HCC - Case Study

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1 HCC - Case Study

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In the bustling world of healthcare, efficient and effective communication between patients and healthcare providers is paramount. The Hospital System's Call Center (HCC) plays a crucial role in this regard, as it serves as the primary hub for handling inbound calls and managing telephonic interactions with patients. These interactions encompass a wide range of issues, from scheduling appointments to resolving queries related to patient care across various outpatient clinics.

In the following analysis, we will embark on a journey through this dataset to unearth insights and address crucial questions. Our goals are to conduct exploratory data analysis to summarize HCC's current state, identify key questions that the HCC manager can pose, define a model for productivity, and create a user-friendly dashboard to empower business leaders to make informed decisions based on this invaluable data resource. This multifaceted approach will not only enhance the efficiency of HCC operations but also elevate the quality of patient care provided by the Hospital System.

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1 - Data Prepocessing

- Load dataset
- Merging
- Check data info

[1]:
```
#Import necessary libraries
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns

import plotly.express as px
import plotly.graph_objs as go
from plotly.subplots import make_subplots

import dash
import dash_core_components as dcc
import dash_html_components as html
from dash.dependencies import Input, Output
```

```
/var/folders/x8/vmspvpd557j0gjkqkwzhf08m0000gn/T/ipykernel_40140/1656482956.py:1
2: UserWarning:
The dash_core_components package is deprecated. Please replace
`import dash_core_components as dcc` with `from dash import dcc`
  import dash_core_components as dcc
/var/folders/x8/vmspvpd557j0gjkqkwzhf08m0000gn/T/ipykernel_40140/1656482956.py:1
3: UserWarning:
The dash_html_components package is deprecated. Please replace
`import dash_html_components as html` with `from dash import html`
  import dash_html_components as html
```

[2]:
```
# Load the dataset
sheet1 = pd.read_excel("Case Study Data.xlsx", sheet_name="Total logged-in␣
↪time")
sheet2 = pd.read_excel("Case Study Data.xlsx", sheet_name="Not_Ready_Time")
sheet3 = pd.read_excel("Case Study Data.xlsx",␣
↪sheet_name="Handled_Calls&Handle_Time")
sheet4 = pd.read_excel("Case Study Data.xlsx", sheet_name="Agent Team Lookup")
```

[3]:
```
# Check first 5 rows to see the dataset is loaded correctly
sheet1.head()
```

[3]:
```
  Agent ID Interval Start Time   Interval End Time Total Logged In Time  \
0  Agent 1 2022-08-01 08:00:00 2022-08-01 08:30:00             00:27:02
1  Agent 1 2022-08-01 08:30:00 2022-08-01 09:00:00             00:30:00
2  Agent 1 2022-08-01 09:00:00 2022-08-01 09:30:00             00:30:00
3  Agent 1 2022-08-01 09:30:00 2022-08-01 10:00:00             00:30:00
4  Agent 1 2022-08-01 10:00:00 2022-08-01 10:30:00             00:30:00

  Not Ready Time Ready Time Reserved Time Talk Time Next Call Prep Time
0       00:03:26   00:00:07      00:00:22  00:21:51            00:01:16
1       00:01:33   00:01:52      00:00:33  00:24:29            00:01:33
2       00:04:16   00:00:00      00:00:37  00:23:01            00:02:06
3       00:06:14   00:00:00      00:00:15  00:22:23            00:01:08
4       00:01:49   00:00:00      00:00:15  00:26:57            00:00:59
```

[4]:
```
# Check first 5 rows to see the dataset is loaded correctly
sheet2.head()
```

[4]:
```
   Agent ID Interval Start Time   Interval End Time Total Logged-in  \
0  Agent 1 2022-08-01 08:00:00 2022-08-01 08:30:00        00:27:02
1  Agent 1 2022-08-01 08:30:00 2022-08-01 09:00:00        00:30:00
2  Agent 1 2022-08-01 09:00:00 2022-08-01 09:30:00        00:30:00
3  Agent 1 2022-08-01 09:30:00 2022-08-01 10:00:00        00:30:00
4  Agent 1 2022-08-01 10:00:00 2022-08-01 10:30:00        00:30:00

  Total Not Ready     Break     Lunch Team Support   Meeting After Call Work  \
0        00:03:26  00:00:00  00:00:00     00:00:00  00:00:00        00:03:23
1        00:01:33  00:00:00  00:00:00     00:00:00  00:00:00        00:01:33
2        00:04:16  00:00:01  00:00:00     00:00:00  00:00:00        00:04:15
3        00:06:14  00:06:14  00:00:00     00:00:00  00:00:00        00:00:00
4        00:01:49  00:00:00  00:00:00     00:00:00  00:00:00        00:01:49

  Special Projects  Training System Issues     Other
0         00:00:00  00:00:00      00:00:00  00:00:03
1         00:00:00  00:00:00      00:00:00  00:00:00
2         00:00:00  00:00:00      00:00:00  00:00:00
3         00:00:00  00:00:00      00:00:00  00:00:00
4         00:00:00  00:00:00      00:00:00  00:00:00
```

[5]:
```
# Check first 5 rows to see the dataset is loaded correctly
sheet3.head()
```

[5]:
```
   Agent ID       Date  Number of Calls Handled Average Handle Time
0  Agent 1 2022-08-01                       94            00:04:40
1  Agent 1 2022-08-02                       80            00:04:42
2  Agent 1 2022-08-03                       81            00:04:34
3  Agent 1 2022-08-04                       73            00:05:12
4  Agent 1 2022-08-05                       75            00:04:51
```

[6]:
```
# Check first 5 rows to see the dataset is loaded correctly
sheet4.head()
```

[6]:
```
   Agent ID Agent Team
0  Agent 1     team_1
1  Agent 2     team_3
2  Agent 3     team_3
3  Agent 4     team_4
4  Agent 5     team_4
```

Since sheet 1 and sheet 2 and sheet 4 have the common column 'Agent ID', 'Interval Start Time', 'Interval End Time', we will merge these two sheets. Sheet 3 will be left as is for further analysis (if we merge, the information will be duplicated).

[7]:
```
# Merge sheet1 and sheet2 on 'Agent ID', 'Interval Start Time', and 'Interval␣
↪End Time'
hcc_df = pd.merge(sheet1, sheet2, on=['Agent ID', 'Interval Start Time',␣
↪'Interval End Time'])
hcc_df = pd.merge(hcc_df, sheet4, on=['Agent ID'])
```

