Yonder Technical Test Analysis - Shahin Hussain

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This notebook presents the results of the analysis conducted for the Yonder Technical Test. The tasks include:

- Exploratory analysis to answer specific questions about the dataset.
- A regression analysis to identify drivers influencing brand recommendations.

Goals:

- Provide insights into brand perceptions and recommendations.
- Identify key drivers of recommendations for Charlotte Tilbury.
- Suggest actionable recommendations based on findings.

Data Overview: - Import libraries & export relevant meta data from .sav file to .txt file.

[63]:
```
import pandas as pd
import pyreadstat

data, meta = pyreadstat.read_sav("Test Data.sav")

# Prepare metadata for saving
metadata_content = []

# Column names and their labels
metadata_content.append("Variable Names and Labels:\n")
for var_name, var_label in zip(meta.column_names, meta.column_labels):
    metadata_content.append(f"{var_name}: {var_label}\n")

# Value labels
metadata_content.append("\nValue Labels:\n")
for label_set, label_dict in meta.value_labels.items():
    metadata_content.append(f"\n{label_set}:\n")
    for value, label in label_dict.items():
        metadata_content.append(f"  {value}: {label}\n")

# Save the metadata to a text file
metadata_file_path = "metadata_output.txt"
with open(metadata_file_path, "w") as file:
    file.writelines(metadata_content)

print(f"Metadata successfully exported to {metadata_file_path}")
```

```
data.iloc[:, :8].head()
```

```
Metadata successfully exported to metadata_output.txt
```

[63]:

	respid	q01	q02	q03_uk	q03_us	country	q04_uk	q04_us
0	4400136.0	6.0	2.0	11.0	NaN	1.0	6.0	NaN
1	4400138.0	4.0	2.0	9.0	NaN	1.0	6.0	NaN
2	4400140.0	5.0	2.0	9.0	NaN	1.0	6.0	NaN
3	4400142.0	4.0	2.0	9.0	NaN	1.0	6.0	NaN
4	4400144.0	2.0	2.0	8.0	NaN	1.0	2.0	NaN

[76]:

```
# Dataset Overview
print(f"Dataset Shape: {data.shape}")
```

```
Dataset Shape: (1233, 1213)
```

Note on null values: We will focus more on the null values on a task specific basis.

1 Task 1: Exploratory Analysis

1.1 Subtask 1a: Bobbi Brown Value for Money

Question: How many respondents in the UK think Bobbi Brown offers good value for money?

Approach:

1. Filter for UK respondents using the `country` column.
2. Focus on the `q16o_03` column, which captures opinions about Bobbi Brown's value for money.
3. Count responses for "Strongly agree" and "Slightly agree".

Note:

1. For the columns using the scale: "Strongly agree" to "Strongly disagree" or "Don't know", the following mapping has been used:
   - "Strongly agree" = 1.0
   - "Slightly agree" = 2.0
2. And, 'UK' refers to a value of '1.0' in the 'country' column.

[65]:

```
data['q16o_03'].isnull().sum()
```

[65]: 1038

The filter which we'll apply will take care of these null values.

[66]:

```
uk_data = data.loc[data['country'] == 1.0]
filtered_data = uk_data[uk_data['q16o_03'].isin([1.0, 2.0])]
print(f"{len(filtered_data)} respondents in the UK think Bobbi Brown offers␣
 ↪good value for money.")
```

```
24 respondents in the UK think Bobbi Brown offers good value for money.
```

The chart describing the response distribution can be found in the ***Key Insights*** section.

1.2 Subtask 1b: Diversity Across Brands

Question: Out of all respondents, how many agree that at least 3 brands embrace diversity?

Approach:

1. Identify all columns starting with `q16r_`, which capture diversity perceptions for various brands.
2. Count the number of "Strongly agree" and "Slightly agree" responses per respondent.
3. Filter respondents who agree with at least 3 brands.

Code and Results:

[81]:
```
# Filter relevant columns
q16r_columns = [col for col in data.columns if col.startswith("q16r")]

# Count agreements per respondent
data['agreement_count'] = data[q16r_columns].isin([1.0, 2.0]).sum(axis=1)

# Filter respondents with at least 3 agreements
respondents_with_3_agreements = data[data['agreement_count'] >= 3]

# Output the count
print(f"{len(respondents_with_3_agreements)} respondents agree that at least 3␣
 ↪brands embrace diversity.")
```

```
334 respondents agree that at least 3 brands embrace diversity.
```

The chart describing the response distribution can be found in the* Key Insights *section.

2 Task 2: Regression Analysis

Objective: Identify drivers influencing recommendations for Charlotte Tilbury.

Steps:

1. Filter independent variables: All columns starting with `q16` and ending with `01`.
2. Define dependent variable: `q15_01` (recommendation score for Charlotte Tilbury).
3. Handle missing values by dropping rows where `q15_01` is null.
4. Train a linear regression model and evaluate results.

