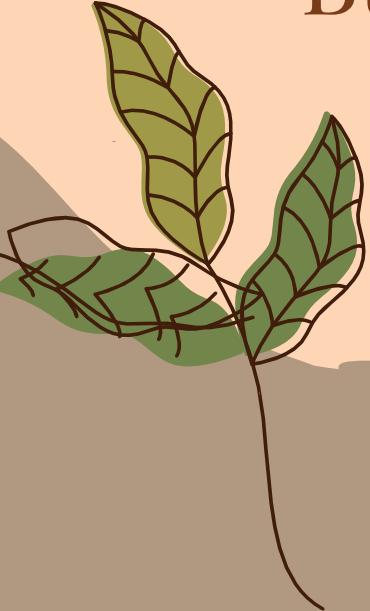


Building Customer Loyalty: Lucky Lab vs. Starbucks



Our team

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Minor: Business Analytics

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01

Introduction

Lucky Lab's historical development
+ present day opportunities

Lucky Lab's Growth



Coffee Truck

Founded as a mobile food truck, ideated in Hawaii & built in South Carolina.

2015



Flagship

Moved its headquarters in order "to offer Austinites the best coffee experience in the country."

2017



UT Campus

Signed on with UT Austin to establish 2 on campus locations to reach the student population.

2022

Motivation



As UT students ourselves, we noticed the growing presence of Lucky Lab on campus.



How aware are UT students of Lucky Lab's brand?



How Lucky Lab differentiates itself in this saturated market?



What can Lucky Lab do to increase customer loyalty with their new on-campus locations?

Competitor Analysis

	Locations on Campus	Market Presence	Product Offering	Reward Program
	2	<p>Localized presence</p> <p>Strong community connection</p>	<p>Specialty drinks and pastries</p> <p>Pet-friendly offerings</p>	<p>“Lucky Club”</p> <p>Profit shares</p>
	4	<p>Extensive global presence</p> <p>High brand awareness and visibility</p>	<p>Wide range of beverages, snacks, and merchandise</p> <p>Emphasis on consistency and standardization across locations</p>	<p>“Starbucks Rewards”</p>



02

Research Question

Research Question



“How can Lucky Lab Coffee Co. optimize pricing, order personalization, and promotion strategies to better compete with Starbucks and enhance customer loyalty and satisfaction?”



03

Methodology

Conjoint Analysis



Brand

Brand of coffee shop

- Lucky Lab
- Starbucks



Price

Price of the order

- \$4
- \$5
- \$7



Order

Type of the order

- Go-to
- Surprise
(seasonal)



Promotion

Coffee shop's promotion

- Punch card
- BOGOF
- Refill for half price

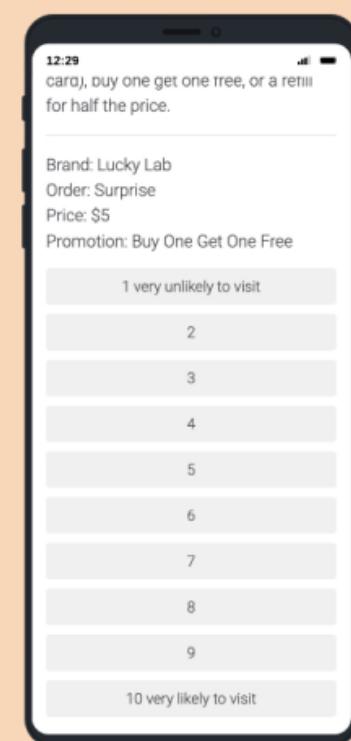
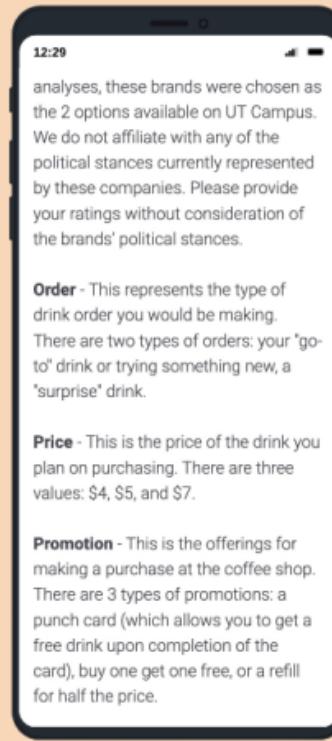
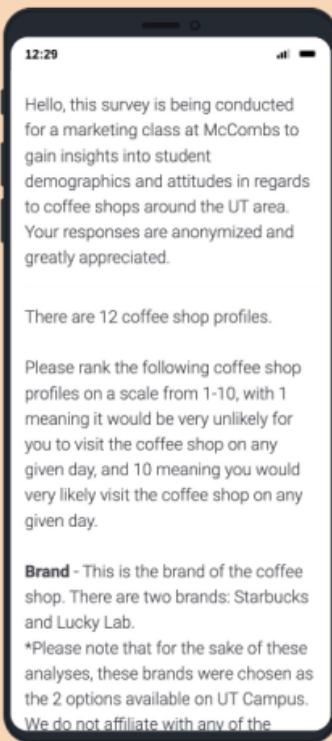
Conjoint Analysis

