# Recent Customer Shopping Trends

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## Research Topic: Latest Customer Shopping Trends

This research focuses on recent customer shopping trends, a topic that is both familiar and increasingly important to each member of our team. The rise of online shopping, particularly after the Covid-19 pandemic, combined with rapid technological advancements, has made this subject more relevant than ever. Our research will revolve around gaining a better understanding on what customers tend to purchase pertaining to gender, age, geographical location, season, item, price, and other features.Through a series of research questions and data visualizations, we will explore these relationships to uncover insights and draw connections between key attributes. Our goal is to contribute new knowledge to the reader and deepen our understanding of modern consumer behavior.

## Research Questions

The first research question we will explore is, how do different demographics such as age, gender, location, and price affect the shopping trends of customers. We will create different visuals to present our findings and explain the correlation between each one of these features and customer shopping behavior. We are also curious to know, does gender have an affect on how much the customer spends, what item(s) they buy, and what reviews they left on the product. We predict that there will be large differences between the shopping trends of males versus the shopping trends of females, and intend to explore this further using multiple types of visualizations and tables. We must be aware of bias, as we are all females who experience the female shopping trends ourselves, and we cannot allow this to alter the conclusions we make. We are also curious on if the time of year (season) and geographical location of a customer changes what specific item they purchase. For example, does someone who is experiencing summer in Florida tend to buy something different from a customer experiencing winter in Maine? Overall, this is not an exhaustive list on what we intend to explore, as there are many different combinations of features that allow for different discoveries.

## Provenance Of Our Data

We are utilizing a data set that we found on Kaggle. Kaggle is a website focused towards data scientists with a goal in helping others learn about data. The author of the data is Bhadra Mo-

hit, and they describe it as offering a comprehensive view of consumer shopping trends, aiming to uncover patterns and behaviors in retail purchasing. It contains detailed transactional data across various product categories, customer demographics, and purchase channels. This data set was last updated 20 days ago, and is expected to be updated 4 times a year. This ensures that the data remains relevant and is as accurate as possible. In this data set, case is an individual transaction. This includes the attributes, customer ID, age, gender, item purchased, category, purchase amount USD, location, size, color, season, review rating, subscription status, payment method, shipping type, discount applies, promo code used, previous purchases, preferred payment method, and frequency of purchases. We intend to focus on age, gender, item purchased, location, season, review rating, and previous purchases. All of the attributes come from the data set, but we also created the attribute of region, which groups all fifty states into four regions: Northeast, South, Midwest, and West. This is based upon the national recognized regions in the United States.

## FAIR Principles

The data we are utilizing meets the FAIR principles. The data is **findable**, and includes unique identifiers as well rich and substantial metadata. Each case is given an ID number, and there are numerous attributes that they are defined by. The data is **accessible** and can be found in our public repository. We also downloaded the data from Kaggle, which is public and we were able to easily locate it and access it. The data is **interoperable** and uses the R language which is widely known and accepted. This way our data can be exchanged between collaborators and allows for open communication. By citing our sources and explaining the provenance of our data, this ensure our data is also **reusable**. By meeting the FAIR principles we are ensuring that our data is universal, and can be easily understood.

## Data Exploration

Table 1: Summary Statistics on Purchase Amount by Category

| category | count | min | Q1 | median | max | mad | mean | Q3 | sd |
|---|---|---|---|---|---|---|---|---|---|
| Accessories | 1240 | 20 | 39.75 | 60.0 | 100 | 29.6520 | 59.83871 | 80 | 23.30123 |
| Clothing | 1737 | 20 | 38.00 | 60.0 | 100 | 31.1346 | 60.02533 | 81 | 23.79246 |
| Footwear | 599 | 20 | 39.00 | 60.0 | 100 | 31.1346 | 60.25543 | 81 | 23.63844 |
| Outerwear | 324 | 20 | 34.00 | 54.5 | 100 | 33.3585 | 57.17284 | 80 | 24.59003 |

Before creating any visualizations, we created a table of several descriptive statistics of customers' purchase amounts by the category of the item they purchased. Table 1 shows a summary table including *count*, *minimum*, *Q1*, *median*, *Q3*, *maximum*, *median absolute deviation*, *mean*, and *standard deviation* of item category and purchase amount. Each item in the original data set was categorizes into one of the four categories. We can utilize this table to not only see simple statistics, but also the spread and deviations of the data. We were interested in gaining a better understanding of customer spending trends, and therefore we chose this summary table. From the table we can make numerous conclusions. Looking at the count column, we can see that the Clothing category

has the highest count, followed by Accessories, Footwear, and Outerwear respectively. This means that out of the entire data set, items that fall under the clothing category are the most popular and most frequently bought. The minimum and maximum price for each item are the same, 20 and 100 respectively. This could mean that the original data set only chose to collect information on items within that price range. We found it interesting that while accessories, clothing, and footwear all have the same median of 60, outerwear has a lower median of just 54.5. This could mean that