[68]:
```
# Filter independent variables
independent_vars = [col for col in data.columns if col.startswith("q16") and␣
 ↪col.endswith("01")]
print("Independent Variables:", independent_vars)
```

```
Independent Variables: ['q16a_01', 'q16b_01', 'q16c_01', 'q16d_01', 'q16e_01',
'q16f_01', 'q16g_01', 'q16h_01', 'q16i_01', 'q16j_01', 'q16k_01', 'q16l_01',
'q16m_01', 'q16n_01', 'q16o_01', 'q16p_01', 'q16q_01', 'q16r_01', 'q16s_01',
'q16t_01']
```

[69]:
```
# Null value count for q15_01
print(f"Null values in q15_01: {data['q15_01'].isnull().sum()}")
print(f"% of column null: {data['q15_01'].isnull().sum()/len(data) * 100:.2f}%␣
↪")
```

```
Null values in q15_01: 543
% of column null: 44.04%
```

[70]:
```
# Filter rows where q15_01 is non-zero
data_cleaned = data.dropna(subset=['q15_01'])
print(f"Number of rows after dropping nulls in q15_01: {len(data_cleaned)}")
```

```
Number of rows after dropping nulls in q15_01: 690
```

[84]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score

# Define X (independent) and y (dependent)
X = data_cleaned[independent_vars]
y = data_cleaned['q15_01']

## Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Train the regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Evaluate the model
y_pred = model.predict(X_test)
r2 = r2_score(y_test, y_pred)

coefficients = pd.DataFrame({
    'Variable': independent_vars,
    'Coefficient': model.coef_
}).sort_values(by='Coefficient', ascending=False)

print(f"R-squared: {r2}, \nVisual of coefficients can be found in the key␣
↪insights section.")
```

```
R-squared: 0.47302466511376406,
Visual of coefficients can be found in the key insights section.
```

2.1 Results:

- **R-squared**: Indicates that the model explains 47% of the variance in recommendations.
- **Coefficients**: Highlight the impact of each independent variable.

Code to Display Coefficients:

2.2 Explanation

This table shows the most influential factors driving recommendations for Charlotte Tilbury:

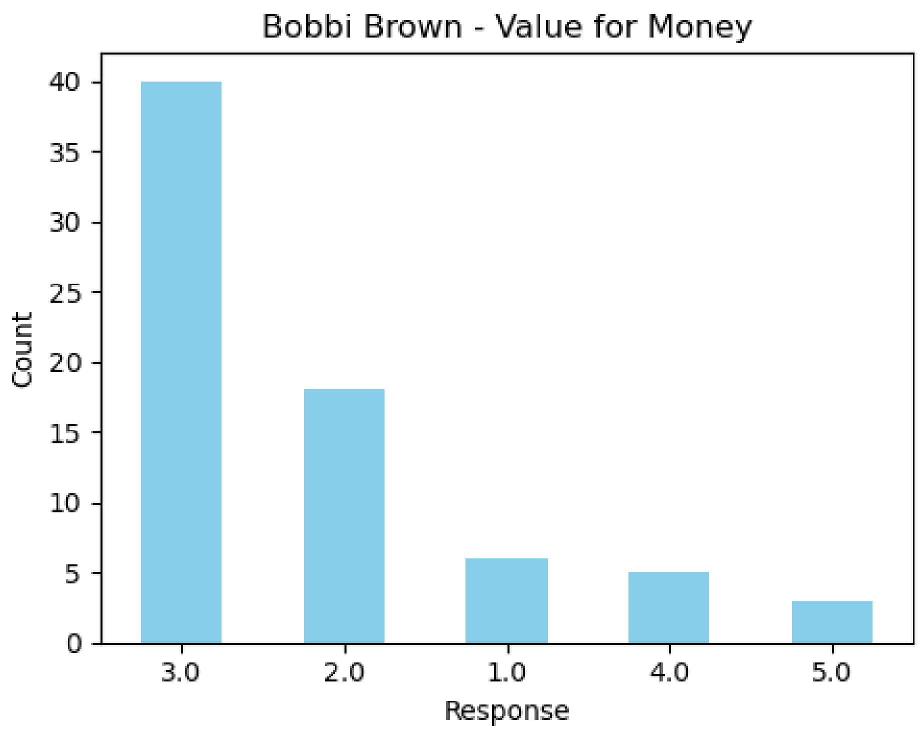
- **Positive Drivers**:
  - Variables like `q16q_01` and `q16r_01` have positive coefficients, meaning they increase the likelihood of high recommendations.
- **Negative Drivers**:
  - Variables like `q16p_01` and `q16b_01` have negative coefficients, suggesting these factors decrease recommendations.

For example: - `q16q_01` (coefficient = 0.193): The more respondents agree with this factor, the more likely they are to recommend Charlotte Tilbury. - `q16p_01` (coefficient = -0.605): This has the strongest negative influence, indicating it may require attention.

3 Key Insights

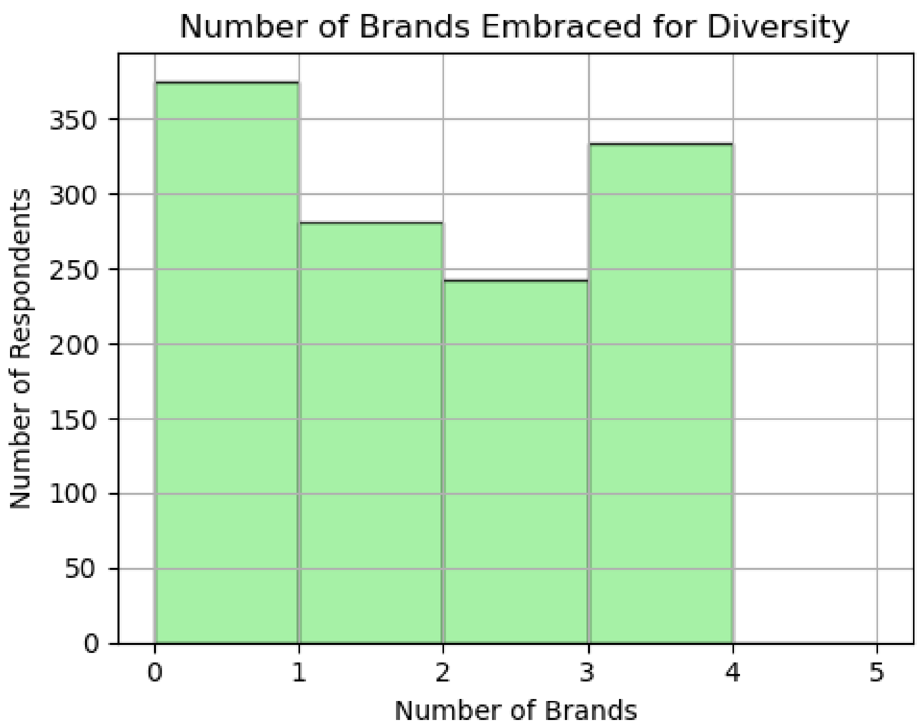
1. **Bobbi Brown - Value for Money**:
   - 24 respondents in the UK think Bobbi Brown offers good value for money.
   - This highlights potential for targeted marketing to reinforce its perception among UK audiences.

[79]:
```
import matplotlib.pyplot as plt

