



# Final Presentation

University of Utah MSBA Capstone Project

Group 3

|

April '25

# Team Members



**Adam**  
Bushman

 [Profile](#)



**Georgia**  
Christodoulou

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**Tyler**  
Swanson

 [Profile](#)



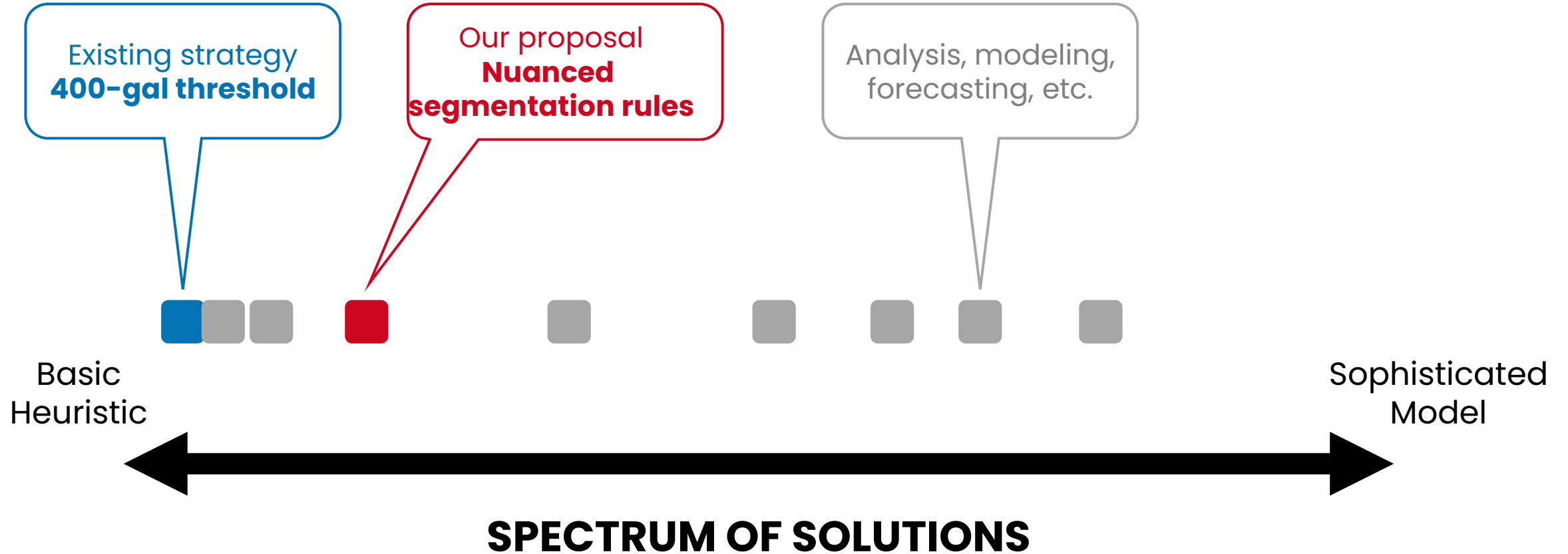
**Zac**  
Mendenhall

 [Profile](#)

# Topics

- Insights that formulated our proposal
- Proposed segmentation strategy (red vs white truck)
- Business potential over on incumbent strategy (400-gal threshold)
- How to leverage our solution
- Appendix

# Project overview



# Insights

that formulated our proposal



# Annual volume thresholds obscure vital context for proper segmentation

25

gallons + cases

describes the 75%tile customer in average transaction amount

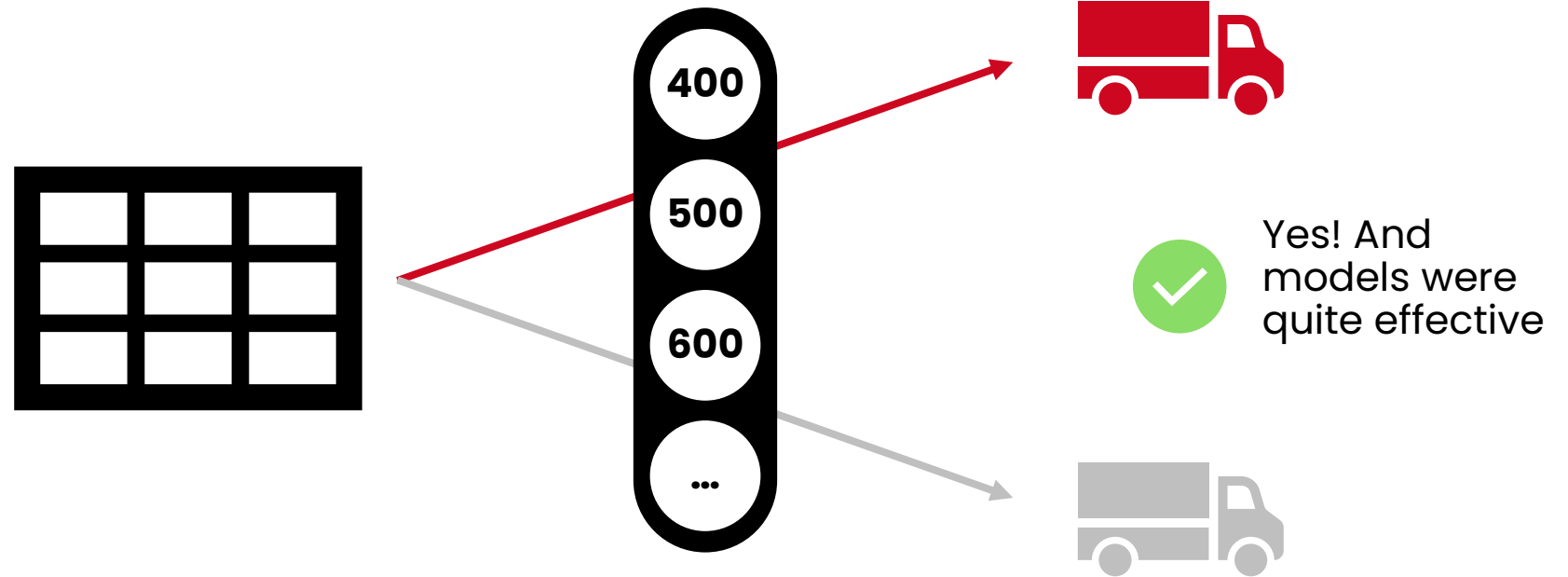
49%

of customers who met 400-gal threshold boasted an average transaction amount <25 gallons + cases

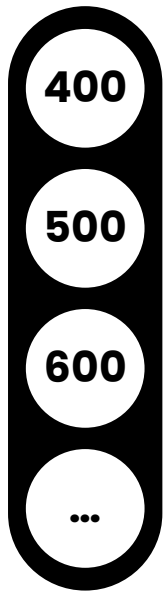
💡 **INSIGHT:** annual volume is a noisy measure for segmentation

# Customer characteristics are indicators of growth potential

Do predictors unrelated to volume hold predictive power for customers segmented by annual volume thresholds?



# Customer characteristics are indicators of growth potential



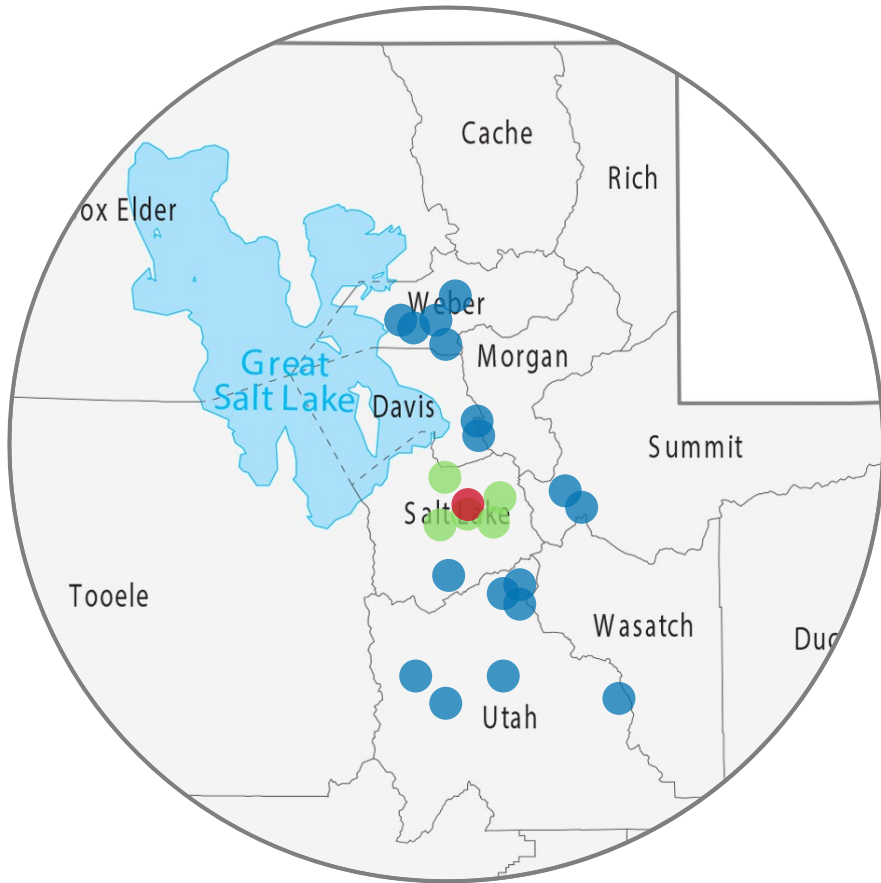
Independent of which threshold was chosen, the same groups of customer characteristics were found to be powerful predictors



