



UNITED AIRLINES HACKATHON-SKYHACK 2.0

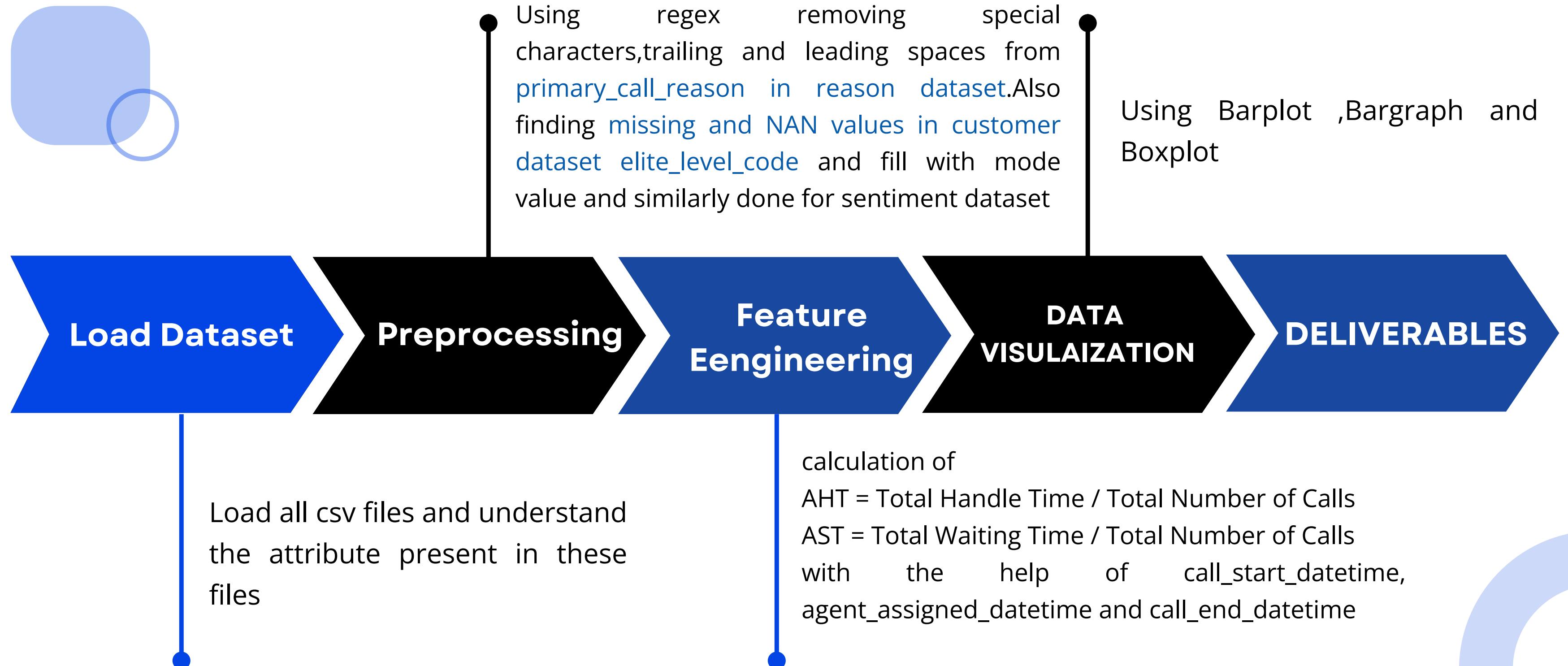
TEAMMATES

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STEPS



DELIVERABLE 1

Explore the factors contributing to extended call durations, such as agent performance, call types, and sentiment. Identify key drivers of long AHT and AST, especially during high volume call periods.

Agent Performance-: The tone and behavior of agents during calls can significantly influence call durations. Agents who maintain a calm and friendly tone may handle calls more efficiently, whereas those who are neutral or frustrated may lead to longer calls.

Call types:-Different types of calls, categorized by the primary reason for the call (i.e checkouts,irrops), may require varying levels of complexity. Calls that involve more detailed explanations or troubleshooting are likely to take longer.The most frequent call reason is irrops and least frequent call reason is unaccompanied minor.

Customer Sentiment:-The sentiment of customers (i.e frustrated, calm) can greatly influence both AHT and AST. Frustrated customers may require more time and attention, resulting in longer AHT. Additionally, higher silence percentages during calls may indicate hesitation or confusion from the customer.

Total Handle Time Of All Calls (sec): 46468920.0
Total Waiting Time Of All Calls (sec): 29125500.0
Total Number Of Calls: 66653

The Average Handle Time Of Calls (sec) 697.1767212278517
The Average Speed To Answer Time Of Calls(sec) 436.97207927625163