$2 \times 2 \times 3 \times 3 = 36$ total possible profiles.

Utilizing the fractional factorial design, we simplified it down to 12 key profiles, which we then imported and made into a Qualtrics survey.

Profile	Brand	Order	Price	Promotion
	2 Levels	2 Levels	3 Levels	3 Levels
1	Lucky Lab	Go-to	4	Refill for Half the Price
2	Lucky Lab	Surprise	5	Buy One Get One Free
3	Starbucks	Go-to	7	Buy One Get One Free
4	Lucky Lab	Go-to	7	Refill for Half the Price
5	Lucky Lab	Surprise	4	Punch Card
6	Starbucks	Surprise	4	Buy One Get One Free
7	Starbucks	Surprise	7	Refill for Half the Price
8	Starbucks	Go-to	5	Punch Card
9	Starbucks	Go-to	4	Punch Card
10	Lucky Lab	Go-to	5	Buy One Get One Free
11	Lucky Lab	Surprise	7	Punch Card
12	Starbucks	Surprise	5	Refill for Half the Price

Surveying Students



Data Collection

Our Effort to Reduce Bias

- Used a scale to mitigate default effect
- Randomized profile order in survey
- Asked respondents to rate profiles without consideration of the brands' current political stance

Distribution Method

- Administered survey to students from distinct student organizations
- A total of 8 respondents

Persisting Limitations

- Social desirability effect
- Unrepresentative sample
- Limitations of Conjoint Analysis

Respondent Statistics

Gender		Classification		Housing		Area	
Female	7	Junior	3	On-campus	2	West Campus	8
Male	1	Senior	5	Off-campus	6		



04

Analysis

Organization of Data into Python to Automate Conjoint Analysis

	Starbucks	Surprise	5 Dollars	7 Dollars	BOGOF	Refill for Half	Customer 1 Rating	Customer 2 Rating	Customer 3 Rating	Customer 4 Rating	Customer 5 Rating	Customer 6 Rating	Customer 7 Rating	Customer 8 Rating
1	0	0	0	0	0	1	5	3	7	4	3	7	6	5
2	0	1	1	0	1	0	6	3	6	3	5	5	7	6
3	1	0	0	1	1	0	5	6	4	9	8	3	6	1
4	0	0	0	1	0	1	2	4	3	3	6	2	4	1
5	0	1	0	0	0	0	5	3	9	3	8	3	4	5
6	1	1	0	0	1	0	6	9	9	8	8	9	5	7
7	1	1	0	1	0	1	3	5	3	3	3	2	3	1
8	1	0	1	0	0	0	6	7	7	3	4	5	7	5
9	1	0	0	0	0	0	8	6	8	5	4	3	8	5
10	0	0	1	0	1	0	7	3	7	7	3	5	7	8
11	0	1	0	1	0	0	2	3	3	7	2	4	1	
12	1	1	1	0	0	1	4	7	8	4	1	6	4	5

Long Term Goal: Significantly reduce time required to perform conjoint analysis when we want to include many more respondents with minimal user-required modifications!