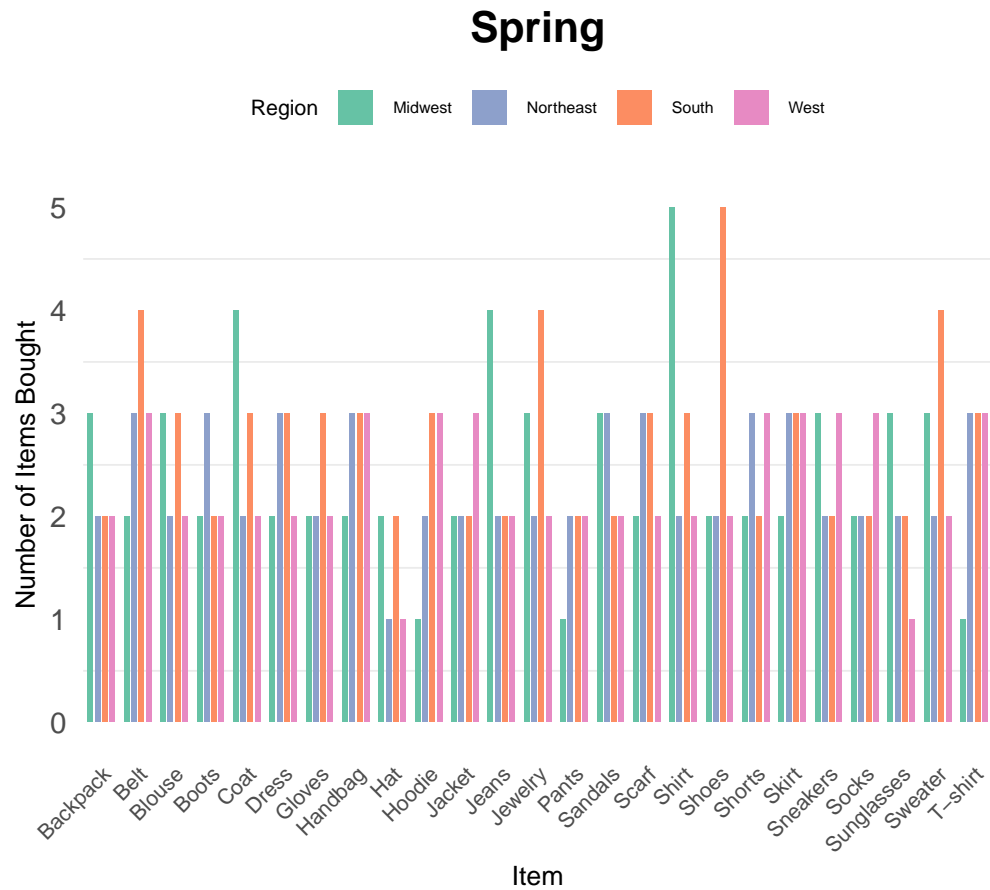Figure 1: Popularity of Items by Region and Season