[8]:
```
hcc_df.head()
```

[8]:
```
  Agent ID Interval Start Time   Interval End Time Total Logged In Time  \
0  Agent 1 2022-08-01 08:00:00 2022-08-01 08:30:00             00:27:02
1  Agent 1 2022-08-01 08:30:00 2022-08-01 09:00:00             00:30:00
2  Agent 1 2022-08-01 09:00:00 2022-08-01 09:30:00             00:30:00
3  Agent 1 2022-08-01 09:30:00 2022-08-01 10:00:00             00:30:00
4  Agent 1 2022-08-01 10:00:00 2022-08-01 10:30:00             00:30:00

  Not Ready Time Ready Time Reserved Time Talk Time Next Call Prep Time  \
0       00:03:26   00:00:07      00:00:22  00:21:51            00:01:16
1       00:01:33   00:01:52      00:00:33  00:24:29            00:01:33
2       00:04:16   00:00:00      00:00:37  00:23:01            00:02:06
3       00:06:14   00:00:00      00:00:15  00:22:23            00:01:08
4       00:01:49   00:00:00      00:00:15  00:26:57            00:00:59

  Total Logged-in  …     Break     Lunch Team Support   Meeting  \
0        00:27:02  …  00:00:00  00:00:00     00:00:00  00:00:00
1        00:30:00  …  00:00:00  00:00:00     00:00:00  00:00:00
2        00:30:00  …  00:00:01  00:00:00     00:00:00  00:00:00
3        00:30:00  …  00:06:14  00:00:00     00:00:00  00:00:00
4        00:30:00  …  00:00:00  00:00:00     00:00:00  00:00:00

  After Call Work Special Projects  Training System Issues     Other  \
0        00:03:23         00:00:00  00:00:00      00:00:00  00:00:03
1        00:01:33         00:00:00  00:00:00      00:00:00  00:00:00
2        00:04:15         00:00:00  00:00:00      00:00:00  00:00:00
3        00:00:00         00:00:00  00:00:00      00:00:00  00:00:00
4        00:01:49         00:00:00  00:00:00      00:00:00  00:00:00

  Agent Team
0     team_1
1     team_1
2     team_1
3     team_1
4     team_1

[5 rows x 21 columns]
```

[9]:
```
# Split the "Interval Start Time" column into "Date" column (in case we need␣
↪analysis in daily basis)
```

```python
hcc_df['Date'] = hcc_df['Interval Start Time'].dt.date
hcc_df['Date'] = pd.to_datetime(hcc_df['Date'])

# Create a list of column names in the desired order
desired_order = ['Agent ID','Agent Team','Date'] + [col for col in hcc_df.
↪columns if col not in ['Agent ID','Agent Team','Date']]

# Reorder the columns based on the desired order, drop duplicated columns
hcc_df = hcc_df[desired_order]
hcc_df = hcc_df.drop(['Total Not Ready','Total Logged-in'], axis =1)

hcc_df.head()
```

[9]:
```
  Agent ID Agent Team       Date Interval Start Time   Interval End Time  \
0  Agent 1     team_1 2022-08-01 2022-08-01 08:00:00 2022-08-01 08:30:00
1  Agent 1     team_1 2022-08-01 2022-08-01 08:30:00 2022-08-01 09:00:00
2  Agent 1     team_1 2022-08-01 2022-08-01 09:00:00 2022-08-01 09:30:00
3  Agent 1     team_1 2022-08-01 2022-08-01 09:30:00 2022-08-01 10:00:00
4  Agent 1     team_1 2022-08-01 2022-08-01 10:00:00 2022-08-01 10:30:00

  Total Logged In Time Not Ready Time Ready Time Reserved Time Talk Time  \
0             00:27:02       00:03:26   00:00:07      00:00:22  00:21:51
1             00:30:00       00:01:33   00:01:52      00:00:33  00:24:29
2             00:30:00       00:04:16   00:00:00      00:00:37  00:23:01
3             00:30:00       00:06:14   00:00:00      00:00:15  00:22:23
4             00:30:00       00:01:49   00:00:00      00:00:15  00:26:57

  Next Call Prep Time     Break     Lunch Team Support   Meeting  \
0            00:01:16  00:00:00  00:00:00     00:00:00  00:00:00
1            00:01:33  00:00:00  00:00:00     00:00:00  00:00:00
2            00:02:06  00:00:01  00:00:00     00:00:00  00:00:00
3            00:01:08  00:06:14  00:00:00     00:00:00  00:00:00
4            00:00:59  00:00:00  00:00:00     00:00:00  00:00:00

  After Call Work Special Projects  Training System Issues     Other
0        00:03:23         00:00:00  00:00:00      00:00:00  00:00:03
1        00:01:33         00:00:00  00:00:00      00:00:00  00:00:00
2        00:04:15         00:00:00  00:00:00      00:00:00  00:00:00
3        00:00:00         00:00:00  00:00:00      00:00:00  00:00:00
4        00:01:49         00:00:00  00:00:00      00:00:00  00:00:00
```

[10]:
```python
hcc_df.shape
```

[10]: (24912, 20)

[11]:
```python
hcc_df.isnull().sum()
```

[11]:
```
Agent ID               0
Agent Team             0
Date                   0
Interval Start Time    0
Interval End Time      0
Total Logged In Time   0
Not Ready Time         0
Ready Time             0
Reserved Time          0
Talk Time              0
Next Call Prep Time    0
Break                  0
Lunch                  0
Team Support           0
Meeting                0
After Call Work        0
Special Projects       0
Training               0
System Issues          0
Other                  0
dtype: int64
```

[12]:
```
hcc_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24912 entries, 0 to 24911
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Agent ID              24912 non-null  object
 1   Agent Team            24912 non-null  object
 2   Date                  24912 non-null  datetime64[ns]
 3   Interval Start Time   24912 non-null  datetime64[ns]
 4   Interval End Time     24912 non-null  datetime64[ns]
 5   Total Logged In Time  24912 non-null  object
 6   Not Ready Time        24912 non-null  object
 7   Ready Time            24912 non-null  object
 8   Reserved Time         24912 non-null  object
 9   Talk Time             24912 non-null  object
 10  Next Call Prep Time   24912 non-null  object
 11  Break                 24912 non-null  object
 12  Lunch                 24912 non-null  object
 13  Team Support          24912 non-null  object
 14  Meeting               24912 non-null  object
 15  After Call Work       24912 non-null  object
 16  Special Projects      24912 non-null  object
 17  Training              24912 non-null  object
 18  System Issues         24912 non-null  object
```

```
 19  Other                   24912 non-null  object
dtypes: datetime64[ns](3), object(17)
memory usage: 4.0+ MB
```

Re-format the time-related columns for more appropriate analysis. We will change from column **'Total Logged In Time'** to column **'Other'** as **timedelta64**.

[13]:
```
# Specify the columns that contain time-related data
time_related_columns = hcc_df.columns[5:20]

# Convert the time-related columns to float as Days
for col in time_related_columns:
    #hcc_df[col] = pd.to_timedelta(hcc_df[col].astype(str)).dt.total_seconds() /
 ↪ (3600 * 24)
    hcc_df[col] = pd.to_timedelta(hcc_df[col].astype(str))
```

[14]:
```
hcc_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24912 entries, 0 to 24911
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Agent ID              24912 non-null  object
 1   Agent Team            24912 non-null  object
 2   Date                  24912 non-null  datetime64[ns]
 3   Interval Start Time   24912 non-null  datetime64[ns]
 4   Interval End Time     24912 non-null  datetime64[ns]
 5   Total Logged In Time  24912 non-null  timedelta64[ns]
 6   Not Ready Time        24912 non-null  timedelta64[ns]
 7   Ready Time            24912 non-null  timedelta64[ns]
 8   Reserved Time         24912 non-null  timedelta64[ns]
 9   Talk Time             24912 non-null  timedelta64[ns]
 10  Next Call Prep Time   24912 non-null  timedelta64[ns]
 11  Break                 24912 non-null  timedelta64[ns]
 12  Lunch                 24912 non-null  timedelta64[ns]
 13  Team Support          24912 non-null  timedelta64[ns]
 14  Meeting               24912 non-null  timedelta64[ns]
 15  After Call Work       24912 non-null  timedelta64[ns]
 16  Special Projects      24912 non-null  timedelta64[ns]
 17  Training              24912 non-null  timedelta64[ns]
 18  System Issues         24912 non-null  timedelta64[ns]
 19  Other                 24912 non-null  timedelta64[ns]
dtypes: datetime64[ns](3), object(2), timedelta64[ns](15)
memory usage: 4.0+ MB
```

