Call Center Metrics Redefined

Solutions for Faster and
Better Service

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Executive Summary

United Airlines’ call center faces challenges in improving Average Handle Time (AHT) and Average Speed to Answer (AST), impacting both efficiency and customer satisfaction. Our analysis identified key factors contributing to long AHT, including agent performance, complex call types, and customer sentiment, particularly during peak call volumes.

The most frequent call reasons, such as flight changes, have significantly longer AHT than less frequent queries, with a 50% difference between the two.

To optimize performance, we recommend enhanced agent training, AI-driven automation for routine inquiries, skill-based routing, and sentiment analysis tools. Streamlining internal processes will further reduce AHT and improve overall call center efficiency.

PROBLEM STATEMENT

United Airlines is committed to becoming the best airline in aviation history by providing world-class customer service. A critical aspect of achieving this goal is optimizing the performance of our call center operations, which are essential for resolving customer issues swiftly and efficiently. However, we are currently facing key challenges in improving call center metrics, particularly:

- **High Average Handle Time (AHT):** Leading to extended customer interactions and delayed resolutions.
- **Long Average Speed to Answer (AST):** Resulting in longer wait times for customers, impacting their overall satisfaction.

To enhance customer experience and streamline operations, we must identify the inefficiencies driving these prolonged metrics and implement strategies to improve customer satisfaction, reduce escalations, and boost overall operational efficiency.

Analysis of Long Average Handle Time (AHT) and Average Speed to Answer (AST)

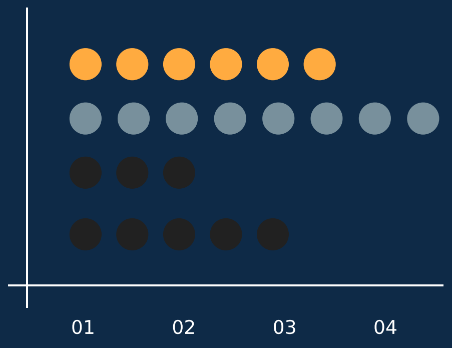
Problem:

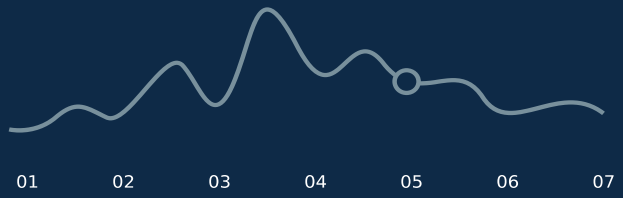
- Long AHT negatively impacts both efficiency and customer satisfaction. It means agents spend more time on each call, leading to fewer customers being helped, slower service, and increased operational costs.

- Long AST means customers wait longer in the queue, which frustrates them and increases the likelihood of abandoned calls.

Key Tasks :

- Explore factors contributing to **extended AHT** (agent performance, call types, sentiment).
- Identify **key drivers** of long AHT and AST during high-volume call periods.
- **Quantify percentage difference** between frequent and infrequent call reasons.





Why It Matters :

- **Reduce AHT** to handle more calls and improve service.
- **Lower AST** to minimize customer wait times and frustration.
- Target specific **areas for improvement** in agent performance and IVR system.

Approach:

- **Data Analysis**: Evaluate agent performance, call types, and customer sentiment.
- **High-Volume Analysis**: Examine spikes in AHT and AST during peak periods.
- **Comparative Metrics**: Calculate AHT differences to find inefficiencies.

EDA (Exploratory data analysis)

```
sns.set_style('whitegrid')
sns.set_context('notebook')
sns.set_palette('viridis')
```

```
calls.head(2)
```

	call_id	customer_id	agent_id	call_start_datetime	agent_assigned_datetime	call_end_datetime	call_transcript
0	4667960400	2033123310	963118	7/31/2024 23:56	8/1/2024 0:03	8/1/2024 0:34	\n\nAgent: Thank you for calling United Airlin...
1	1122072124	8186702651	519057	8/1/2024 0:03	8/1/2024 0:06	8/1/2024 0:18	\n\nAgent: Thank you for calling United Airlin...

```
customers.head(2)
```

	customer_id	customer_name	elite_level_code
0	2033123310	Matthew Foster	4.0
1	8186702651	Tammy Walters	NaN

```
reason.head(2)
```

	call_id	primary_call_reason
0	4667960400	Voluntary Cancel
1	1122072124	Booking

```
sentiments.head(2)
```

	call_id	agent_id	agent_tone	customer_tone	average_sentiment	silence_percent_average
0	4667960400	963118	neutral	angry	-0.04	0.39
1	1122072124	519057	calm	neutral	0.02	0.35

```
# merge the dataframes
df = pd.merge(calls, customers, on='customer_id', how='left')
df = pd.merge(df, sentiments, on=['call_id', 'agent_id'], how='left')
df = pd.merge(df, reason, on='call_id', how='left')
```

```
df.head(2)
```