💡 **INSIGHT:** customer characteristics should drive part of the segmentation strategy

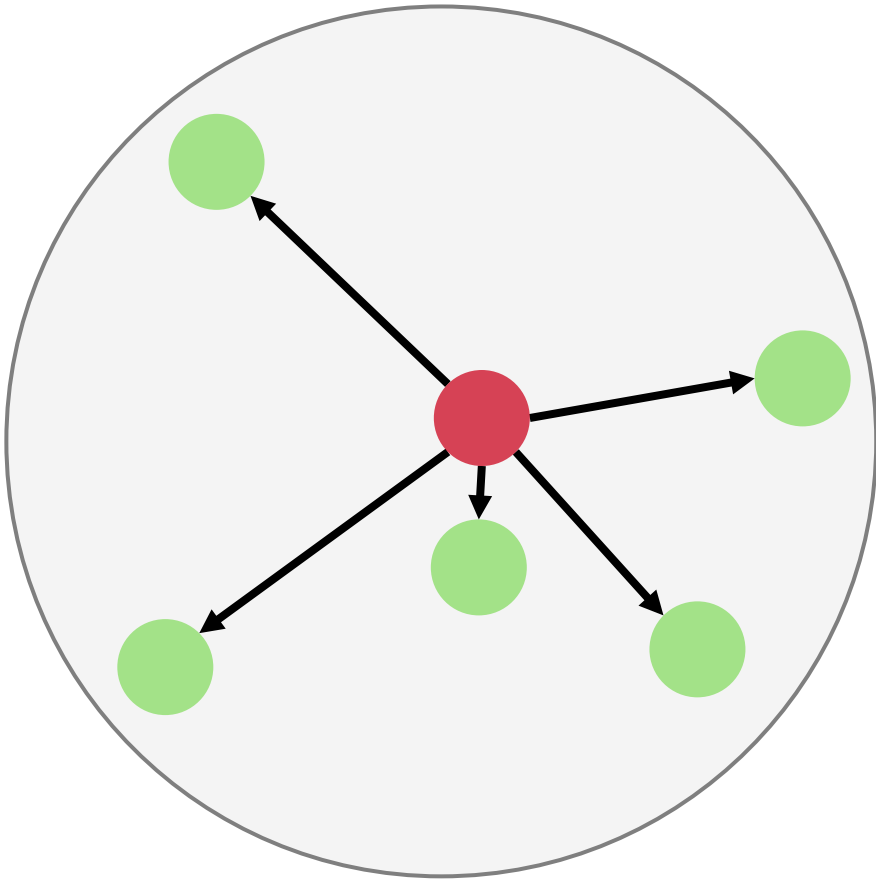


# Neighboring customers enrich our understanding of the market



Neighboring customers to a single customer serve as a proxy to describe local market conditions.

# Neighboring customers enrich our understanding of the market



💡 **INSIGHT:** summary figures for these neighboring customers proved to be powerful features of our segmentation strategy.

# Segmentation Strategy

for **RED** vs **WHITE** truck customers



# Initial segmentation

These customers are segmented first due their strong association with the respective program



**FAIRLY NEW**

- CUSTOMER TENURE  $\leq 1$  yr



OR

**CHANNELS TO AVOID**

- SPECIALIZED GOODS, PROFESSIONAL SERVICES,  
VEHICLE CARE, MOBILE RETAIL, OUTDOOR ACTIVITIES

**AVG TRANSACTION AMOUNT**

$\leq 9$

# Proposed segmentation strategy spans two perspectives



**CUSTOMER  
PROFILE**

OR

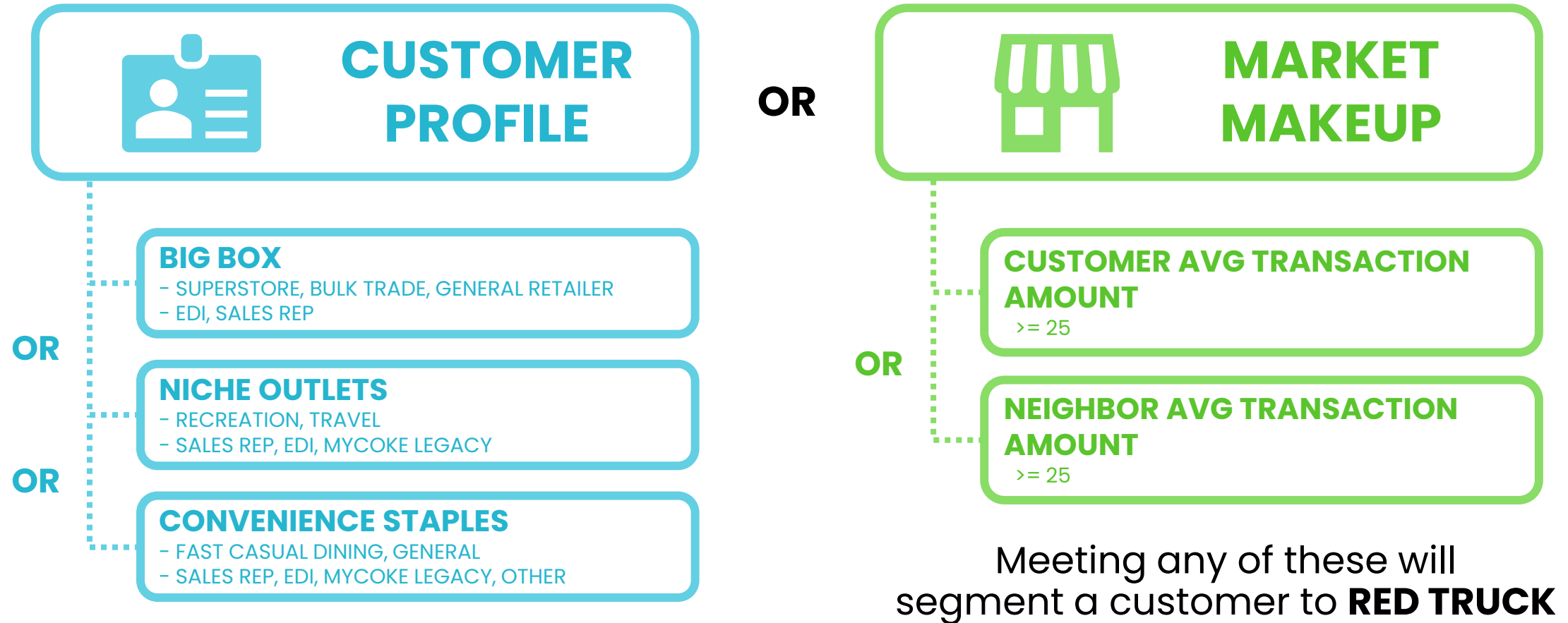


**MARKET  
MAKEUP**

Identify '**RED TRUCK** material' via  
customer profile characteristics

Identify '**RED TRUCK** material' via  
growth conducive markets

# Proposed segmentation strategy spans two perspectives



# Results of segmentation strategy



**RED  
TRUCK**

**~18K**  
customers

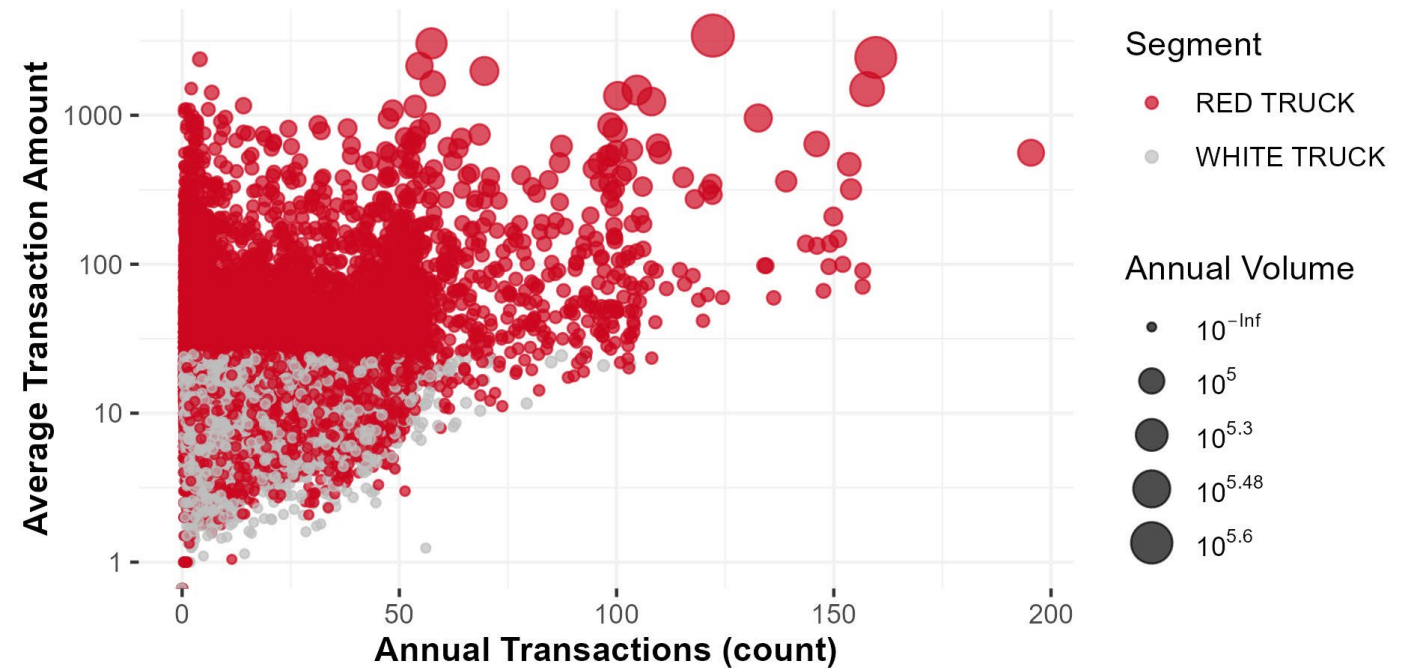


**WHITE  
TRUCK**

**~12K**  
customers

## Distribution of Customers by Segment

*Comparison across measures of volume and efficiency*




# Results of segmentation strategy



**~18K**  
customers

**59%**   
of original  
customer count

**88%**   
of annual  
gallons + cases

**70%**   
higher avg  
transaction amount

**40%**   
higher annual  
neighbor volume



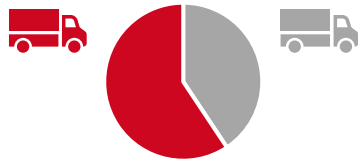
# Business Potential

over incumbent strategy



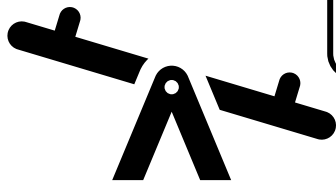
# Available strategies weigh priorities differently