[15]:
```
hcc_df.head()
```

```
[15]:   Agent ID Agent Team       Date Interval Start Time   Interval End Time  \
0  Agent 1     team_1 2022-08-01 2022-08-01 08:00:00 2022-08-01 08:30:00
1  Agent 1     team_1 2022-08-01 2022-08-01 08:30:00 2022-08-01 09:00:00
2  Agent 1     team_1 2022-08-01 2022-08-01 09:00:00 2022-08-01 09:30:00
3  Agent 1     team_1 2022-08-01 2022-08-01 09:30:00 2022-08-01 10:00:00
4  Agent 1     team_1 2022-08-01 2022-08-01 10:00:00 2022-08-01 10:30:00

  Total Logged In Time  Not Ready Time      Ready Time   Reserved Time  \
0      0 days 00:27:02 0 days 00:03:26 0 days 00:00:07 0 days 00:00:22
1      0 days 00:30:00 0 days 00:01:33 0 days 00:01:52 0 days 00:00:33
2      0 days 00:30:00 0 days 00:04:16 0 days 00:00:00 0 days 00:00:37
3      0 days 00:30:00 0 days 00:06:14 0 days 00:00:00 0 days 00:00:15
4      0 days 00:30:00 0 days 00:01:49 0 days 00:00:00 0 days 00:00:15

        Talk Time Next Call Prep Time           Break  Lunch Team Support  \
0 0 days 00:21:51     0 days 00:01:16 0 days 00:00:00 0 days       0 days
1 0 days 00:24:29     0 days 00:01:33 0 days 00:00:00 0 days       0 days
2 0 days 00:23:01     0 days 00:02:06 0 days 00:00:01 0 days       0 days
3 0 days 00:22:23     0 days 00:01:08 0 days 00:06:14 0 days       0 days
4 0 days 00:26:57     0 days 00:00:59 0 days 00:00:00 0 days       0 days

  Meeting After Call Work Special Projects Training System Issues  \
0  0 days 0 days 00:03:23           0 days   0 days        0 days
1  0 days 0 days 00:01:33           0 days   0 days        0 days
2  0 days 0 days 00:04:15           0 days   0 days        0 days
3  0 days 0 days 00:00:00           0 days   0 days        0 days
4  0 days 0 days 00:01:49           0 days   0 days        0 days

            Other
0 0 days 00:00:03
1 0 days 00:00:00
2 0 days 00:00:00
3 0 days 00:00:00
4 0 days 00:00:00
```

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1.1 2 - EDA:

Conduct exploratory (descriptive) data analysis and summarize key findings pertaining to HCC's current state.

- 2a. Overall

- 2b. By team
- 2c. By Agent
- 2d. Staffing Plan

a) Overall time estimation for all the activities:

[16]:
```
hcc_df.describe()
```

[16]:
```
             Total Logged In Time                Not Ready Time  \
count                       24912                         24912
mean    0 days 00:22:47.069845857  0 days 00:03:37.874638728
std     0 days 00:12:22.696562502  0 days 00:06:40.461289026
min               0 days 00:00:00               0 days 00:00:00
25%        0 days 00:21:51.750000               0 days 00:00:00
50%               0 days 00:30:00               0 days 00:00:11
75%               0 days 00:30:00               0 days 00:04:14
max               0 days 00:30:00               0 days 00:30:00

                       Ready Time                 Reserved Time  \
count                       24912                         24912
mean    0 days 00:02:14.546202633  0 days 00:00:17.288334938
std     0 days 00:04:25.724780060  0 days 00:00:19.288031934
min               0 days 00:00:00               0 days 00:00:00
25%               0 days 00:00:00               0 days 00:00:00
50%               0 days 00:00:05               0 days 00:00:15
75%        0 days 00:02:18.250000               0 days 00:00:27
max               0 days 00:30:00               0 days 00:14:26

                        Talk Time           Next Call Prep Time  \
count                       24912                         24912
mean    0 days 00:15:30.948859987  0 days 00:01:06.411809569
std     0 days 00:10:40.340246808  0 days 00:00:58.443825965
min               0 days 00:00:00               0 days 00:00:00
25%        0 days 00:01:49.750000               0 days 00:00:05
50%               0 days 00:19:09               0 days 00:01:00
75%               0 days 00:24:59               0 days 00:01:44
max               0 days 00:30:00               0 days 00:08:38

                            Break                         Lunch  \
count                       24912                         24912
mean    0 days 00:00:39.447736030  0 days 00:01:00.675417469
std     0 days 00:02:32.250826455  0 days 00:04:46.022551244
min               0 days 00:00:00               0 days 00:00:00
25%               0 days 00:00:00               0 days 00:00:00
50%               0 days 00:00:00               0 days 00:00:00
75%               0 days 00:00:00               0 days 00:00:00
max               0 days 00:30:00               0 days 00:30:00
```

```
                      Team Support                    Meeting  \
count                        24912                      24912
mean    0 days 00:00:00.636159280  0 days 00:00:06.517501605
std     0 days 00:00:23.855751314  0 days 00:01:12.196593646
min               0 days 00:00:00            0 days 00:00:00
25%               0 days 00:00:00            0 days 00:00:00
50%               0 days 00:00:00            0 days 00:00:00
75%               0 days 00:00:00            0 days 00:00:00
max               0 days 00:30:00            0 days 00:30:00

                   After Call Work           Special Projects  \
count                        24912                      24912
mean    0 days 00:01:02.020110789  0 days 00:00:06.772840398
std     0 days 00:02:14.947299607  0 days 00:01:15.055259239
min               0 days 00:00:00            0 days 00:00:00
25%               0 days 00:00:00            0 days 00:00:00
50%               0 days 00:00:00            0 days 00:00:00
75%               0 days 00:01:00            0 days 00:00:00
max               0 days 00:29:33            0 days 00:30:00

                          Training              System Issues  \
count                        24912                      24912
mean    0 days 00:00:30.285444765  0 days 00:00:02.215237636
std     0 days 00:03:23.426900289  0 days 00:00:25.820708740
min               0 days 00:00:00            0 days 00:00:00
25%               0 days 00:00:00            0 days 00:00:00
50%               0 days 00:00:00            0 days 00:00:00
75%               0 days 00:00:00            0 days 00:00:00
max               0 days 00:30:00            0 days 00:27:48

                             Other
count                        24912
mean    0 days 00:00:09.304190751
std     0 days 00:01:00.932564703
min               0 days 00:00:00
25%               0 days 00:00:00
50%               0 days 00:00:00
75%               0 days 00:00:00
max               0 days 00:30:00
```