	call_id	customer_id	agent_id	call_start_datetime	agent_assigned_datetime	call_end_datetime	call_transcript	customer_name	el
0	4667960400	2033123310	963118	7/31/2024 23:56	8/1/2024 0:03	8/1/2024 0:34	\n\nAgent: Thank you for calling United Airlin...	Matthew Foster	
1	1122072124	8186702651	519057	8/1/2024 0:03	8/1/2024 0:06	8/1/2024 0:18	\n\nAgent: Thank you for calling United Airlin...	Tammy Walters	

```
# shape of dataset
df.shape
```

```
(71810, 14)
```

```
# dtypes in dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71810 entries, 0 to 71809
Data columns (total 14 columns):
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71810 entries, 0 to 71809
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   call_id                  71810 non-null  int64
 1   customer_id              71810 non-null  int64
 2   agent_id                 71810 non-null  int64
 3   call_start_datetime      71810 non-null  object
 4   agent_assigned_datetime  71810 non-null  object
 5   call_end_datetime        71810 non-null  object
 6   call_transcript          71810 non-null  object
 7   customer_name            71810 non-null  object
 8   elite_level_code         46043 non-null  float64
 9   agent_tone               71593 non-null  object
 10  customer_tone            71810 non-null  object
 11  average_sentiment        71701 non-null  float64
 12  silence_percent_average  71810 non-null  float64
 13  primary_call_reason      66653 non-null  object
dtypes: float64(3), int64(3), object(8)
memory usage: 7.7+ MB
```

8]:

```
# datetime columns have dtype='object' , should be converted
df['call_start_datetime'] = pd.to_datetime(df['call_start_datetime'])
df['agent_assigned_datetime'] = pd.to_datetime(df['agent_assigned_datetime'])
df['call_end_datetime'] = pd.to_datetime(df['call_end_datetime'])
```

9]:

```
# are there any missing values in dataframe
df.isnull().sum()
```

9]:

```
call_id                        0
customer_id                    0
agent_id                       0
call_start_datetime            0
agent_assigned_datetime        0
call_end_datetime              0
call_transcript                0
customer_name                  0
elite_level_code           25767
agent_tone                   217
customer_tone                  0
average_sentiment            109
silence_percent_average        0
primary_call_reason         5157
dtype: int64
```

EDA continued.

Creating Features

AHT (Average Handle Time):

- Time from when the agent picks up the call to when they hang up
- Formula:
- AHT = Total Handle Time / Total Number of Calls

AST (Average Speed to Answer):

- Time spent by the customer in queue till the agent answers the call
- Formula:
- AST = Total Waiting Time / Total Number of Calls

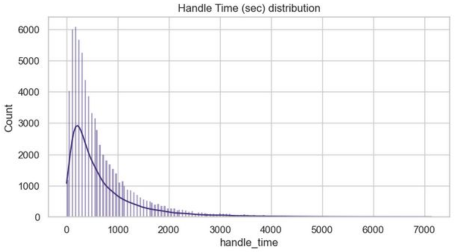
```python
# handle_time = call_end_datetime - agent_assigned_datetime, in seconds
df['handle_time'] = (df['call_end_datetime'] - df['agent_assigned_datetime']).dt.total_seconds()

# speed_to_answer = agent_assigned_datetime - call_start_datetime, in seconds
df['speed_to_answer'] = (df['agent_assigned_datetime'] - df['call_start_datetime']).dt.total_seconds()
```

```python
df.head(2)
```

	call_id	customer_id	agent_id	call_start_datetime	agent_assigned_datetime	call_end_datetime	call_transcript	customer_name	el
0	4667960400	2033123310	963118	2024-07-31 23:56:00	2024-08-01 00:03:00	2024-08-01 00:34:00	\n\nAgent: Thank you for calling United Airlin...	Matthew Foster	
1	1122072124	8186702651	519057	2024-08-01 00:03:00	2024-08-01 00:06:00	2024-08-01 00:18:00	\n\nAgent: Thank you for calling United Airlin...	Tammy Walters	

AHT (Average Handle Time)

```python
# lets see the distribution of handle_time for each call:
plt.figure(figsize=(8,4))
sns.histplot(df.handle_time,kde=True)
plt.title('Handle Time (sec) distribution')
plt.show()
```



Right Skewed Distribution, though some outliers/extreme Customer Handle Times!

```python
AHT = np.mean(df.handle_time)
print(f"AHT (Average Handle Time) is {AHT:.2f} seconds")
```

```
AHT (Average Handle Time) is 697.05 seconds
```

This Average Handle Time is quite high! Approximately 12 minutes, this should be low.


```python
AHT = np.mean(df.handle_time)
print(f"AHT (Average Handle Time) is {AHT:.2f} seconds")
```

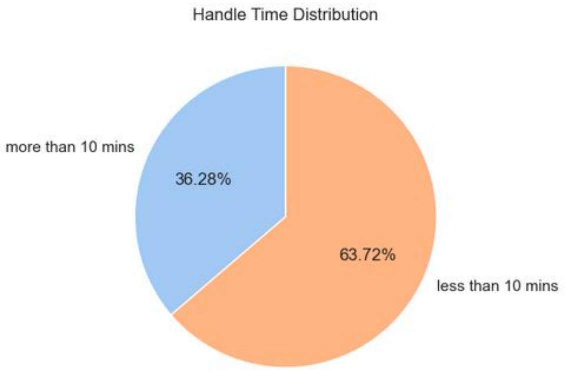
```
AHT (Average Handle Time) is 697.05 seconds
```

