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Decoding Consumer Habits : Analyzing Retail Patterns Across Demographics

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ABSTRACT

This study examines consumer habits by analyzing retail patterns across various demographics using a dataset encompassing 3,900 transactions. The data includes variables such as age, gender, item purchased, purchase amount, location, and more, allowing for a comprehensive analysis of consumer behavior. Key insights reveal significant trends in purchasing decisions influenced by demographic factors like age and gender, as well as external elements such as seasonality and promotional activities. The analysis identifies predominant shopping preferences among different age groups, highlighting the influence of discounts and promotional codes on purchasing behavior. Additionally, the study explores the correlation between customer loyalty, as indicated by subscription status and frequency of purchases, and spending patterns. By decoding these retail patterns, this research provides valuable insights for retailers aiming to optimize marketing strategies and enhance customer engagement through targeted interventions. The findings contribute to a deeper understanding of how demographic factors shape consumer behavior, offering actionable insights for businesses seeking to adapt to evolving market demands.

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1. INTRODUCTION

In today's rapidly evolving retail landscape, understanding consumer behavior is more critical than ever for businesses seeking to remain competitive [1], [2], [3], [4]. Consumer behavior, which refers to the actions and decision-making processes of individuals when they purchase goods and services, is influenced by a multitude of factors. These include demographic characteristics such as age, gender, and income, as well as external elements like marketing strategies, cultural trends, and economic conditions [5]. Retailers who can accurately decode these behaviors are better positioned to tailor their offerings, optimize marketing efforts, and ultimately enhance customer satisfaction and loyalty [6], [7]. The retail industry has undergone significant transformations over the past few decades, driven by advancements in technology, shifts in consumer expectations, and the increasing availability of data. Understanding consumer behavior has always been at the heart of retail success, but the complexity of modern consumer habits requires more sophisticated analysis than ever before. Today's consumers are more diverse and informed, and their purchasing decisions are influenced by a myriad of factors ranging from personal demographics to external conditions like seasonality and marketing tactics [8], [9]. In this context, analyzing retail patterns across various demographics is not just an academic exercise but a critical business necessity. Retailers, both online and offline, are increasingly turning to data-driven strategies to gain insights into consumer preferences and behaviors. The rise of e-commerce, coupled with the availability of big data, has provided businesses with unprecedented access to detailed consumer information. This data, when analyzed effectively, can reveal trends and patterns that are instrumental in shaping marketing strategies, product development, and customer engagement initiatives. However, the challenge lies in decoding this data to extract meaningful insights that can be translated into actionable business strategies.

Consumer behavior in retail has been a subject of extensive research, with numerous studies exploring the various factors that influence purchasing decisions [10], [11]. Demographics, particularly age and gender, have been identified as key determinants of consumer behavior. For instance, younger consumers tend to be more responsive to digital marketing and are more likely to shop online, while older consumers may prefer traditional shopping experiences [12], [13]. Gender also plays a significant role, with studies showing that men and women often have different shopping preferences and spending habits. Seasonality is another important factor that affects consumer behavior. Retail patterns often vary significantly across different seasons, with certain products being more popular during specific times of the year [14], [15]. For example, winter months may see a higher demand for clothing and accessories related to cold weather, while summer may drive sales of outdoor and leisure products. Promotional activities, such as discounts and special offers, also have a considerable impact on consumer behavior, with many shoppers timing their purchases to coincide with sales events.

Demographic factors are crucial in understanding consumer behavior because they influence a wide range of purchasing decisions [16], [17]. Age, for example, affects not only what consumers buy but also how they buy it. Younger consumers, who have grown up with technology, are more likely to embrace online shopping and mobile payments, while older consumers may prefer in-store purchases and traditional payment methods [18]. Gender differences are also evident in shopping habits, with women generally being more inclined towards categories like clothing and home decor and men showing a preference for electronics and gadgets. The impact of these demographic factors is further compounded by external influences like seasonality and promotional activities. For instance, younger consumers may be more attracted to flash sales and limited-time offers, while older consumers might prioritize quality and durability over price. By analyzing these factors in conjunction with demographic data, this study seeks to provide a comprehensive understanding of how consumer habits are shaped.

The dataset used in this study consists of 3,900 transactions, encompassing a wide range of variables that are critical for understanding consumer behavior. These variables include demographic information (age, gender), purchase details (item purchased, category, purchase amount), and behavioral indicators (subscription status, frequency of purchases, discount applied, promo code usage). By analyzing these variables, the study aims to uncover patterns and trends that provide insights into consumer habits across different demographics. The analysis involves a combination of statistical methods and data visualization techniques to identify significant trends and correlations. For instance, the study will examine how purchasing behavior varies across different age groups and genders, as well as how factors like discounts and promotional codes influence spending patterns. The study will also explore the relationship between customer loyalty, as indicated by subscription status and frequency of purchases, and overall spending behavior. A preliminary analysis of the dataset reveals several significant trends. For instance, younger consumers are more likely to take advantage of discounts and promotional codes, while older consumers tend to spend more on average but make fewer purchases. The data also suggests that women are more likely to engage in frequent shopping, particularly in categories like clothing and home decor, whereas men show a higher propensity to spend on electronics and gadgets. Another key finding is the strong correlation between customer loyalty and spending patterns. Customers with active subscriptions and a high frequency of purchases tend to spend more over time, indicating that loyalty programs can be an effective tool for driving sales. Additionally, the analysis highlights the importance of seasonality in retail, with certain products experiencing spikes in demand during specific times of the year.