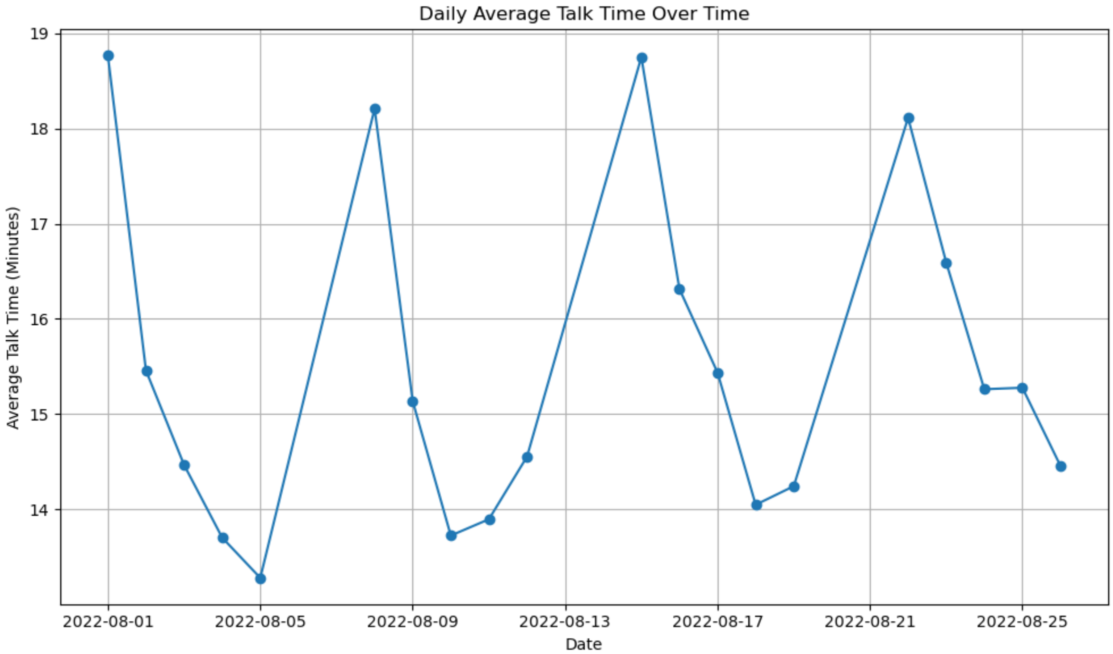
[17]:
```python
#Daily average Talk Time trend

daily_average_talk_time = hcc_df.groupby(hcc_df['Date'].dt.date)['Talk Time'].
 ↪mean().reset_index()
daily_average_talk_time['Talk Time'] = daily_average_talk_time['Talk Time'].dt.
 ↪total_seconds() / 60
```

[18]:
```
# Rename the column
daily_average_talk_time.rename(columns={'Talk Time': 'Talk Time (Minutes)'},␣
↪inplace=True)
```

[19]:
```
# Convert the 'Date' column to datetime
daily_average_talk_time['Date'] = pd.
↪to_datetime(daily_average_talk_time['Date'])
daily_average_talk_time.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 2 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Date                 20 non-null     datetime64[ns]
 1   Talk Time (Minutes)  20 non-null     float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 448.0 bytes
```

[20]:
```
# Create a line plot
plt.figure(figsize=(10, 6))
plt.plot(daily_average_talk_time['Date'], daily_average_talk_time['Talk Time␣
↪(Minutes)'], marker='o', linestyle='-')
plt.xlabel('Date')
plt.ylabel('Average Talk Time (Minutes)')
plt.title('Daily Average Talk Time Over Time')
plt.grid(True)
plt.tight_layout()

plt.show()
```



b) By team:

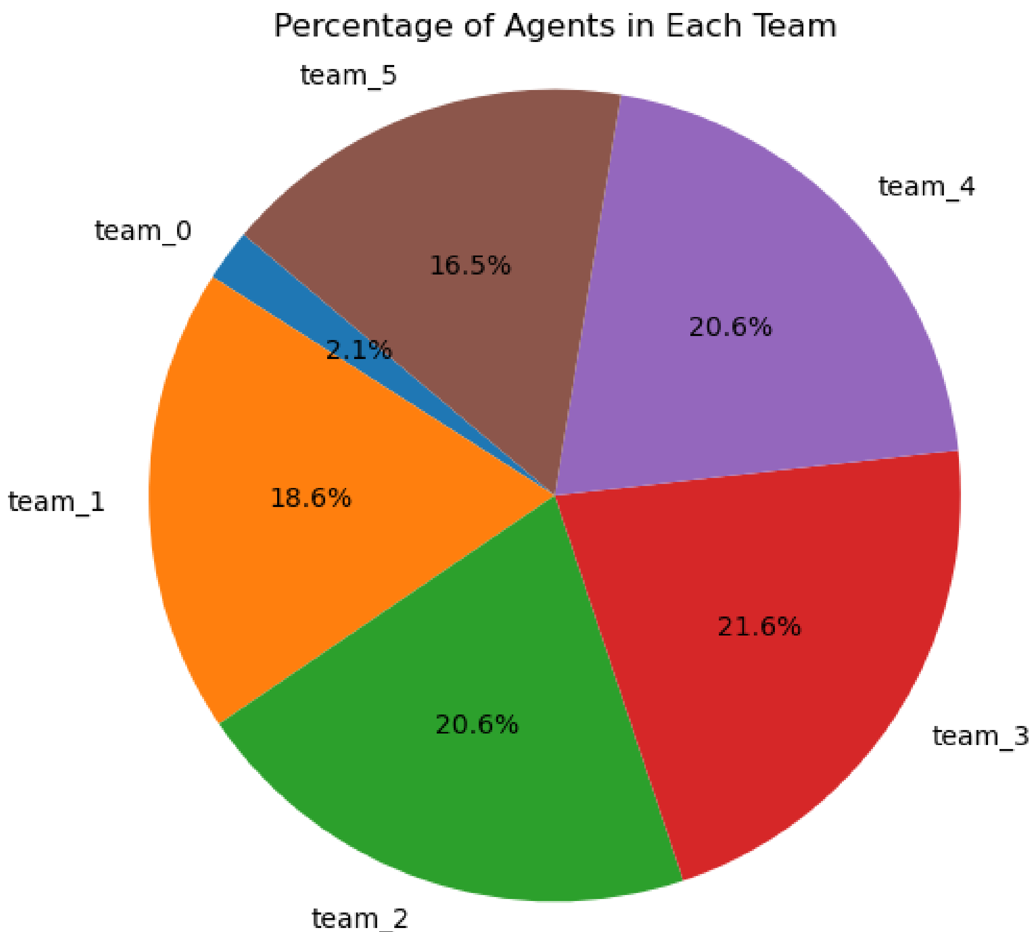
[21]:
```
team = sheet4.groupby(['Agent Team']).count().reset_index()

# Calculate the total count of agents in the dataset
total_agents = team["Agent ID"].sum()

# Calculate the percentage of each team
team["Percentage"] = (team["Agent ID"] / total_agents) * 100

team
```

[21]:

	Agent Team	Agent ID	Percentage
0	team_0	2	2.061856
1	team_1	18	18.556701
2	team_2	20	20.618557
3	team_3	21	21.649485
4	team_4	20	20.618557
5	team_5	16	16.494845

[22]:
```
# Create a pie chart
plt.figure(figsize=(6, 6))
plt.pie(team["Percentage"], labels=team["Agent Team"], autopct="%1.1f%%",␣
↪startangle=140)
plt.title("Percentage of Agents in Each Team")
plt.axis("equal")  # Equal aspect ratio ensures that pie is drawn as a circle.
```

```
# Show the pie chart
plt.show()
```



