ANALYSIS OF WEHKAMP WANNAGIVE DAYS 2024

Key Insights & Recommendations

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KEY CONCLUSION AND MANAGERIAL IMPLICATIONS

Were Wannagive Days a Success?

- The daily open count remained consistently high, especially in the middle and later stages of the event. The entry count was strong, showing good initial interest.
- Wannagive Days had a positive impact on sales.
- Customer Engagement: The streak system successfully motivated some users to return daily. Gamification elements (streaks, win cards, and discount rewards) contributed to sustained engagement.
- Women (30-44 age group) were the most engaged segment. The most popular product category was ladies fashion.
- Coupon Effectiveness: Customers who completed the 22-day streak mostly selected higher-value coupons (€20 and €25 discounts).

CHALLENGES AND AREAS FOR IMPROVEMENT

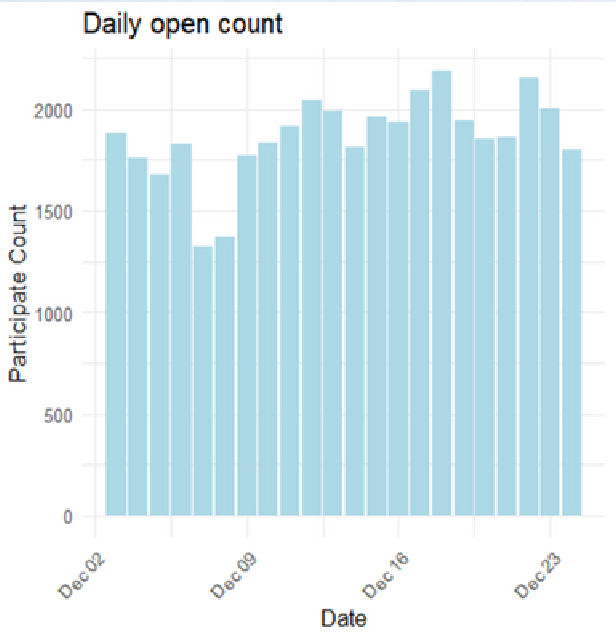
- The number of customers completing 22-day streaks was quite low, meaning most users dropped off before maximizing rewards.
- Coupons had a relatively low claim rate (39.2%) compared to win cards (88.4%).
- This suggests that discounts alone were not strong enough to drive engagement.
- Some clusters (e.g., "High-Value Buyers") were underrepresented, indicating a potential missed opportunity to target high-spending customers.

RECOMMENDATIONS

- **Increase Retention & Streak Completion**: Introduce smaller milestones (e.g., rewards for 3, 7, 14 days) to keep customers engaged. Personalized reminders for users who miss a day, encouraging them to return before losing progress. Add a "second-chance" mechanic (e.g., bonus cards or streak-recovery options) to prevent frustration from breaking streaks.
- **Improve Coupon Effectiveness**: Offer a mix of low and high-threshold discounts to cater to both casual and high-value shoppers.
- Introduce personalized coupons based on past purchases (e.g., fashion buyers get apparel discounts, tech buyers get gadget deals).