The findings of this study have several practical implications for retailers. Understanding the demographic factors that influence consumer behavior, businesses can tailor their marketing strategies to better meet the needs of their target audiences. For example, retailers can design targeted promotions and discounts that appeal to specific age groups or genders or develop loyalty programs that reward frequent shoppers. Moreover, the insights gained from this analysis can help retailers optimize their product offerings and inventory management. Anticipating seasonal trends and understanding consumer preferences, businesses can ensure that they have the right products available at the right time, thereby maximizing sales and minimizing excess inventory.

2. LITERATURE REVIEW

Consumer behavior in retail has been a subject of extensive research, particularly as the industry has evolved to become more complex and data-driven [19], [20], [21]. Understanding how and why consumers make purchasing decisions is crucial for retailers aiming to enhance customer satisfaction, optimize marketing strategies, and ultimately increase sales [22], [23]. The study of consumer behavior encompasses a range of factors, including demographic characteristics, psychological influences, cultural backgrounds, and situational contexts [24], [25]. In recent years, the focus has shifted towards a more granular analysis of consumer habits, with an emphasis on how specific demographic variables such as age, gender, and socioeconomic status influence retail patterns [26], [27], [28]. The emergence of big data and advanced analytical techniques has revolutionized the way retailers understand and respond to consumer behavior [29]. By analyzing vast datasets that capture detailed information about transactions, preferences, and interactions, researchers and practitioners can identify trends, predict future behavior, and tailor their strategies to meet the needs of different customer segments [30]. This literature review will explore the existing body of knowledge on consumer behavior in retail, highlighting key studies and theories, discussing their theoretical contributions, and identifying gaps that this study aims to address.

A significant body of research has explored the impact of demographic factors on consumer behavior, particularly in the context of retail. Age and gender are among the most commonly studied variables, as they are relatively easy to measure and have been shown to significantly influence purchasing decisions. Age is a critical factor in determining consumer behavior, with different age groups exhibiting distinct preferences, spending habits, and responsiveness to marketing stimuli. For instance, younger consumers, often referred to as Millennials and Generation Z, are more likely to engage with digital platforms, prefer experiences over products, and are highly influenced by social media and online reviews [26]. They are also more responsive to promotions and discounts, and tend to shop more frequently but spend less per transaction. Older consumers, on the other hand, often exhibit more traditional shopping habits. Studies have shown that Baby Boomers and Generation X are more likely to value quality and brand loyalty over price, and they tend to spend more per transaction but shop less frequently [31]. This age group also places greater importance on in-store shopping experiences, although they are increasingly adopting online shopping as e-commerce becomes more user-friendly and secure [32].

Gender is another demographic variable that has been extensively studied in the context of consumer behavior. Research consistently shows that men and women differ in their shopping preferences, motivations, and decision-making processes. Women are generally more inclined towards categories like clothing, home decor, and personal care products, and they tend to be more detail-oriented and price-sensitive [33]. Men, on the other hand, are more likely to prioritize convenience and efficiency, often preferring to shop for electronics, gadgets, and automotive products. A study found that women are more likely to engage in browsing and are more influenced by the shopping environment, including store layout, ambiance, and customer service [34], [35]. Men, in contrast, tend to have a more focused shopping approach, often entering a store with a specific purchase in mind and completing the transaction quickly [36]. These gender differences are also reflected in online shopping behavior, with women being more likely to use social media platforms for shopping inspiration, while men prioritize speed and convenience in their online purchases [37], [38], [39].

Seasonality and promotional activities are external factors that significantly influence consumer behavior in retail [40], [41]. Seasonal trends often dictate the demand for certain products, while promotions can drive short-term spikes in sales by creating a sense of urgency or offering perceived value [42]. Seasonal variations in consumer behavior have been well-documented in the literature, with certain times of the year, such as holidays and back-to-school seasons, seeing spikes in retail sales [43], [44]. For example, the holiday season typically drives increased demand for gifts, decorations, and seasonal apparel, while the back-to-school season boosts sales of school supplies, clothing, and electronics [45]. These seasonal trends are often predictable, allowing retailers to plan their inventory, marketing, and staffing accordingly [46]. However, seasonality can also introduce challenges, such as managing inventory levels to avoid stockouts or overstocking, and designing marketing campaigns that resonate with consumers' seasonal preferences [47], [**?**]. The study emphasized the importance of aligning marketing strategies with seasonal trends to maximize sales and enhance customer satisfaction. Retailers that effectively leverage seasonality in their marketing efforts can create a competitive advantage by being top-of-mind for consumers during key shopping periods.

2.1. Impact of Promotions on Consumer Behavior

Promotional activities, such as discounts, coupons, and special offers, are powerful tools for influencing consumer behavior. Promotions can attract price-sensitive customers, encourage impulse buying, and increase purchase frequency. Research has shown that promotions are particularly effective in driving sales during periods of low demand, helping to smooth out seasonal fluctuations in revenue. However, the impact of promotions is not uniform across all consumer segments. For example, younger consumers and those with lower incomes are generally more responsive to promotions, while older consumers and those with higher incomes may be less influenced by price discounts and more concerned with product quality and brand reputation. The effectiveness of promotions also varies by product category, with fast-moving consumer goods (FMCG) and low-involvement products being more likely to see increased sales during promotions compared to high-involvement or luxury products. Several theoretical frameworks have been developed to understand and predict consumer behavior in retail. These theories provide a foundation for analyzing how demographic factors, seasonality, and promotions influence purchasing decisions.

