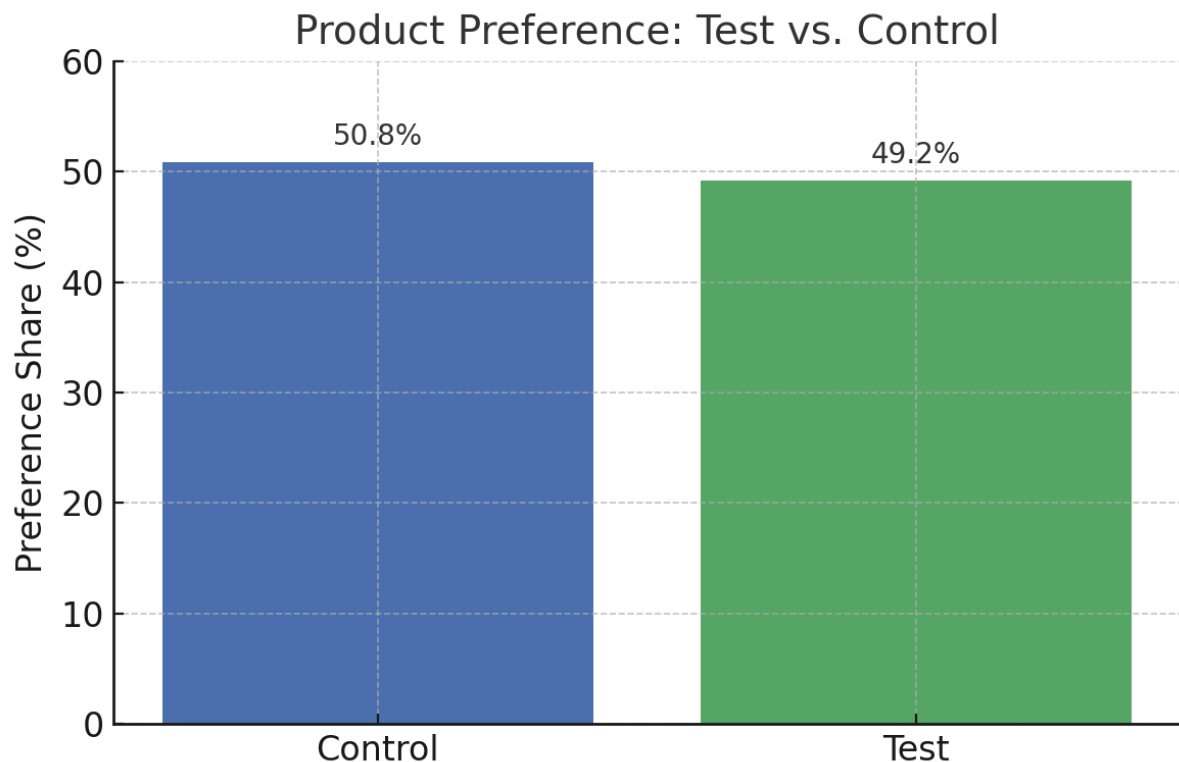


## SECTION 8: Product Test Comparison (Q32–Q38)

### 1. Preference & Value Summary

Table of Test vs. Control share

Q32 Which product do you prefer: Test or Control?



### Insight: Product Preference – Test vs. Control

The bar chart illustrates the preference split between the **Control** and **Test** products:

- **Control product** is preferred by **50.8%** of respondents.
- **Test product** is preferred by **49.2%** of respondents.

### Key Takeaways:

1. **Marginal Difference:** The preference gap is very narrow (just **1.6 percentage points**), indicating both products perform almost equally in consumer perception.