Calculating Average Handle Time And Average Speed Time To Answer

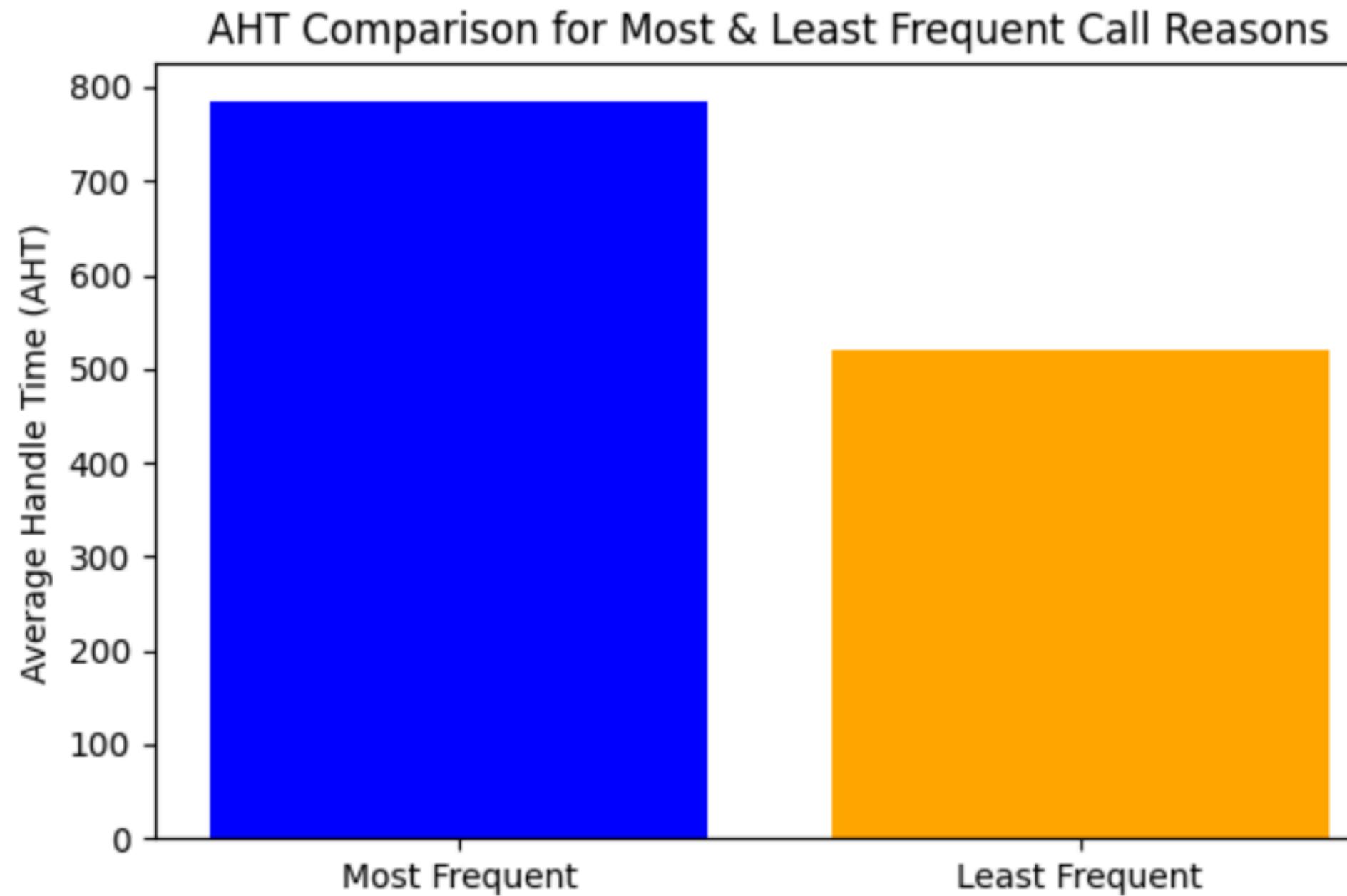
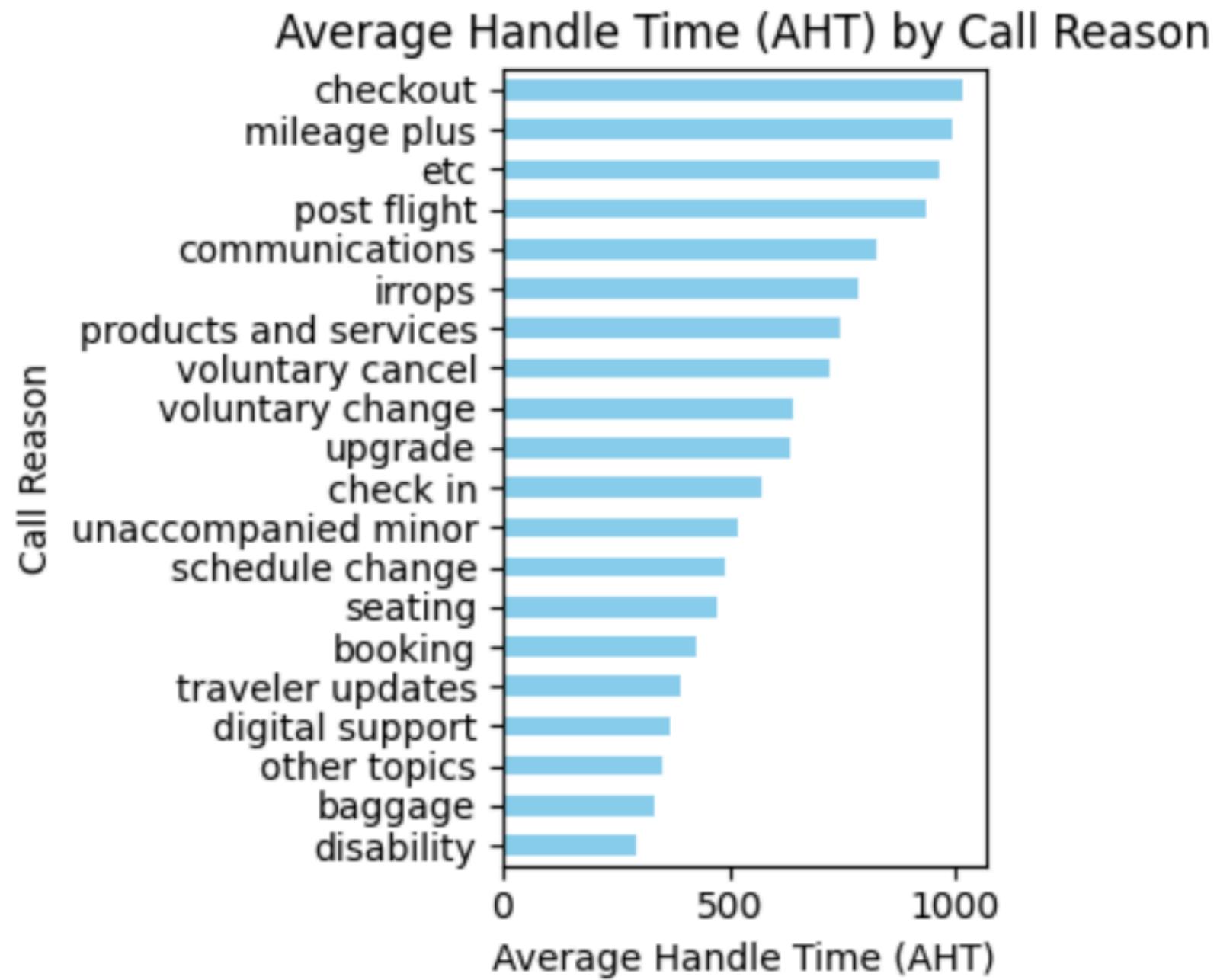
```
[ ] # Calculate AHT and AST
total_handle_time = merged_data['Handle_Time'].sum()
total_waiting_time = merged_data['Waiting_Time'].sum()
total_calls = merged_data.call_id.value_counts().sum()
print("Total Handle Time Of All Calls (sec):",total_handle_time)
print("Total Waiting Time Of All Calls (sec):",total_waiting_time)
print("Total Number Of Calls:",total_calls)
```

→ Total Handle Time Of All Calls (sec): 46468920.0
Total Waiting Time Of All Calls (sec): 29125500.0
Total Number Of Calls: 66653

```
▶ AHT = total_handle_time / total_calls
print("The Average Handle Time Of Calls (sec)",AHT)
AST = total_waiting_time / total_calls
print("The Average Speed To Answer Time Of Calls(sec)",AST)
```

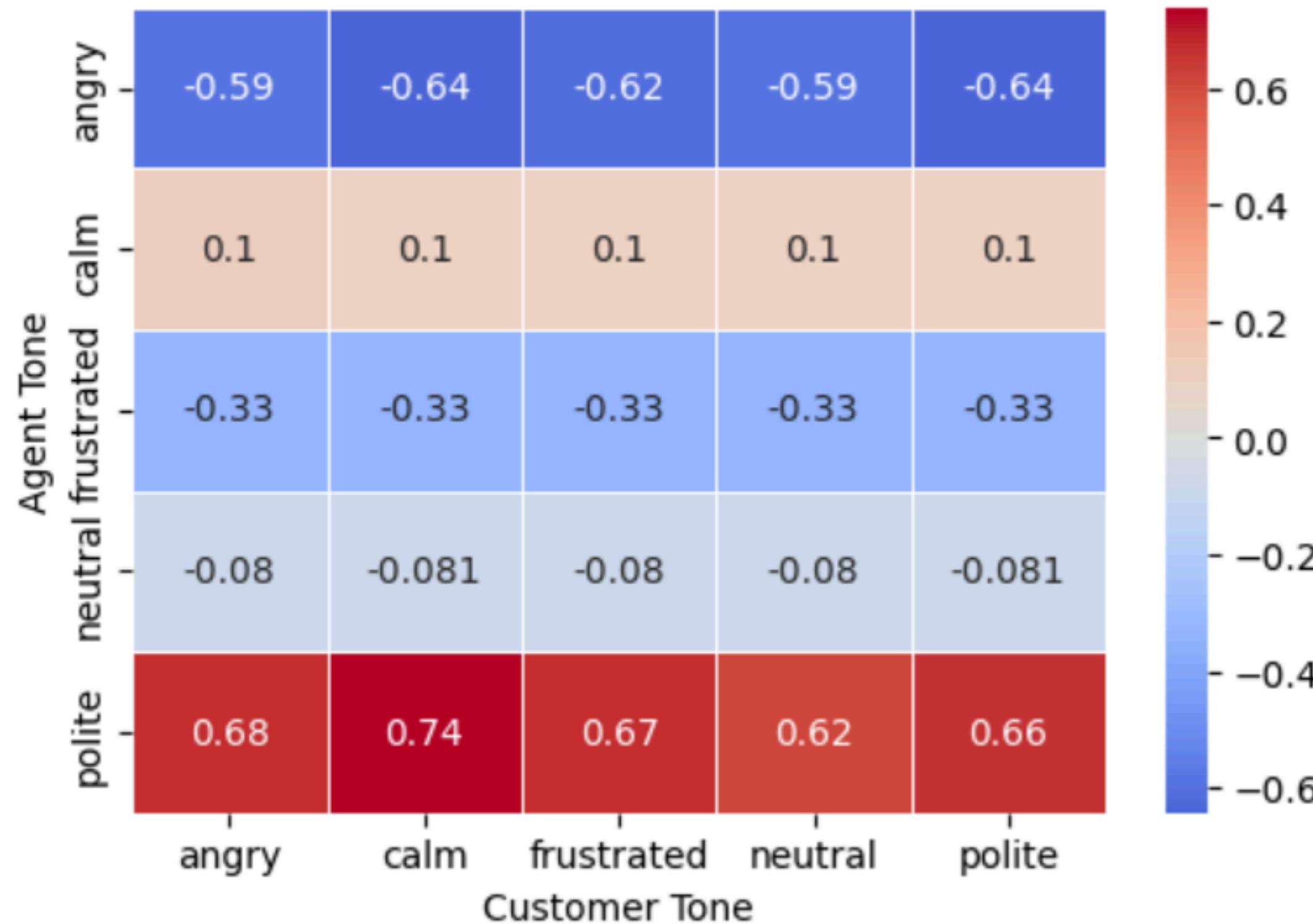
→ The Average Handle Time Of Calls (sec) 697.1767212278517
The Average Speed To Answer Time Of Calls(sec) 436.97207927625163