# Visualizing response counts for Bobbi Brown
bobbi_brown_responses = uk_data['q16o_03'].value_counts()

plt.figure(figsize=(5, 4))
bobbi_brown_responses.plot(kind='bar', color='skyblue')
plt.title('Bobbi Brown - Value for Money')
plt.xlabel('Response')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



2. **Diversity Perceptions Across Brands**:
    - 334 respondents agree that at least 3 brands embrace diversity.
    - This underscores the importance of diversity-related messaging in building positive brand perceptions.

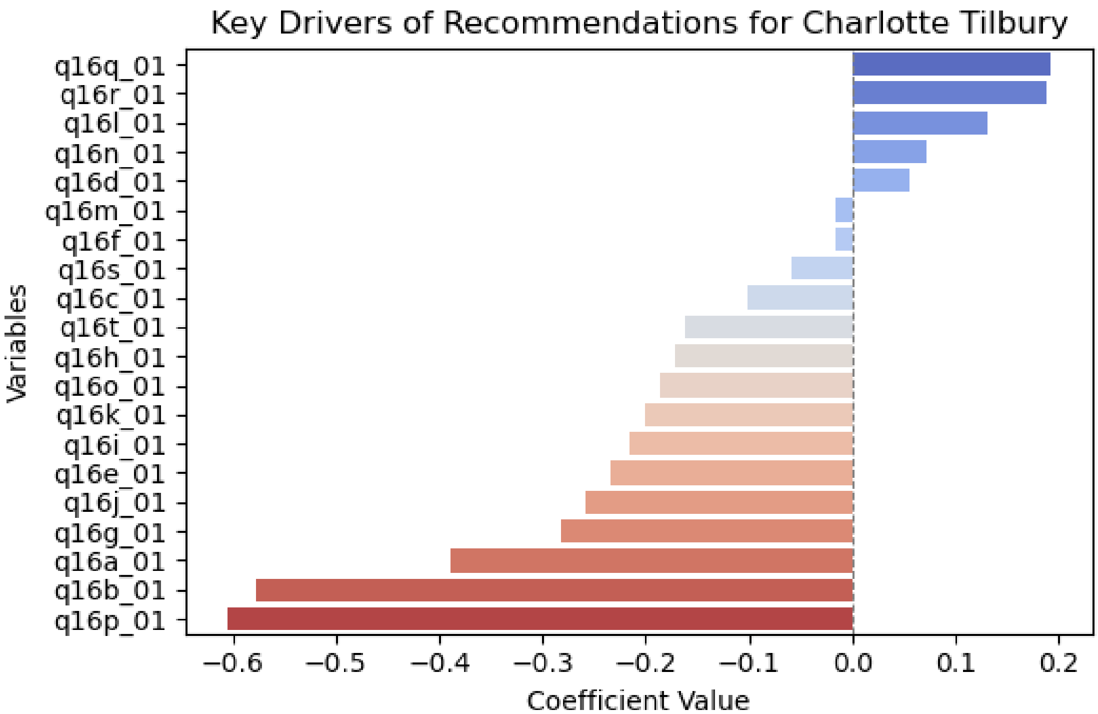
[80]:
```
# Histogram of diversity agreement counts
plt.figure(figsize=(5, 4))
data['agreement_count'].hist(bins=range(0, 6), color='lightgreen',␣
↪edgecolor='black', alpha=0.8)
plt.title('Number of Brands Embraced for Diversity')
plt.xlabel('Number of Brands')
plt.ylabel('Number of Respondents')
plt.tight_layout()
plt.show()
```