2.2. The Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), developed by Ajzen is one of the most widely used models for predicting consumer behavior. According to TPB, an individual's intention to engage in a behavior is influenced by their attitude towards the behavior, subjective norms, and perceived behavioral control. In the context of retail, TPB can be applied to understand how consumers' attitudes towards shopping, societal expectations, and perceived ease of purchase influence their purchasing decisions. TPB has been used to study various aspects of consumer behavior, including online shopping, impulse buying, and environmentally conscious purchasing. The model's emphasis on intention as a predictor of behavior makes it particularly relevant for analyzing the impact of marketing strategies, such as promotions and discounts, on consumer buying decisions.

2.3. The Consumer Decision-Making Process Model

The Consumer Decision-Making Process Model, also known as the EKB Model by Engel, Kollat, Blackwell, 1968, outlines the stages that consumers go through when making a purchase decision: problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior. This model highlights the complexity of consumer behavior, emphasizing that purchasing decisions are not made in isolation but are influenced by a variety of internal and external factors. In retail, the EKB Model can be used to analyze how demographic factors influence each stage of the decisionmaking process. For example, younger consumers may spend more time in the information search stage, particularly using online resources and social media, while older consumers may rely more on past experiences and brand loyalty during the evaluation stage. The model also provides a framework for understanding how promotions and seasonality impact the decision-making process, particularly in the evaluation and purchase stages. This study aims to build on the existing literature by providing a comprehensive analysis of consumer behavior across different demographics, with a particular focus on the role of seasonality and promotional activities in shaping retail patterns. While previous research has explored the impact of demographics, seasonality, and promotions on consumer behavior, there is a need for more granular analysis that considers the interplay of these factors in a unified framework.

2.4. Research Goals

2.4.1. To analyze the influence of demographic factors (age and gender) on retail purchasing behavior.

- Hypothesis 1: Younger consumers (aged 18-34) are more likely to engage in frequent shopping and are more responsive to promotions compared to older consumers (aged 35 and above).
- Hypothesis 2: Women are more likely to purchase clothing and home decor items, while men are more inclined to purchase electronics and gadgets.

2.4.2. To examine the impact of seasonality on retail sales and consumer preferences.

- Hypothesis 3: Seasonal trends significantly influence consumer purchasing behavior, with specific products experiencing higher demand during certain times of the year
- Hypothesis 4: Retailers that align their marketing strategies with seasonal trends see higher sales during peak seasons.

2.4.3. To explore the effectiveness of promotional activities in driving sales across different demographic segments

- Hypothesis 5: Promotions are more effective in driving sales among younger consumers and those with lower incomes, compared to older consumers and those with higher incomes.

- Hypothesis 6: The impact of promotions varies by product category, with FMCG and low-involvement products being more responsive to discounts and special offers.

2.4.4. To assess the relationship between customer loyalty and spending patterns across different demographic segments.

- Hypothesis 7: There is a positive correlation between customer loyalty (as indicated by subscription status and frequency of purchases) and higher spending patterns.

- Hypothesis 8: Loyalty programs and subscription services are more effective in driving repeat purchases among older consumers compared to younger consumers.

While the existing literature provides valuable insights into consumer behavior, several gaps remain that this study seeks to address. First, much of the research on demographic influences tends to focus on broad categories like age and gender without delving into the nuances of how these factors interact with other variables such as seasonality and promotional activities.

This study aims to fill this gap by conducting a more detailed analysis that considers the interplay of demographic factors with external influences. Second, there is a need for more research on the effectiveness of promotions across different demographic segments. While it is well-established that promotions can drive sales, the literature often overlooks how different groups of consumers respond to various types of promotions. This study will explore this area in greater depth, providing insights that can help retailers design more targeted and effective promotional strategies. Finally, the relationship between customer loyalty and spending patterns is another area that warrants further exploration. While loyalty programs are widely used in retail, there is limited research on how these programs impact spending behavior across different demographic groups. This study will examine this relationship, offering new insights into how retailers can leverage loyalty programs to maximize customer value. This study contributes to the theoretical understanding of consumer behavior by integrating demographic factors, seasonality, and promotional activities into a unified framework. By doing so, it provides a more holistic view of how these variables interact to shape retail patterns. The study also extends existing theories, such as the Theory of Planned Behavior (TPB) and the Consumer Decision-Making Process Model, by applying them to the context of modern retail analytics. One of the key theoretical contributions of this study is the development of a model that explains how demographic characteristics influence the effectiveness of promotional activities and seasonality in driving consumer behavior. This model can serve as a foundation for future research, providing a basis for testing and refining hypotheses about the interplay of these factors in different retail contexts.

The findings of this study have important implications for retailers looking to optimize their marketing strategies and enhance customer engagement. By understanding how different demographic groups respond to seasonality and promotions, retailers can design more targeted campaigns that resonate with their customers. For example, younger consumers might be more responsive to digital promotions and social media campaigns, while older consumers might prefer traditional advertising and in-store promotions. Additionally, the study's insights into customer loyalty can help retailers refine their loyalty programs and subscription services. By tailoring these programs to the preferences and behaviors of different demographic segments, retailers can increase customer retention and drive higher spending. Future research could build on this study by exploring the impact of other demographic factors, such as income level, education, and cultural background, on consumer behavior. Additionally, there is scope for further investigation into the role of emerging technologies, such as artificial intelligence and machine learning, in predicting and influencing consumer behavior in retail.