## Spring

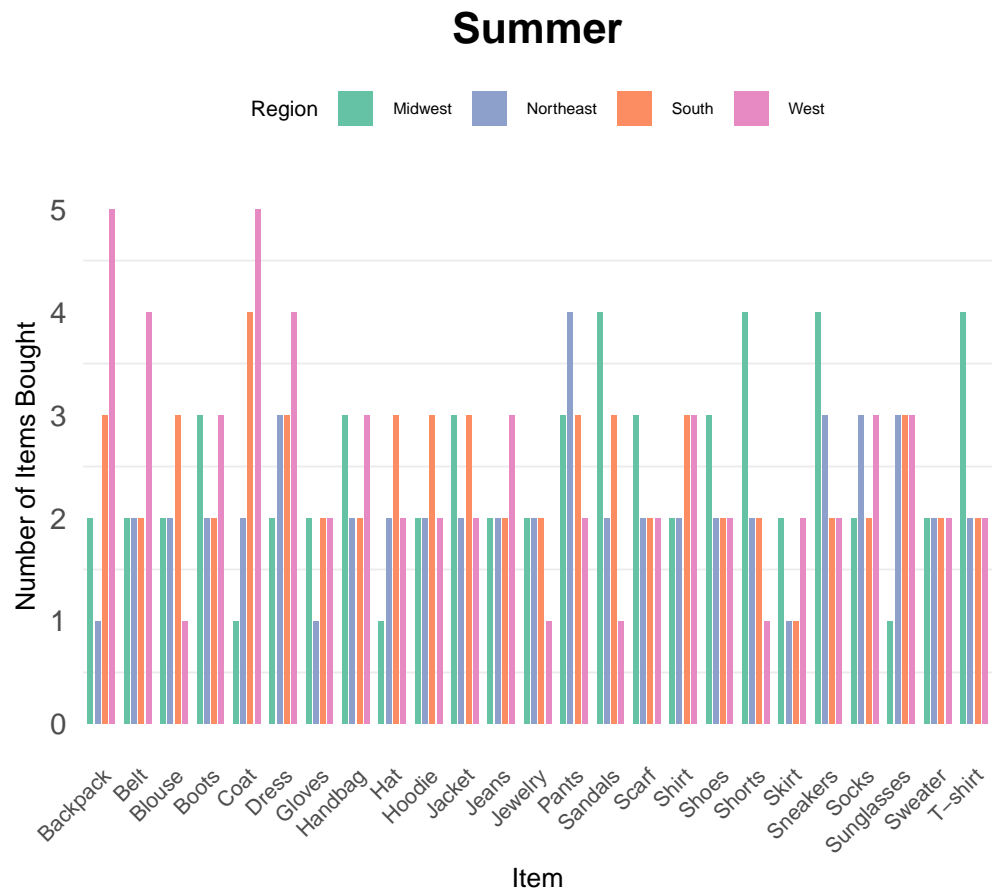Number of Items Bought

Item

Figure 2: Popularity of Items by Region and Season

Figure 3: Popularity of Items by Region and Season



**Fall**

**Winter**
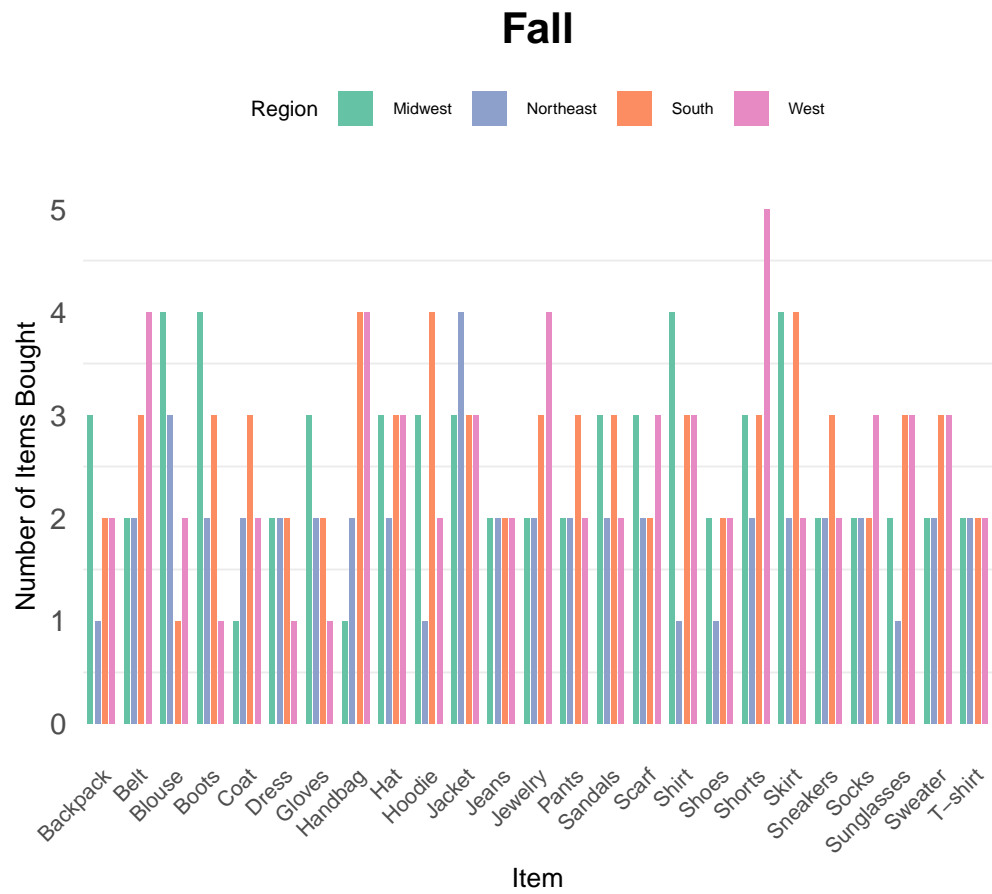