INSIGHTS

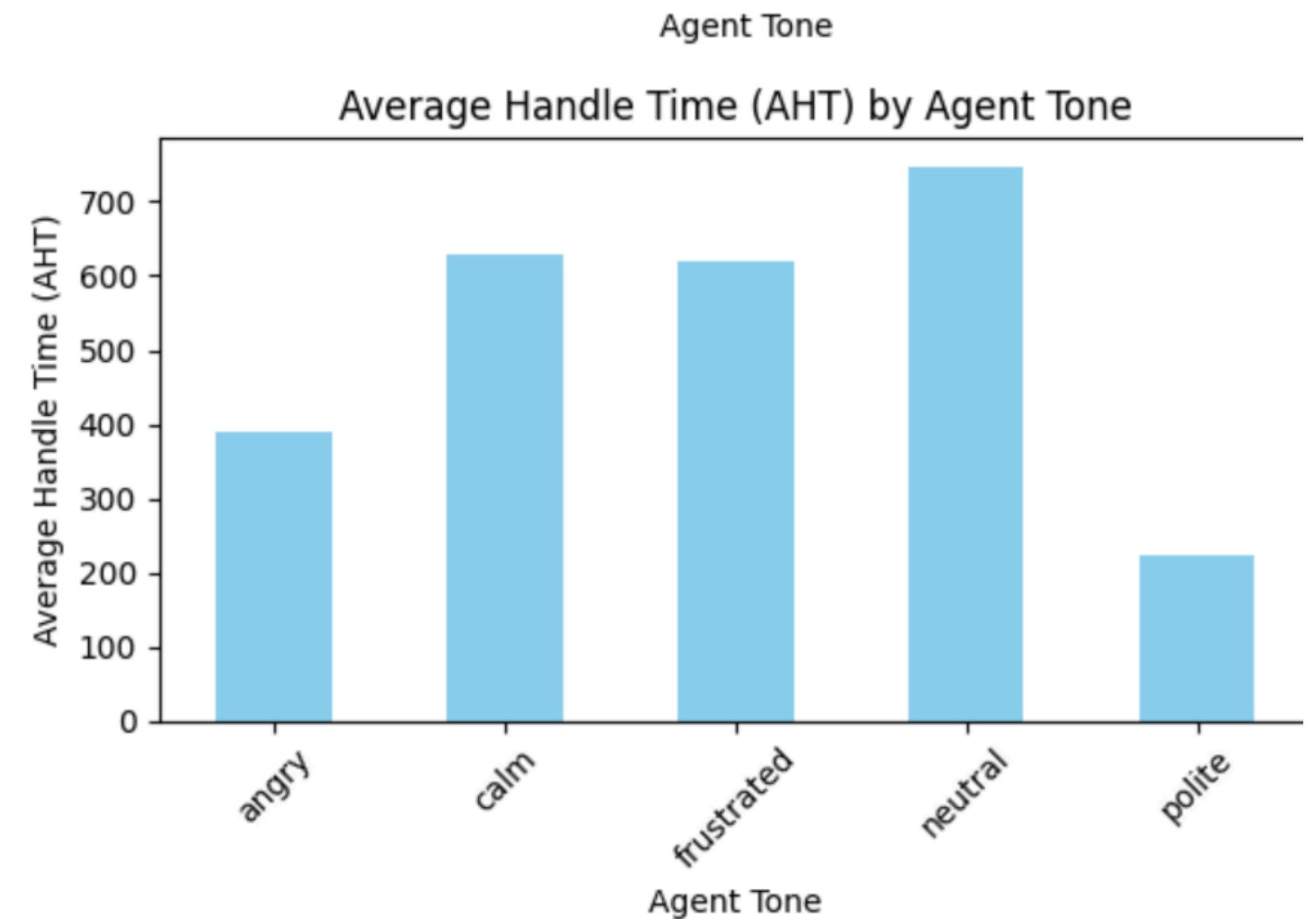
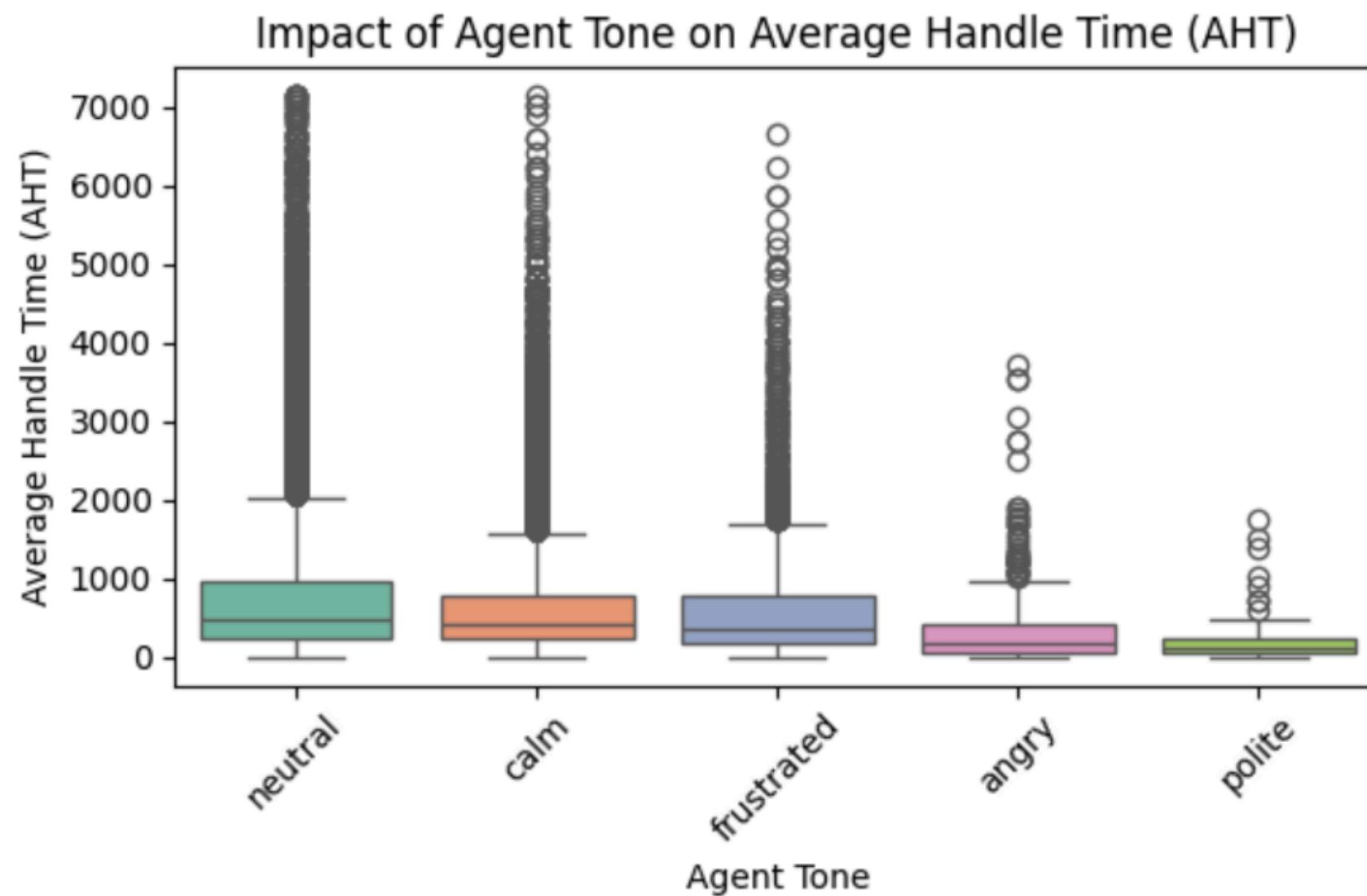