Proposed  
segmentation strategy

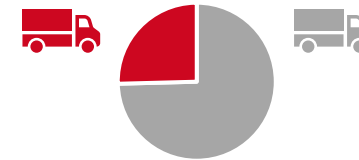


★  
Opportunity  
Capture

Program  
Efficiency

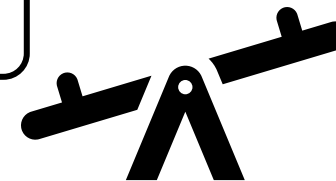


Incumbent 400-gallon  
threshold strategy



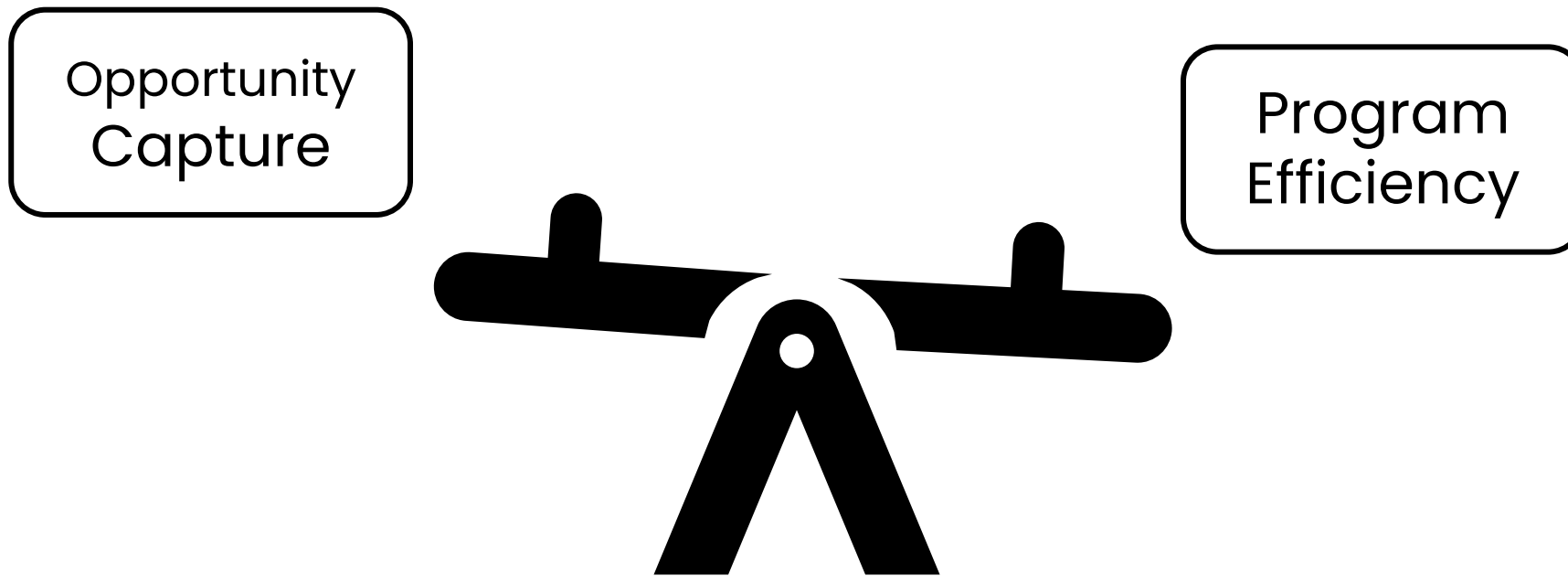
Opportunity  
Capture

★  
Program  
Efficiency



# Our strategy achieves a better balance

**Our strategy strikes a balance between preserving opportunity and heightening efficiency**



# Future opportunity

**\*2025 gallons + cases retained in RED TRUCK program that other strategy would have missed**

Proposed  
segmentation strategy

vs

Incumbent 400-gallon  
threshold strategy

**7.6M**

**3.0M**

💡 **156% more opportunity**  
than the incumbent strategy

\*Refer to 2025 estimate logic in appendix

# RED TRUCK program efficiency

**\*\*2025 gallons + cases in RED TRUCK per \$100 of delivery cost**

Proposed  
segmentation strategy

vs

Incumbent 400-gallon  
threshold strategy

65.2

76.7

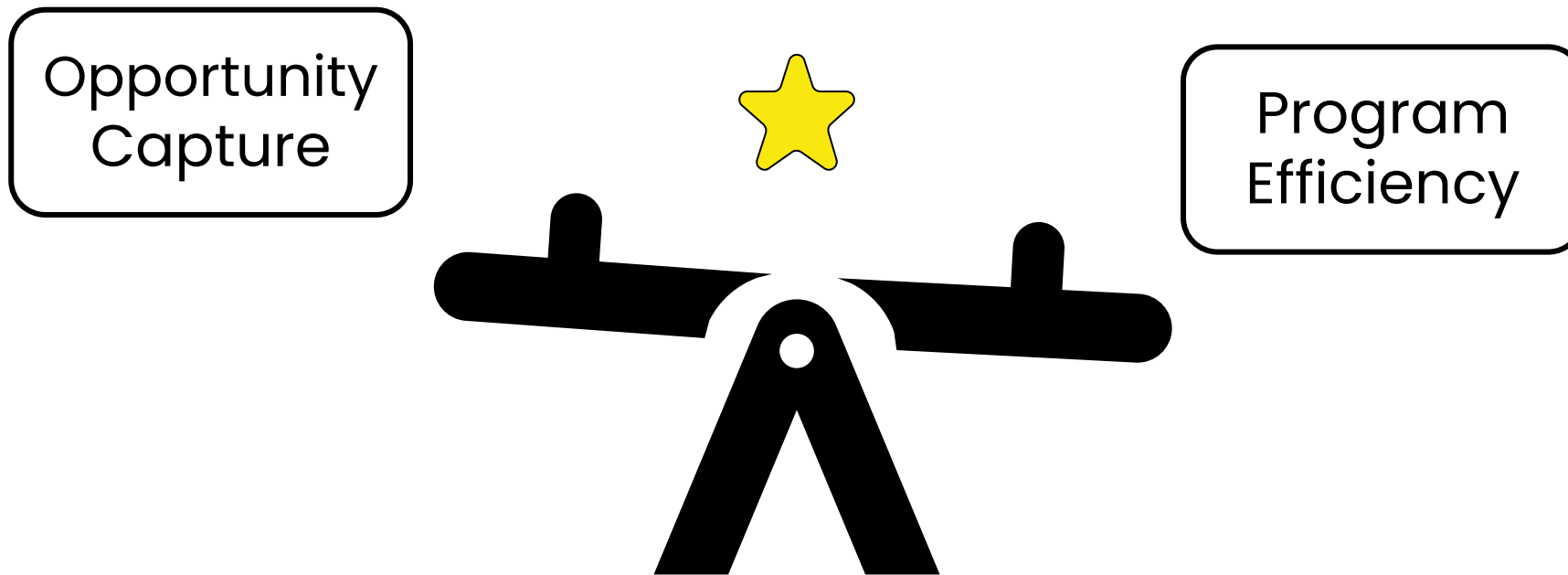
💡 **86%** of the efficiency seen  
from the incumbent strategy