Figure 5: Distribution of Spending With and Without a Promo Code



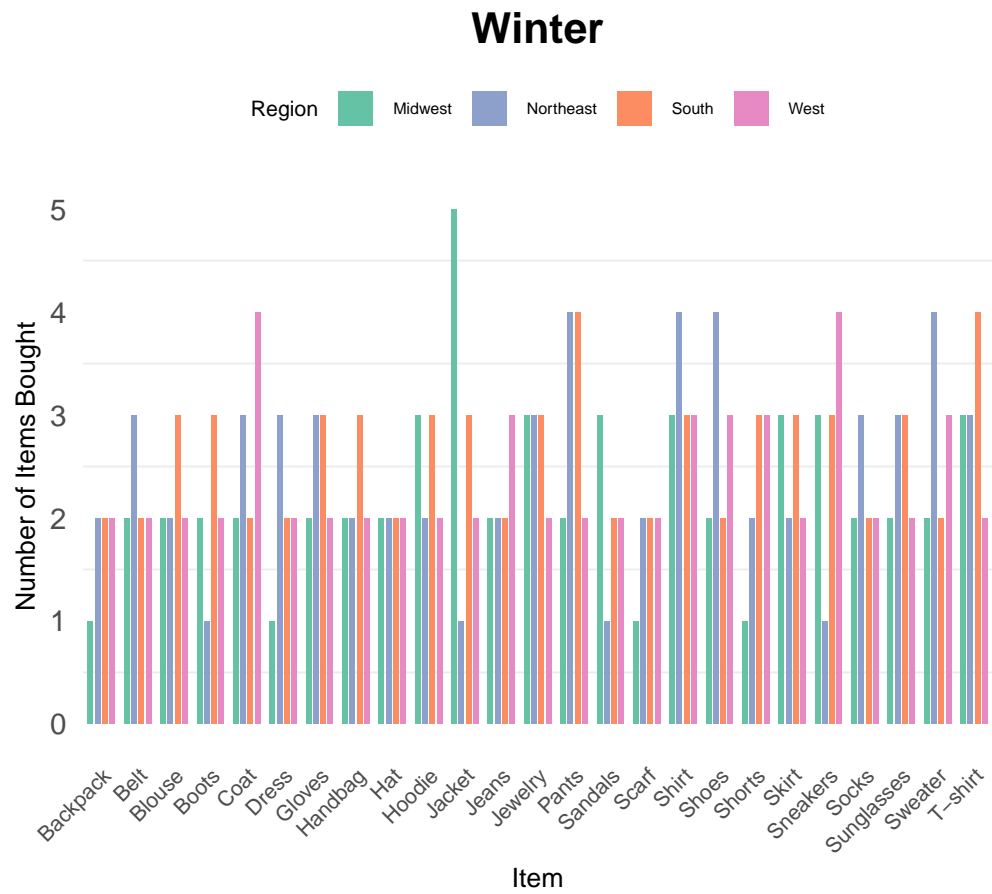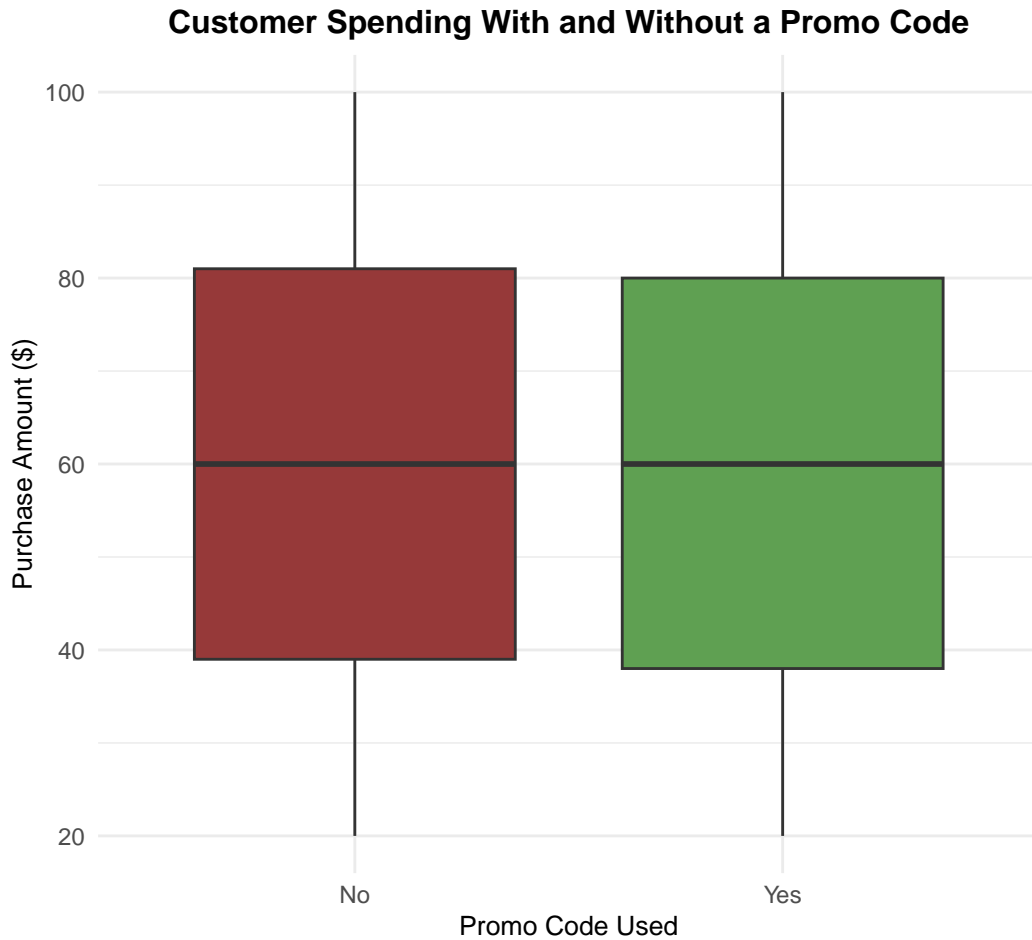**Customer Spending With and Without a Promo Code**