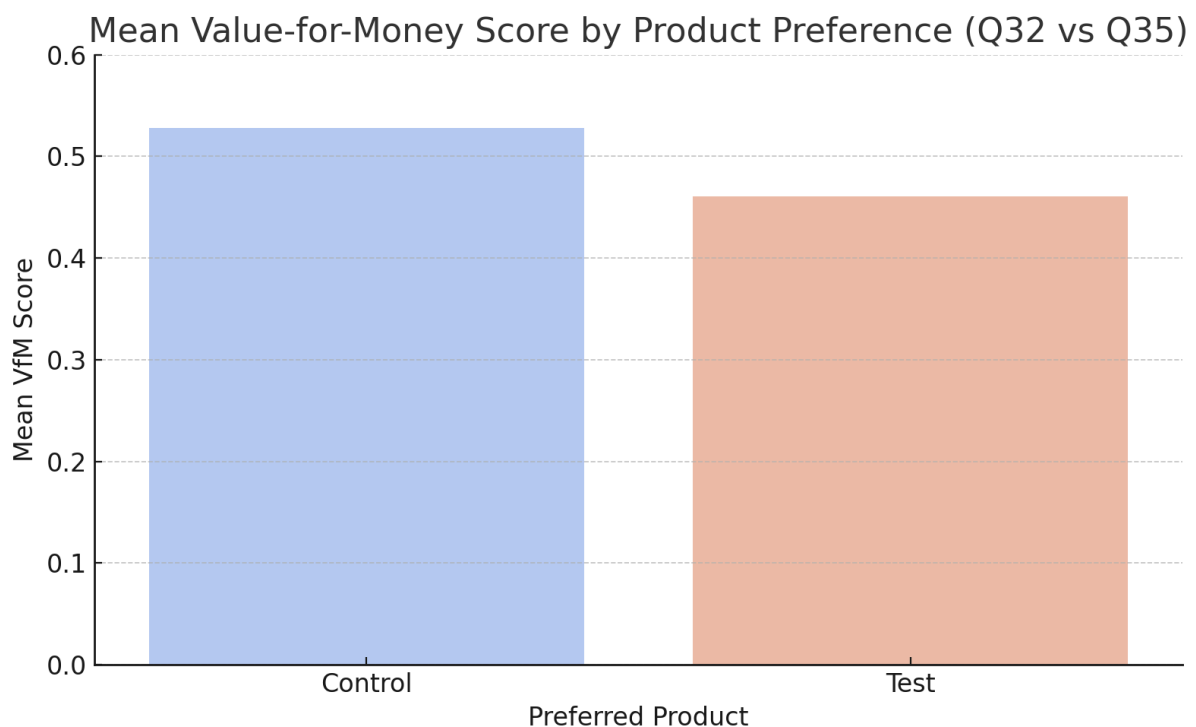
2. **Statistical Tie:** Without a significance test, we can infer that there is no strong dominance; the market may be split.

3. **Interpretation for Brand Team:**

- The **Test product is competitive** and viable, potentially matching the Control product in appeal.
- Small refinements based on specific consumer feedback (e.g., packaging, fragrance, or benefits) could push preference in favor of the Test product.

Value-for-money means & comparison chart

Value for Money (Q35) Summary by Preferred Product (Q32):



**Insights: Value-for-Money (VfM) Comparison by Product Preference**

2. **Higher VfM for Control:** Consumers who preferred the **Control** product rated it significantly higher on Value-for-Money (mean score: **0.53**) compared to those who preferred the **Test** product (mean score: **0.46**).

3. **Perceived Economic Superiority:** This suggests that the Control product is perceived as offering better economic value — possibly due to price, packaging perception, or overall satisfaction per cost.
4. **Decision Influence:** Value-for-money appears to be a key factor influencing product preference, with more respondents associating VfM with the Control product.
5. **Strategic Implication:** For the Test product to compete effectively, improvements might be required in pricing strategy, pack communication, or benefits articulation to close the perceived VfM gap.