\*Refer to other measures of efficiency in appendix

\*\*Refer to 2025 estimate logic in appendix

# To summarize

**Our strategy strikes a better balance between competing priorities than incumbent strategy**

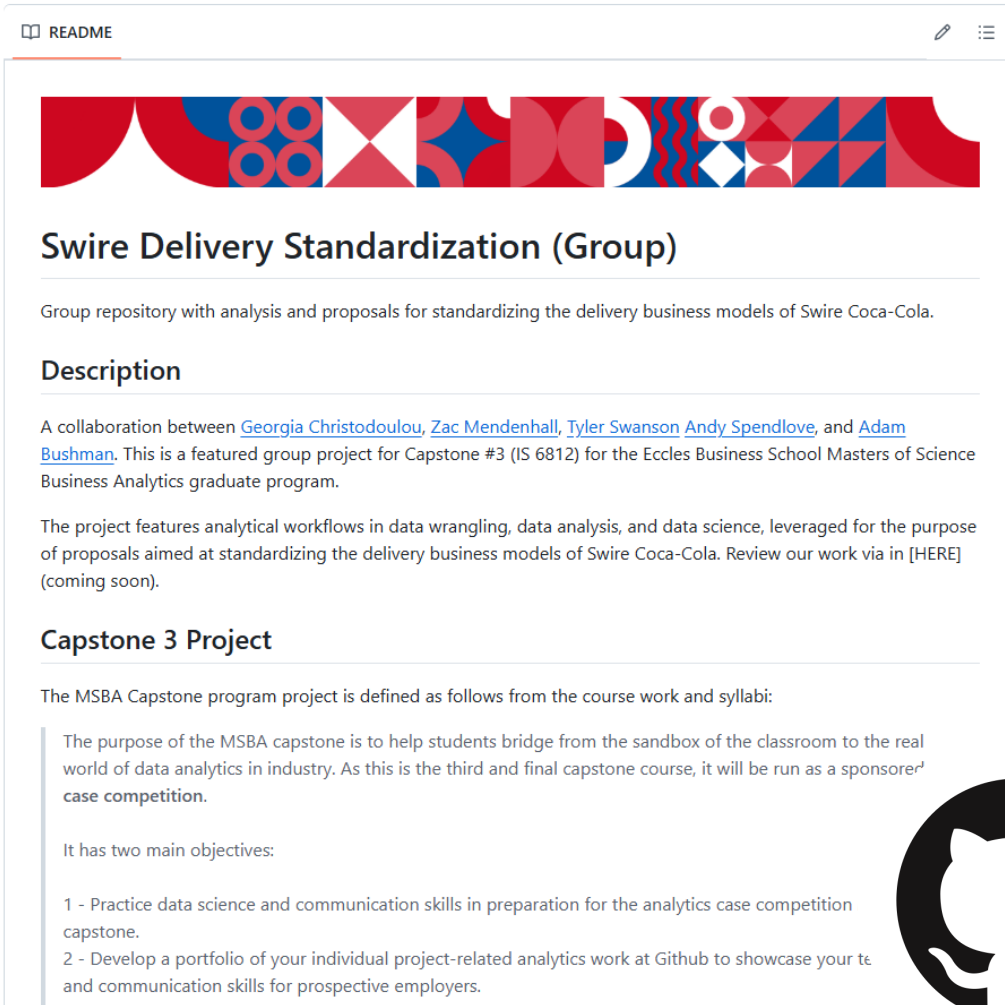


# How-To

leverage our work



# GitHub repository



The screenshot shows a GitHub repository page for 'Swire Delivery Standardization (Group)'. The README file is open, displaying a colorful geometric pattern at the top. The title 'Swire Delivery Standardization (Group)' is followed by a description: 'Group repository with analysis and proposals for standardizing the delivery business models of Swire Coca-Cola.' Below this is a 'Description' section, which states: 'A collaboration between [Georgia Christodoulou](#), [Zac Mendenhall](#), [Tyler Swanson](#), [Andy Spendlove](#), and [Adam Bushman](#). This is a featured group project for Capstone #3 (IS 6812) for the Eccles Business School Masters of Science Business Analytics graduate program.' It then describes the project's focus on analytical workflows in data wrangling, data analysis, and data science, aimed at standardizing the delivery business models of Swire Coca-Cola. A 'Capstone 3 Project' section follows, defining the MSBA Capstone program project and its purpose: to help students bridge from the classroom to the real world of data analytics in industry. It also lists two main objectives: 1 - Practice data science and communication skills in preparation for the analytics case competition capstone, and 2 - Develop a portfolio of your individual project-related analytics work at Github to showcase your technical and communication skills for prospective employers.

README

## Swire Delivery Standardization (Group)

Group repository with analysis and proposals for standardizing the delivery business models of Swire Coca-Cola.

### Description

A collaboration between [Georgia Christodoulou](#), [Zac Mendenhall](#), [Tyler Swanson](#), [Andy Spendlove](#), and [Adam Bushman](#). This is a featured group project for Capstone #3 (IS 6812) for the Eccles Business School Masters of Science Business Analytics graduate program.

The project features analytical workflows in data wrangling, data analysis, and data science, leveraged for the purpose of proposals aimed at standardizing the delivery business models of Swire Coca-Cola. Review our work via in [HERE] (coming soon).

### Capstone 3 Project

The MSBA Capstone program project is defined as follows from the course work and syllabi:

The purpose of the MSBA capstone is to help students bridge from the sandbox of the classroom to the real world of data analytics in industry. As this is the third and final capstone course, it will be run as a sponsored case competition.

It has two main objectives:

- 1 - Practice data science and communication skills in preparation for the analytics case competition capstone.
- 2 - Develop a portfolio of your individual project-related analytics work at Github to showcase your technical and communication skills for prospective employers.

- All work has been localized to GitHub
- Careful consideration given to organization and interpretation
- Comprehensive README file to get oriented





# Reproducible work



All work is reproducible via notebook files, provided:

- Replacement data matches original format
- Installation of required R libraries

# Thank you



# Appendix

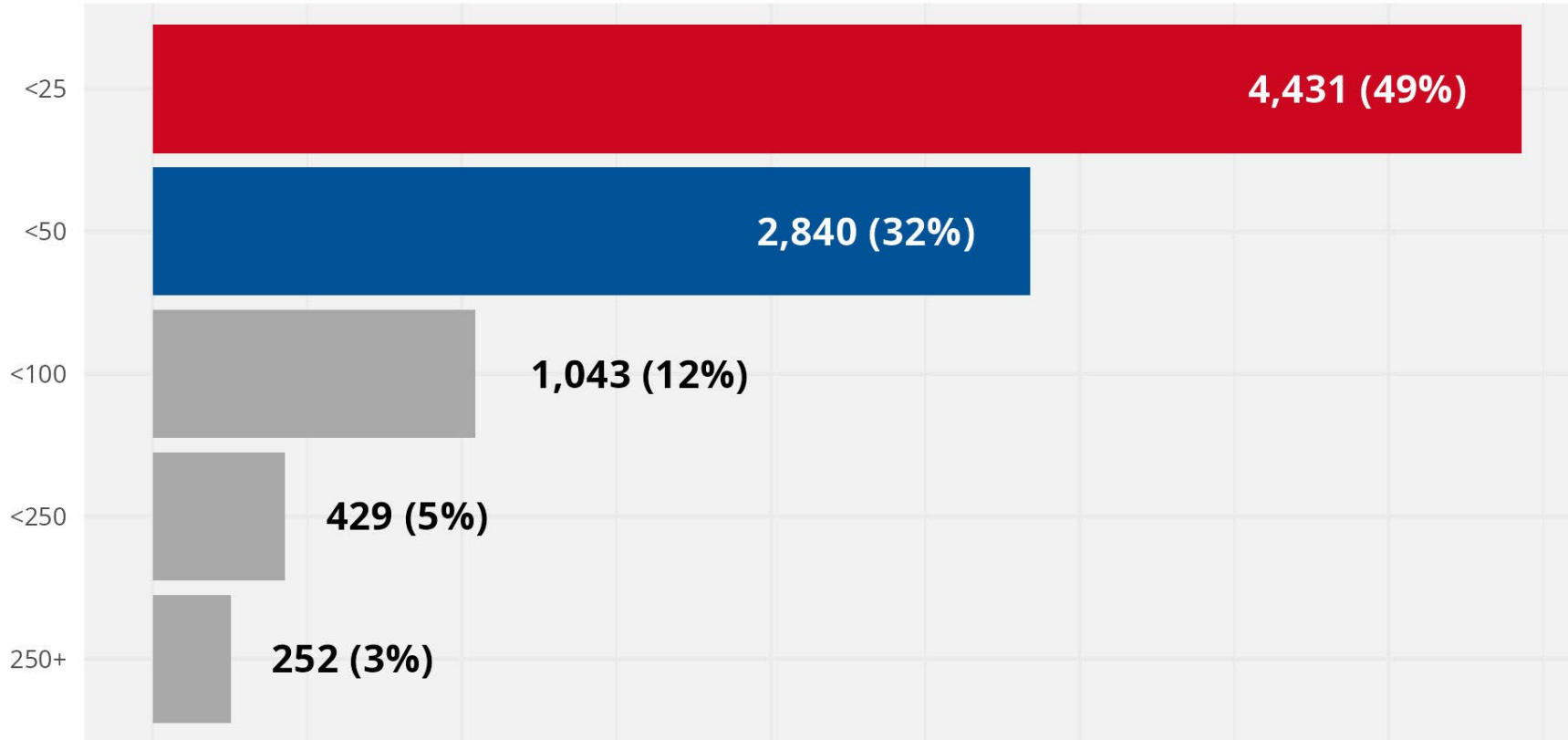
supplemental detail relevant to proposal