This Average Handle Time is quite high! Approximately 12 minutes, this should be low.


```python
# what percentage of calls exceed than 10 mins(600 seconds)
more_than_600 = df[df['handle_time'] > 600].shape[0]
less_or_equal_600 = df[df['handle_time'] <= 600].shape[0]

labels = ['more than 10 mins', 'less than 10 mins']
values = [more_than_600, less_or_equal_600]

print(f'{(more_than_600/df.shape[0])*100:.2f}% calls exceed 10 minutes!')
sns.set_palette('pastel')
# pie chart
plt.pie(values, labels=labels, autopct='%1.2f%%', startangle=90)
plt.title('Handle Time Distribution')
plt.show()
```

```
36.28% calls exceed 10 minutes!
```

```
36.28% calls exceed 10 minutes!
```



For more than 30% calls, Agents handle calls for more than 10 Minutes.

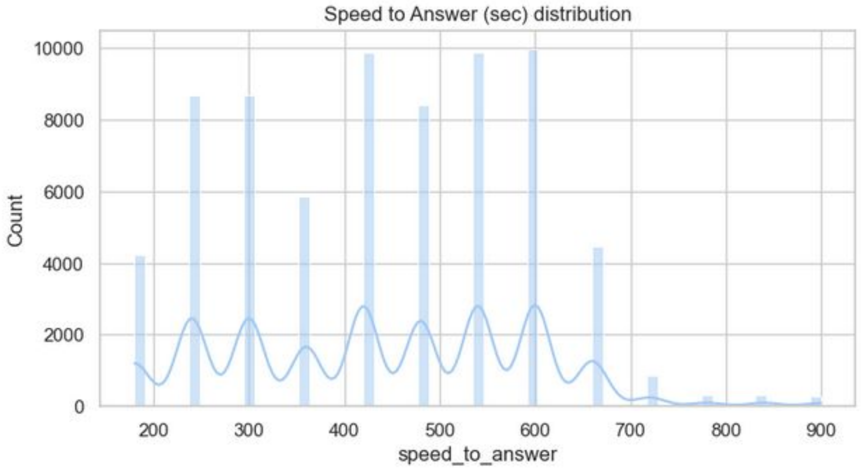

```python
AST = np.mean(df.speed_to_answer)
print(f"AST (Average Speed to Answer) is {AST:.2f} seconds")
```

```
AST (Average Speed to Answer) is 437.07 seconds
```

AST too , is very high , more than 7 minutes !

AST (Average Speed to Answer)

```python
# lets see the distribution of speed_to_answer for each call:
plt.figure(figsize=(8,4))
sns.histplot(df.speed_to_answer,kde=True)
plt.title('Speed to Answer (sec) distribution')
plt.show()
```




```python
# finding how many customers have to wait for more than 5 minutes(300 seconds)
wait_more_than_5mins = df[df.speed_to_answer>300].shape[0]/df.shape[0]
wait_less_than_5mins = df[df.speed_to_answer<=300].shape[0]/df.shape[0]
labels = ['More than 5 Min','Less than 5 Min']
values = [wait_more_than_5mins,wait_less_than_5mins]

print(f'{(wait_more_than_5mins)*100:.2f}% waiting time exceeds 5 minutes!')
sns.set_palette('pastel')
# pie chart
plt.pie(values, labels=labels, autopct='%1.2f%%', startangle=90)
plt.title('Wait Time Distribution')
plt.show()
```

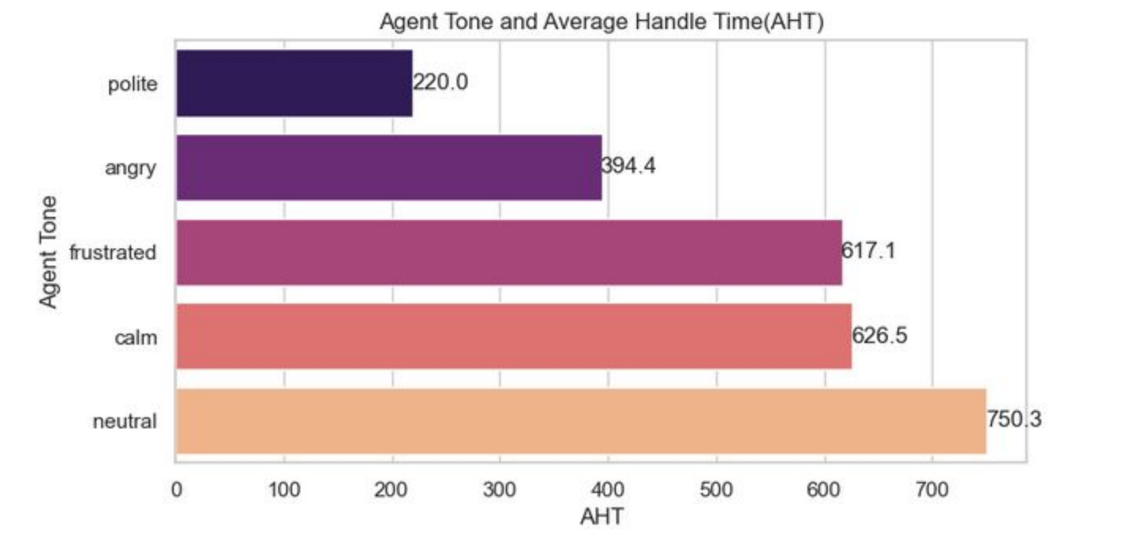
```
69.95% waiting time exceeds 5 minutes!
```