[23]:
```
team_sorted = hcc_df.groupby(['Agent Team'])[time_related_columns].sum().
  ↪reset_index()
team_sorted
```

[23]:
```
  Agent Team Total Logged In Time   Not Ready Time       Ready Time  \
0     team_0      3 days 16:24:03  0 days 12:57:57  0 days 22:44:08
1     team_1     75 days 04:53:42 12 days 19:19:08  5 days 19:34:04
2     team_2     84 days 12:28:05 10 days 06:51:17 11 days 12:33:22
3     team_3     79 days 19:29:40 12 days 06:22:59  4 days 05:44:38
4     team_4     81 days 12:40:30 13 days 00:49:38  8 days 05:19:06
5     team_5     69 days 10:11:24 13 days 21:20:34  8 days 01:08:17

    Reserved Time        Talk Time Next Call Prep Time           Break  \
```

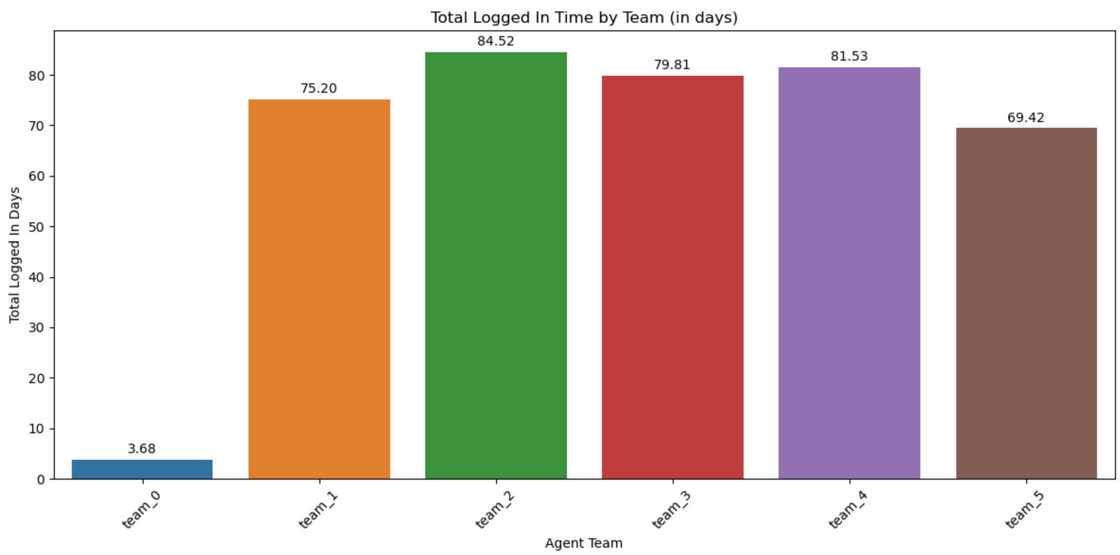
```
0 0 days 00:48:24  2 days 00:13:49     0 days 03:39:45 0 days 01:55:04
1 1 days 02:31:59 51 days 14:01:33     3 days 21:26:58 1 days 23:02:38
2 1 days 00:48:21 57 days 11:53:13     4 days 04:21:52 1 days 21:51:45
3 0 days 23:58:18 58 days 04:10:55     4 days 03:12:50 2 days 08:05:57
4 1 days 00:34:39 55 days 13:12:15     3 days 16:44:52 2 days 10:08:54
5 0 days 18:56:26 43 days 14:38:13     3 days 02:07:54 2 days 15:54:24

            Lunch    Team Support          Meeting After Call Work  \
0 0 days 04:03:32 0 days 00:00:25 0 days 00:48:54 0 days 02:04:47
1 3 days 05:50:09 0 days 02:07:37 0 days 10:11:58 4 days 02:43:24
2 3 days 17:02:24 0 days 00:27:27 0 days 02:25:50 2 days 05:15:26
3 3 days 11:11:05 0 days 00:38:48 0 days 05:12:53 3 days 04:32:12
4 3 days 14:35:12 0 days 00:07:33 0 days 16:25:29 4 days 06:23:59
5 3 days 07:10:04 0 days 01:02:18 0 days 10:01:00 4 days 00:10:57

  Special Projects        Training   System Issues           Other
0  0 days 00:00:00 0 days 03:40:08 0 days 00:00:00 0 days 00:25:07
1  0 days 15:41:54 1 days 14:41:09 0 days 01:59:19 0 days 15:01:00
2  0 days 07:24:13 1 days 11:00:38 0 days 02:35:05 0 days 10:48:29
3  0 days 10:52:08 1 days 20:25:28 0 days 05:54:10 0 days 11:30:18
4  0 days 08:08:02 1 days 02:46:10 0 days 03:23:45 0 days 10:50:34
5  0 days 04:45:48 2 days 13:00:58 0 days 01:27:27 0 days 15:47:38
```

[24]:
```
time_columns = ['Total Logged In Time','Not Ready Time', 'Ready Time',␣
↪'Reserved Time', 'Talk Time', 'Next Call Prep Time', 'Break', 'Lunch',
                    'Team Support', 'Meeting', 'After Call Work', 'Special␣
↪Projects', 'Training', 'System Issues', 'Other']
```

[25]:
```
#By days
team_sorted2 = team_sorted.copy()

for col in time_columns:
    team_sorted2[col] = team_sorted2[col].dt.days + team_sorted2[col].dt.
↪seconds / (3600 * 24)
```

[26]:
```
# Create a bar plot of Total Logged In Time by Team in days
plt.figure(figsize=(12, 6))
ax = sns.barplot(x='Agent Team', y='Total Logged In Time', data=team_sorted2)
plt.title('Total Logged In Time by Team (in days)')
plt.xlabel('Agent Team')
plt.ylabel('Total Logged In Days')
plt.xticks(rotation=45)

# Annotate each bar with its respective data
for p in ax.patches:
```

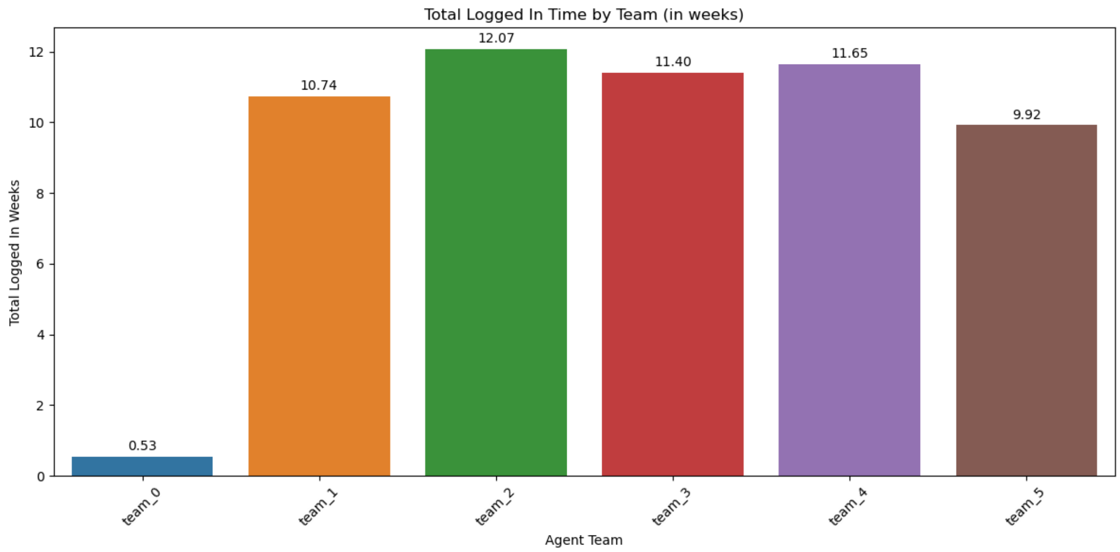
```
    ax.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2., p.
↪get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
↪xytext=(0, 5), textcoords='offset points')

plt.tight_layout()

plt.show()
```