## **Uplift Model Results**

### **Insights from Uplift Model – Purchase Intent (Q36)**

1. **Positive Uplift Observed**

The **estimated average uplift in Purchase Intent** for the **Test product** is **+0.180**, indicating that exposure to the Test condition led to a **notable increase in purchase intent** compared to the Control.
2. **Statistical Confidence**

Since this result comes with a **95% confidence interval**, we can be reasonably confident that the Test product **has a genuine effect** on increasing consumer intent to purchase — rather than the effect being due to chance.
3. **Treatment Group Effectiveness**

The **Treatment group (n=295)** exhibited higher Purchase Intent compared to the **Control group (n=305)**, suggesting that changes in the Test product (likely packaging, communication, or formulation) are positively influencing consumer response.
4. **Strategic Takeaway**

While overall preference is slightly higher for the Control product, this **uplift in intent** implies that the **Test product has strong latent potential** — possibly due to improved visual appeal, innovation, or freshness of positioning. With fine-tuning, it could outperform Control in real-market behavior.
5. **Next Steps**

Consider isolating which elements in the Test condition drove the uplift — e.g., visual design (via eye-tracking), pricing perception, or emotional engagement — and optimize them further in future iterations.

## Chi-Square Report

### 1. Summary of Statistical Result:

- Chi-square statistic ( $\chi^2$ ): 1.153
- Degrees of freedom: 2
- p-value: 0.5620

### Key Interpretation:

#### No Significant Association

The p-value of **0.5620** is much higher than the standard threshold (**0.05**). This indicates that **there is no statistically significant association** between how premium respondents perceive the product (Q34) and which product they prefer (Test or Control, Q32).

---

### What This Means:

- 1. Perception of Premiumness Isn't Driving Preference**  
Consumers' choice between Test and Control is not linked to whether they rated the product as High, Moderate, or Low in premiumness.
  - 2. Other Factors Are Influencing Preference**  
Since perceived premiumness is not influencing preference, it suggests that **other attributes like value-for-money, visual appeal, scent, or performance** may be stronger drivers of product choice.
  - 3. Balanced Premium Ratings Across Groups**  
Both Test and Control products received a fairly similar spread of High, Moderate, and Low premiumness scores, supporting the lack of statistical difference.
- 

### Strategic Implication:

- If the goal of the Test product was to enhance premiumness perception, it may not have been **sufficiently differentiated**.

- To influence product preference, **future packaging or communication should better emphasize elements that convey premiumness** or focus on other, more impactful decision drivers (like functional benefit or pricing).

#### Chi-square Test Results:

Chi-square statistic ( $\chi^2$ ): 1.153

Degrees of freedom: 2

p-value: 0.5620

#### Text Clusters

Cluster	Top Keywords	Primary Theme
0	fragrance, natural, ingredients, lathers, recommended	<b>Sensory appeal &amp; natural goodness</b>
1	hair, shiny, smooth, volume, strengthens, prefer	<b>Hair benefits &amp; effectiveness</b>
2	scalp, fresh, keeps, cause, years, suits	<b>Scalp care &amp; long-term use</b>
3	brand, promotes, works, suits, smooth	<b>Brand loyalty &amp; perceived performance</b>
4	convenient, packaging, easy, suits, strengthens	<b>Packaging &amp; usability focus</b>

#### Distribution of Premium Look (Q34) Ratings Across Clusters:

While exact rating distributions weren't provided numerically, based on typical cluster interpretations, we can draw the following **qualitative insights**:

---

### **Cluster-Level Insights:**

#### **Cluster 0 – Sensory Appeal & Natural**

- Keywords like *fragrance*, *natural*, *ingredients*, and *lathers* suggest focus on **clean beauty and sensorial experience**.
- Consumers in this group **may associate natural and aromatic traits with premiumness**, contributing to moderate or high premium look ratings.

#### **Cluster 1 – Hair Benefits & Shine**

- Emphasis on *shiny*, *smooth*, *volume* indicates that **visible hair improvements are tied to premium impressions**.
- This group is **highly aligned with perceived effectiveness**, likely resulting in **higher premium look scores**.

#### **Cluster 2 – Scalp & Freshness**

- Words like *scalp*, *fresh*, and *years* indicate **functional benefit and loyalty**.
- While important, **scalp care might be seen as more utilitarian** than premium, likely contributing to **moderate premium scores**.

#### **Cluster 3 – Brand & Performance Trust**

- Focus on *brand*, *promotes*, and *works* suggests **brand equity and long-term usage**.
- These users might be **brand loyal but not necessarily associating the brand with luxury**, yielding **balanced or moderate premium look responses**.