While we assumed there would be a greater difference between amount spent by customers when they use a promo code, this plot shows that people without a promo code only spend slightly more. This can possibly be due to confounding variables like the item purchased, where the item was purchased, and how high end the product was. Despite all of those, we found a vary little correlation between purchase amount and whether or not customers used a promo code.

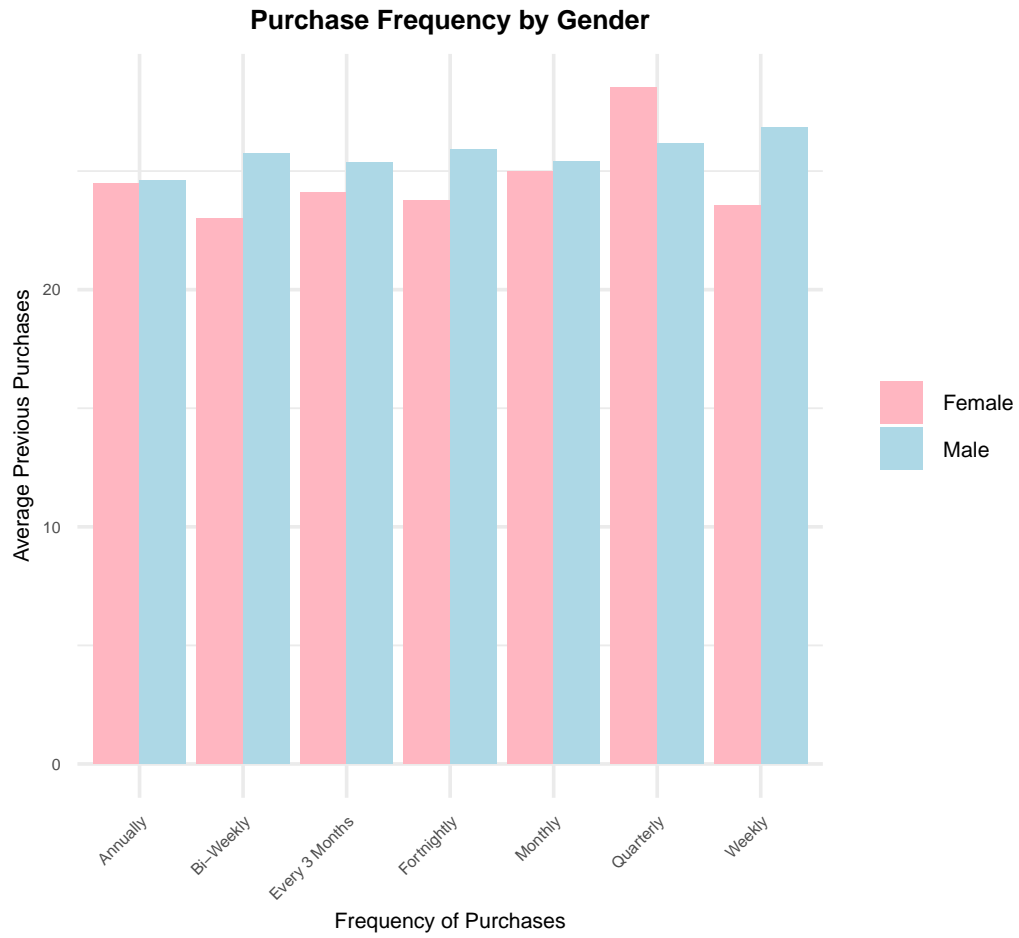Figure 6: Distribution of Purchase Frequency by Gender