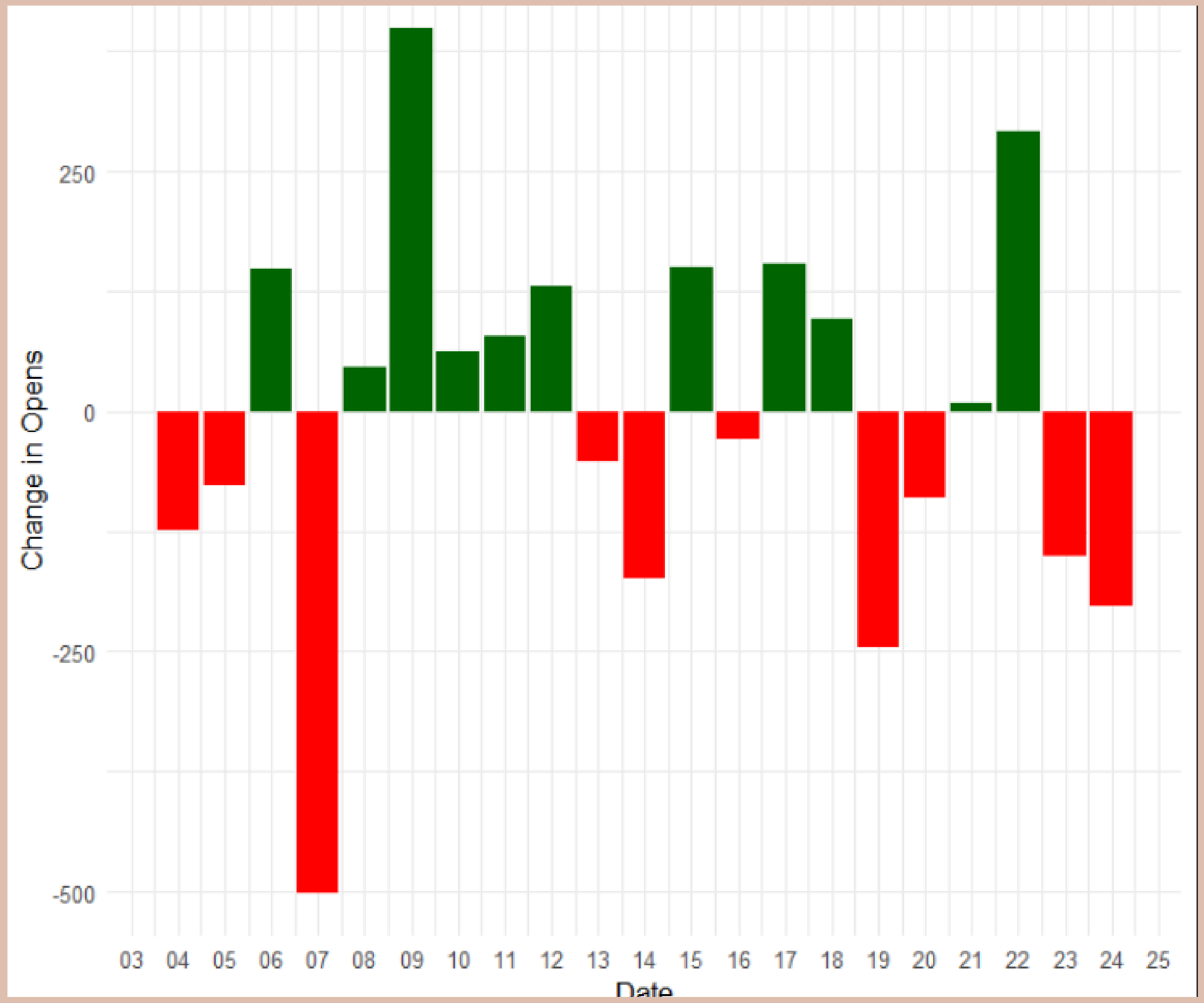
PARTICIPATION & ENGAGEMENT RESULTS

- **A total of 7764 unique participants**
- **Open rate = 0.72, with the opens per day presented in graph 2.0: Daily open count**



Graph 2.0: Daily open count

By analysing the data, we observed a couple of large drops in opens. As shown by graph 3.0, the largest drop happened during the Sinterklaas weekend, thus a lot of our clients were spending time with their families during these days. This could lead to a a lower time spent in the app, which caused the drop in opens



Graph 3: Daily Change in Opens (Drop Highligted)

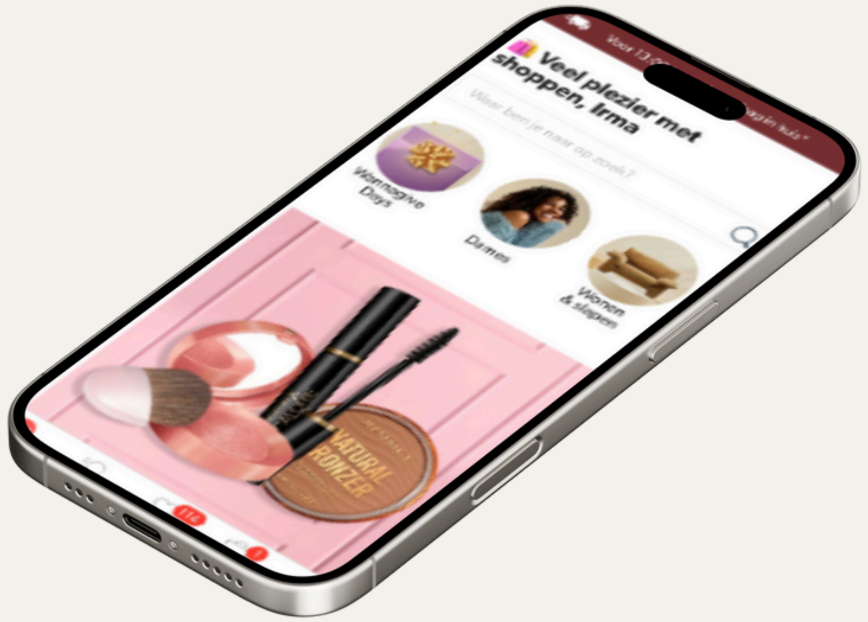
DATA ANOMALIES AND LIMITATIONS

We first cleaned the data to ensure the results were not affected by impossible values or app errors such as:

- participants who claimed one card multiple times - 1484
- participants who claimed the card without entering the app - 1
- participants that disrupt process relationships of

  Enter > Participate > Claim - 293

Moreover, we observed a few odd values such as an age of 105, but we decided to keep these in the data since they did not have a noticeable impact on the calculations



LIMITATIONS

Customer Personalization Challenges

The data does not focus much on personalized communication such as push notifications, email marketing or in-app messages. For customers contacted on multiple media sources it is hard to determine which one drove the engagement.

Engagement metrics vs business impact

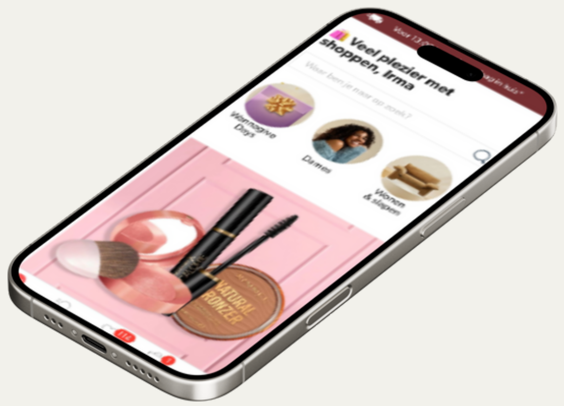
The analysis may not fully capture the long-term engagement of these customers, thus after the campaign ends. Moreover, open rates and streak participation might not be the best estimation for sales. Revenue could be a better indicator.

Data Completeness and Accuracy

Technical glitches and errors such as the ones described on earlier.