Three Steps for All Respondents

1. Fit an ordinary least squares (OLS) linear regression and obtain the independent variable coefficients to be used as the part-worths.
2. Calculate Feature Importances (Ranges).
3. Calculate the Relative Importances.

```
# Run regression for each customer and get coefficients
models = {}
part_worths = {}
attribute_ranges = {}
relative_importances = {}

for i in range(1, 9): # Replace with the actual number of customers
    y = df[f"Customer_{i} Rating"]
    X = df.drop(columns=[f"Customer_{j} Rating" for j in range(1, 9)]) # Replace with the actual number
    X = sm.add_constant(X)

    model = sm.OLS(y, X).fit()
    models[f"Customer_{i}"] = model

    # Store coefficients (part-worths) and initialize baselines to 0
    part_worths[f"Customer_{i}"] = model.params.drop('const').to_dict()
    for baseline in baselines.values():
        # Set baseline part-worths to 0 if not already present
        part_worths[f"Customer_{i}"].setdefault(baseline, 0)

# Calculate ranges for each attribute and store in attribute_ranges
for customer in part_worths:
    attribute_ranges[customer] = {}
    total_range = 0 # Initialize total range sum for the customer

    for attribute, levels in attribute_mapping.items():
        # Get part-worths for all levels of this attribute, including the baseline
        level_part_worths = [part_worths[customer].get(level, 0) for level in levels]
        level_part_worths.append(0) # Add the baseline to the level_part_worths
        # Calculate the range
        attribute_range = max(level_part_worths) - min(level_part_worths)
        attribute_ranges[customer][attribute] = attribute_range
        total_range += attribute_range # Add to total range

# Calculate relative importance for each attribute
relative_importances[customer] = {attribute: (range_val / total_range) * 100
                                    for attribute, range_val in attribute_ranges[customer].items()}
```

User-Defined Attributes and Baselines

```
# Define a structure that maps each independent variable to its attribute
attribute_mapping = {
    'Brand': ['Starbucks'],
    'Order': ['Surprise'],
    'Price': ['5 Dollars', '7 Dollars'],
    'Promotion': ['BOGOF', 'Refill for Half']
}

# Define the baselines for each attribute
baselines = {
    'Brand': 'Lucky Lab',
    'Order': 'Go-to',
    'Price': '4 Dollars',
    'Promotion': 'Punch card'
}
```

This gives the structure necessary in order to automatically calculate feature and relative importances! The only other setting that needs to be changed is the number of respondents to be analyzed!

Sample Output for Respondent 1

Part-Worths for Customer 1

Starbucks : 0.83
Surprise : -1.17
5 Dollars : -0.47
7 Dollars : -2.73
BOGOF : 0.87
Refill for Half : -1.07
Lucky Lab : 0
Go-to : 0
4 Dollars : 0
Punch card : 0