INSIGHTS

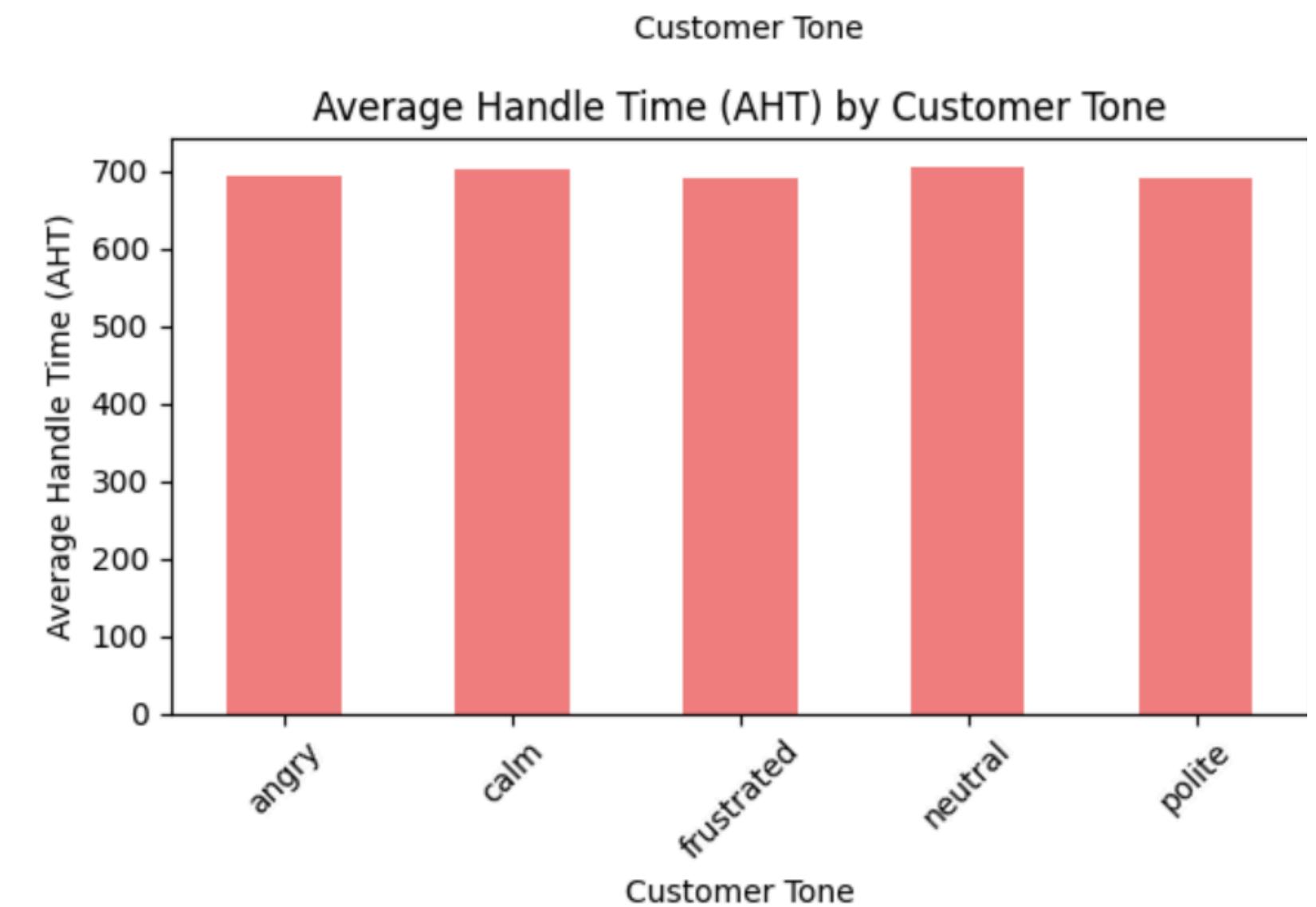
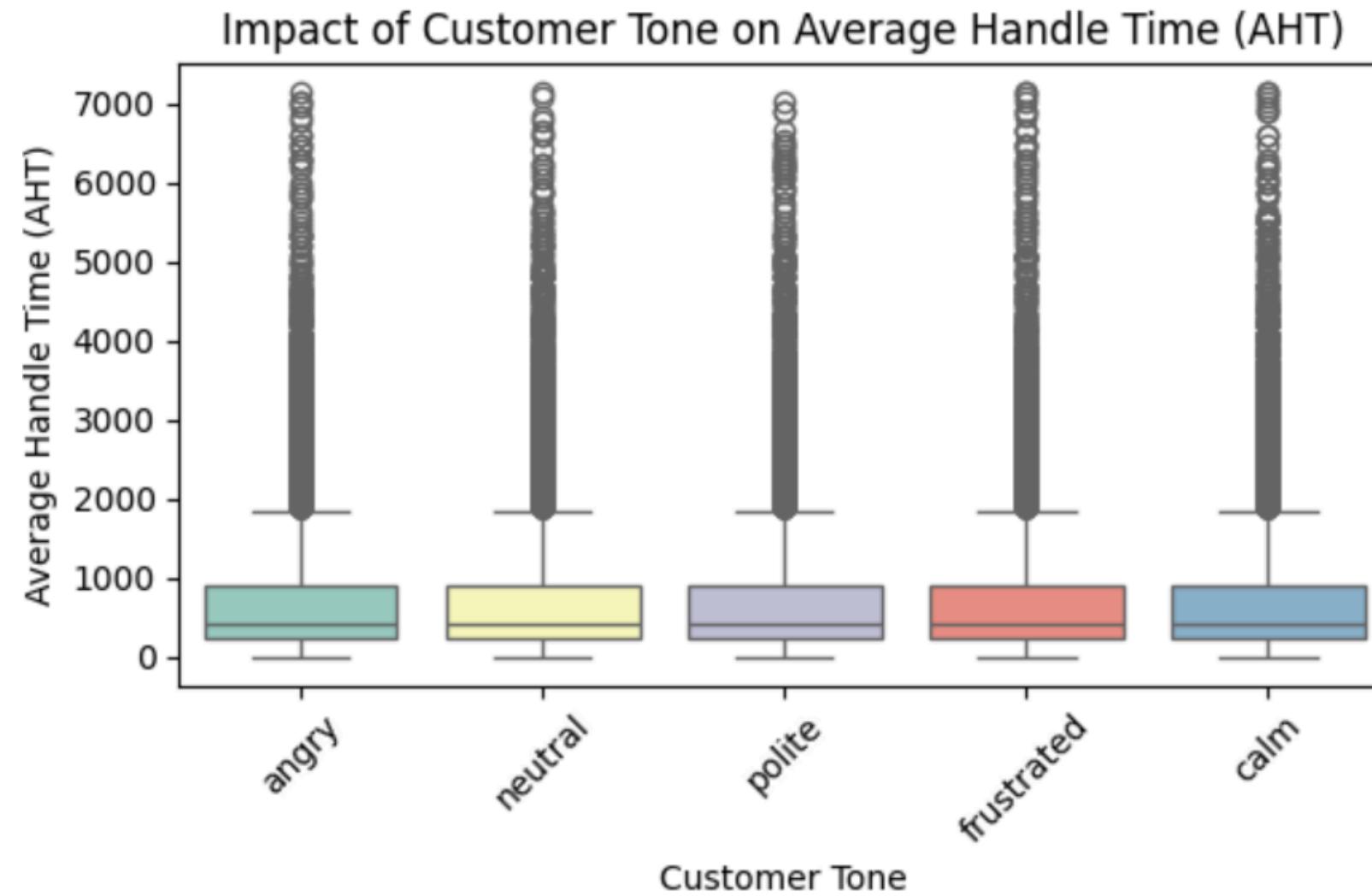
Relationship between Agent Tone, Customer Tone, and Average Sentiment