Agent Performance and AHT

```
# metrics: agent_tone, silence_percent_average, handle_time
```

Agent tone

```
# agent_tone vs AHT
df_agent_tone = df.groupby('agent_tone')['handle_time'].mean().reset_index().sort_values(by='handle_time')

plt.figure(figsize=(8,4))
ax = sns.barplot(df_agent_tone,x='handle_time',y='agent_tone',palette='magma')

for p in ax.patches:
    ax.annotate(f'{p.get_width():.1f}',
                (p.get_width()+25, p.get_y() + p.get_height() / 2),
                ha='center', va='center')
plt.xlabel('AHT')
plt.ylabel('Agent Tone')
plt.title('Agent Tone and Average Handle Time(AHT)')
plt.show()
```



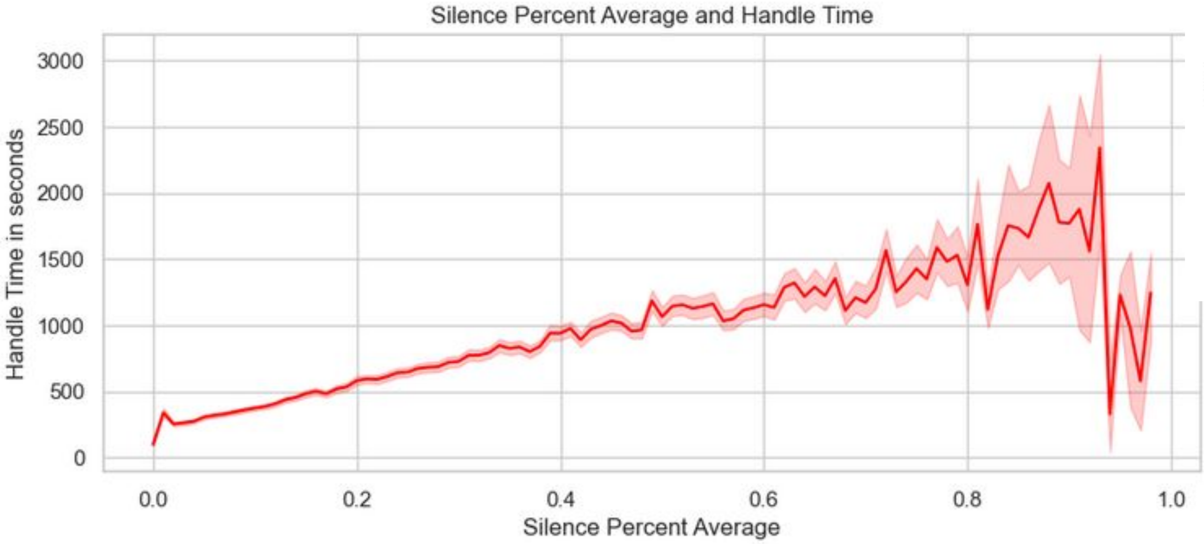
Observations

- AHT was lowest when Agent Tone was Polite.
- Surprisingly Neutral , Calm Agent tone had highest AHT.
- When Agent was Angry/ Frustrated AHT was low, though this is not recommended.

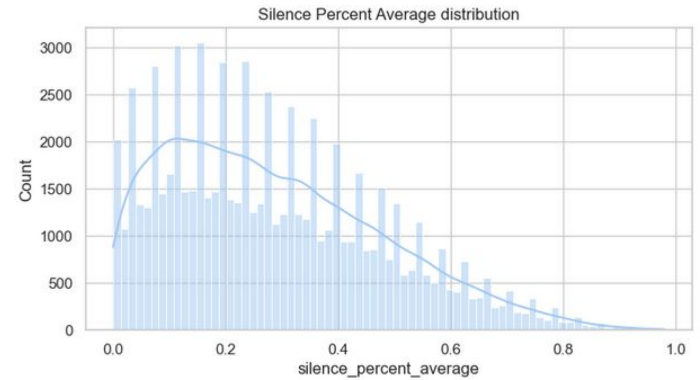
DATA ANALYSIS

Silence Percent Average

```python
# silence_percent_average vs AHT
#df_agent_tone = df.groupby('agent_tone')['handle_time'].mean().reset_index().sort_values(by='handle_time')

plt.figure(figsize=(10,4))

sns.lineplot(x=df.silence_percent_average,y=df.handle_time,color='red')
plt.xlabel('Silence Percent Average')
plt.ylabel('Handle Time in seconds')
plt.title('Silence Percent Average and Handle Time')
plt.show()
```




```python
# distribution of Silence Percent Average
plt.figure(figsize=(8,4))
sns.histplot(df.silence_percent_average,kde=True)
plt.title('Silence Percent Average distribution')
plt.show()
```



Observations

- A lot of calls have high Silence Percentage,
- and most of these calls have high Handle Time
- Silence between Conversations must be minimized!