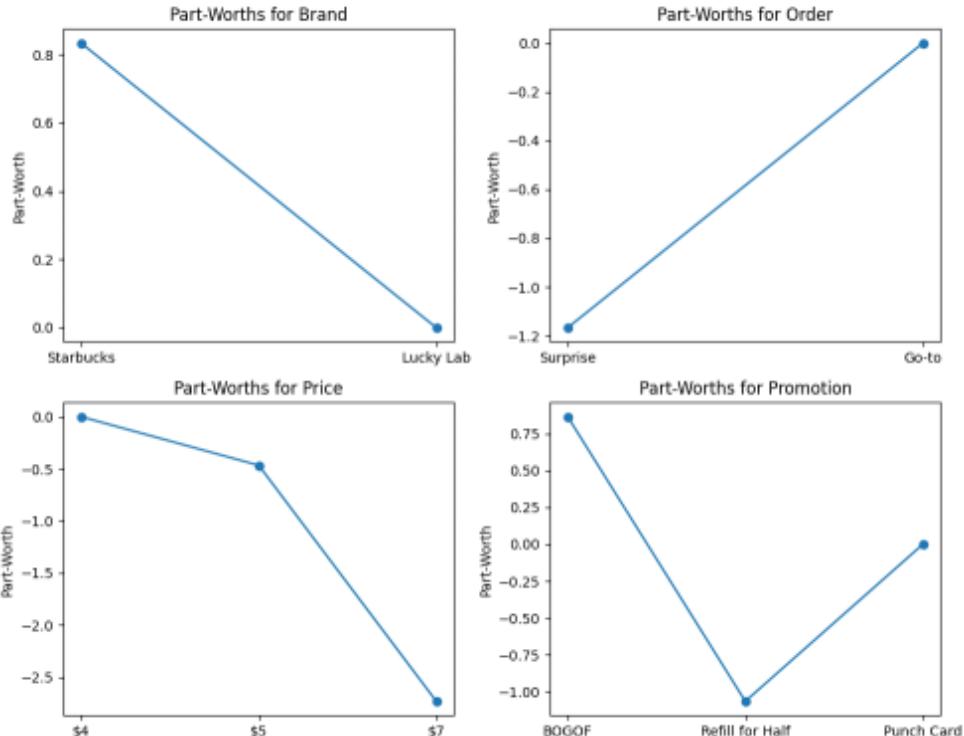
Attribute Ranges for Customer 1

Brand : 0.83
Order : 1.17
Price : 2.73
Promotion : 1.93

Relative Importances for Customer 1

Brand : 12.5
Order : 17.5
Price : 41.0
Promotion : 29.0

Part-Worth Plots for Customer 1





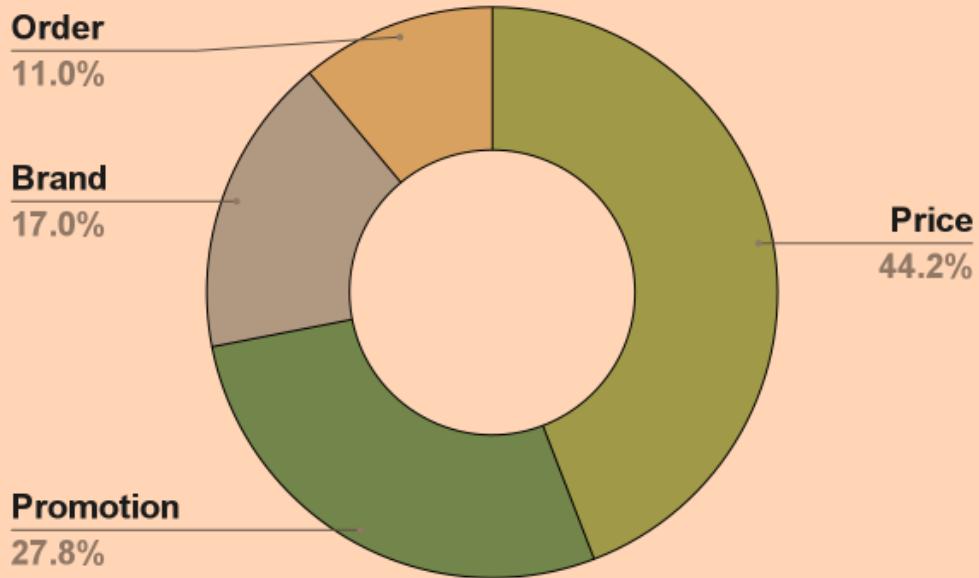
05

Results

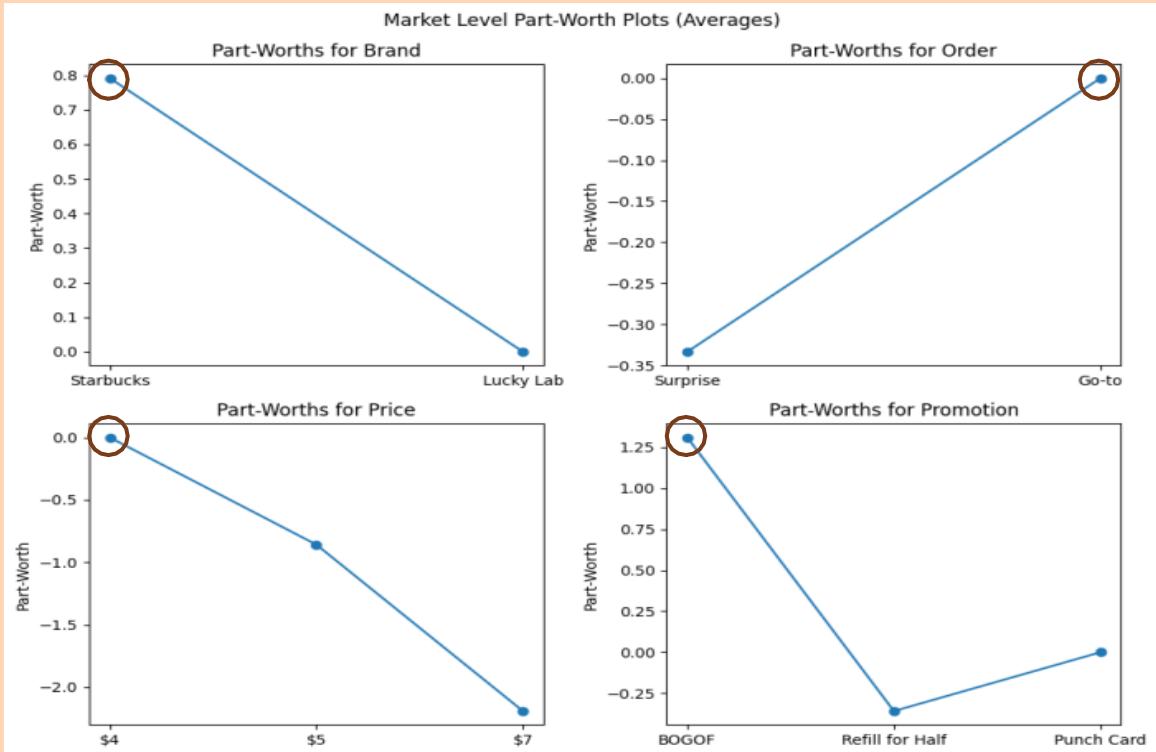
Market Level - Relative Importance

Importance Ranked:

1. Pricing strategies
2. Substantial promotions
3. Brand
4. Ordering type



What is the market level ideal profile?



Ideal profile

Level	Part-worth
Starbucks	0.792
Lucky Lab	0
Surprise	-0.333
Go-to	0
\$4	0
\$5	-0.858
\$7	-2.192
Buy One Get One Free	1.308
Refill for Half the Price	-0.358
Punch Card	0

Ideal profile

Brand: Starbucks



Level	Part-worth
Starbucks	0.792
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Ideal profile

Brand: Starbucks

Order: Go-to



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Ideal profile

Brand: Starbucks

Order: Go-to

Price: \$4



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Ideal profile

Brand: Starbucks

Order: Go-to

Price: \$4

Promotion: Buy One Get One Free



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Market Level - Price Per Util

Customer	Price per Util (\$)
Customer 1	-1.51
Customer 2	-3.75
Customer 3	-0.67
Customer 4	0.58
Customer 5	0.09
Customer 6	-0.93
Customer 7	0.62
Customer 8	3.54
Market Level - Average	-0.25

Market Level - Price Per Util

Customer 1: would be willing to pay \$1.51 more for each additional util

Customer	Price per Util (\$)
Customer 1	-1.51
Customer 2	-3.75
Customer 3	-0.67
Customer 4	0.58
Customer 5	0.09
Customer 6	-0.93
Customer 7	0.62
Customer 8	3.54
Market Level - Average	-0.25