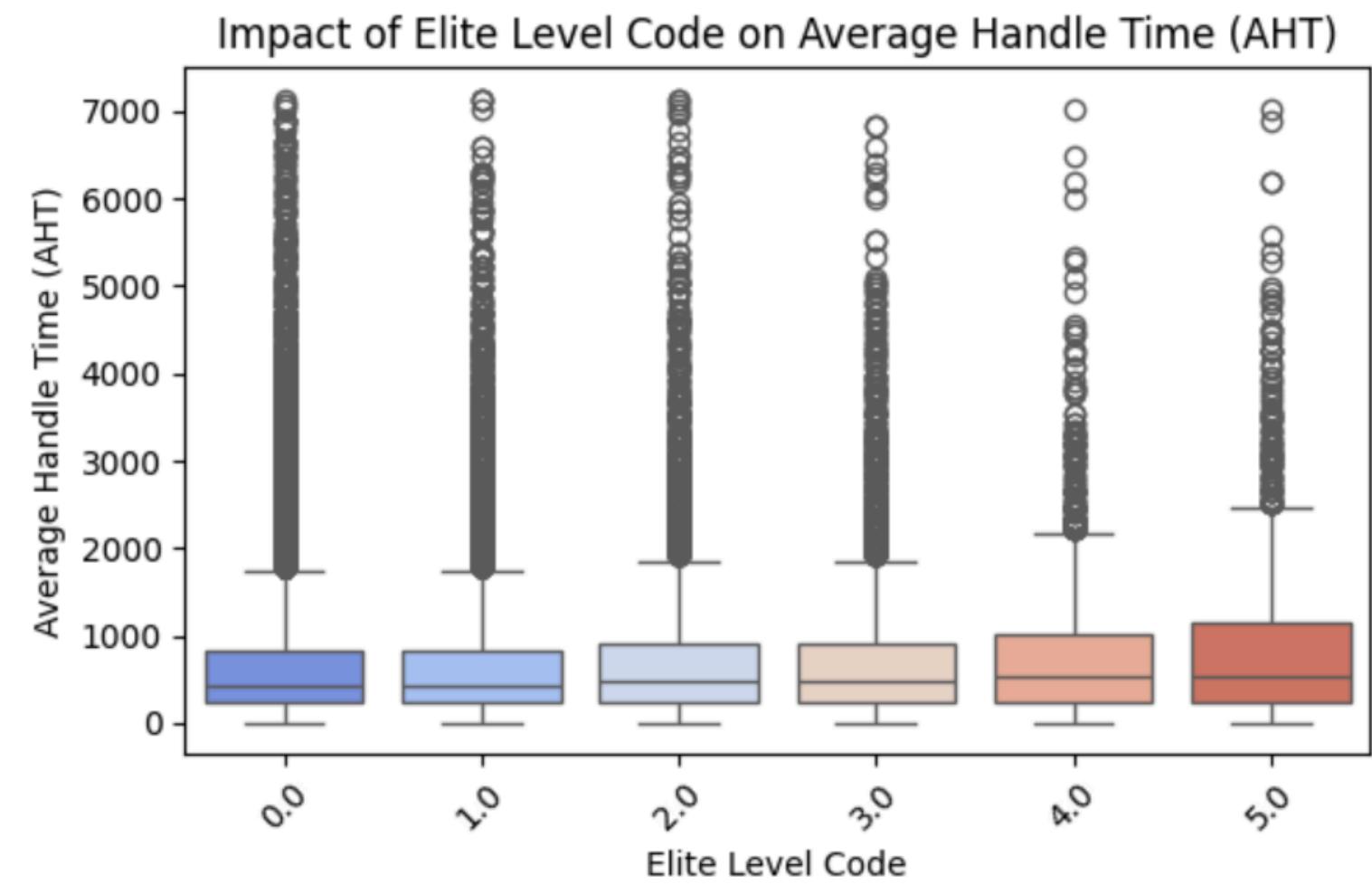
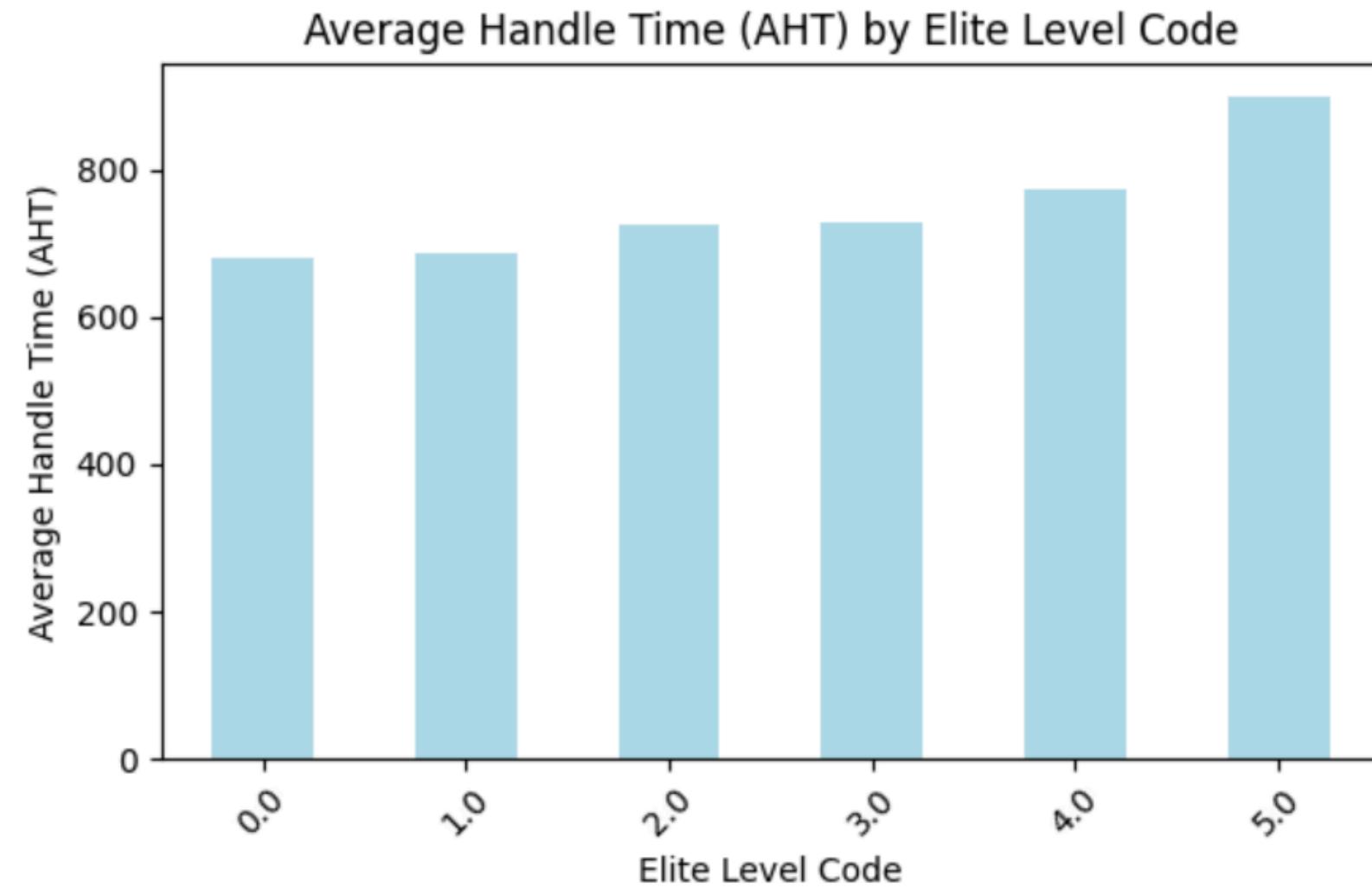
INSIGHTS



