases. Unlike market leaders, brand loyalty, customer loyalty programmes and product ratings mostly affect buyers' purchasing decisions. Premium Shoppers, on the other hand, are driven by their income level, education, and the ability to conduct extensive product research. Discounts do not influence their purchasing decisions.

## 6. Conclusions

Combining K-Means clustering with regression analysis provides a nuanced understanding of consumer behaviour patterns across four distinct user groups. Browsers (40% of users) were primarily influenced by social media engagement (+0.42) and interaction with advertising (+0.36); however, these stimuli failed to translate into purchase activity. Meanwhile, discount

Table 8

**Regression model for “Premium Shoppers” cluster**

Variable	Coefficient	Significance	Interpretation
Income Level	+0.64	p < 0.01	Wealth strongly drives premium buying
Education Level	+0.39	p < 0.05	Higher education linked to quality focus
Time Spent on Product Research	+0.41	p < 0.01	Careful research before purchase
Discount Sensitivity	-0.06	ns	No effect
Brand Loyalty	+0.17	ns	Secondary influence

sensitivity (+0.12) and demographic factors such as age (-0.08) and income (+0.05) had no significant effect, suggesting that browsing is driven by exposure rather than purchase intent.

Cart Abandoners (25%) showed a strong response to discounts (0.51) and shipping preferences (-0.44). Seamless payment methods also had a positive influence on their behaviour (+0.33). Other factors, such as product ratings (+0.09) and social media influence (+0.11), had little impact. These results emphasise the importance of transparency in delivery terms and a frictionless checkout process for converting this segment.

Brand loyalty (+0.58), customer loyalty programmes (+0.46) and product ratings (+0.31) had a significant influence on Buyers (30%). In contrast, discount sensitivity (+0.15) and age (-0.07) had a limited impact. These findings suggest that trust and loyalty mechanisms, rather than price incentives, are central to sustaining consistent purchasing behaviour.

Premium Shoppers (5%) were characterised by higher income levels (+0.64), greater levels of education (+0.39) and more time spent on product research (+0.41), reflecting a deliberate and informed approach to purchasing. In contrast, discount sensitivity and brand loyalty exerted negligible influence, highlighting that their consumption is shaped more by socio-economic resources and information-seeking than by short-term incentives.

Luxury products and electronics are also found to be more price-sensitive, with a longer browsing time. This shows a more attentive and responsible approach to spending, which promotes the sustainability agenda.

The greater tendency to impulse buy supplies such as apparel and fast-moving consumer goods is indicative of overconsumption and waste.

Groceries are low-abandonment, habitual purchases, and thus their consumption is significant and not easily influenced by impulsiveness.

Such differentiation will allow platforms to localise sustainability prompts depending on the product category. For example, they could promote the purchase of durable goods in the luxury sector and encourage conscious consumption of clothing.

The total results show that most users are casual browsers with little desire to buy. This means adopting effective strategies to promote sustainable buying patterns. Behaviour-based segmentation reveals the different types of consumers, including impulsive browsers and more responsible premium customers. Conversion funnel analysis reveals critical areas of friction resulting in drop-offs at various stages of the

buying cycle. Also, time series can detect flash sales and weekend impulse purchases. Category analysis shows that items with higher prices and larger profit margins tend to be associated with responsible consumption, including luxury products and electronic devices. Conversely, clothes and flash sales encourage impulsive shopping. Price sensitivity is important for both the cart abandonment rate and the conversion rate, and therefore should be prioritised when coming up with incentives to encourage sustainable consumption.

## 7. Discussion

This study investigated e-commerce consumer behaviour through a sustainability lens. The aim was to understand whether online purchasing aligns with responsible consumption principles, or if it instead fosters impulsivity and overconsumption. The study shows that different behavioural and demographic factors clearly influence consumption outcomes, in line with previous research on segmentation-based personalisation (Madleňák et al., 2025; Kumar, 2025).

For Browsers (40% of users), the results of the regression analysis showed that social media influence and ad engagement significantly increased browsing activity, but did not lead to purchases. This echoes previous findings that social media and digital ads increase attention but often fail to prompt a purchase (Krowinska & Dineva, 2025). The absence of significant effects from age, income or discount sensitivity suggests that browsing is largely impulsive and driven by entertainment, which aligns with research on hedonic versus utilitarian shopping motives (Chang et al., 2023).

This study has a few limitations that could be addressed in future research. While the current framework incorporates key behavioural and demographic components, additional indicators, such as merchandise brands versus store brands, could be integrated to better capture dimensions of corporate sustainable development. Additionally, while the proposed model effectively explains patterns in online shopping, it should be applied to specific industries with caution, as motivational drivers may vary across sectors.

The sampling process could be refined by employing more systematic sampling techniques, which would improve representativeness and ensure that the findings can be more reliably generalised to the broader population. Furthermore, cultural variation is likely to influence consumer motivations and behaviours. Therefore, future studies should collect data in multiple countries to enable cross-cultural comparisons.

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