[27]:
```
#By weeks
team_sorted3 = team_sorted2.copy()

for col in time_columns:
    team_sorted3[col] = team_sorted3[col] / 7
```

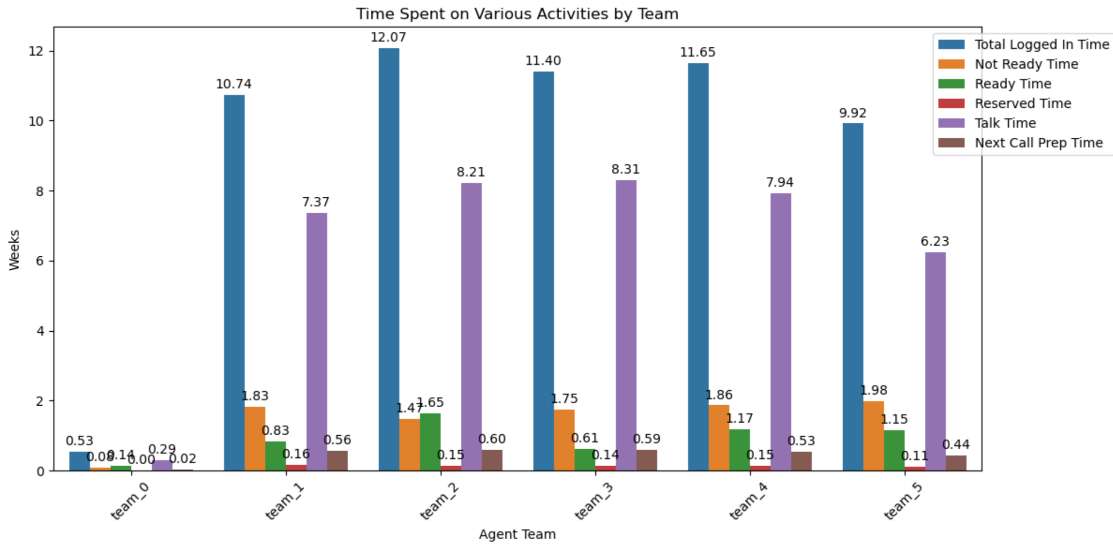
[28]:
```
# Create a bar plot of Total Logged In Time by Team in weeks
plt.figure(figsize=(12, 6))
ax = sns.barplot(x='Agent Team', y='Total Logged In Time', data=team_sorted3)
plt.title('Total Logged In Time by Team (in weeks)')
plt.xlabel('Agent Team')
plt.ylabel('Total Logged In Weeks')
plt.xticks(rotation=45)

# Annotate each bar with its respective data
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2., p.
↪get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
↪xytext=(0, 5), textcoords='offset points')
```

```
plt.tight_layout()

plt.show()
```



[29]:
```
overall_activity = ['Total Logged In Time','Not Ready Time', 'Ready Time',␣
↪'Reserved Time', 'Talk Time', 'Next Call Prep Time']

# Create a stacked bar plot of various activities by Team
stacked_data = team_sorted3[['Agent Team'] + overall_activity].
↪melt(id_vars='Agent Team', var_name='Activity', value_name='Time (Days)')

#Plotting
plt.figure(figsize=(12, 6))
ax = sns.barplot(x='Agent Team', y='Time (Days)', hue='Activity',␣
↪data=stacked_data)
plt.title('Time Spent on Various Activities by Team')
plt.xlabel('Agent Team')
plt.ylabel('Weeks')
plt.xticks(rotation=45)
plt.legend(loc='upper right', bbox_to_anchor=(1.15, 1))

# Annotate each bar with its respective data
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2., p.
↪get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
↪xytext=(0, 5), textcoords='offset points')

plt.tight_layout()
```

```python
plt.show()
```



What percentage of logged-in time on average did teams spend on each task per time interval (on daily/weekly basis)?

[30]:
```python
# Calculate the percentage of time spent on each task
team_sorted22 = team_sorted2.iloc[:,:7].copy()

activity_columns = team_sorted22.columns[2:]  # Exclude 'Agent Team' and 'Total␣
↪Logged In Time'
for activity in activity_columns:
    team_sorted22[activity] = (team_sorted22[activity] / team_sorted22['Total␣
↪Logged In Time']) * 100

# Rename the column
team_sorted22 = team_sorted22.drop(['Total Logged In Time'], axis = 1)

# Display the result
team_sorted22.reset_index()
```

[30]:
```
   index Agent Team  Not Ready Time  Ready Time  Reserved Time  Talk Time  \
0      0     team_0       14.667094   25.718712       0.912510  54.558623
1      1     team_1       17.026968    7.732737       1.470061  68.592679
2      2     team_2       12.169515   13.633742       1.222885  68.026062
3      3     team_3       15.368515    5.311625       1.251461  72.888854
4      4     team_4       15.987695   10.084369       1.256085  68.136209
5      5     team_5       20.006288   11.591599       1.136758  62.816182
```

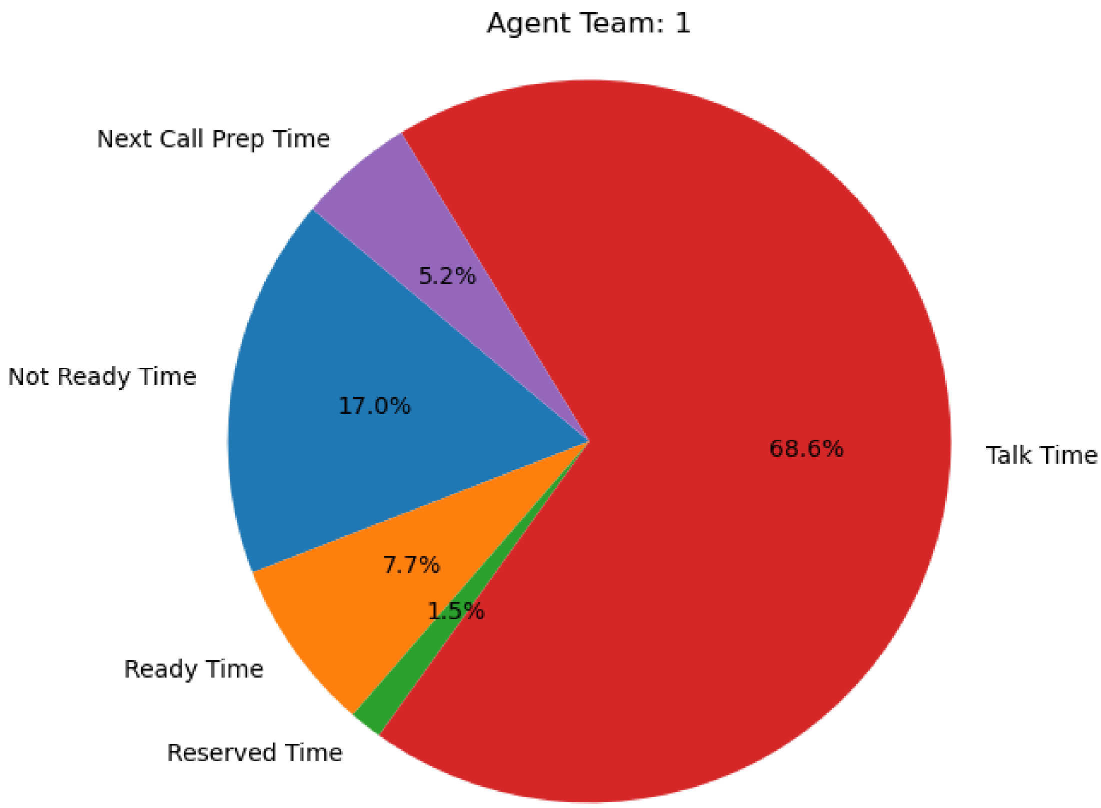
```
   Next Call Prep Time
0             4.143060
1             5.177556
2             4.947795
3             5.179545
4             4.535642
5             4.449172
```