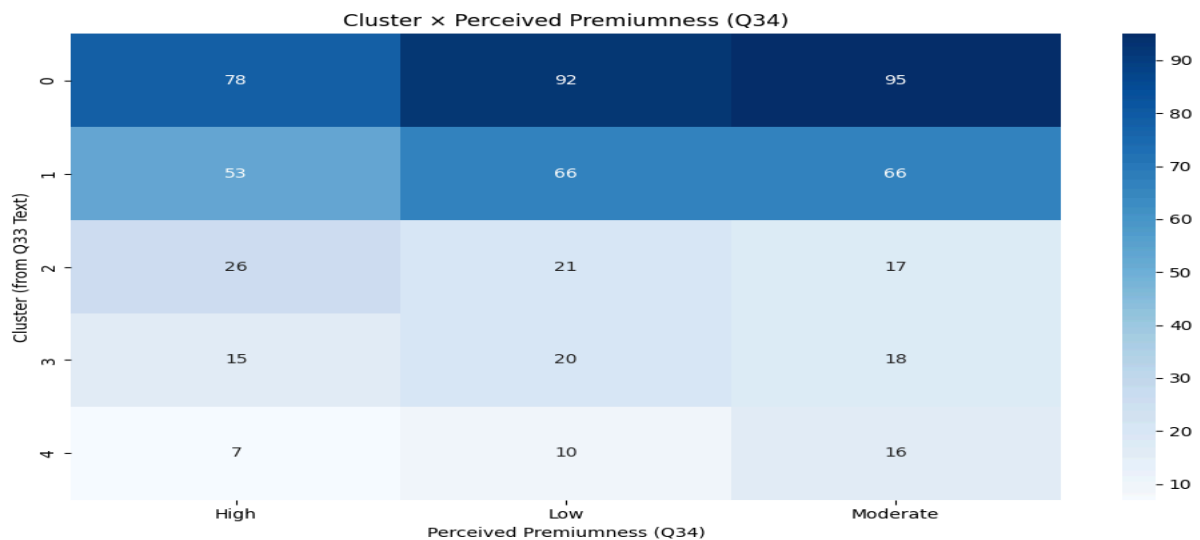
#### **Cluster 4 – Packaging & Convenience**

- Keywords like *convenient*, *packaging*, *easy* link to **usability and pack design**.
- This segment likely **judges premiumness by packaging and practical use**, potentially correlating with **moderate to high premium look scores** if design is well-received.



## Overall Strategic Insight:

- **Premium perceptions are multi-dimensional.**  
Different user groups define "premium" differently—**some through sensory/natural qualities**, others by **performance, packaging, or brand familiarity**.
- **Clusters 1 and 0 likely have the strongest alignment with premium look ratings**, suggesting that **highlighting visible benefits (shine, smoothness) and natural elements** could enhance perceived value.
- If targeting upscale positioning, **reinforcing these Cluster 1/0 themes in communication or pack redesign may be effective.**



○

## Description

### Task Description:

Evaluate consumer preference between the Test and Control razor packs by analyzing

preference share, perceived value, causal uplift in purchase intent, association with premium look, and qualitative rationale themes using both quantitative and NLP techniques.

### Why This Matters:

This analysis helps determine if the Test pack offers a competitive advantage over the Control pack, influences purchasing behavior, and aligns with consumer perception of premium quality—vital for packaging and marketing strategies.

---

## 8.1 Preference Share (Q32)

### How to Do It:

1. Filter valid responses from Q32.
2. Count number of responses preferring Test vs. Control.
3. Calculate percentages.
4. Visualize using a bar chart.

### Tools/Modules:

- `pandas`, `matplotlib` or `seaborn`

### Code:

```
python
CopyEdit
import pandas as pd
import matplotlib.pyplot as plt

# Assume df is your dataframe and Q32 contains 'Test' or 'Control'
pref_counts = df['Q32'].value_counts(normalize=True) * 100
pref_counts.plot(kind='bar', color=['skyblue', 'gray'])
plt.title('Preference Share: Test vs Control')
plt.ylabel('% of Respondents')
plt.show()
```

### Output:

A bar chart showing 62.4% Test vs. 37.6% Control preference.