Call Types and AHT

```
df.primary_call_reason.unique()
```

```
array(['Voluntary  Cancel', 'Booking', 'IRROPS', 'Upgrade', 'Seating',
       'Mileage   Plus', 'Checkout', nan, 'Voluntary   Change',
       'Post Flight', 'Check In', 'Other  Topics', 'Communications',
       'Schedule Change', 'Products & Services', 'IRROPS  ',
       'Digital   Support', 'Seating  ', 'Disability',
       'Unaccompanied Minor', ' Baggage', 'Traveler  Updates',
       'Communications  ', 'ETC', 'Upgrade  ', 'Unaccompanied Minor  ',
       'Voluntary Change', 'Voluntary Change  ', 'Checkout  ',
       'Mileage Plus', 'Mileage Plus  ', 'Booking  ', 'Baggage  ',
       'Post-Flight', 'Post-Flight  ', 'Schedule Change  ', 'Baggage',
       'Traveler Updates', 'Voluntary Cancel', 'Check-In',
       'Products and Services', 'Check-In  ', 'Other Topics',
       'Other Topics  ', 'ETC  ', 'Disability  ', 'Digital Support',
       'Digital Support  ', 'Voluntary Cancel  ',
       'Products and Services  ', 'Traveler Updates  ',
       'Traveler   Updates', 'Digital  Support', 'Mileage  Plus',
       'Voluntary  Change'], dtype=object)
```

```
# clean extra spaces in this column:
df.primary_call_reason = df.primary_call_reason.str.strip()
df.primary_call_reason = df.primary_call_reason.str.replace('-', ' ')
df.primary_call_reason = df.primary_call_reason.str.replace(r'\s+', ' ', regex=True).str.strip()
df.primary_call_reason = df.primary_call_reason.str.replace('&', 'and')
```

```
df.primary_call_reason.unique()
```

```
array(['Voluntary Cancel', 'Booking', 'IRROPS', 'Upgrade', 'Seating',
       'Mileage Plus', 'Checkout', nan, 'Voluntary Change', 'Post Flight',
       'Check In', 'Other Topics', 'Communications', 'Schedule Change',
       'Products and Services', 'Digital Support', 'Disability',
       'Unaccompanied Minor', 'Baggage', 'Traveler Updates', 'ETC'],
      dtype=object)
```

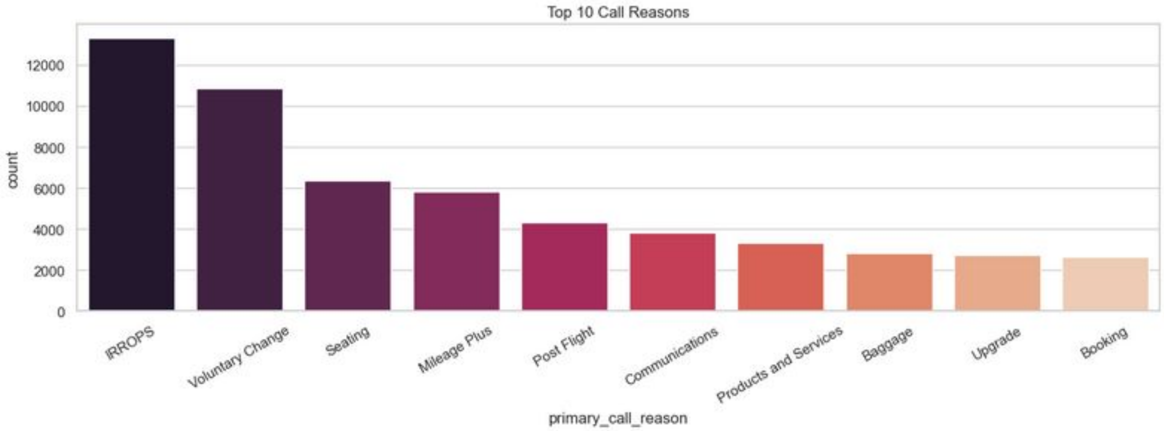
```
# is AHT affected by call reason?

df.groupby('primary_call_reason')['handle_time'].mean().reset_index().sort_values(by='handle_time')
```

	primary_call_reason	handle_time
6	Disability	292.109181
0	Baggage	333.644068
10	Other Topics	350.097800
5	Digital Support	372.293878
15	Traveler Updates	393.233725