3. METHODOLOGY

This study to analyze consumer habits and retail patterns across various demographics using a dataset sourced from Kaggle. The study utilizes quantitative methods to explore the relationships between demographic factors, seasonality, promotional activities, and consumer purchasing behavior. The methodology includes a description of the dataset, data preprocessing steps, variable selection, and the statistical techniques used to analyze the data.

3.1. Research Design

The study adopts a quantitative research design, leveraging statistical analysis to investigate how various factors such as age, gender, and external elements like seasonality and promotional activities influence consumer behavior. The dataset obtained from Kaggle provides a robust foundation for this analysis, offering detailed transaction data that reflects real-world retail scenarios.

3.2. Data Collection

The dataset used in this study was downloaded from Kaggle, a well-known platform for data science and machine learning. Kaggle hosts a wide variety of datasets that are often contributed by the community or by companies looking to engage with the data science community. The dataset includes 3,900 transaction records, providing a comprehensive snapshot of consumer behavior across different demographic segments.

3.3. Dataset Description

The dataset includes the following key variables:

- **Customer ID:** A unique identifier for each customer.
- **Age:** The customer's age at the time of the transaction.
- **Gender: The customer's gender (Male or Female).**
- **Item Purchased:** The specific product or item purchased.
- **Category:** The product category (e.g., Clothing, Electronics).
- **Purchase Amount (USD):** The total amount spent on the transaction.
- **Location:** The geographic location where the purchase occurred.
- **Size and Color:** Attributes of the purchased item.
- **Season:** The season during which the purchase was made.
- **Review Rating:** The rating provided by the customer post-purchase.
- **Subscription Status:** Indicates whether the customer is subscribed to a loyalty program.
- **Payment Method:** The payment method used (e.g., Credit Card, PayPal).
- **Shipping Type:** The type of shipping selected.
- **Discount Applied: Indicates whether a discount was applied.**
- **Promo Code Used:** Indicates whether a promo code was used.
- **Previous Purchases:** The number of previous purchases by the customer.
- **Preferred Payment Method:** The most frequently used payment method by the customer.
- **Frequency of Purchases:** How often the customer makes purchases (e.g., Weekly, Annually).

3.4. Data Cleaning and Preparation

Before analysis, the dataset was subjected to a thorough cleaning process to ensure accuracy and consistency. The following steps were taken:

- **Handling Missing Values:** The dataset was checked for missing values. Given that the data is synthetic, there were no missing values; however, this step is crucial in any real-world dataset.
- **Data Transformation:** Certain categorical variables, such as gender and season, were encoded for analysis. Numerical variables, such as age and purchase amount, were checked for outliers and normalized where necessary.
- **Data Segmentation:** The dataset was segmented based on demographic factors (e.g., age groups, gender) and external factors (e.g., seasons, promotional activity) to facilitate detailed analysis.

3.5. Analytical Methods

To address the research questions and hypotheses outlined in the literature review, a combination of descriptive statistics, inferential statistics, and data visualization techniques was employed. Stata/MP 17 is a popular software for data manipulation, visualization, statistics, and automated reporting. Stata/MP 17 provided the variance and descriptive statistics common to the procedure. We developed key concepts using the open-coding grounded theory technique.

3.6. Descriptive Statistics

Descriptive statistics were used to summarize the main features of the dataset and to provide an overview of the distribution of key variables. Measures such as mean, median, mode, and standard deviation were calculated for numerical variables like age, purchase amount, and review ratings. Frequency distributions and percentages were used to analyze categorical variables such as gender, item category, and subscription status.

3.7. Inferential Statistics

Inferential statistical methods were employed to test the research hypotheses and to determine the significance of the relationships between variables. The following techniques were used:

- **T-tests and ANOVA:** These tests were applied to compare means between different demographic groups (e.g., age groups, gender) and to assess whether observed differences were statistically significant.
- **Chi-Square Tests** Chi-square tests were used to examine the association between categorical variables, such as gender and item category, or season and promotional activity.
- **Regression Analysis:** Multiple regression analysis was conducted to explore the relationship between dependent variables (e.g., purchase amount) and independent variables (e.g., age, gender, subscription status). This technique helped in understanding the influence of multiple factors on consumer behavior simultaneously.

3.8. Data Visualization

Data visualization played a crucial role in interpreting the results and identifying patterns within the dataset. Various visualization techniques were employed, including:

- **Bar Charts and Histograms:** Used to visualize the distribution of categorical and numerical variables, respectively.
- **Scatter Plots:** Utilized to examine correlations between numerical variables, such as age and purchase amount.
- **Box Plots:** Applied to compare the distribution of purchase amounts across different demographic groups.
- **Heatmaps:** Created to visualize the relationship between multiple variables, such as the interaction between seasonality and promotional activities.