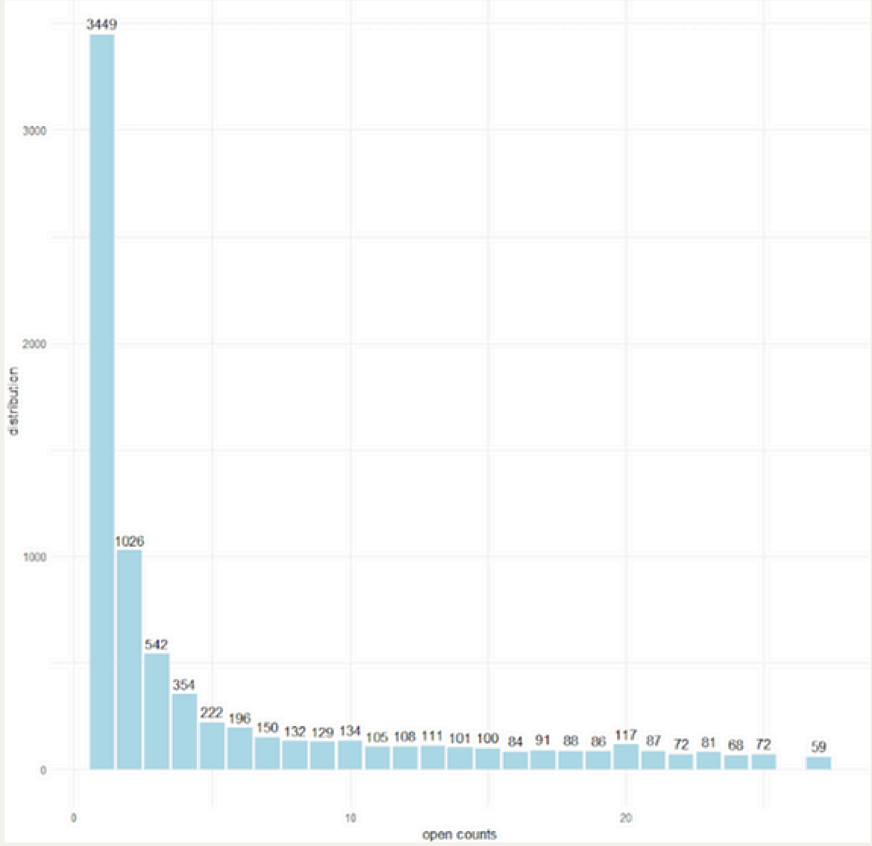
Lack of previous data

To better understand to market fluctuations we should compare the results to previous years

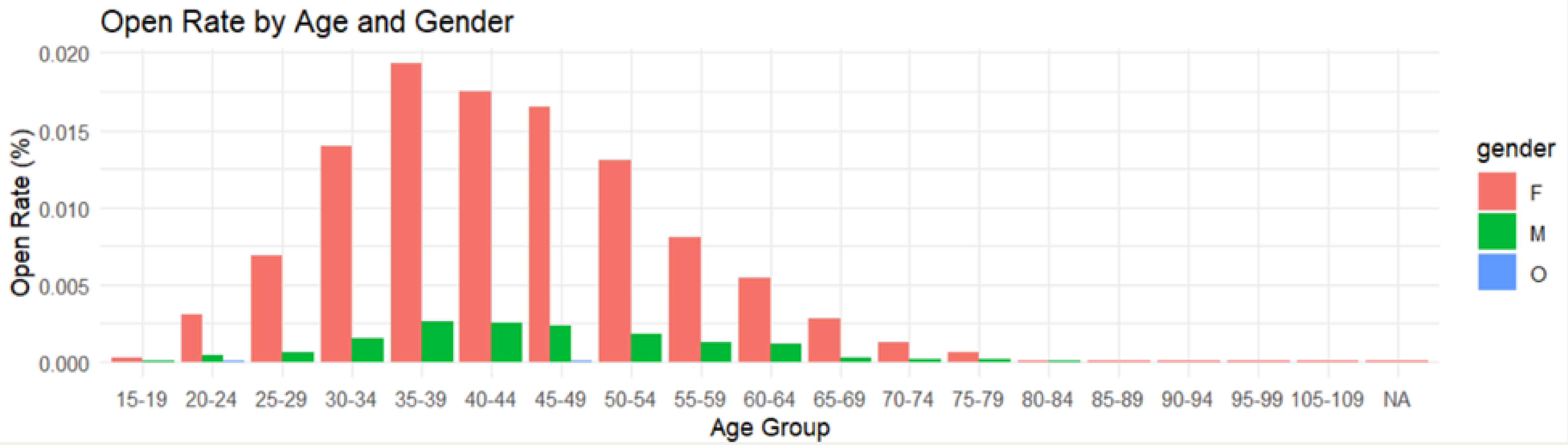


CONSUMER BEHAVIOR AND STREAK PERFORMANCE

- 18 December, and 22 December were the days with the most effect on the number of ordering customers. We believe this might result from the discounts existing on the website during these dates.
- A total of 59 customers achieved the ultimate streak of 22 cards opened. The distribution of this data can be observed in Graph 6.1 and Graph 7.1 . This means that less than 1% of the unique entries translated into fully committed strike participants.