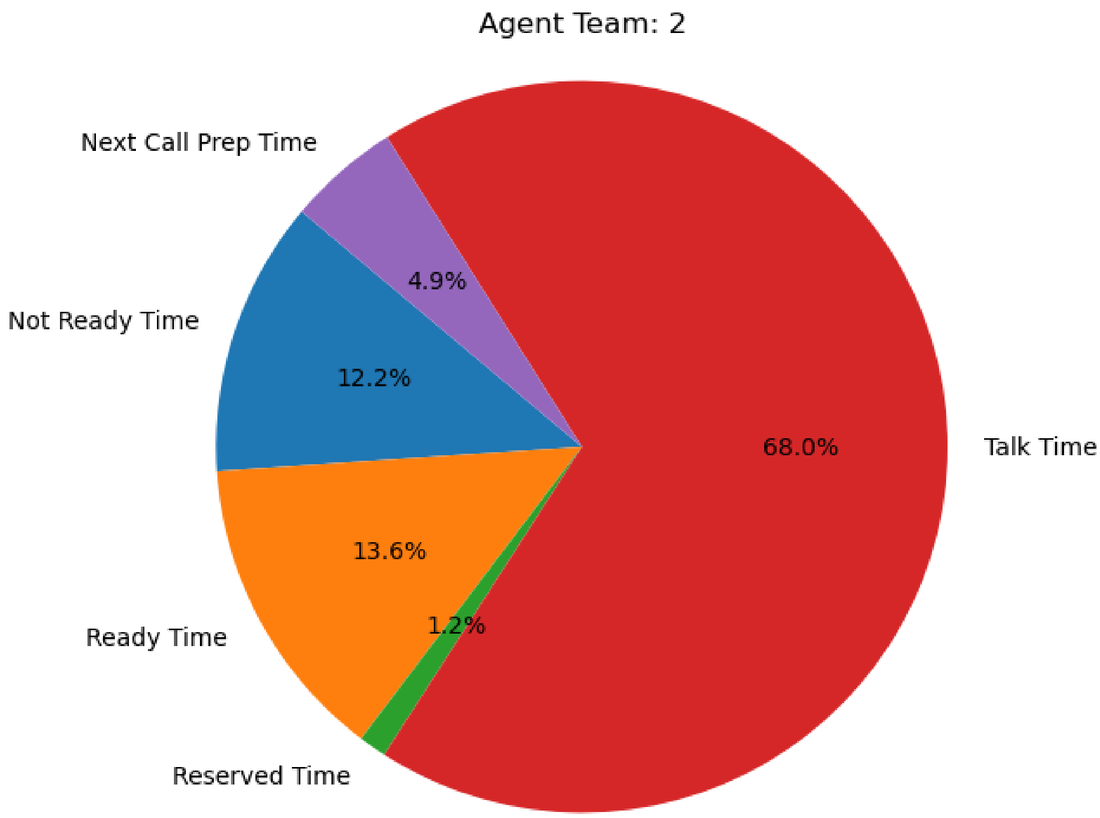
[31]:
```python
team_sorted22.columns
```

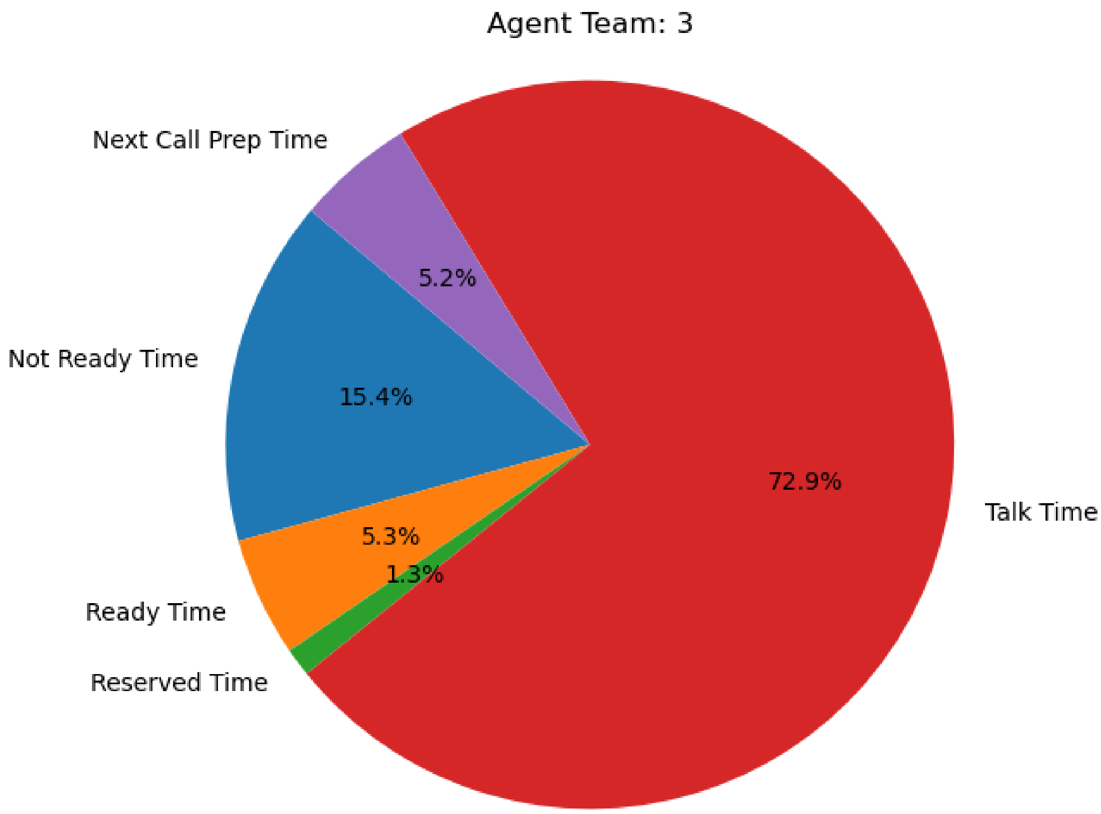
[31]:
```
Index(['Agent Team', 'Not Ready Time', 'Ready Time', 'Reserved Time',
       'Talk Time', 'Next Call Prep Time'],
      dtype='object')
```