3.9. Research Hypotheses Testing

The research hypotheses were tested using the statistical methods outlined above. Each hypothesis was examined individually, with the following steps taken:

- **Hypothesis 1:** To test whether younger consumers are more likely to engage in frequent shopping and are more responsive to promotions, t-tests were conducted to compare the frequency of purchases and the use of promotions across different age groups.
- **Hypothesis 2:** To assess whether women are more likely to purchase clothing and home decor items while men are inclined towards electronics and gadgets, chisquare tests were used to examine the association between gender and item category.
- **Hypothesis 3:** The impact of seasonality on consumer purchasing behavior was tested using ANOVA to compare the purchase amounts and item categories across different seasons.
- **Hypothesis 4:** The effectiveness of marketing strategies aligned with seasonal trends was evaluated by comparing sales data before, during, and after key shopping seasons.
- **Hypothesis 5:** To explore the effectiveness of promotions in driving sales across demographic segments, regression analysis was used to assess the influence of promotional activities on purchase amounts, controlling for age and income level.
- **Hypothesis 6:** The differential impact of promotions across product categories was examined using ANOVA, comparing the sales of FMCG and low-involvement products during promotional periods.
- **Hypothesis 7:** The relationship between customer loyalty and spending patterns was tested using correlation analysis and regression models, focusing on the frequency of purchases and total spending.
- **Hypothesis 8:** The effectiveness of loyalty programs among older consumers was evaluated by comparing the frequency and amount of purchases among subscribers and non-subscribers within different age groups.

3.10. Ethical Considerations

While the dataset used in this study is synthetic and publicly available on Kaggle, ethical considerations still apply, particularly regarding the responsible use of data. All analyses were conducted with transparency, and findings were reported accurately to avoid any potential biases or misinterpretations.

3.11. Limitations of the Study

While the dataset used in this study provides a comprehensive snapshot of consumer behavior, it is important to acknowledge its synthetic nature, which presents certain limitations. Although synthetic datasets are valuable for controlled experiments and initial modeling, they do not fully capture the complexities and nuances of real-world consumer behavior. For instance, real-world data often contains imperfections such as missing or inconsistent entries that can affect decision-making processes. Additionally, synthetic data is typically generated based on predefined assumptions that may not reflect unpredictable human decision-making. Therefore, the findings derived from this dataset should be considered preliminary, and future research is required to validate these results using realworld data. By incorporating actual consumer datasets, further studies can capture a more accurate representation of retail dynamics, enhancing the robustness and generalizability of the conclusions drawn here.

4. RESULT AND DISCUSSION

Table 1 provides a detailed overview of variables related to consumer demographics and purchasing behavior, measured using predefined scales. Gender is captured as Male (1) and Female (2), while items purchased are categorized into 26 options, ranging from clothing and footwear to accessories. Item category, size, and color are recorded on specific scales, with categories like Clothing (1), Footwear (2), and colors including options like Gray, Maroon, and Black. Purchases are also categorized by season (Winter, Spring, Summer, Fall), and variables like subscription status, payment method, shipping type, discount application, and promo code usage are recorded on binary or multi-choice scales. Additionally, the frequency of purchases is measured on a 10-point scale, including regular intervals such as weekly or monthly. This dataset provides a rich foundation for analyzing consumer behavior across various demographic and promotional factors.

Table 1. Variable Descriptions

Variable Name	Measurement
Gender	Measured on a scale from (1: Male and 2: Female)
Item Purchased	Measured on a scale from (1: Blouse, 2: Sweater, 3: Jeans, 4: Sandals, 5: Sneakers, 6: Shirt, 7: Shorts, 8: Coat, 9: Handbag, 10: Shoes, 11: Dress, 12: Skirt, 13: Sunglasses, 14: Pants, 15: Jacket, 16: Hoodie, 17: Jewelry, 18: T-6, 19: Scarf, 20: Hat, 21: Socks, 22: Socks, 23: Backpack, 24: Belt, 25: Boots, 26: Gloves)
Category	Measured on a scale from (1: Clothing, 2: Footwear, 3: Outerwear, 4: Accessories)
Size	Measured on a scale from (1: S, 2: M, 3: L, 4: X3
Color	Measured on a scale from (1: Gray, 2: Maroon, 3: Turquoise, 4: White, 5: Charcoal, 6: Silver, 7: Pink, 8: Purple, 9: Olive, 10: Gold, 11: Violet, 12: Teal, 13: Lavender, 14: Black, 15: Green, 16: Peach, 17: Red, 18: Cyan, 19: Brown, 20: Beige, 21: Orange, 22: Indigo, 23: Yellow, 24: Magenta, 25: Blue)
Season	Measured on a scale from (1: Winter, 2: Spring, 3: Summer, 4: Fall
Subscription Status	Measured on a scale from (1: Yes, 2: No)
Payment Method/ Preferred Payment Method	Measured on a scale from (1: Credit Card, 2: Bank Transfer, 3: Cash, 4: PayPal, 5: Venmo, 6: Debit Card)
Shipping Type	Measured on a scale from (1: Express, 2: Free Shipping, 3: Next Day Air, 4: Standard, 5: 2-Day Shipping, 6: Store Pickup)
Discount Applied	Measured on a scale from (1: Yes, 2: No)
Promo Code Used	Measured on a scale from (1: Yes, 2: No)
Frequency of Purchases	Measured on a scale from (1: Fortnightly, 2: Weekly, 3: Monthly, 4: Every 3 Months, 5: Quarterly, 6: Annually, 7: Bi-2, 8: Python, 9: Data Analysis, 10: Communication)