**Purchase Frequency by Gender**

Figure 7: Distribution of Review Ratings by Gender
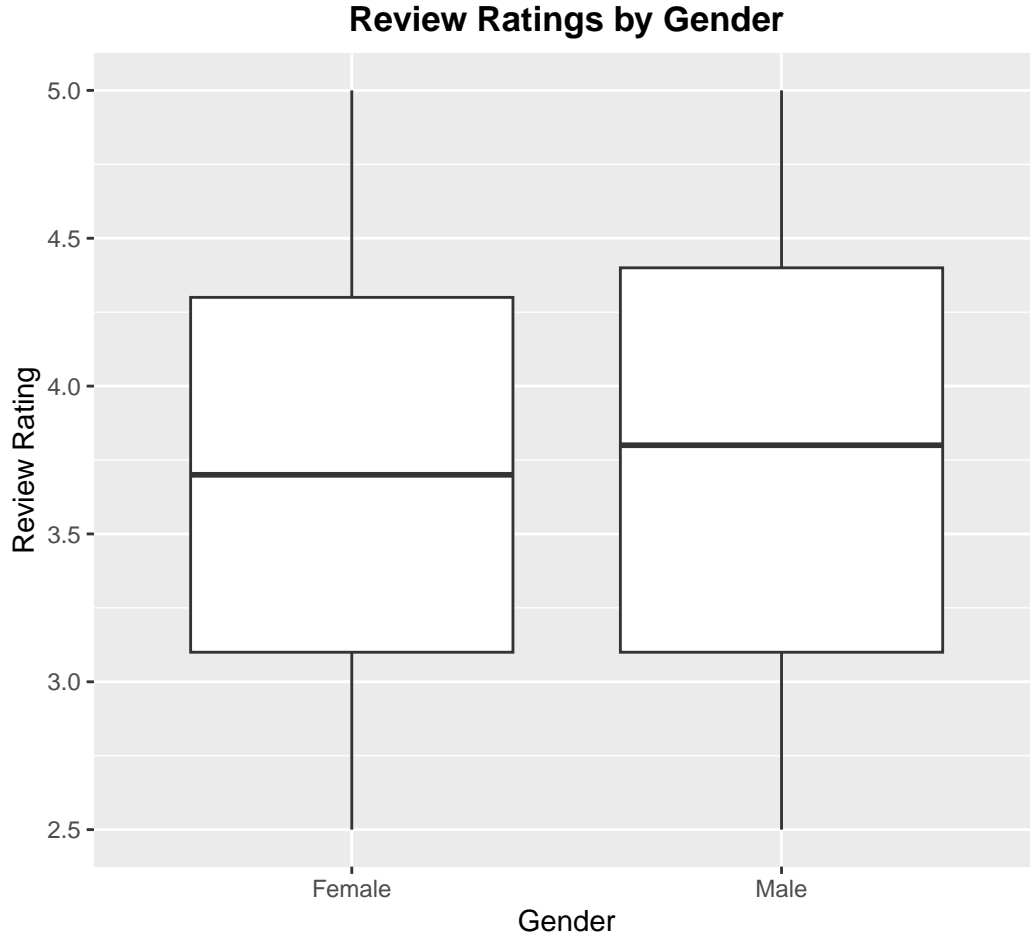


**Review Ratings by Gender**

Figure Four shows the average review ratings a customer leaves after making a purchase, by Gender. Each customer was able to leave a review rating between 0-5, and we took the average of both the female reviews, and the male reviews to graph. The results we found were different than our initial expectations. We can conclude from Figure One that males tend to leave slighter high reviews than women do. While we thought this to be true before graphing the data, we expected the results to be much more drastic. Females tend to leave, on average, a rating of approximately 3.7, while males leave approximately a 3.8. This is based on the grid lines and Y-axis scale. However, we found that there are also more men in our original data set which can lead to skewed and biased results. The unbalanced number of each gender could be what is making the males average appear higher than the females. Overall, figure one gives us an insight into the reviews typically left by each gender, and whether female or males tend to be "harsher" when reviewing a product. The use of a box plot appropriately displays the data and therefore the difference in average review ratings by gender can be easily compared.

# Works Cited

Disease Control, Centers for, and Prevention. *Geographic Regions.* 2024, https://www.cdc.gov/nchs/hus/sources-definitions/geographic-region.htm#:~:text=Geographic%20region,Ohio%2C%20South%20Dakota%2C%20and%20Wisconsin.

Mohit, Bhadra. "Customer Shopping (Latest Trends) Dataset." *Kaggle*, Nov. 2024, https://www.kaggle.com/datasets/bhadramohit/customer-shopping-latest-trends-dataset.