3. **Regression Analysis - Charlotte Tilbury**:
   - Diversity perceptions (`q16r_01`) and innovation factors (`q16q_01`) are the strongest positive drivers of recommendations for Charlotte Tilbury.
   - Negative drivers, such as concerns highlighted by `q16p_01`, indicate areas for potential improvement.
   - The model explains 47% of the variance in recommendations, suggesting other unmeasured factors may also play a significant role.

[75]:
```
import seaborn as sns

# Sort coefficients for plotting
coefficients = coefficients.sort_values(by='Coefficient', ascending=False)

# Horizontal bar chart of regression coefficients
plt.figure(figsize=(6, 4))
sns.barplot(y=coefficients['Variable'], x=coefficients['Coefficient'],
    hue=coefficients['Variable'], dodge=False, palette='coolwarm'
)
plt.title('Key Drivers of Recommendations for Charlotte Tilbury')
plt.xlabel('Coefficient Value')
plt.ylabel('Variables')
plt.axvline(0, color='gray', linestyle='--', linewidth=0.8)  # Mark positive vs␣
 ↪negative
```

```
plt.tight_layout()
plt.show()
```



4 Recommendations

Based on the analysis, here are the actionable recommendations:

Recommendation	Action	Benefit
Focus on Diversity	Emphasize diversity messaging (`q16r`)	Improves recommendations.
Address Negative Drivers	Investigate `q16p_01`	Identifies dissatisfaction.
Target Key Demographics	Refine marketing for specific groups	Tailored strategies.

5 Limitations of the Regression Analysis

While the regression analysis provides valuable insights, there are several limitations to consider:

1. **Missing Data**:
    - **44% of rows** were dropped due to missing values in `q15_01` (recommendation scores).
    - **Potential Bias**: Missingness may not be random, leading to skewed results (e.g., those who didn't respond might rate lower if forced to answer).

2. **Model Fit**:
   - Explains 47% of the variance; unmeasured factors likely impact results.
3. **Multicollinearity**:
   - Correlated variables may distort coefficients.

6 Implications for Decision-Making

Based on the analysis, here are the key implications:

1. **Focus on Diversity Messaging**:
   - Diversity perceptions (e.g., `q16r_01`) are strong positive drivers of recommendations.
   - **Action**: Emphasize diversity-related campaigns in marketing strategies to improve brand perceptions.
2. **Address Areas of Concern**:
   - Negative drivers, such as `q16p_01`, highlight potential dissatisfaction.
   - **Action**: Investigate these factors further to address pain points and improve recommendations.
3. **Expand Data Collection**:
   - The model explains 47% of the variance, suggesting other factors (e.g., demographics or qualitative feedback) are influencing recommendations.
   - **Action**: Incorporate additional predictors or open-ended survey questions in future analyses.
4. **Validate Across Demographics**:
   - The dataset may not fully represent all customer segments.
   - **Action**: Test findings on broader or more diverse populations to ensure generalizability.

6.1 Additional Analysis Suggestions

1. **Segmentation Analysis**:
   - Segment respondents by demographics (e.g., age, gender, region) to uncover group-specific insights about brand perceptions.
   - **Benefit**: Helps the client tailor marketing strategies to specific audience groups.
2. **Cross-Brand Comparison**:
   - Compare perceptions and recommendations across brands.
   - **Benefit**: Helps identify competitive advantages and areas for improvement relative to competitors.