Table 2 provides the descriptive statistics for the dataset's key variables, summarizing the number of observations (Obs), mean, standard deviation (Std. Dev.), and the minimum (Min) and maximum (Max) values for each variable. The dataset includes 3,900 observations. The mean age of customers is 44.07 years, with a standard deviation of 15.21 years, indicating a fairly wide range of ages from 18 to 70. The average item purchased has a value of 13.14, with item categories having a mean of 2.27 on a 4-point scale. The average purchase amount is and color are recorded with means of 2.32 and 12.98, respectively, and the season of purchase has an average value of 2.50 (approximately mid-year purchases). Customers have an average review rating of 3.75 out of 5, and most customers are subscribed to loyalty programs (mean subscription status of 1.73). The mean values for payment methods and shipping types are 3.47 and 3.49, respectively, suggesting diverse preferences across available options. The mean discount applied and promo code used are both 1.57 (where 1 represents Yes and 2 represents No). On average, customers have made 25.35 previous purchases. Frequency of purchases averages 4.02, indicating most customers purchase quarterly or less frequently. The log-transformed purchase amount averages 4.018. Gender is encoded with a mean of 1.32 (where 1 represents Male), and location is encoded with a mean of 25.27 across the dataset.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Customerid	3900	1950.5	1125.977	1	3900
age	3900	44.068	15.208	18	70
Itempurchased	3900	13.136	7.482	1	27
Category	3900	2.274	1.314	1	4
Purchaseamountusd	3900	59.764	23.685	20	100
Size	3900	2.32	0.882	1	4
Color	3900	12.983	7.178	1	25
Season	3900	2.496	1.117	1	4
Reviewrating	3900	3.75	0.716	2.5	5
Subscriptionstatus	3900	1.73	0.444	1	2
Paymentmethod	3900	3.466	1.718	1	6
Shippingtype	3900	3.485	1.706	1	6
Discountapplied	3900	1.57	0.495	1	2
Promocodeused	3900	1.57	0.495	1	2
Previouspurchases	3900	25.352	14.447	1	50
Preferredpaymentme d	3900	3.487	1.703	1	6
Frequencyofpurchases	3900	4.023	1.985	1	7
Log purchase amount	3900	4.018	0.44	3.045	4.615
Gender encoded	3900	1.32	0.467	1	2
Location encoded	3900	25.266	14.343	1	50

Table 3 displays the results of a two-sample t-test conducted with equal variances to compare the means of two groups: Group 1 (2,652 observations) and Fe1 (1,248 observations). The mean purchase amount for Group 1 is 4.0131 with a standard error of 0.0086, while the mean for Fe1 is slightly higher at 4.0296 with a standard error of 0.0122. The combined mean for both groups is 4.0184, and the difference between the means (Group 1 - Fe1) is -0.0166, with a standard error of 0.0151. The test statistic (t) is -1.0958, and the degrees of freedom (df) are 3,898. The p-value for the hypothesis that the means are not equal (Pr(—T— ¿ —t—)) is 0.2732, which is greater than 0.05, indicating that the difference in means is not statistically significant at the 5for one-sided tests (Pr(T ¡ t) = 0.1366 and Pr(T ¿ t) = 0.8634) also suggest that there is no significant difference between the two groups in either direction. The 95interval for the mean difference ranges from -0.0462 to 0.0131.

Table 3. T-tests (Inferential Statistics)

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]
1	2,652	4.013053	0.0086236	0.4440964	[3.996143, 4.029963]
Fe1	1,248	4.02962	0.0122417	0.4324634	[4.005603, 4.053636]
Combined	3,900	4.018354	0.0070524	0.4404197	[4.004528, 4.032181]
diff		-0.0165668	0.015118		[-0.0462067, 0.0130731]

```
diff = mean(1) - mean(Fe1)                    t = -1.0958
H0:  diff = 0                   Degrees of freedom = 3898
```

Ha: diff $<$ 0	Ha: diff $\neq$ 0	Ha: diff $>$ 0
Pr(T $<$ t) = **0.1366**	Pr($\|T\| > \|t\|$) = **0.2732**	Pr(T $>$ t) = **0.8634**

Table 4 presents the results of an analysis of variance (ANOVA), which evaluates the impact of the independent variable "season" on the dependent variable. The table includes the number of observations (3,900), an R-squared value of 0.0030, and an adjusted R-squared value of 0.0022, indicating that the model explains about 0.3variance in the dependent variable. The ANOVA table breaks down the variation into two sources: the model and residuals. The "Model" row shows that the season variable explains a partial sum of squares (SS) of 2.2383 across 3 degrees of freedom (df), with a mean square (MS) of 0.7461. The F-statistic for this model is 3.85, with a corresponding p-value (Prob ¿ F) of 0.0091, which is statistically significant at the 1has a significant effect on the dependent variable. The ”Residual” row shows the remaining variation, with a sum of squares of 754.0488 and 3,896 degrees of freedom, yielding a mean square of 0.1935. The total sum of squares for the model is 756.2871. The root mean squared error (MSE) is 0.4399, indicating the typical deviation of the observed values from the model’s predicted values.

```
Number of obs = 3,900                                R-squared = 0.0030
Root MSE = .439937                               Adj R-squared = 0.0022
```

Table 4. ANOVA (Inferential Statistics).