# Appendix to slide 6

## Distribution of customers by average transaction amount bin

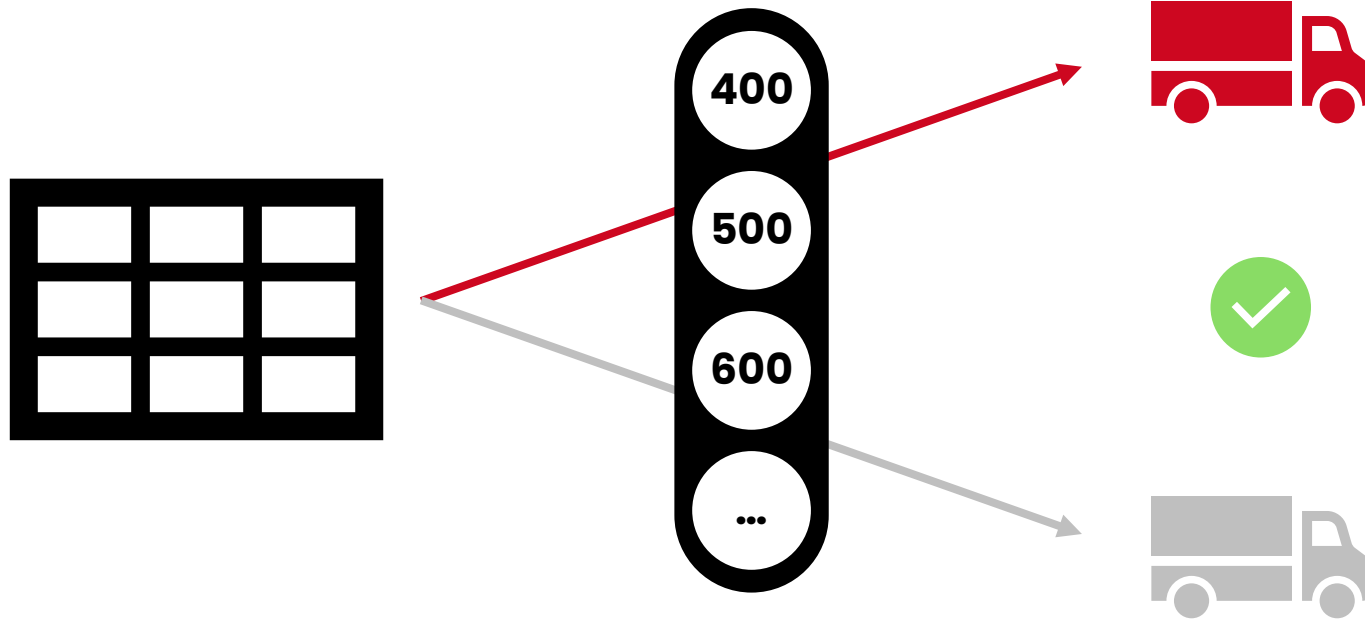
*Among customers who met incumbent 400-gallon threshold in 2023 or 2024*



As explained, not all customers previously thought of as RED TRUCK are created equal.

In fact, most would be described as extremely high maintenance 

# Appendix to slides 7 – 8



Use of random forest classification models, paired with PAM clustering.

These models were consistently effective:

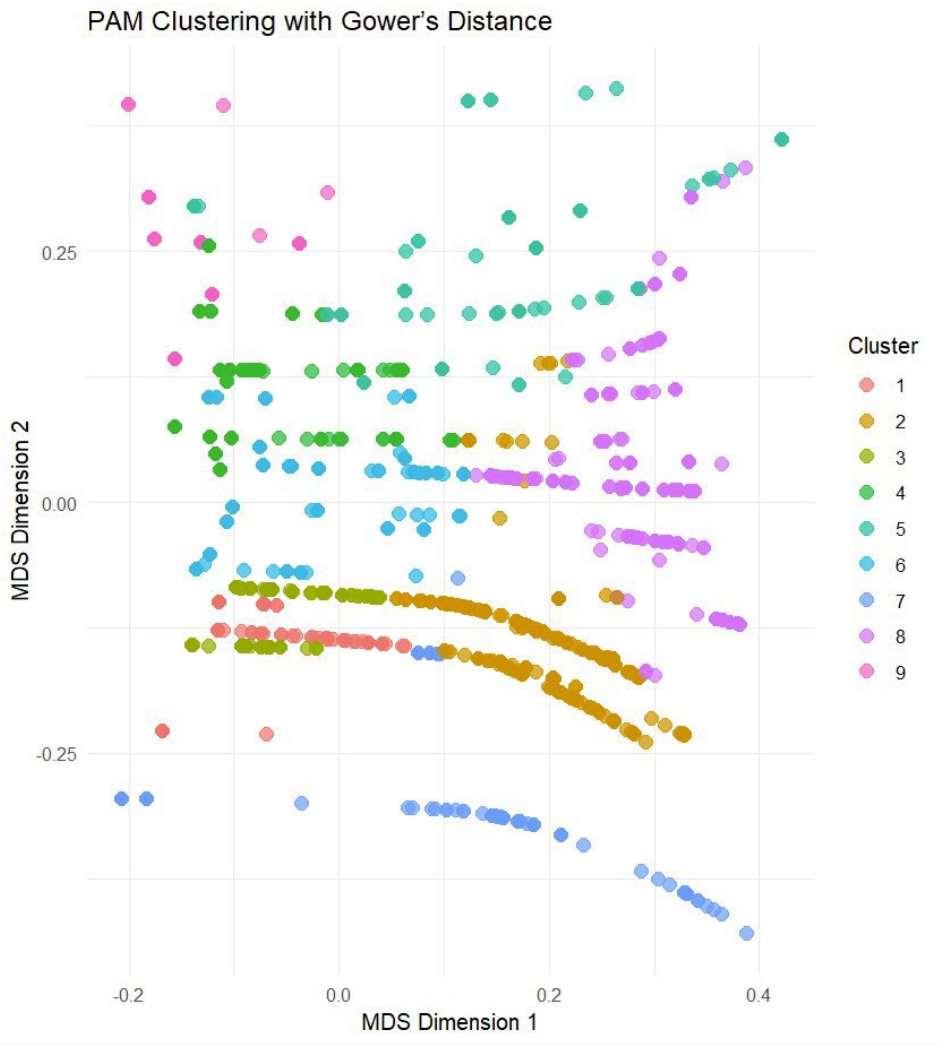
~90% accuracy

~80% precision and recall

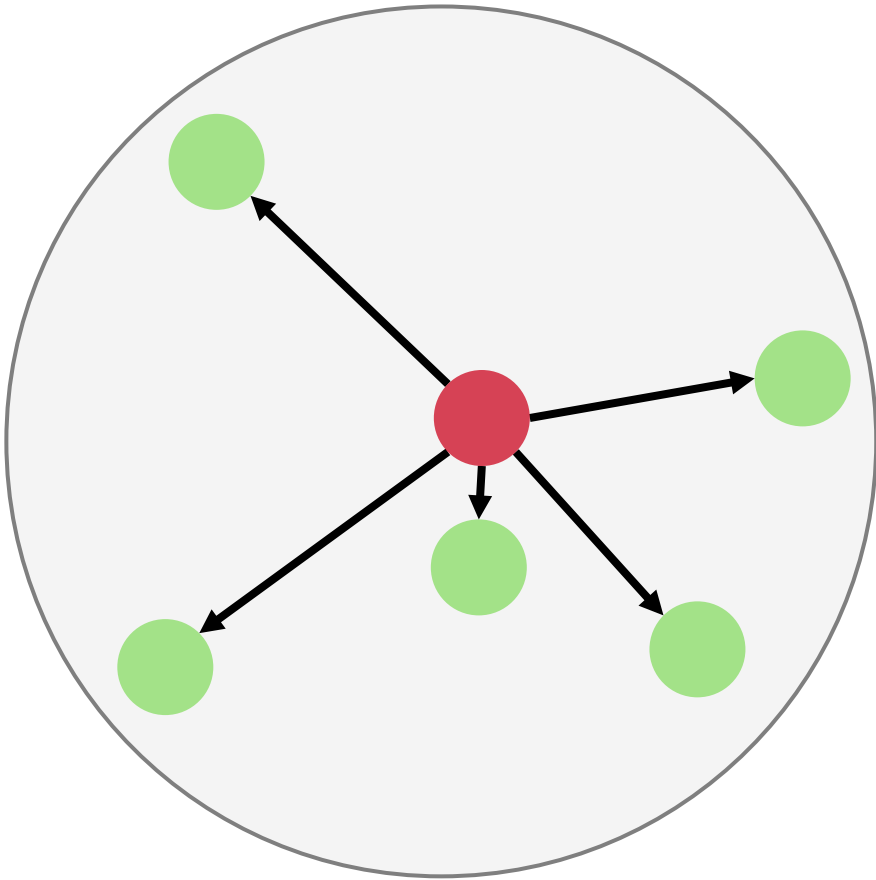
# Appendix to slides 7 – 8

## SMOTE-Enhanced Random Forest Model with Hyperparameter Tuning for Predicting High-Value

Metric	Value	Meaning
Accuracy	90.12%	% of total predictions that were correct
Sensitivity (Recall for Class 0)	94.44%	% of <i>non-high-value</i> customers correctly identified
Specificity	72.29%	% of <i>high-value</i> customers correctly identified
Balanced Accuracy	83.37%	Average of sensitivity and specificity (good for class imbalance)
Kappa	0.68	Strong agreement between prediction and actual
McNemar's Test	$p < 0.00$	Statistically significant improvement over random guessing



# Appendix to slides 9 – 10



Distance was estimated using the *Haversine Formula* →

This formula leverages latitude and longitude, adjusting for the earth's curvature, to estimate a distance "as the crow flies"