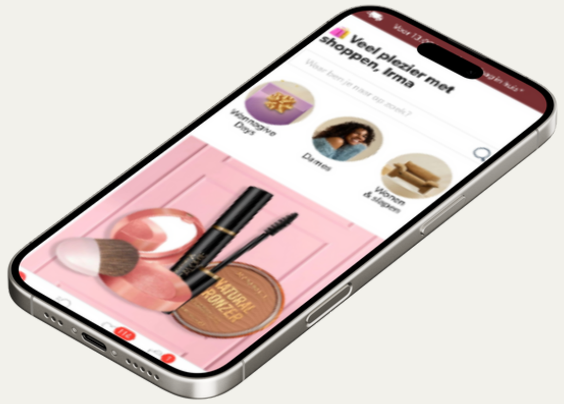


Graph 6.1: Frequency of customer card streak

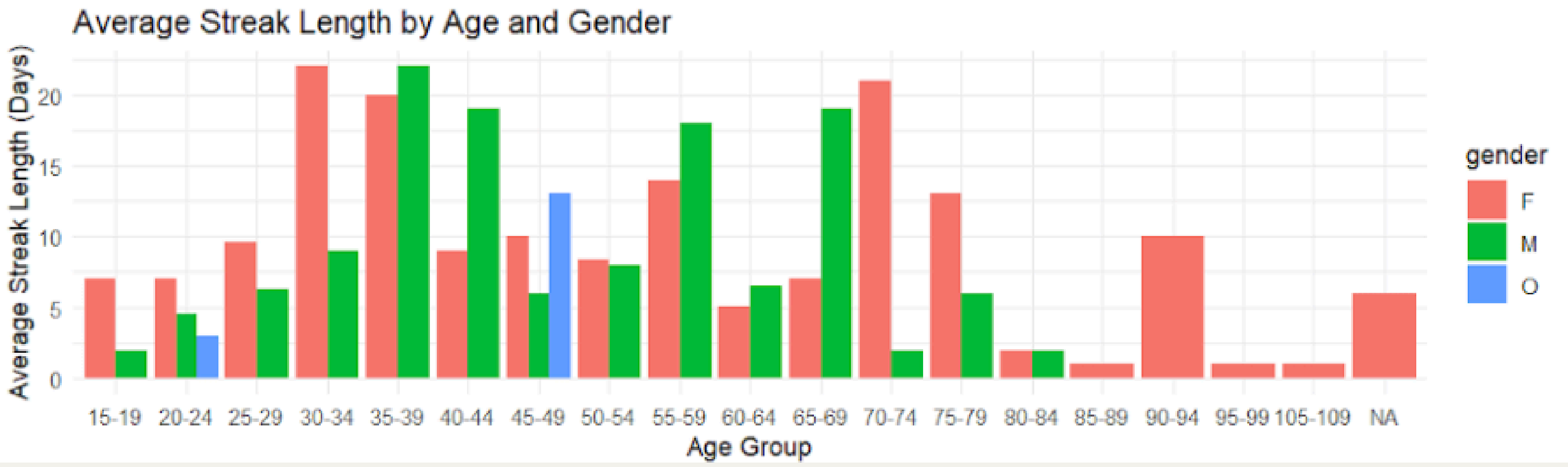


Graph 7.1: Open Rate by Age and Gender

- The open rate and claim rate graphs show similar results: the most engagement came from female participants aged between 30 to 54 years. Moreover, in both graphs, there was a huge discrepancy between the scores of females and males.