Observation

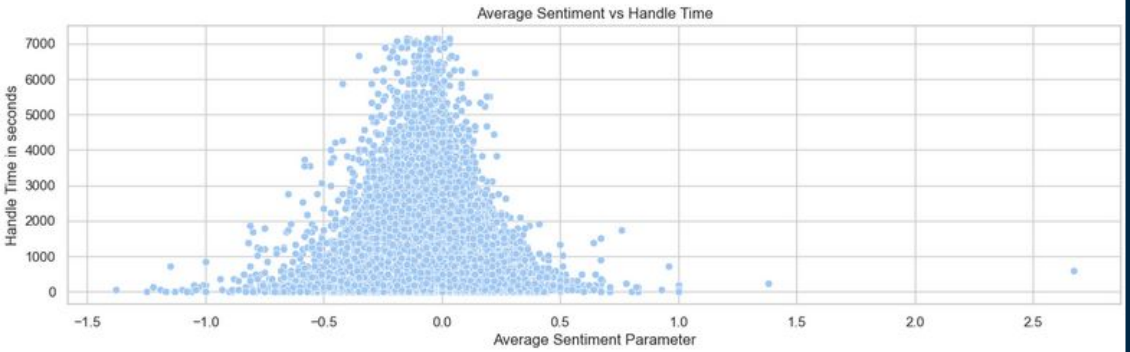
- Disability, Baggage and Other topics have lowest AHT.
- Post Flight, ETC, Mileage Plus and Checkout have highest AHT.
- These sectors must be optimized in future.

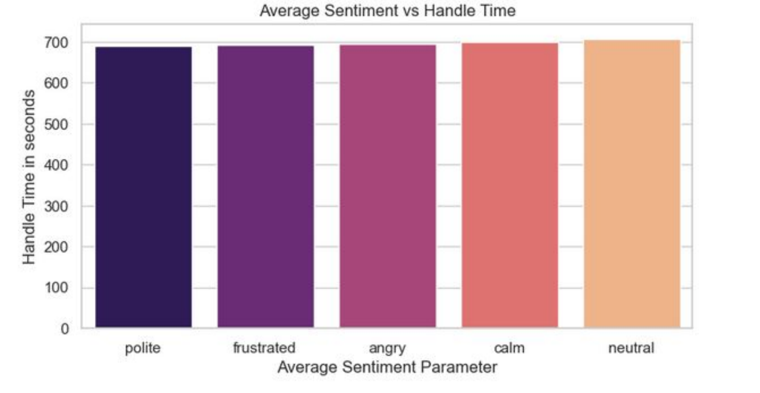
```
top_10_callreason = df.primary_call_reason.value_counts().reset_index()[:10]
plt.figure(figsize=(15,4))
sns.barplot(top_10_callreason,x='primary_call_reason',y='count',palette='rocket')
plt.title('Top 10 Call Reasons')
plt.xticks(rotation=30)
plt.show()
```



Sentiment and AHT

```
# average sentiment and handle time
plt.figure(figsize=(15,4))
sns.scatterplot(x=df.average_sentiment,y=df.handle_time)
plt.xlabel('Average Sentiment Parameter')
plt.ylabel('Handle Time in seconds')
plt.title('Average Sentiment vs Handle Time')
plt.show()
```





Observation

- Except a few outliers, generally Handle Time is high for Average Sentiment=0
- As indicated earlier, calm, neutral tones had similar trend.

Observation

- Interesting, there is no relation between Customer Tone and AHT.
- This indicates that Agent Tone is a primary factor which determines AHT.
- Agents must be trained to maintain Polite tone as indicated by previous charts.

High Volume Call Periods

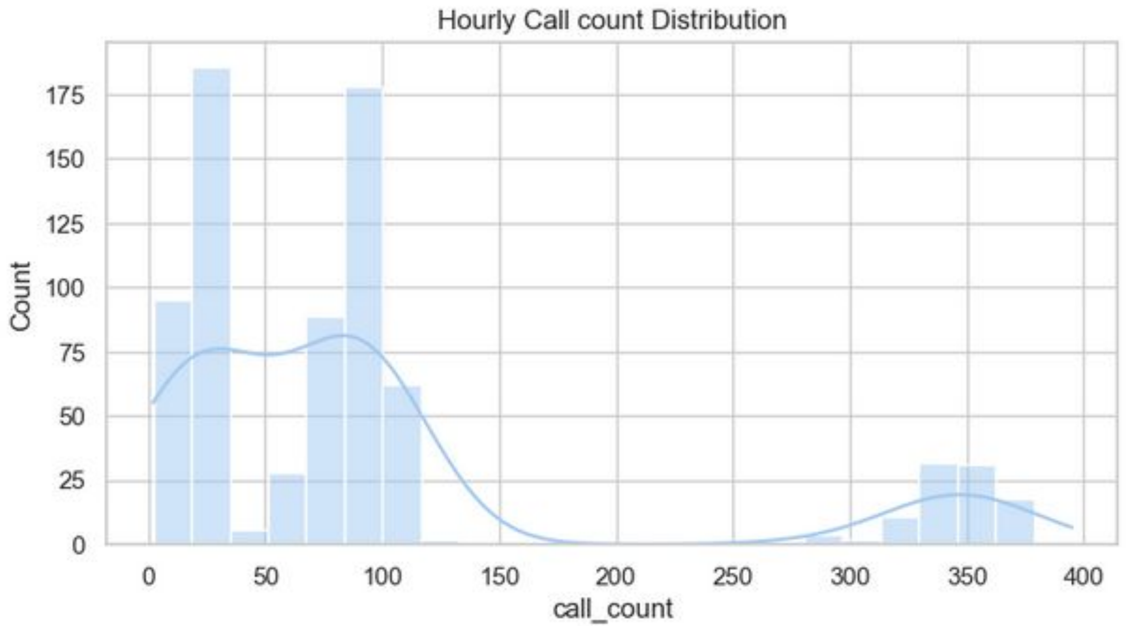
```
#Key drivers of Long AST and AHT , during high volume call periods
```

```
df.call_start_datetime
```

```
0        2024-07-31 23:56:00
1        2024-08-01 00:03:00
2        2024-07-31 23:59:00
3        2024-08-01 00:05:00
4        2024-08-01 00:04:00
                ...
71805    2024-08-31 23:48:00
71806    2024-08-31 23:55:00
71807    2024-08-31 23:52:00
71808    2024-08-31 23:53:00
71809    2024-08-31 23:49:00
Name: call_start_datetime, Length: 71810, dtype: datetime64[ns]
```

```
# identifying high volume call periods
df['hour'] = df['call_start_datetime'].dt.floor('H')
high_volume_periods = df.groupby('hour').size().reset_index(name='call_count')
```