# Appendix to slide 12

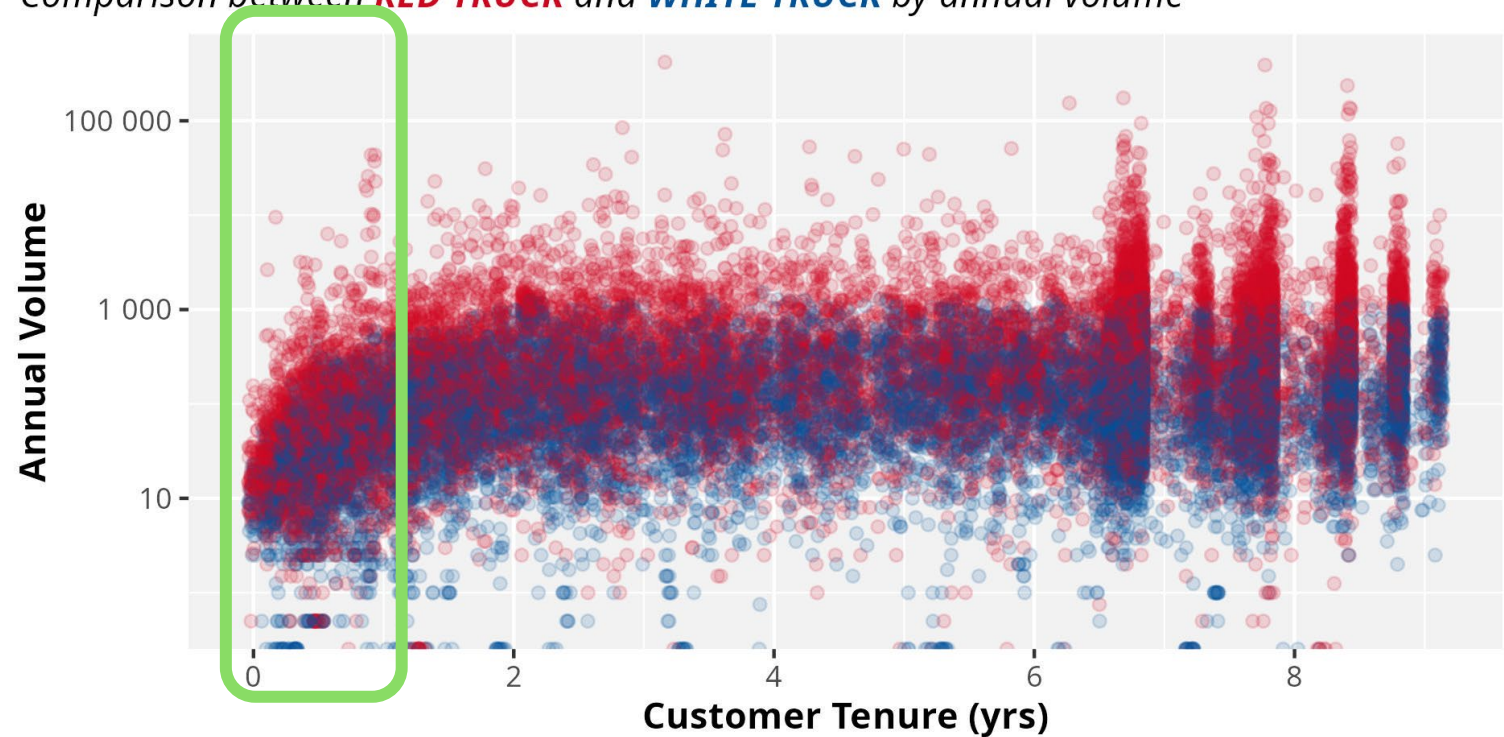
Why retain customers with <1 yr tenure in RED TRUCK program?

This was an addition after evaluating the chart with the remaining segmentation logic.

As seen in this graph, the first year of a customer's tenure is a ramp up period. It's important to have a sample of data before considering a new customer for WHITE TRUCK.

## Segmentation variability by tenure

Comparison between **RED TRUCK** and **WHITE TRUCK** by annual volume





# Appendix to slide 32

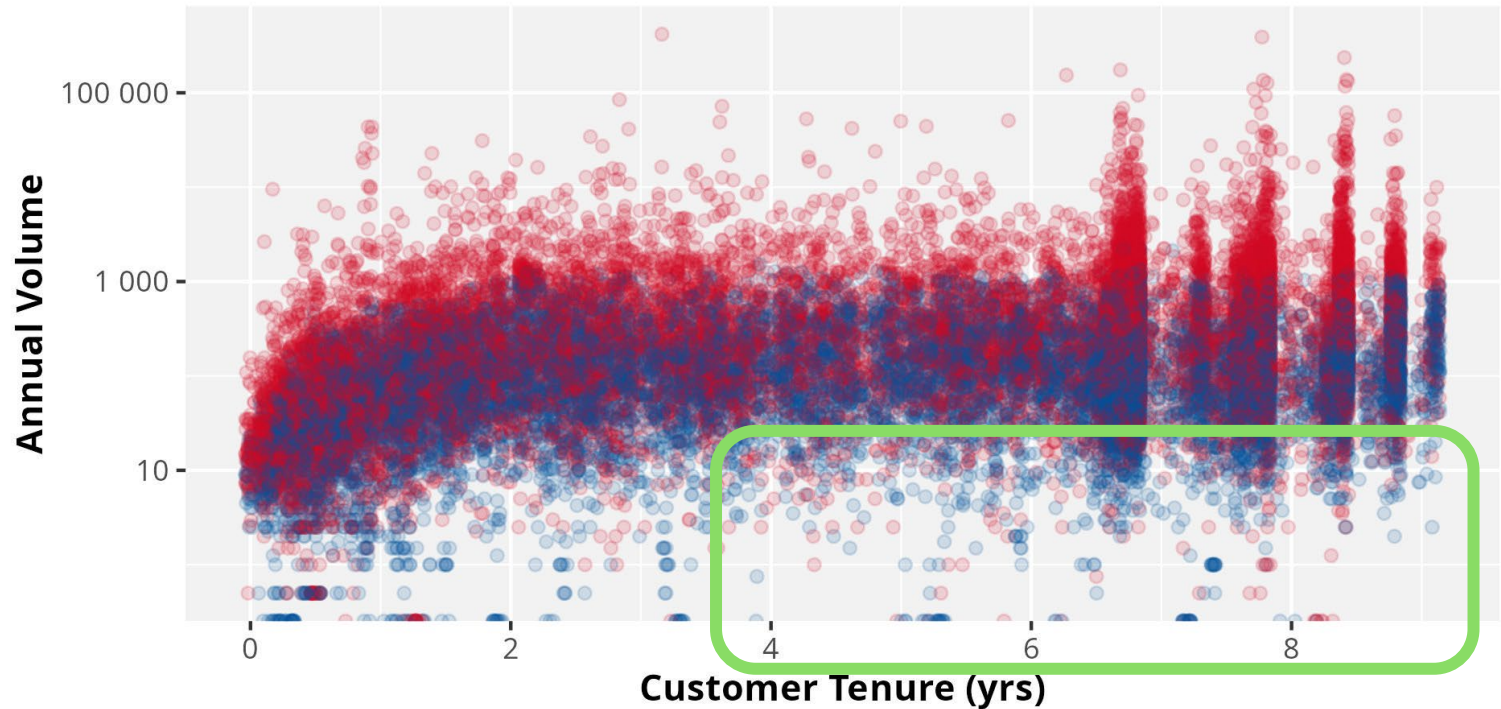
Why retain high tenure, low annual volume customers in RED TRUCK?

Segmented customers in this region are estimated to still be RED TRUCK material thanks to:

- Negligible costs for servicing
- Qualified thanks to a strong market
- Little is known of their performance prior to 2023; Swire could address this blind spot

## Segmentation variability by tenure

Comparison between **RED TRUCK** and **WHITE TRUCK** by annual volume



# Appendix to slide 12 – 14

```
1 swire_segmentation <-
2   swire_cust_enriched >
3   mutate(
4     # CRITERIA
5     # Automatically white truck
6     avoid = (
7       trade_channel %in% c("SPECIALIZED GOODS", "PROFESSIONAL SERVICES", "VEHICLE CARE", "MOBILE RETAIL", "OUTDOOR ACTIVITIES")
8       & avg_transaction_amt < 9
9     ),
10    # Automatically red truck
11    fairly_new = customer_tenure_yrs ≤ 1,
12    # "Growth conducive customer profiles"
13    big_box = (
14      trade_channel %in% c("SUPERSTORE", "BULK TRADE", "GENERAL RETAILER")
15      & frequent_order_type %in% c("EDI", "SALES REP")
16    ),
17    niche_outlets = (
18      trade_channel %in% c("RECREATION", "TRAVEL")
19      & frequent_order_type %in% c("SALES REP", "EDI", "MYCOKE LEGACY")
20    ),
21    convenience_staples = (
22      trade_channel %in% c("FAST CASUAL DINING", "GENERAL")
23      & frequent_order_type %in% c("EDI", "MYCODE LEGACY", "SALES REP", "OTHER")),
24    # "Growth conducive markets"
25    avg_tx_amt_flag = avg_transaction_amt ≥ 25,
26    larger_neighbors_flag = avg_neighbor_transaction_amt ≥ 25,
27
28    # SEGMENTATION LOGIC
29    segment = case_when(
30      avoid ~ "WHITE TRUCK",
31      fairly_new ~ "RED TRUCK",
32      ((big_box + niche_outlets + convenience_staples) > 0
33      | (avg_tx_amt_flag + larger_neighbors_flag)) > 0 ~ "RED TRUCK",
34      TRUE ~ "WHITE TRUCK"
35    )
36  )
```

R code matching the segmentation logic described earlier in the deck.

Also found in GitHub repository.