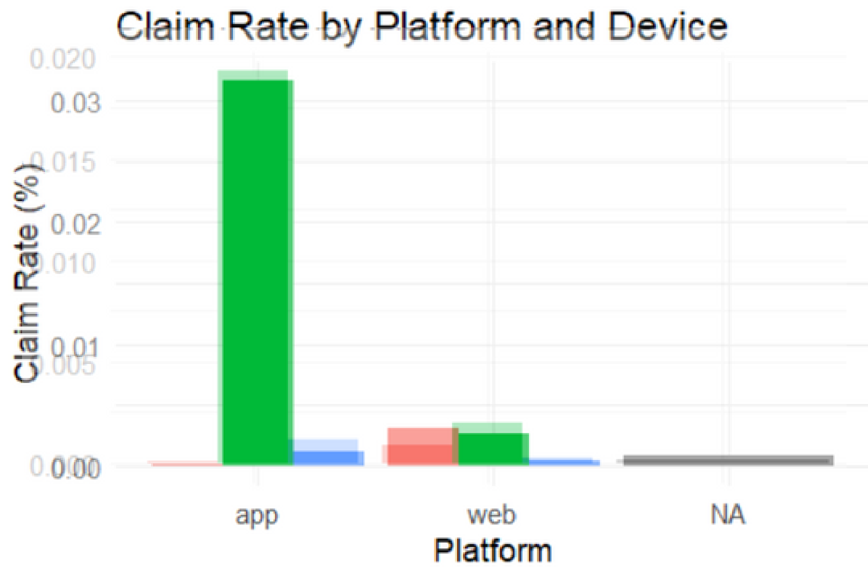


CONSUMER BEHAVIOR AND STREAK PERFORMANCE

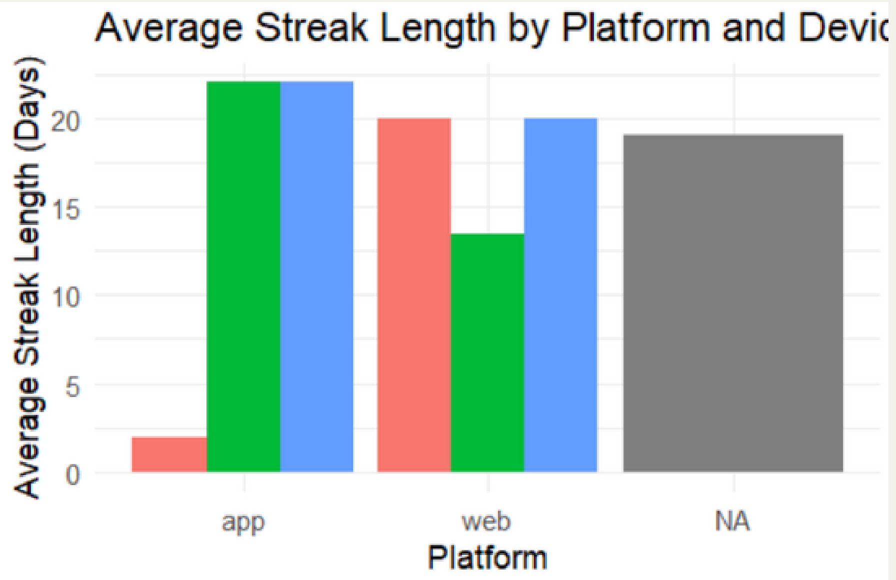


Graph 7.2 Average Streak Length by Age and Gender

- When comparing the average streak length by age and gender with the open rate and claim rate graphs, there is a remarkable change in male engagement, as well as a more balanced distribution alongside different age groups. Thus, we can see that males engaged less frequently but more consistently. This gives us important insights into age and gender-based shifts in engagement patterns, which can allow the company to understand better the different motivations between these groups.



Graph 7.3: Overlap of Claim and Open Rate by Platform and Device



Graph 7.4: Average Streak Length by Platform and Device

- Regarding the type of platform preferred by our participants, the claim rate and open rate were way higher for the app (Graph 7.3). However, the average streak was consistently high over all channels, proving once again that the streak incentitive leads costumers to access our platforms more.

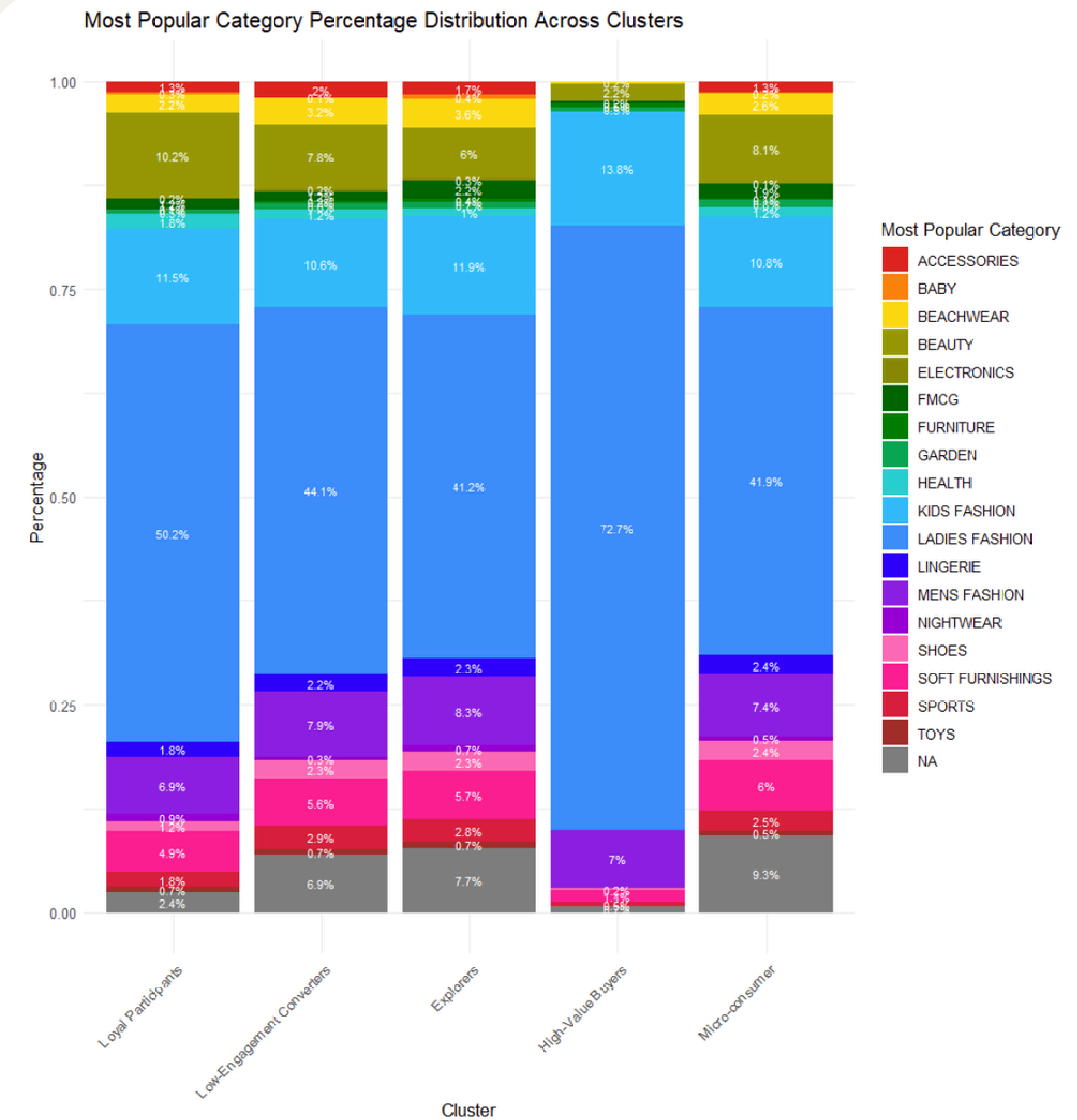
Furthermore, the analysing the streak length by province we discovered that people from Zuid-Holland, Gelderland, and Utrecht engaged the most with over 200 participants daily. For the Claim Rate and Open Rate, Noord-Brabant outperformed Utrecht but the other two remained consistent. Thus, the highest densities of Wehkamp's target audience can most probably be found in these provinces.