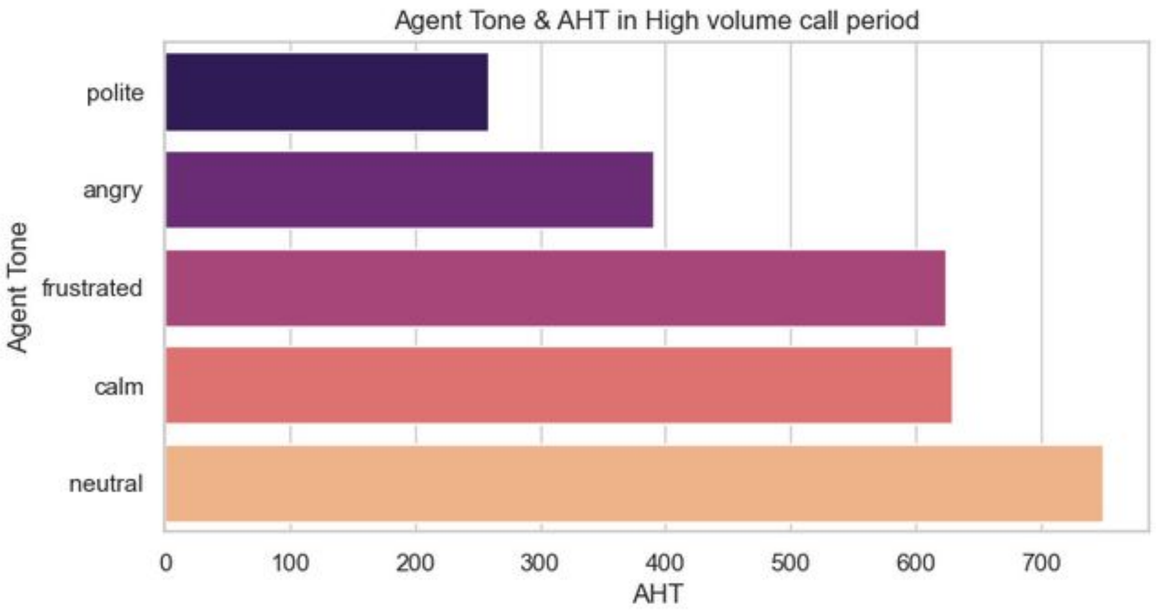
```
plt.figure(figsize=(8,4))
sns.histplot(high_volume_periods.call_count,kde=True)
plt.title('Hourly Call count Distribution')
plt.show()
```



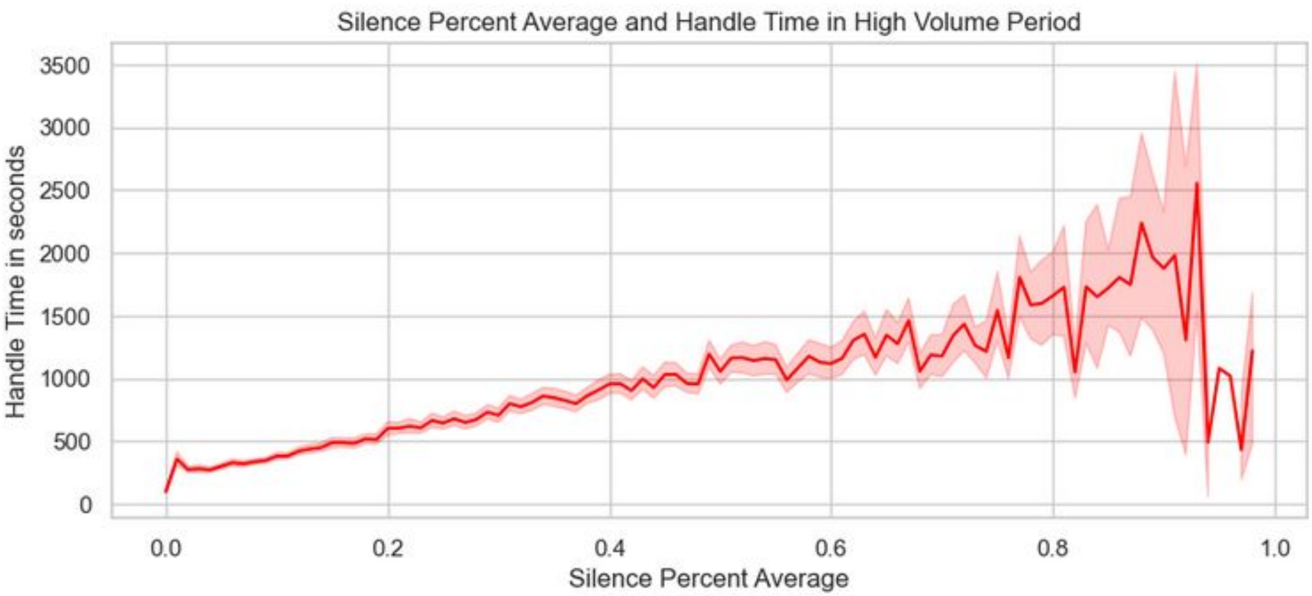

```
# lets take call count> 250 as high volume period
high_volume_periods = high_volume_periods[high_volume_periods.call_count>250]
high_volume_periods
```