# Appendix to slides 12 – 14

- These attributes define **RED** vs **WHITE** truck
  - Cluster
  - Order and Channel Type
  - Tenure & Frequency
  - Neighbor Patterns
  - Order Size
- These “lenses” improve your understanding of the customer base
  - Capturing hidden behavioral groupings
  - Differentiating between strategic and transactional ordering behaviors
  - Highlighting customer maturity and growth potential
  - Surfacing local market dynamics that influence buying behavior



# Appendix to slides 12 - 14

Customer characteristic combinations found to be helpful predictors of RED TRUCK material

Categorical Combinations with >50% Probability of High-Value Orders (order\_over\_500)

Trade Channel	Order Type	Frequent Order Type	Cluster	Total	High-Value Orders	% High-Value	% of Total Customers	% of High-Value Customers
SUPERSTORE	EDI	OTHER	1	32	32	100.0	0.1	0.3
GENERAL RETAILER	EDI	SALES REP	2	105	103	98.1	0.2	0.8
GENERAL RETAILER	EDI	SALES REP	7	159	155	97.5	0.3	1.2
HEALTHCARE	SALES REP	SALES REP	2	35	34	97.1	0.1	0.3
GENERAL	MYCOKE LEGACY	SALES REP	2	118	109	92.4	0.2	0.9
RECREATION	MYCOKE LEGACY	SALES REP	2	45	41	91.1	0.1	0.3
GENERAL	CALL CENTER	SALES REP	2	33	29	87.9	0.1	0.2
OUTDOOR ACTIVITIES	SALES REP	SALES REP	2	97	76	87.4	0.2	0.6
GENERAL	SALES REP	SALES REP	2	142	124	87.3	0.3	1.0
GENERAL	SALES REP	SALES REP	7	93	81	87.1	0.2	0.6
RECREATION	SALES REP	SALES REP	2	31	27	87.1	0.1	0.2
ACTIVITIES	SALES REP	SALES REP	2	46	40	87.0	0.1	0.3
HEALTHCARE	SALES REP	SALES REP	7	36	31	86.1	0.1	0.2
FAST CASUAL DINING	MYCOKE LEGACY	MYCOKE LEGACY	2	149	127	85.2	0.3	1.0
HEALTHCARE	MYCOKE LEGACY	SALES REP	7	22	27	84.4	0.1	0.2
GENERAL RETAILER	EDI	SALES REP	1	220	179	81.4	0.4	1.4
GENERAL	MYCOKE LEGACY	SALES REP	7	65	52	80.0	0.1	0.4
OUTDOOR ACTIVITIES	MYCOKE LEGACY	SALES REP	2	85	68	80.0	0.2	0.5
FAST CASUAL DINING	MYCOKE LEGACY	SALES REP	2	549	437	79.6	1.0	3.4
FAST CASUAL DINING	MYCOKE LEGACY	OTHER	2	287	226	78.7	0.5	1.8
COMPREHENSIVE DINING	MYCOKE LEGACY	SALES REP	2	194	150	77.3	0.3	1.2
BULK TRADE	MYCOKE LEGACY	SALES REP	1	30	23	76.7	0.1	0.2
GOURMET FOOD RETAILER	SALES REP	SALES REP	7	37	28	75.7	0.1	0.2
ACCOMMODATION	SALES REP	SALES REP	2	53	40	75.5	0.1	0.3
ACADEMIC INSTITUTION	SALES REP	SALES REP	2	59	44	74.6	0.1	0.3
COMPREHENSIVE DINING	SALES REP	SALES REP	2	265	197	74.3	0.5	1.5
COMPREHENSIVE DINING	MYCOKE LEGACY	OTHER	2	51	37	72.5	0.1	0.3
FAST CASUAL DINING	SALES REP	SALES REP	2	190	133	70.0	0.3	1.0
OTHER DINING & BEVERAGE	MYCOKE LEGACY	OTHER	2	40	28	70.0	0.1	0.2
ACCOMMODATION	MYCOKE LEGACY	SALES REP	2	66	46	69.7	0.1	0.4
OTHER DINING & BEVERAGE	MYCOKE LEGACY	SALES REP	2	94	65	69.1	0.2	0.5
GENERAL	MYCOKE LEGACY	SALES REP	1	328	221	67.4	0.6	1.7
OTHER DINING & BEVERAGE	SALES REP	SALES REP	2	57	36	66.7	0.1	0.3
FAST CASUAL DINING	MYCOKE LEGACY	SALES REP	7	152	98	64.5	0.3	0.8
GENERAL RETAILER	SALES REP	SALES REP	2	116	74	63.8	0.2	0.6
OUTDOOR ACTIVITIES	SALES REP	SALES REP	7	92	58	63.0	0.2	0.5
GENERAL	MYCOKE LEGACY	OTHER	1	94	59	62.8	0.2	0.5
ACADEMIC INSTITUTION	SALES REP	SALES REP	7	53	33	62.3	0.1	0.3

Top 10 Most Important Features for Predicting order\_over\_500

	Feature	MeanDecreaseAccuracy	MeanDecreaseGini
neighbor_avg_order_transaction_std_2024	neighbor_avg_order_transaction_std_2024	200.55	2207.39
neighbor_avg_dist_km	neighbor_avg_dist_km	183.65	2182.84
neighbor_avg_order_transactions_2024	neighbor_avg_order_transactions_2024	180.65	2022.98
neighbor_avg_ordered_total_2024	neighbor_avg_ordered_total_2024	177.91	2101.18
cluster	cluster	170.49	4817.82
customer_tenure	customer_tenure	134.36	4184.83
neighbor_avg_return_freq	neighbor_avg_return_freq	111.47	562.86
order_type	order_type	97.54	1357.02
neighbor_local_market_partners	neighbor_local_market_partners	87.05	721.95
return_frequency	return_frequency	82.09	840.76

Categorical Combinations with <23% Probability of High-Value Orders (order\_over\_500)

Trade Channel	Order Type	Frequent Order Type	Cluster	Total	High-Value Orders	% High-Value	% of Total Customers	% of High-Value Customers
COMPREHENSIVE DINING	CALL CENTER	OTHER	4	80	0	0.0	0.1	0.0
EDUCATION	null	SALES REP	1	36	0	0.0	0.1	0.0
FAST CASUAL DINING	MYCOKE360	MYCOKE360	3	45	0	0.0	0.1	0.0
FAST CASUAL DINING	MYCOKE360	SALES REP	3	30	0	0.0	0.1	0.0
FAST CASUAL DINING	SALES REP	SALES REP	9	41	0	0.0	0.1	0.0
GENERAL RETAILER	CALL CENTER	SALES REP	4	64	0	0.0	0.1	0.0
GENERAL RETAILER	MYCOKE LEGACY	MYCOKE360	3	104	0	0.0	0.2	0.0
GENERAL RETAILER	MYCOKE LEGACY	MYCOKE360	4	33	0	0.0	0.1	0.0
GENERAL RETAILER	MYCOKE LEGACY	OTHER	3	42	0	0.0	0.1	0.0
GENERAL RETAILER	MYCOKE LEGACY	OTHER	4	31	0	0.0	0.1	0.0
GENERAL RETAILER	MYCOKE LEGACY	SALES REP	4	76	0	0.0	0.1	0.0
LICENSED HOSPITALITY	CALL CENTER	OTHER	4	33	0	0.0	0.1	0.0
LICENSED HOSPITALITY	CALL CENTER	SALES REP	4	63	0	0.0	0.1	0.0
LICENSED HOSPITALITY	SALES REP	SALES REP	4	30	0	0.0	0.1	0.0
OTHER DINING & BEVERAGE	CALL CENTER	CALL CENTER	3	43	0	0.0	0.1	0.0
OTHER DINING & BEVERAGE	MYCOKE LEGACY	MYCOKE LEGACY	1	61	0	0.0	0.1	0.0
OTHER DINING & BEVERAGE	MYCOKE LEGACY	MYCOKE LEGACY	3	59	0	0.0	0.1	0.0
OUTDOOR ACTIVITIES	MYCOKE LEGACY	MYCOKE LEGACY	1	40	0	0.0	0.1	0.0
PROFESSIONAL SERVICES	CALL CENTER	OTHER	4	32	0	0.0	0.1	0.0
PROFESSIONAL SERVICES	MYCOKE LEGACY	OTHER	8	34	0	0.0	0.1	0.0
PROFESSIONAL SERVICES	MYCOKE LEGACY	SALES REP	3	50	0	0.0	0.1	0.0
SPECIALIZED GOODS	CALL CENTER	CALL CENTER	1	30	0	0.0	0.1	0.0
SPECIALIZED GOODS	CALL CENTER	OTHER	1	44	0	0.0	0.1	0.0
SPECIALIZED GOODS	CALL CENTER	SALES REP	4	34	0	0.0	0.1	0.0
SPECIALIZED GOODS	MYCOKE LEGACY	MYCOKE360	3	60	0	0.0	0.1	0.0
SPECIALIZED GOODS	MYCOKE LEGACY	MYCOKE360	4	50	0	0.0	0.1	0.0
VEHICLE CARE	CALL CENTER	CALL CENTER	3	98	0	0.0	0.2	0.0
VEHICLE CARE	CALL CENTER	CALL CENTER	4	133	0	0.0	0.2	0.0