Market Level - Price Per Util

Customer	Price per Util (\$)
Customer 1	-1.51
Customer 2	-3.75
Customer 3	-0.67
Customer 4	0.58
Customer 5	0.09
Customer 6	-0.93
Customer 7	0.62
Customer 8	3.54
Market Level - Average	-0.25

Customer 4: would need to be paid \$0.58 for each additional util



06

Recommendations

Key Insights

“How can Lucky Lab Coffee Co. better compete with Starbucks and enhance customer loyalty and satisfaction?”

- 1** Students are not going to on-campus cafes for an “experience” and are instead going on a typical coffee-runs for functional purposes.
- 2** Students are price-conscious and comparing these pricing across cafes are vital in choosing their brand of choice.
- 3** Students prefer instantaneous gratification over long-term promotional options when it comes to rewards programs.

Recommendations

Market Level Relative Importance	44.2%	27.8%	11%
Attribute	Price	Promotion	Order
Ideal Profile	\$4	BOGOF	Go-To
Strategy	<p><u>Decreasing price discrepancy</u> for sizes</p> <p>Offer milk substitutes for <u>little/no additional cost</u></p> <p>Introduce <u>more frequent</u> BOGOF deals (during holidays or peak study times) either as a standalone deal or through student org collabs</p> <p>Rebrand menu to highlight <u>year-long classics</u> in addition to seasonal drinks</p>		

Conclusion

1

Our goal was to optimize pricing, order, and promotional strategies to help Lucky Lab increase its customer loyalty at UT.

2

We designed and performed a conjoint analysis, surveyed 8 current UT students, and found key insights regarding our attributes.

3

Based on our analysis of students' preferences, we devised strategic recommendations for Lucky Lab to implement.





Thank you!
Any Questions?