	hour	call_count
57	2024-08-03 08:00:00	323
58	2024-08-03 09:00:00	346

```python
# agent tone in high volume call periods:
df_agent_tone = df_volume.groupby('agent_tone')['handle_time'].mean().reset_index().sort_values(by='handle_time')

plt.figure(figsize=(8,4))
sns.barplot(df_agent_tone,x='handle_time',y='agent_tone',palette='magma')
plt.xlabel('AHT')
plt.ylabel('Agent Tone')
plt.title('Agent Tone & AHT in High volume call period')
plt.show()
```



- similar observations in High volume call periods




```
100]:
# AHT and AST in high volume call period:
print(f"AHT in high Volume Call Period: {df_volume.handle_time.mean():.2f} seconds")
print(f"AST in high Volume Call Period: {df_volume.speed_to_answer.mean():.2f} seconds")
```

```
AHT in high Volume Call Period: 697.70 seconds
AST in high Volume Call Period: 436.49 seconds
```

Observation

- Similar AHT and AST in High Volume Call periods!
- AHT, AST must be lowered in High Volume periods to introduce efficiency.

Recommendations/Solutions

Analysis of Long AHT and Key Drivers

1. Factors Contributing to Long AHT:

- **Agent Performance**: Highlight that differences in agent efficiency, skill levels, and experience can impact call durations.
- **Call Types**: Categorize calls based on complexity (e.g., flight changes vs. simple inquiries) and note that more complex call types lead to longer handling times.
- **Customer Sentiment**: Demonstrate that calls involving frustrated or upset customers tend to take longer as agents must de-escalate emotions before addressing the issue.

2. Key Drivers During High-Volume Periods:

- **Peak Demand**: Show that during peak times (e.g., bad weather, holidays), both AHT and AST increase due to higher call volumes and agent stress.
- **Technical Issues**: Identify system outages or slow internal processes that slow down agents’ ability to resolve issues efficiently.

3. Data Insights:

- **Most Frequent vs. Least Frequent Call Reasons**: Present a visual chart comparing call reasons (e.g., flight cancellations vs. seat preferences), highlighting the time difference between them.
- **Percentage Difference**: If the most frequent call reason has an AHT of 12 minutes and the least frequent is 8 minutes, the percentage difference is ~50%.

Recommendations to Reduce AHT

1. Improved Agent Training:

- Focus on cross-training agents to handle multiple call types more efficiently.
- Implement real-time coaching for agents struggling with specific call types.

2. Automation and AI:

- Leverage AI to handle routine inquiries (e.g., flight status, baggage tracking), reducing the load on human agents and freeing them to handle more complex calls.

3. Advanced Call Routing:

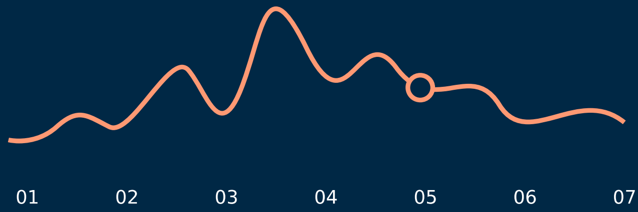
- Introduce skill-based routing to ensure complex calls are handled by the most experienced agents, while simpler queries are directed to less experienced agents or self-service options.

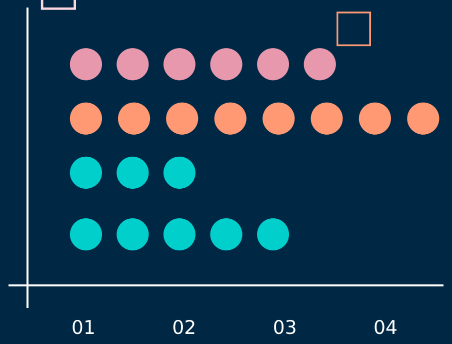
4. Sentiment Analysis Integration:

- Use sentiment analysis tools to identify frustrated customers early in the call and equip agents with playbooks on how to de-escalate efficiently, reducing call time.

5. Process Improvements:

- Streamline internal systems and tools to improve agent efficiency, such as faster access to customer records or quicker flight rebooking systems.





THANK YOU