INSIGHTS



INSIGHTS



Percentage difference between the average handling time for the most frequent and least frequent call reasons

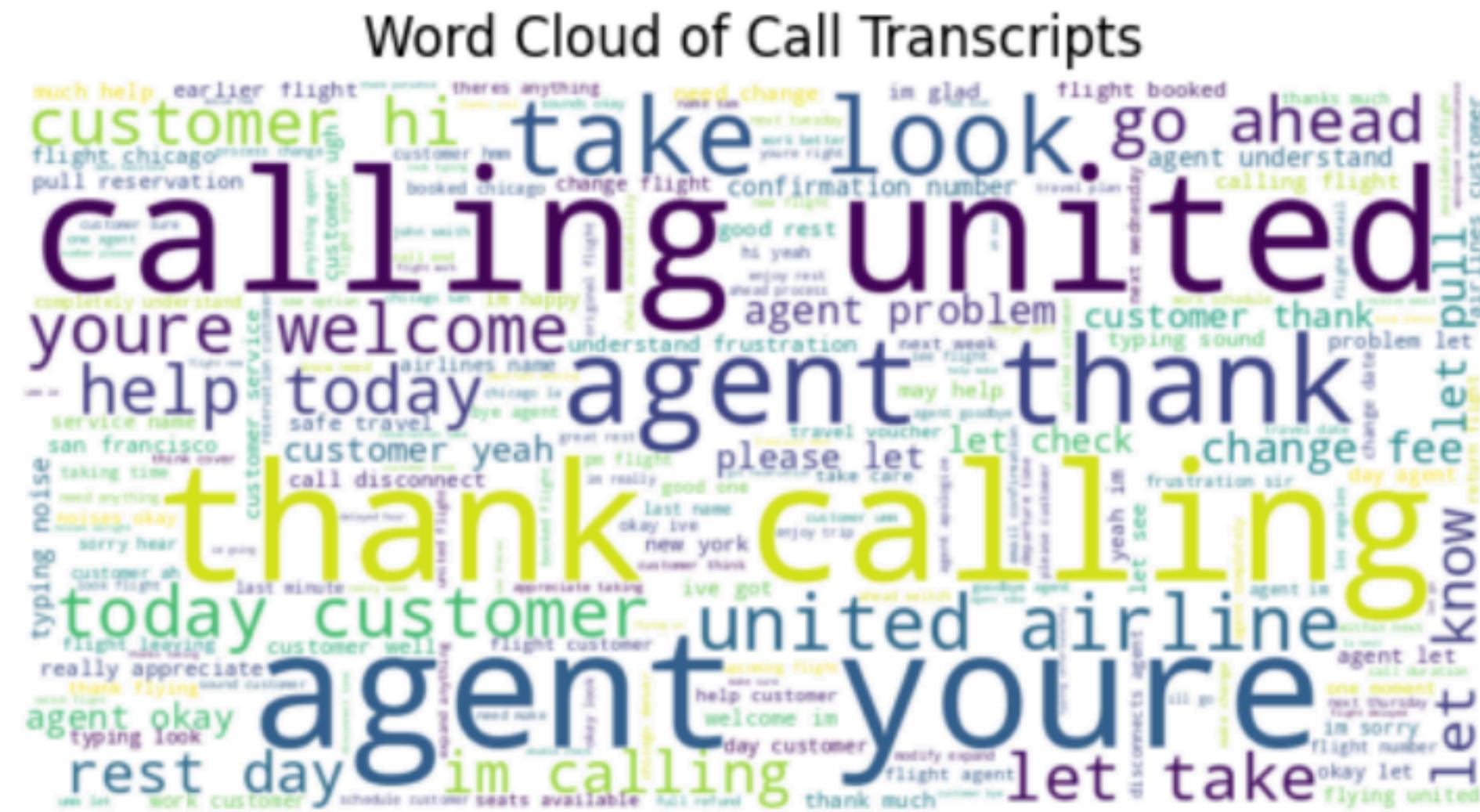
Most Frequent Call Reason: irrops, AHT: 785.1160694162722
Least Frequent Call Reason: unaccompanied minor, AHT: 519.2307692307693
Percentage Difference in AHT: 51.21%

```
Call Reason vs Handle Time:  
primary_call_reason  
checkout          1016.853814  
mileage plus      995.573406  
etc               962.899160  
post flight        932.896074  
communications     826.718750  
irrops             785.116069  
products and services 746.560624  
voluntary cancel   721.866833  
voluntary change   639.153761  
upgrade            632.344777  
check in           574.128151  
unaccompanied minor 519.230769  
schedule change    490.013680  
seating             474.994501  
booking             427.736064  
traveler updates   393.233725  
digital support     372.293878  
other topics        350.097800  
baggage             333.644068  
disability          292.109181  
Name: AHT, dtype: float64
```

DELIVERABLE 2

Analyse the transcripts and call reasons to identify granular reasons associated to recurring problems that could be resolved via self-service options in the IVR system.