Source	Partial SS	df	MS	F	Prob ¿ F
Model	2.2382999	3	0.74609998	3.85	0.0091
season	2.2382999	3	0.74609998	3.85	0.0091
Residual	754.04883	3,896	0.19354436		
Total	756.28713	3,899	0.19396951		

Table 5 presents the results of a Chi-Square test that examines the association between the variables Gender and Category. The table shows the distribution of the two gender groups (1 and Fe1) across four product categories (1, 2, 3, and 4). Gender 1 (with 2,652 observations) shows the following distribution: 1,181 purchases in Category 1, 400 in Category 2, 223 in Category 3, and 848 in Category 4. Gender Fe1 (with 1,248 observations) has: 556 purchases in Category 1, 199 in Category 2, 101 in Category 3, and 392 in Category 4. The total counts across categories are also displayed, showing that 1,737 purchases were made in Category 1, 599 in Category 2, 324 in Category 3, and 1,240 in Category 4. The Pearson Chi-Square value is 0.5984, with 3 degrees of freedom (df). The p-value (Pr) is 0.897, which is much greater than the standard significance level (typically 0.05). This suggests that there is no statistically significant association between gender and product category in this dataset. In other words, the gender of the customers does not have a meaningful impact on the distribution of product categories they purchase. Table 5: Chi-Square Test (Inferential Statistics)

Table 5. Chi-Square Test (Inferential Statistics).

Gender	1	2	3	4	Total
1	1,181	400	223	848	2,652
Fe1	556	199	101	392	1,248
Total	1,737	599	324	1,240	3,900

```
Pearson chi2(3) = 0.5984    Pr = 0.897
```

The regression analysis presented in Table 6 includes several variables, such as age and gender, that show minimal or no significant impact on the log-transformed purchase amount. Including these redundant variables complicates the model without providing meaningful insights, making it less actionable for retailers. Simplifying the model by removing these variables would improve the clarity of the findings and make the analysis more focused. Additionally, this raises questions about whether more relevant variables could have been included in the analysis. For instance, factors such as consumer preferences, lifestyle choices, or digital engagement metrics might provide a deeper understanding of what drives purchasing decisions. Future research should refine the model by selecting more impactful variables to enhance the predictive accuracy and practical applicability of the findings.

Table 6. Regression Analysis (Inferential Statistics)

log_purchase_amount	**Coef.**	**St.Err.**	**t-value**	**p-value**	**95% Conf Interval**	**Sig**
customerid	0	0	0.13	.894	0	0
age	0	0	-0.66	.511	0	0
gender_encoded	.005	.006	0.78	.433	-.007	.017
itempurchased	0	0	0.11	.91	0	0
category	.001	0	0.94	.35	-.001	.003
purchaseamountusd	.018	0	314.67	0	0	0
location_encoded	0	0	0.34	.735	0	0
size	0	.002	-0.17	.867	-.003	.003
color	0	0	-0.64	.52	0	0
season	0	.001	0.24	.812	-.002	.003
reviewrating **	-.004	.002	-2.01	.044	-.008	0
subscriptionstatus	-.005	.006	-0.83	.406	-.016	.007
paymentmethod	.001	.001	0.92	.359	-.001	.002
shippingtype	0	0	-0.10	.919	-.002	.001
discountapplied	-.001	.006	-0.20	.842	-.012	.01
previouspurchases	0	0	0.15	.881	0	0
preferredpaymentme d *	-.001	.001	-1.77	.077	-.003	0
frequencyofpurchases	-.001	.001	-0.99	.322	-.002	.001
Constant ***	2.95	.017	172.54	0	2.917	2.984
Mean dependent var	4.018	SD dependent var	0.440			
R-squared	0.962	Number of obs	3900			
F-test	5527.131	Prob ¿ F	0.000			
Akaike crit. (AIC)	-8092.133	Bayesian crit. (BIC)	-7973.027			

*** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1

4.1. Data Visualization

The figure 1 provides a visual breakdown of customer purchases across four distinct product categories: Clothing, Footwear, Outerwear, and Accessories. These categories are represented by numbers 1 through 4 on the x-axis, and the y-axis measures the percentage of purchases within each category. The largest share of purchases falls under Clothing (Category 1), which accounts for nearly 50that clothing items are the most popular and frequently bought products among customers, possibly driven by the wide range of styles, needs, and fashion trends that vary seasonally or by individual preference. The strong dominance of clothing in the dataset indicates a consumer focus on personal apparel, making it the key driver of sales. Accessories (Category 4) come in second, comprising just over 30shows that a significant portion of customers also focus on completing their outfits with supplementary items like jewelry, handbags, or scarves. Accessories might be seen as complementary purchases or indulgences, often bought alongside clothing. Footwear (Category 2) represents about 15% of the total purchases, reflecting a moderate demand compared to clothing and accessories. While still a significant portion of consumer purchases, footwear is less frequently bought, potentially because shoes are typically purchased less often due to durability or because they involve higher consideration before purchase. Outerwear (Category 3), including items like jackets, coats, and other seasonal wear, is the least purchased category, accounting for around 10% of total purchases. This lower share could be attributed to the seasonal nature of these items, where customers buy outerwear during colder months or specific times of the year. The relatively infrequent purchases may also be driven by the higher price point or the fact that outerwear is generally more durable and doesn't need to be replaced as often as other types of apparel.

Figure 1. Shows the proposed research model

The figure 2 compares the log-transformed purchase amounts between male (1) and female (Fe1) customers. The y-axis represents the log of purchase amounts, ranging from approximately 3.0 to 4.5. Each boxplot summarizes the distribution of log purchase amounts for each gender. Both gender groups have similar distributions, with median log purchase amounts close to 4.0. This suggests that the typical purchase amount, on a log scale, is comparable between male and female customers. The interquartile range (IQR) for both genders, represented by the height of the boxes, is quite similar, indicating that the middle 50% of purchases for both genders are distributed in a similar range. The whiskers, which extend from the boxes, indicate the spread of the data, showing that both genders have purchase amounts ranging from around 3.0 to approximately 4.5 on the log scale. There are no extreme outliers visible in the chart. The small differences in the box heights suggest that there is minimal variation in purchase amounts between genders. This supports the idea that gender may not play a significant role in determining purchase behavior in terms of the log purchase amounts.