CUSTOMER SEGMENTATION AND CHARACTERISATION

Table 1. Customer Segmentation by K-mean

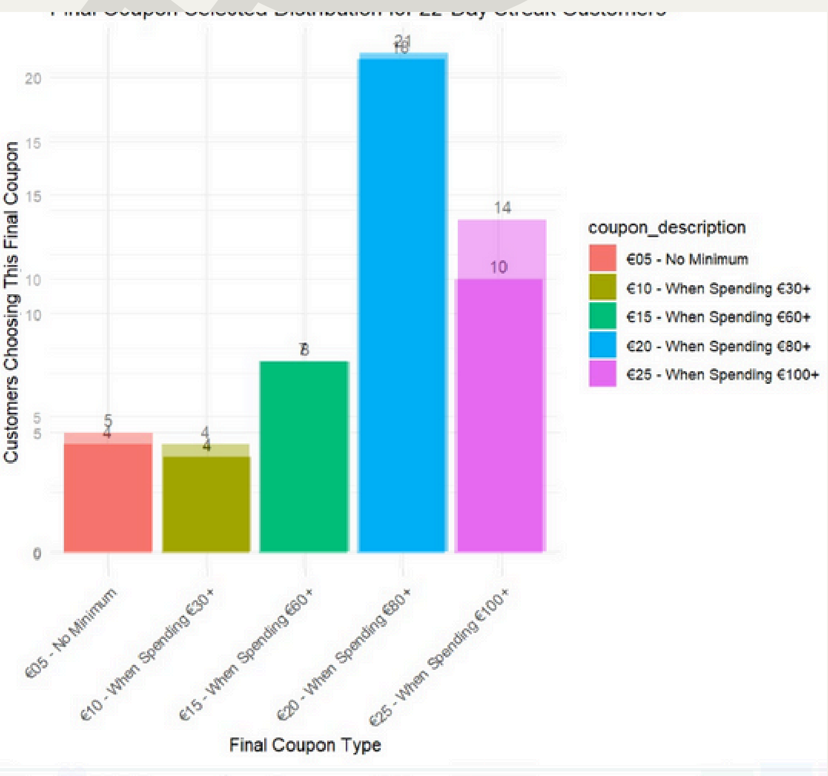
Cluster	Label	Explanation	customer_number	female_rate	Mean Streak	Mean Revenue
1	**Loyal Participants**	Moderate activity, long engagement, and stable revenue, showing platform loyalty.	1015	0.901	14.2	336
2	Low-Engagement Converters	low activity but high conversion, indicating occasional but effective engagement.	1944	0.874	1.85	230
3	Explorers	Very active but low conversion, likely exploring without spending.	2175	0.862	1.63	199
4	**High-Value Buyers**	High engagement and conversion, generating significant revenue.	414	0.925	3.32	1774
5	Micro-consumer	Frequent small purchases with high activity and conversion rates.	2216	0.896	1.59	189

- In this study, we use Open Rate, Claim Rate, Streak, and Revenue as the key variables, and apply K-Means clustering method to classify customers into five categories, from the data in the table, we need to focus on the following clusters:
- High-Value Buyers (Cluster 4)
  - Revenue per customer is 6-10 times higher than the rest of the group.
  - The highest percentage of females (0.925).
- Loyal Participants (Cluster 1)
  - The second highest percentage of females (0.901).
  - Streak (14.2) is much higher than other groups, with stronger spending habits and brand loyalty.
  - Second highest average revenue (336), with a larger cluster volume than cluster 4.
- Suggestion: For high-value users, VIP experiences and limited edition products are used to enhance loyalty and encourage higher-value consumption. For loyal customers, use ongoing rewards (e.g. membership points, exclusive discounts) to deepen relationships and increase lifetime value.