## Code Appendix

```r
# Load necessary packages ----
library(ggplot2)
library(dplyr)
library(knitr)
library(tinytex)
# Load shopping trends dataset ----
shopping_trends_raw <- read.csv(
  file = "shopping_trends.csv",
  header = TRUE,
  sep = ","
)
# Clean column names for consistency ----
shopping_trends_clean <- shopping_trends_raw %>%
  rename(
    customer_id = "Customer.ID",
    age = "Age",
    gender = "Gender",
    item_purchased = "Item.Purchased",
    category = "Category",
    purchase_amount_usd = "Purchase.Amount..USD.",
    location = "Location",
    size = "Size",
    color = "Color",
    season = "Season",
    review_rating = "Review.Rating",
    subscription_status = "Subscription.Status",
    payment_method = "Payment.Method",
    shipping_type = "Shipping.Type",
    discount_applied = "Discount.Applied",
    promo_code_used = "Promo.Code.Used",
    previous_purchases = "Previous.Purchases",
    preferred_payment_method = "Preferred.Payment.Method",
    frequency_of_purchases = "Frequency.of.Purchases"
  )

# Make summary table for purchase amount by category ----
shopping_summary <- shopping_trends_clean %>%
  select(category, purchase_amount_usd) %>%
  group_by(category) %>%
  summarize(
    count = n(),
    min = min(purchase_amount_usd),
    Q1 = quantile(purchase_amount_usd, 0.25),
    median = median(purchase_amount_usd),
```

```r
    Q1 = quantile(purchase_amount_usd, 0.75),
    max = max(purchase_amount_usd),
    mad = mad(purchase_amount_usd),
    mean = mean(purchase_amount_usd),
    count = n(),
    min = min(purchase_amount_usd),
    Q1 = quantile(purchase_amount_usd, 0.25),
    median = median(purchase_amount_usd),
    Q3 = quantile(purchase_amount_usd, 0.75),
    max = max(purchase_amount_usd),
    mad = mad(purchase_amount_usd),
    mean = mean(purchase_amount_usd),
    sd = sd(purchase_amount_usd)
  )

shopping_summary %>%
  knitr::kable()
# Group data by location, season, and item ----
item_purchased_data <- shopping_trends_clean %>%
  group_by(
    location,
    season,
    item_purchased
  ) %>%
  summarize(
    item_count = n(),
    .groups = "drop"
  )
# Map U.S. states to regions ----
state_to_region <- c(
  "Maine" = "Northeast",
  "New Hampshire" = "Northeast",
  "Vermont" = "Northeast",
  "Massachusetts" = "Northeast",
  "Rhode Island" = "Northeast",
  "Connecticut" = "Northeast",
  "New York" = "Northeast",
  "New Jersey" = "Northeast",
  "Pennsylvania" = "Northeast",
  "Delaware" = "South",
  "Maryland" = "South",
  "Virginia" = "South",
  "North Carolina" = "South",
  "South Carolina" = "South",
  "Georgia" = "South",
  "Florida" = "South",
  "West Virginia" = "South",
```

```r
    "Kentucky" = "South",
    "Tennessee" = "South",
    "Alabama" = "South",
    "Mississippi" = "South",
    "Arkansas" = "South",
    "Louisiana" = "South",
    "Oklahoma" = "South",
    "Texas" = "South",
    "Indiana" = "Midwest",
    "Illinois" = "Midwest",
    "Michigan" = "Midwest",
    "Ohio" = "Midwest",
    "Wisconsin" = "Midwest",
    "Missouri" = "Midwest",
    "Iowa" = "Midwest",
    "Minnesota" = "Midwest",
    "North Dakota" = "Midwest",
    "South Dakota" = "Midwest",
    "Nebraska" = "Midwest",
    "Kansas" = "Midwest",
    "Montana" = "West",
    "Wyoming" = "West",
    "Colorado" = "West",
    "Idaho" = "West",
    "Nevada" = "West",
    "Utah" = "West",
    "Arizona" = "West",
    "New Mexico" = "West",
    "Washington" = "West",
    "Oregon" = "West",
    "California" = "West",
    "Alaska" = "West",
    "Hawaii" = "West"
)
# Add region column based on location ----
item_purchased_data <- item_purchased_data %>%
  mutate(
    region = state_to_region[location]
  )
# Filter data by season ----
spring_data <- item_purchased_data %>%
  filter(season == "Spring")

summer_data <- item_purchased_data %>%
  filter(season == "Summer")

fall_data <- item_purchased_data %>%
```

```
    filter(season == "Fall")

winter_data <- item_purchased_data %>%
    filter(season == "Winter")
# Visualize data by region and season ----
plot_items_by_season <- function(
    item_purchased_data,
    season_name
    ) {
ggplot(
  item_purchased_data,