Red Truck vs White Truck Segments: High-Value Order Behavior by Category

Feature	Category	Total	High-Value Orders	% High-Value	Segment
trade_channel	SUPERSTORE	168	162	96.4	Red Truck (High-Performing)
trade_channel	BULK TRADE	187	144	77.0	Red Truck (High-Performing)
trade_channel	TRAVEL	205	140	68.3	Red Truck (High-Performing)
trade_channel	GENERAL	2240	1315	58.7	Red Truck (High-Performing)
trade_channel	ACTIVITIES	553	238	43.0	Red Truck (High-Performing)
trade_channel	ACADEMIC INSTITUTION	760	325	42.8	Red Truck (High-Performing)
trade_channel	DEFENSE	230	96	41.7	Red Truck (High-Performing)
trade_channel	HEALTHCARE	880	366	41.6	Red Truck (High-Performing)
trade_channel	RECREATION	1461	571	39.1	Red Truck (High-Performing)
trade_channel	PUBLIC SECTOR (NON-MILITARY)	659	230	34.9	Red Truck (High-Performing)
trade_channel	COMPREHENSIVE DINING	8827	1862	21.1	White Truck (Low-Performing)
trade_channel	ACCOMMODATION	2307	476	20.6	White Truck (Low-Performing)
trade_channel	GENERAL RETAILER	5418	1075	19.8	White Truck (Low-Performing)
trade_channel	OTHER DINING & BEVERAGE	4639	680	14.7	White Truck (Low-Performing)
trade_channel	INDUSTRIAL	347	42	12.1	White Truck (Low-Performing)
trade_channel	PROFESSIONAL SERVICES	1446	122	8.4	White Truck (Low-Performing)
trade_channel	EDUCATION	1255	105	8.4	White Truck (Low-Performing)
trade_channel	MOBILE RETAIL	652	48	7.4	White Truck (Low-Performing)
trade_channel	LICENSED HOSPITALITY	2768	203	7.3	White Truck (Low-Performing)
trade_channel	PHARMACY RETAILER	104	4	3.8	White Truck (Low-Performing)
trade_channel	SPECIALIZED GOODS	1135	31	2.7	White Truck (Low-Performing)
trade_channel	VEHICLE CARE	3363	48	1.4	White Truck (Low-Performing)
trade_channel	LARGE-SCALE RETAILER	1	0	0.0	White Truck (Low-Performing)
order_type	EDI	1739	846	48.6	Red Truck (High-Performing)
order_type	OTHER	917	169	18.4	White Truck (Low-Performing)
order_type	CALL CENTER	19174	2548	13.3	White Truck (Low-Performing)
order_type	null	1032	135	13.1	White Truck (Low-Performing)
order_type	MYCOKE360	1243	108	8.7	White Truck (Low-Performing)
frequent_order_type	OTHER	10221	2214	21.7	White Truck (Low-Performing)
frequent_order_type	MYCOKE LEGACY	1675	354	21.1	White Truck (Low-Performing)
frequent_order_type	EDI	668	128	19.2	White Truck (Low-Performing)
frequent_order_type	MYCOKE360	3927	349	8.9	White Truck (Low-Performing)
frequent_order_type	CALL CENTER	2442	133	5.4	White Truck (Low-Performing)
cluster	2	5091	3531	69.4	Red Truck (High-Performing)
cluster	7	3322	1399	42.1	Red Truck (High-Performing)
cluster	1	27386	6045	22.1	White Truck (Low-Performing)
cluster	5	1693	260	15.4	White Truck (Low-Performing)
cluster	8	929	91	9.8	White Truck (Low-Performing)
cluster	3	11759	1004	8.5	White Truck (Low-Performing)
cluster	9	1114	65	5.8	White Truck (Low-Performing)
cluster	4	3405	180	5.3	White Truck (Low-Performing)

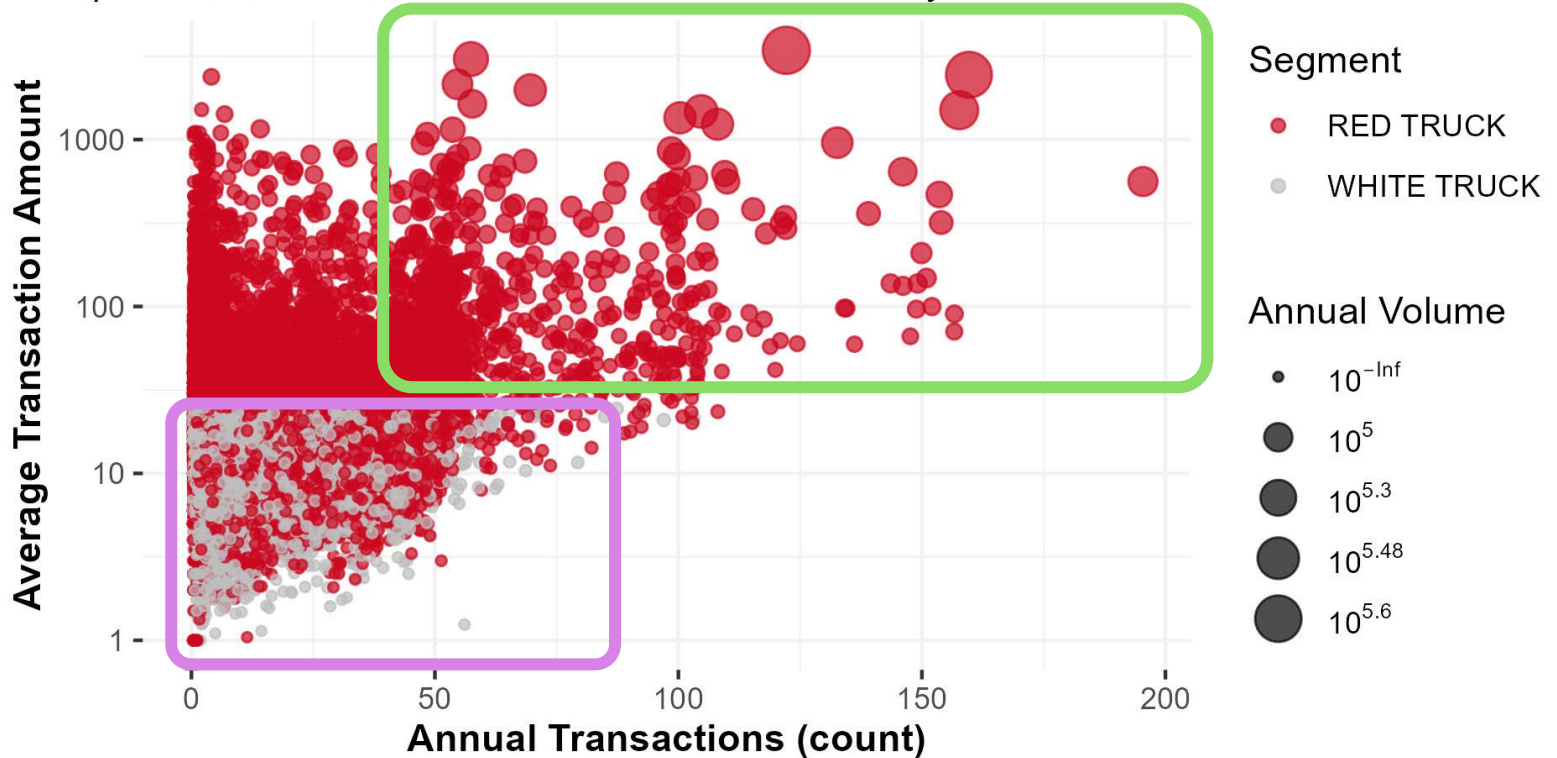
# Appendix to slide 15

Our segmentation strategy correctly captures the highest value customers.

It also captures a mix of customers with potential for long term RED TRUCK partnership while avoiding similar customers without such potential.

## Distribution of Customers by Segment

*Comparison across measures of volume and efficiency*



# Appendix slide to 21

## Opportunity cost of \*2025 gallons + cases routed to white truck program

Proposed  
segmentation strategy

vs

Incumbent 400-gallon  
threshold strategy

2.4M

2.9M

💡 **81%** of the efficiency seen  
from the incumbent strategy

\*Refer to 2025 estimate logic in appendix

# Appendix slide to 21

**\*2025 delivery costs avoided via white truck program**

Proposed  
segmentation strategy

vs

Incumbent 400-gallon  
threshold strategy

**\$9.0M**

**\$13.7M**

💡 **64%** of the efficiency seen  
from the incumbent strategy

\*Refer to 2025 estimate logic in appendix

# Appendix slide to 21

**\*2025 labor hours recouped via white truck program**

Proposed  
segmentation strategy

vs

Incumbent 400-gallon  
threshold strategy

**161K**

**210K**

💡 **73%** of the efficiency seen  
from the incumbent strategy

\*Refer to staff hour assumptions in appendix



# Appendix to slides 20 – 21, 38 – 40

The logic for deriving 2025 volume estimates follows the following rules:

- Growth rate from '23 to '24 by trade channel
  - No sales in '23 defaults to overall growth rate
- 2024 order volumes multiplied by growth rate
- Costs were assumed to linearly increase at same rate as order volumes

Overall results align with observed growth from prior year:

- Growth rate from '23 to '24 across all customers: **5.2%**
- Growth rate from '24 to '25 across all customers: **6.3%**

💡 **RECOMMEND:** replacing this naïve growth logic with more robust forecasting methods given Swire's greater longitudinal data sets

# Appendix to slide 40

“Labor hours” seeks to estimate the annual hours sales & customer service staff members expend to service an account.

ChatGPT 4o suggested these benchmark ranges:

TIER	ANNUAL HOURS PER CUSTOMER
Enterprise	<u>60</u> - 120
Mid-market	<u>25</u> - 50
SMB	<u>4</u> - 20

Swire customers were assigned to these groups based on percentiles across two features (as prescribed by ChatGPT):

Annual Volume

Customers in Primary Group

The resulting count of customers from each tier were multiplied by the minimum hours in the respective tier, and summed for WHITE TRUCK, comparing the two segmentation strategies.

💡 **RECOMMEND:** replacing these heuristic values with Swire’s internal understanding for an improved estimate