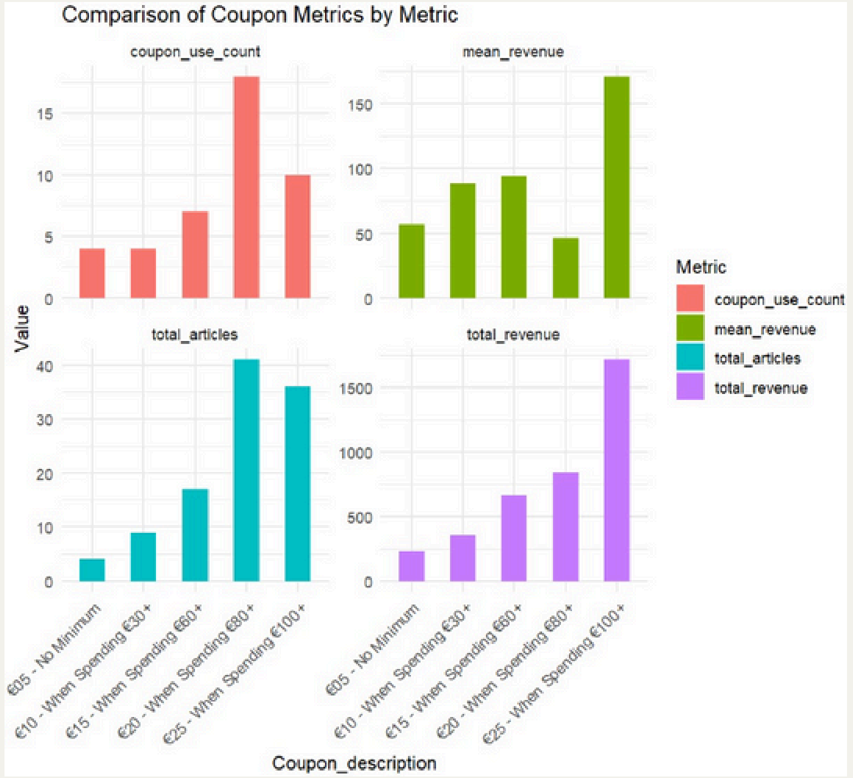


Graph 7.5: Purchasing preferences of customers from different clusters

COUPON PERFORMANCE & ORDERS



Graph 8.1: Overlap of Final Coupon Used Distribution and Final Coupon Selected Distribution for 22-Day Streak Customers

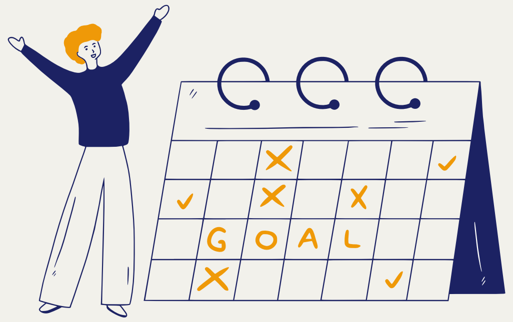


Graph 8.2: Comparison of Coupon Metrics by Metric

- The final coupon distribution graph (Graph 8.1) shows the similarity between the selected and the used coupons. The highest engagement appears in coupon 4 (€20- when spending over €80), with a value almost double that of coupon 5(€25- when spending over €100), which was the second most popular. However, coupon 4 scored higher in the use count and total articles but was second in total revenues and last in mean revenues. For the last categories, coupon 5 had the highest values. (Graph 8.2)

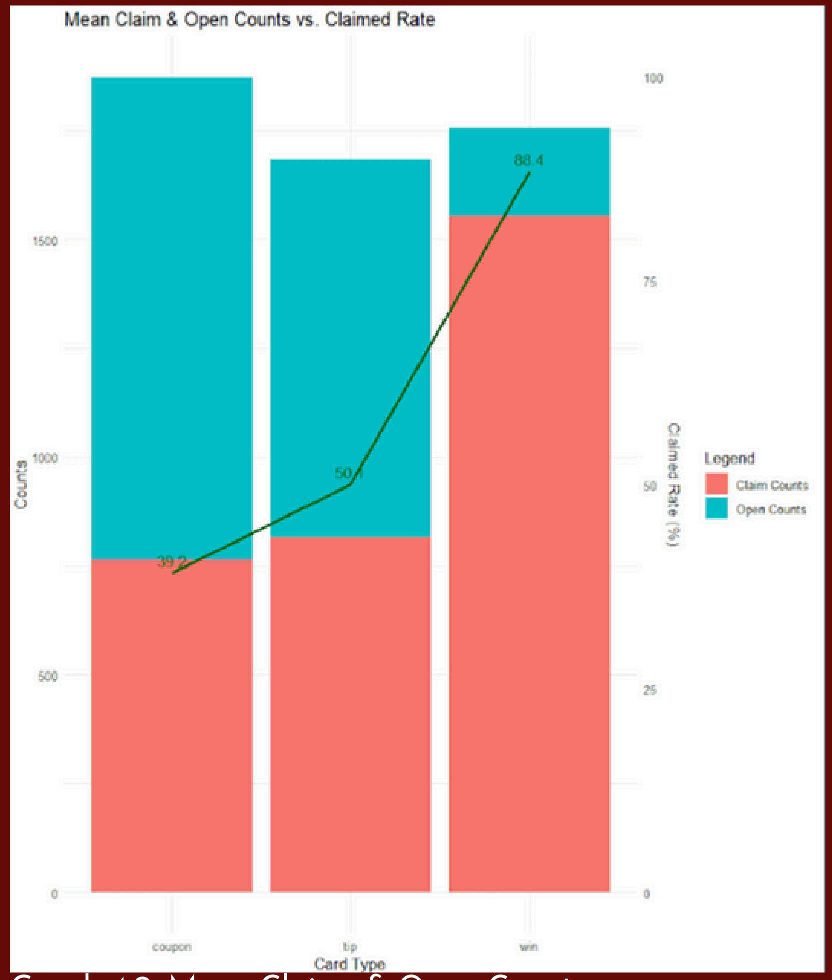
Thus, Coupon 4 had the highest engagement but lower revenue impact, while Coupon 5 drove higher revenues but lower overall engagement.

Goal: mass participation optimize for lower-value coupons like 4



Goal: high revenue/order optimize for higher-value coupons such as 5

- By looking at the unique claims and the claim rate, it can be noticed that the claim rate stands out more (Graph 4.0). This means that the people who do claim rewards are doing so at a high rate even though the total number of unique customers might not be as high. This could show a high incentive to claim rewards or a high engagement among a certain subset of users (loyal users) which would drive up the claim rate.