  aes(
    x = item_purchased,
    y = item_count,
    fill = region
  )
) +
  geom_bar(
    stat = "identity",
    position = position_dodge(width = 0.8),
    width = 0.6
  ) +
  scale_x_discrete(
    expand = expansion(add = c(0.5, 0.5))
  ) +
  labs(
    title = paste(
      season_name
    ),
    x = "Item",
    y = "Number of Items Bought",
    fill = "Region"
  ) +
  scale_fill_manual(
    values = c(
      "Northeast" = "#8DA0CB",
      "South" = "#FC8D62",
      "Midwest" = "#66C2A5",
      "West" = "#E78AC3"
    )
  ) +
  theme_minimal(base_size = 14) +
  theme(
    panel.grid.major = element_blank(),
    axis.text.x = element_text(
      angle = 45,
      hjust = 1,
```

```r
    size = 8
    ),
    axis.title.x = element_text(size = 10),
    axis.title.y = element_text(size = 10),
    legend.position = "top",
    legend.text = element_text(size = 6),
    legend.title = element_text(size = 8),
    legend.key.size = unit(0.5, "cm"),
    plot.title = element_text(
      size = 16,
      hjust = 0.5,
      face = "bold"
    ),
    plot.margin = margin(15, 15, 15, 15)
  )
}
# Generate and display plots for each season ----
spring_plot <- plot_items_by_season(spring_data, "Spring")
summer_plot <- plot_items_by_season(summer_data, "Summer")
fall_plot <- plot_items_by_season(fall_data, "Fall")
winter_plot <- plot_items_by_season(winter_data, "Winter")

print(spring_plot)
print(summer_plot)
print(fall_plot)
print(winter_plot)

# Visualize purchase amount with and without discount codes ----
ggplot(
  shopping_trends_clean,
  aes(
    x = promo_code_used,
    y = purchase_amount_usd,
    fill = promo_code_used,
    table =
  )
) +
  geom_boxplot(
   outlier.color = "black",
   outlier.size = 2
  ) +
  labs(
    x = "Promo Code Used",
    y = "Purchase Amount ($)",
    title = "Customer Spending With and Without a Promo Code"
  ) +
  scale_fill_manual(
```

```r
    values = c(
      "Yes" = "#5fa052",
      "No" = "#963939"
    )
  ) +
  theme_minimal() +
  theme(
    legend.position = "none",
    plot.title = element_text(
      hjust = 0.5,
      face = "bold",
      size = 12
    ),
    axis.title = element_text(size = 10)
  )
# Summarize data by gender and frequency of purchases ----
summary_by_gender_freq <- shopping_trends_clean %>%
  group_by(
    gender,
    frequency_of_purchases
  ) %>%
  summarize(
    average_previous_purchases = mean(previous_purchases),
    .groups = "drop"
  )
# Filter out N/A frequency of purchases values ----
summary_by_gender_freq_filtered <- summary_by_gender_freq %>%
  filter(frequency_of_purchases != "n/a")
# Visualize average previous purchases by gender and frequency of purchases ----
ggplot(
  summary_by_gender_freq_filtered,
  aes(
    x = frequency_of_purchases,
    y = average_previous_purchases,
    fill = gender
  )
) +
  geom_bar(
    stat = "identity",
    position = position_dodge()
  ) +
  labs(
    x = "Frequency of Purchases",
    y = "Average Previous Purchases",
    title = "Purchase Frequency by Gender"
  ) +
  scale_fill_manual(
```

```r
      values = c(
        "Female" = "#FFB6C1",
        "Male" = "#ADD8E6"
      )
    ) +
    theme_minimal(base_size = 14) +
    theme(
      axis.text.x = element_text(
        angle = 45,
        hjust = 1,
        size = 6
      ),
      axis.text.y = element_text(size = 6),
      legend.title = element_blank(),
      legend.text = element_text(size = 8),
      plot.title = element_text(
        size = 10,
        hjust = 0.5,
        face = "bold"
      ),
      axis.title.x = element_text(size = 8),
      axis.title.y = element_text(size = 8)
    )

# Group data by gender and review rating ----
type_reviews <- shopping_trends_clean %>%
  select(
    gender,
    review_rating
  ) %>%
  group_by(
    gender,
    review_rating
  )
# Make boxplot of review ratings by gender ----
ggplot(
  data = type_reviews,
  aes(
    x = gender,
    y = review_rating,
  )
) +
  geom_boxplot() +
  labs(
    x = "Gender",
    y = "Review Rating",
    title = "Review Ratings by Gender"
```

```r
) +
theme(
  plot.title = element_text(
    hjust = 0.5,
    face = "bold"
  )
)
```