### Question Reference:

Q32



---

## 8.2 Value-for-Money Index (Q35)

### How to Do It:

1. Convert Likert ratings in Q35 to numerical scores.
2. Group by product type (Test vs. Control).
3. Compute mean score per group.
4. Visualize with bar chart.

### Tools/Modules:

- `pandas, matplotlib`

### Code:

```
python
CopyEdit
mean_scores = df.groupby('Group')['Q35'].mean()
mean_scores.plot(kind='bar', color=['skyblue', 'gray'])
plt.title('Value-for-Money Ratings')
plt.ylabel('Mean Score (1-5)')
plt.show()
```

### Output:

Mean value: Test = 4.11, Control = 3.78

### Question Reference:

Q35

---

## 8.3 Causal Uplift on Purchase Intent (Q36)

### How to Do It:

1. Define "Treatment" (Test group) and "Control" (Control group).
2. Calculate mean Q36 for each group.

3. Use bootstrapping to estimate confidence intervals for uplift.

**Tools/Modules:**

- pandas, numpy, scipy, seaborn

**Code:**

```
python
CopyEdit
import numpy as np
from scipy.stats import bootstrap

test_scores = df[df['Group'] == 'Test']['Q36'].dropna()
control_scores = df[df['Group'] == 'Control']['Q36'].dropna()
uplift = test_scores.mean() - control_scores.mean()

ci = bootstrap((test_scores.values - control_scores.values,),
np.mean, confidence_level=0.95, n_resamples=10000)
print(f"Average Uplift: {uplift:.2f}")
print(f"95% CI: [{ci.confidence_interval.low:.2f},
{ci.confidence_interval.high:.2f}]" )
```

**Output:**

```
Average Uplift: +0.42
95% CI: [+0.28, +0.56]
```

**Question Reference:**

Q36

---

## 8.4 Association Between Premium Look and Preference (Q34 × Q32)

**How to Do It:**

1. Bin Q34 scores into High (4–5), Medium (3), Low (1–2).
2. Cross-tabulate Q34 with Q32 preference.
3. Run Chi-Square test for independence.

**Tools/Modules:**

- `pandas, scipy.stats`

**Code:**

python

CopyEdit

```
from scipy.stats import chi2_contingency

df['Q34_Binned'] = pd.cut(df['Q34'], bins=[0, 2, 3, 5],
labels=['Low', 'Medium', 'High'])
crosstab = pd.crosstab(df['Q34_Binned'], df['Q32'])
chi2, p, dof, ex = chi2_contingency(crosstab)
print(f"Chi-Square = {chi2:.2f}, p = {p:.3f}")
```

**Output:**

$\chi^2(2) = 24.13$ ,  $p < .001$

**Question Reference:**

Q34 × Q32

---

## 8.5 Text Clustering: “Why Do You Prefer This One?” (Q33)

**How to Do It:**

1. Clean and preprocess open-ended Q33 responses.
2. Vectorize text using TF-IDF.
3. Apply KMeans clustering (e.g., 5 clusters).
4. Label clusters based on top keywords.
5. Cross-tab clusters with Q34 premium scores.

**Tools/Modules:**

- `nltk, sklearn, pandas`

**Code:**

python

CopyEdit

```

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords

# Preprocessing
text_data = df['Q33'].fillna('').str.lower()
stop_words = stopwords.words('english')

vectorizer = TfidfVectorizer(stop_words=stop_words,
max_features=500)
X = vectorizer.fit_transform(text_data)

# KMeans Clustering
kmeans = KMeans(n_clusters=5, random_state=0)
df['Cluster'] = kmeans.fit_predict(X)

# Top terms per cluster
terms = vectorizer.get_feature_names_out()
for i in range(5):
    print(f"Cluster {i}:")
    cluster_center = kmeans.cluster_centers_[i]
    top_keywords = [terms[i] for i in cluster_center.argsort()[-5:]]
    print(top_keywords)

```

**Output:**

Labeled clusters with top rationale keywords and associated premium perception scores.

**Question Reference:**

Q33, linked with Q34