We analyze the call transcripts using NLP(natural language precessing) from which removing trailing and leading spaces,special characters and stop words



Insights and reason

Top 10 most frequent words in call transcripts:

```
[('flight', 584640),  
 ('agent', 514677),  
 ('customer', 506450),  
 ('let', 280207),  
 ('change', 227941),  
 ('im', 220868),  
 ('help', 186566),  
 ('like', 180127),  
 ('thank', 171490),  
 ('would', 163331)]
```

```
Call Reason vs Handle Time:  
 primary_call_reason  
 checkout 1016.853814  
 mileage plus 995.573406  
 etc 962.899160  
 post flight 932.896074  
 communications 826.718750  
 irrops 785.116069  
 products and services 746.560624  
 voluntary cancel 721.866833  
 voluntary change 639.153761  
 upgrade 632.344777  
 check in 574.128151  
 unaccompanied minor 519.230769  
 schedule change 490.013680  
 seating 474.994501  
 booking 427.736064  
 traveler updates 393.233725  
 digital support 372.293878  
 other topics 350.097800  
 baggage 333.644068  
 disability 292.109181  
 Name: AHT, dtype: float64
```



Specific improvements to the IVR options to effectively reduce agent intervention in these cases, along with solid reasoning to support your recommendations.

RECOMMENDATIONS

After Analyze the most commonly associated reasons are irrops ,voluntary change ,seating
So we can add these primary call reasons in our IVR system so that mostly customer queries will resolve through IVR systems without agent intervention

Recommendations for IVR system improvements:

Consider adding a self-service option for: irrops

Consider adding a self-service option for: voluntary change

Consider adding a self-service option for: seating

DELIVERABLE 3

1. Data Preprocessing

- Merged multiple datasets and handled missing values (e.g., filling average_sentiment with the mode,elite_level_code NAN values with mode and agent tone NAN values with mode).
- Created new features like call_duration and vectorized call_transcript using TF-IDF.
- Normalized primary_call_reason and encoded categorical features.

2. EDA

- Visualized distributions of primary_call_reason and explored relationships between sentiment and call reasons.

3. Model Training

- Trained a Random Forest Classifier on the dataset split into training/testing sets.

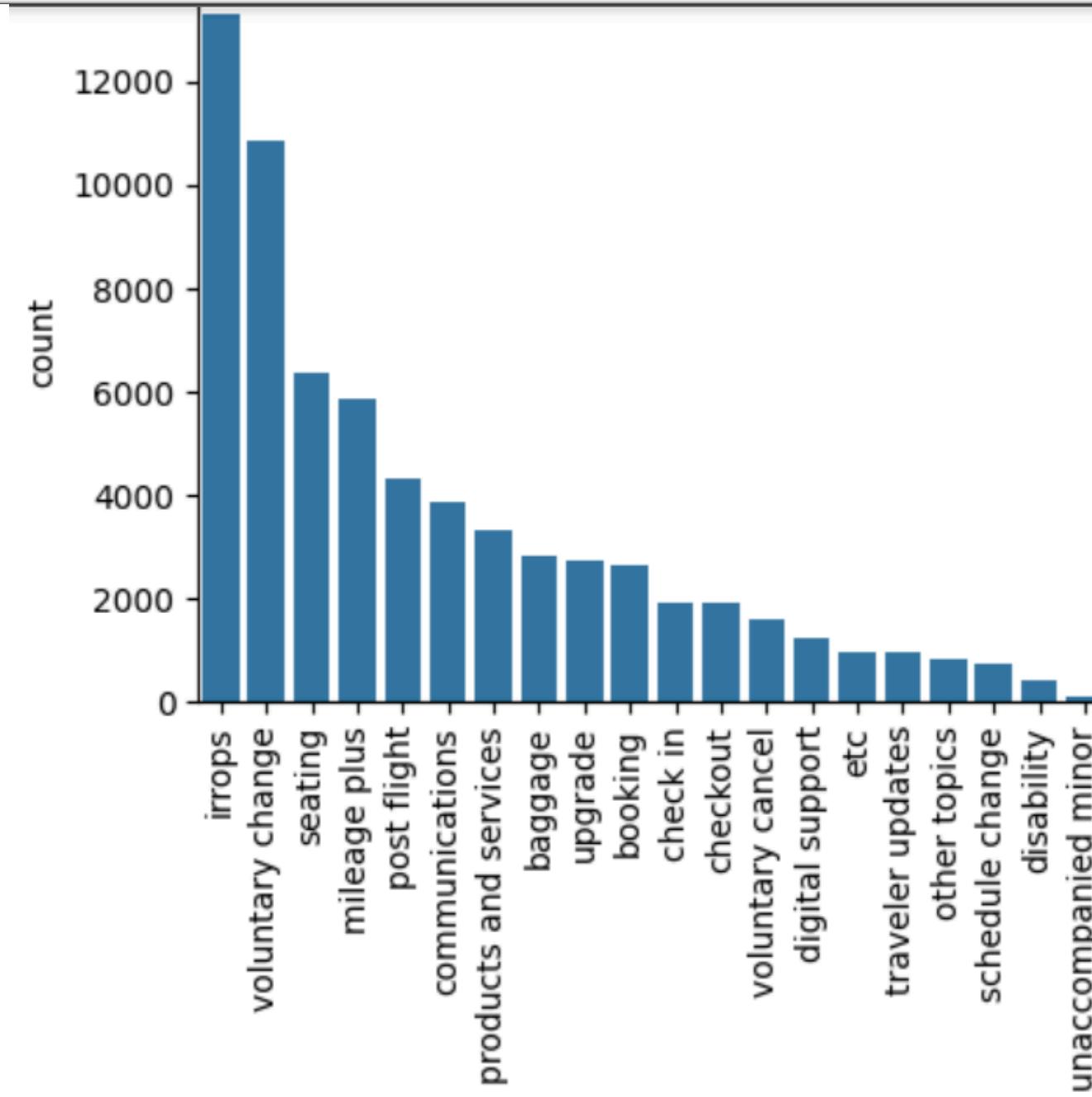
4. Evaluation

- Assessed performance using precision, recall, F1-score, and confusion matrix.