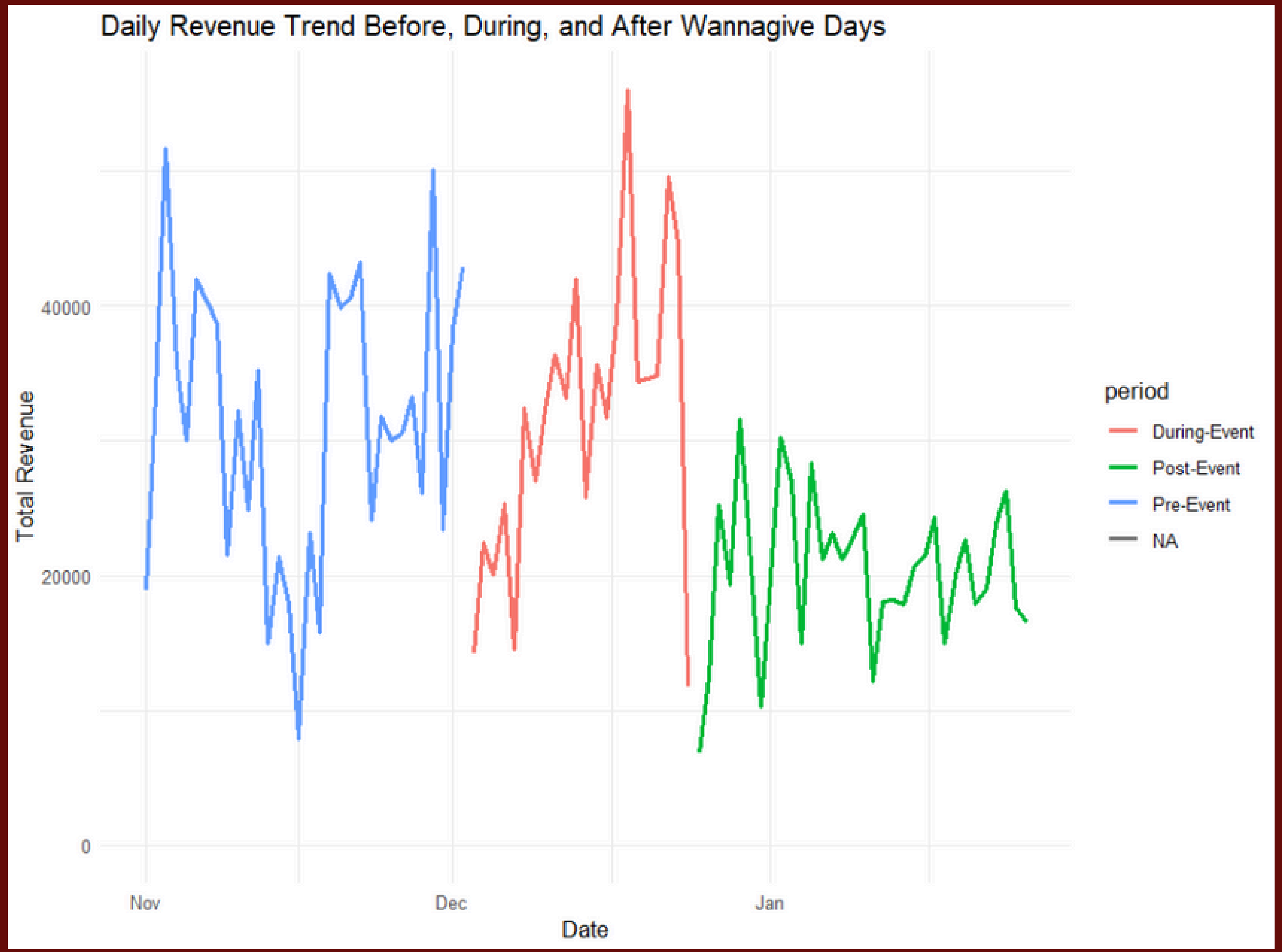


Graph 4.0: Mean Claims & Open Counts vs Claimed Rate

IMPACT ON THE BUSINESS

By comparing the before and during periods we can notice they are almost the same. In the graph, we can even notice a decrease in revenue at the beginning of the campaign, but this is a normal effect of the promotional season. Moreover, there was no significant difference between these 2 periods, as presented in Table 1.

On the other hand, the graph and Table 1 show that the average revenue, order frequency and number of items per day are significantly reduced after the event.



Graph 9.0: Daily Revenue Trend Before, During, and After Wannagive Days

Table 2: Logistic regressions reflect the effect of activity-related periods on daily revenue, order frequency and daily items traded.

Formula	Before (Dummy)	During	After
glm(revenue_per_day ~ period)		E = -0.09 P > 0.05	E = -1.63 P < 0.01 ***
glm(order_frequency ~ period)		E = 0.00 P > 0.05	E = -0.01 P < 0.01 ***
glm(item_per_day ~ period)		E = -0.00 P > 0.05	E = -0.03 P < 0.01 ***

Our hypothesis for this is.

1. the promotion will not increase sales and activity because other merchants are also promoting in the same period. (Further research: Compare customer response to the previous period when there was no Christmas promotion).

2. Due to the festive, most consumers are likely to be less active online at this time. (Further research: cross-comparison of daily activity of other online shopping platform)

THANK YOU!

Veel plezier met shoppen, Irma
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