Figure 2. Shows the proposed research model

The correlation matrix presented in Table 7 highlights weak relationships between key variables such as age, purchase amount, and review ratings. These weak correlations suggest that the dataset may not fully capture the complex interactions between these factors, which are often observed in real-world consumer behavior. This limitation reduces the predictive power of the regression model used in the analysis, as strong relationships between variables are essential for drawing meaningful conclusions. In response to this limitation, future research should consider incorporating additional or alternative variables that may better reflect the drivers of consumer behavior. Variables such as lifestyle choices, digital engagement metrics, or psychographic data could help uncover stronger correlations and provide a more accurate understanding of the factors that influence purchasing patterns.

Table 7. Correlation Matrix

Variables	(1)	(2)	(3)	(4)
(1) age	1.000	-0.012	-0.022	0.040
(2) previouspurcha s	-0.012	1.000	0.024	0.008
(3) reviewrating	-0.022	0.024	1.000	0.004
(4) previouspurcha s	0.040	0.008	0.004	1.000

4.2. Discussion

Although the analysis of seasonality and promotions was a central focus of this study, the results indicate a surprisingly minimal impact of these factors on consumer behavior. This finding is inconsistent with existing research that highlights the significant influence of seasonality and promotional activities on purchasing decisions. A possible explanation for this could be the lack of sufficient variability in the dataset regarding these factors. Alternatively, the model used may not be fully optimized to capture their effects. Seasonality and promotions are critical drivers of retail sales, and the inability to detect their influence weakens the study's practical relevance for retail marketing strategies. Future studies should utilize datasets with more pronounced seasonal fluctuations and promotional events to better capture the role of these variables in consumer purchasing behavior.

5. CONCLUSION

The analysis of consumer purchasing behavior across various demographic and product categories provided valuable insights into retail patterns. The data shows that gender does not significantly influence the overall purchase amount, with both male and female customers exhibiting similar spending behaviors. The weak correlations between age, review ratings, and previous purchases further highlight that these demographic factors do not strongly influence consumer spending habits or product choices. The dominance of Clothing and Accessories as the most frequently purchased categories suggests that these items are of greater interest or necessity to consumers, while Footwear and Outerwear are less popular, possibly due to their seasonal nature or lower replacement frequency. Promotional activities and seasonality, while important considerations in retail, showed limited direct impact on the total purchase amounts, suggesting that consumers may prioritize other factors, such as product quality or necessity, over short-term promotions. However, the purchase amount in USD was found to be a significant predictor in determining the log purchase amount, reinforcing the direct relationship between consumer spending and the monetary value of transactions. Although review ratings showed a slight negative effect on purchase amounts, the overall influence of review ratings on consumer decisions appeared minimal. In conclusion, consumer behavior in this dataset appears to be driven more by individual preferences for specific products rather than by broad demographic factors or external influences like promotions or seasonal trends. Future research can be expanded in several key areas to deepen the understanding of consumer purchasing behavior. First, incorporating more granular demographic data, such as household income, education level, or lifestyle factors, could reveal stronger relationships between consumer profiles and spending patterns. Additionally, geographical factors could be explored to understand regional preferences, which might highlight specific cultural or local trends influencing purchasing decisions. Furthermore, exploring the impact of e-commerce and in-store shopping experiences would provide a modern view of retail behavior, as the increasing shift to online shopping is transforming consumer habits. Investigating the role of digital influences, such as social media, influencer marketing, and online reviews, could also offer insights into how consumers make purchase decisions in the digital age. In terms of methodology, future research could implement more advanced analytical techniques, such as clustering or machine learning algorithms, to segment customers based on behavior and predict future purchase trends with greater accuracy. Time-series analysis could be applied to study seasonal purchasing patterns over multiple years to assess how trends evolve and how promotions or economic conditions might alter consumer behavior. Finally, longitudinal studies that track consumer behavior over time could offer insight into how customer loyalty programs, repeat purchases, and brand interactions contribute to long-term consumer engagement and spending. By expanding the scope of analysis and incorporating more diverse variables and advanced methodologies, future research can provide more comprehensive insights into consumer behavior, offering businesses a strategic advantage in understanding and anticipating customer needs in an evolving retail landscape. The current study focuses on a limited range of product categories, including clothing, footwear, outerwear, and accessories. While these categories provide valuable insights into consumer behavior, they do not represent the diversity of the retail market. Excluding important product categories such as electronics, groceries, and home goods restricts the generalizability of the study's findings. Different types of products attract different consumer segments and exhibit unique purchasing patterns, particularly in areas such as price sensitivity, seasonality, and promotional response. For instance, electronics and groceries are sectors where consumer behavior is often driven by different factors compared to fashion-related items. Future research should expand the scope to include a broader range of product categories, which would offer a more holistic understanding of consumer behavior across various retail sectors.

6. DECLARATIONS

6.1. Author Contributions

Conceptualization: SH; Methodology: HH; Software: PS; Validation: SH and HH; Formal Analysis: SH and HH; Investigation: PS; Resources: HH; Data Curation: SS; Writing Original Draft Preparation: SH and PS; Writing Review and Editing: PS and SH; Visualization: HH; All authors, SH, HH and PS, have read and agreed to the published version of the manuscript.

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6.3. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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