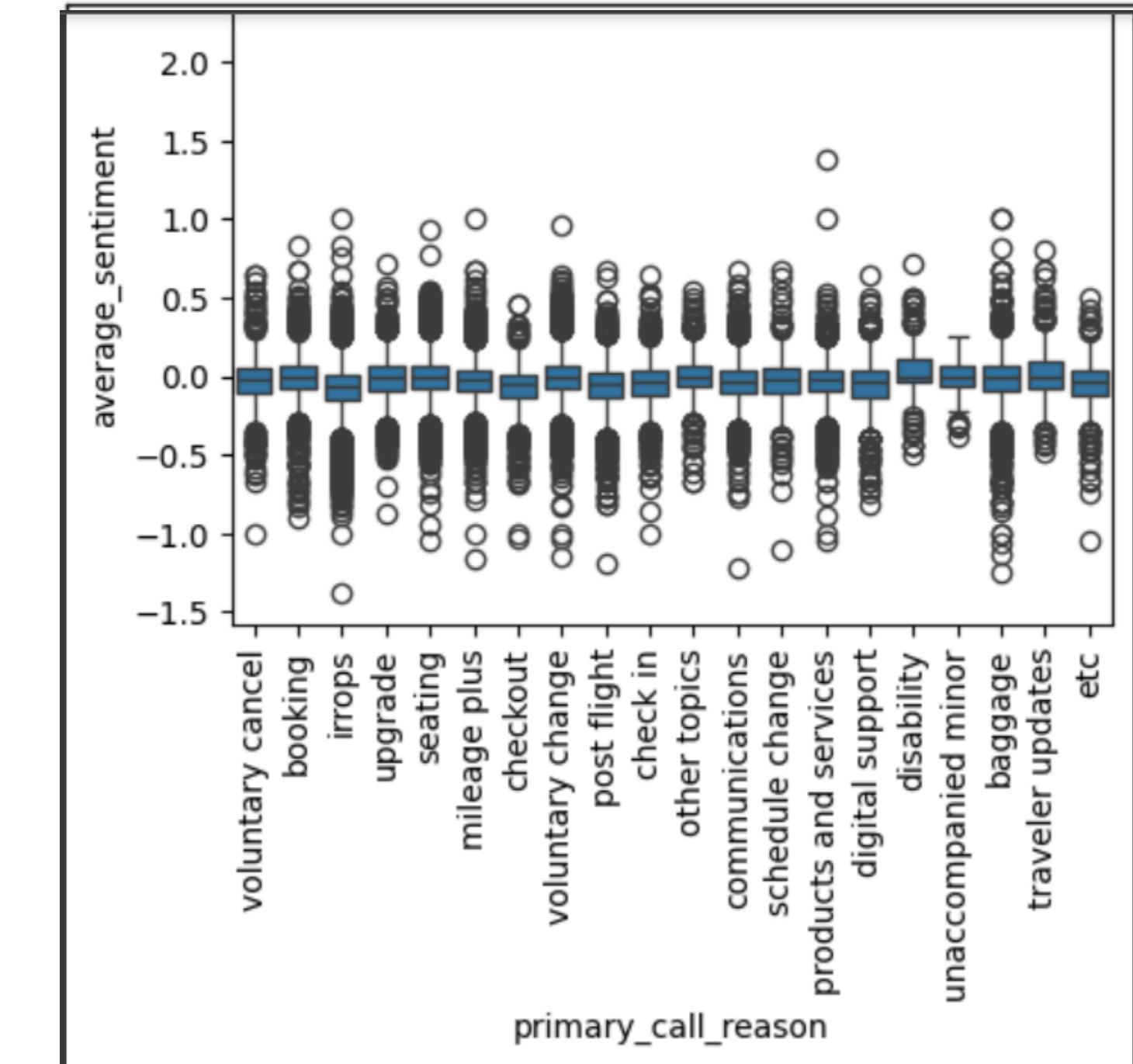
5. Test Prediction

- Made predictions on the test set and saved results to test_output.csv.

Distribution of Primary Call Reasons

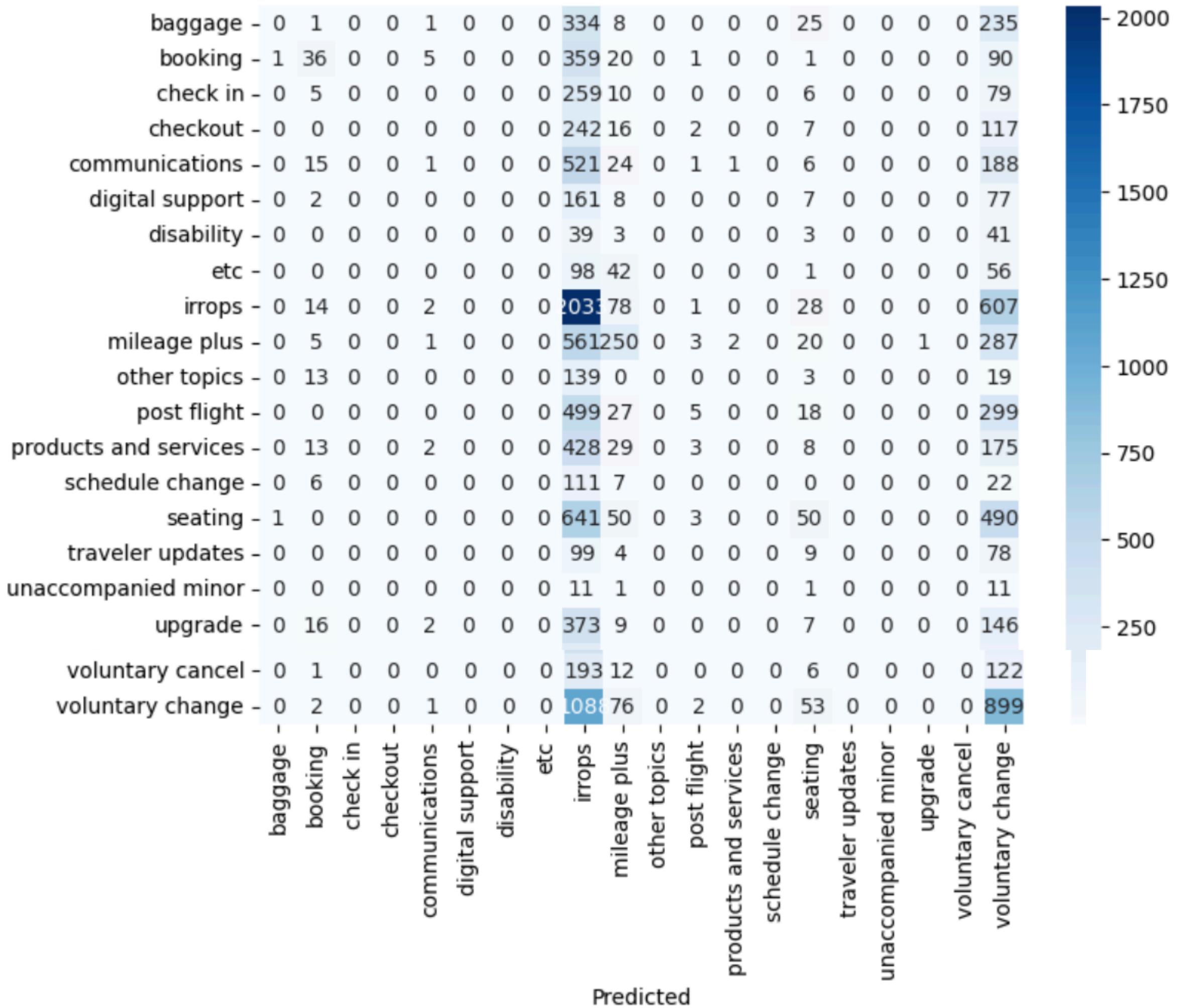


Average Sentiment by Primary Call Reason





Confusion Matrix



Classification metrics

	precision	recall	f1-score	support
baggage	0.00	0.00	0.00	604
booking	0.28	0.07	0.11	513
check in	0.00	0.00	0.00	359
checkout	0.00	0.00	0.00	384
communications	0.07	0.00	0.00	757
digital support	0.00	0.00	0.00	255
disability	0.00	0.00	0.00	86
etc	0.00	0.00	0.00	197
irrops	0.25	0.74	0.37	2763
mileage plus	0.37	0.22	0.28	1130
other topics	0.00	0.00	0.00	174
post flight	0.24	0.01	0.01	848
products and services	0.00	0.00	0.00	658
schedule change	0.00	0.00	0.00	146
seating	0.19	0.04	0.07	1235
traveler updates	0.00	0.00	0.00	190
unaccompanied minor	0.00	0.00	0.00	24
upgrade	0.00	0.00	0.00	553
voluntary cancel	0.00	0.00	0.00	334
voluntary change	0.22	0.42	0.29	2121
accuracy			0.25	13331
macro avg	0.08	0.07	0.06	13331
weighted avg	0.17	0.25	0.16	13331

Model Accuracy: 0.24559297877128497



FINAL OUTPUT

Made predictions on the test set and saved results to `test_shohel.csv`.

	call_id	primary_call_reason
0	7732610078	seating
1	2400299738	baggage
2	6533095063	booking
3	7774450920	baggage
4	9214147168	baggage
...
5152	5300201106	baggage
5153	727694488	baggage
5154	147487837	irrops
5155	5330794838	seating
5156	8332067080	baggage
5157 rows × 2 columns		



THANK YOU
FOR YOUR ATTENTION