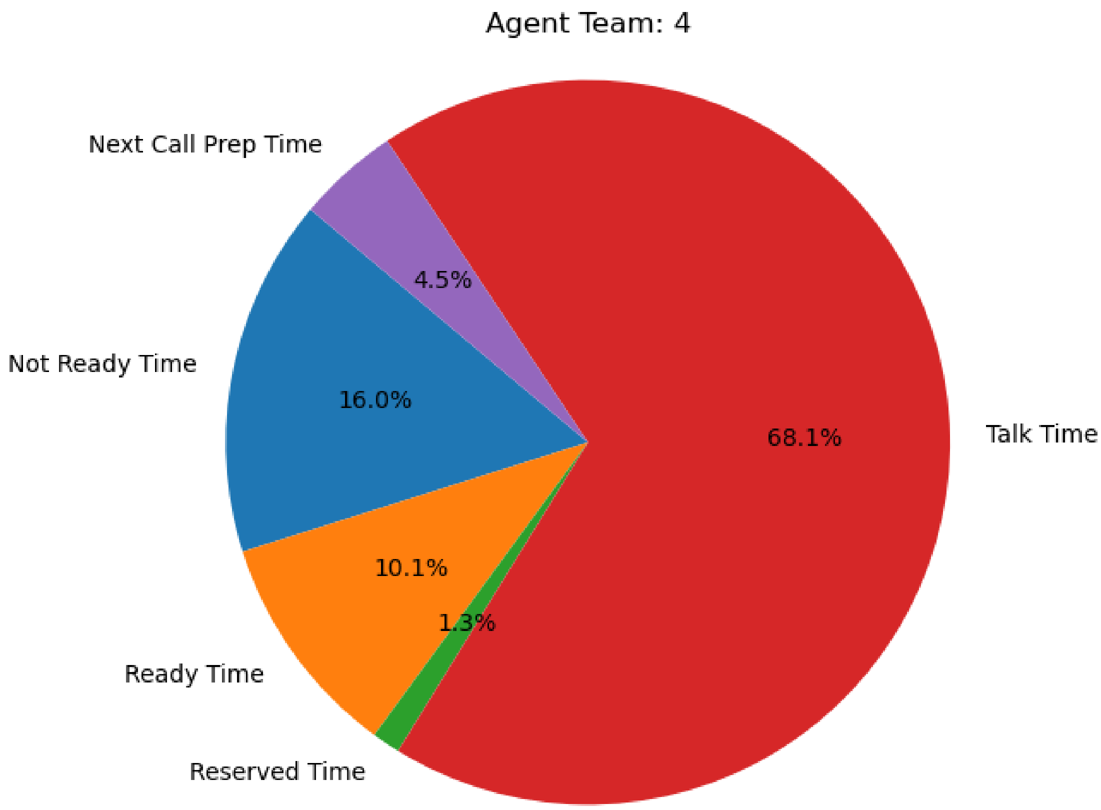
[32]:
```python
# Group the data by 'Agent Team' and sum the time spent in each activity
team_activity_totals = team_sorted22.groupby('Agent Team').sum().reset_index()

# List of activities (excluding 'Agent Team' column)
activities = team_activity_totals.columns[1:]

# Create a pie chart for each agent team
for team in team_activity_totals.index:
    team_data = team_activity_totals.loc[team, activities]
    plt.figure(figsize=(6, 6))
    plt.pie(team_data, labels=activities, autopct='%1.1f%%', startangle=140)
    plt.title(f'Agent Team: {team}')
    plt.axis('equal')
    plt.show()
```

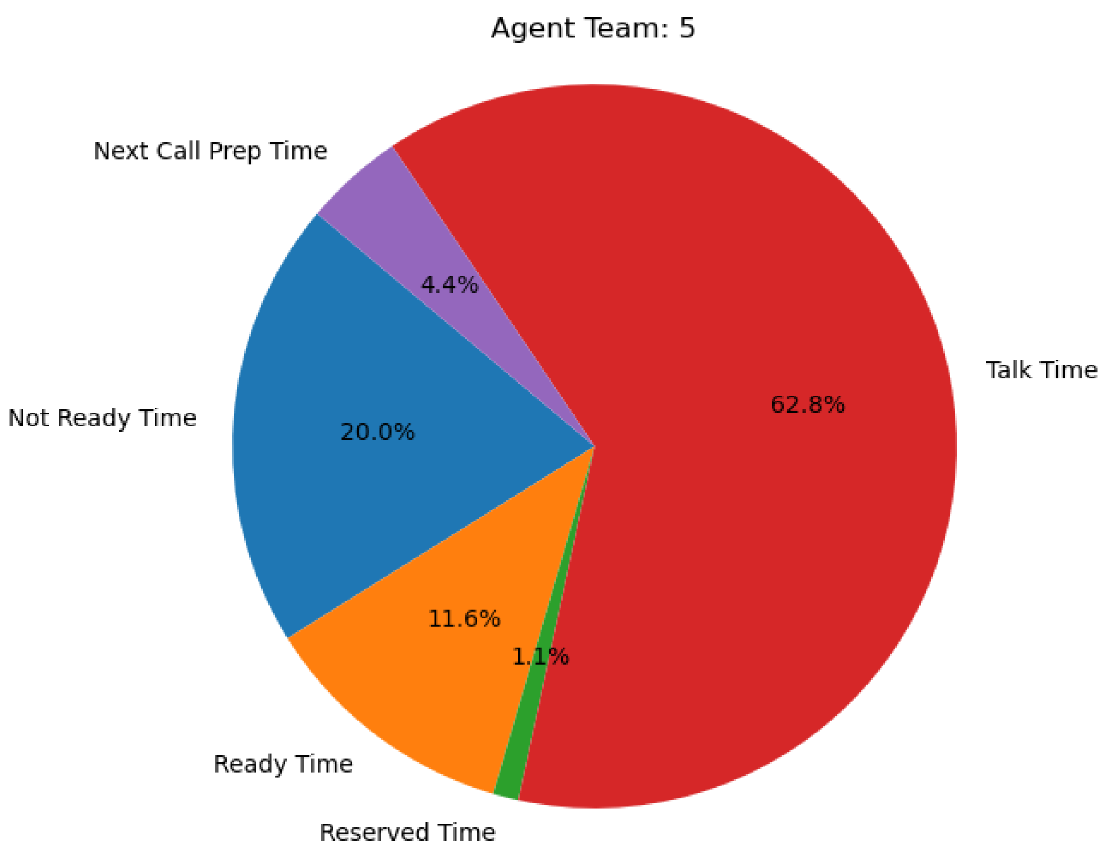

Agent Team: 0
Next Call Prep Time
4.1%
Talk Time
54.6%
Not Ready Time
14.7%
25.7%
0.9%
Ready Time
Reserved Time


Agent Team: 1
Next Call Prep Time
5.2%
Not Ready Time
17.0%
68.6%
Talk Time
7.7%
1.5%
Ready Time
Reserved Time


Agent Team: 2
Next Call Prep Time
4.9%
Not Ready Time
12.2%
68.0%
Talk Time
13.6%
1.2%
Ready Time
Reserved Time

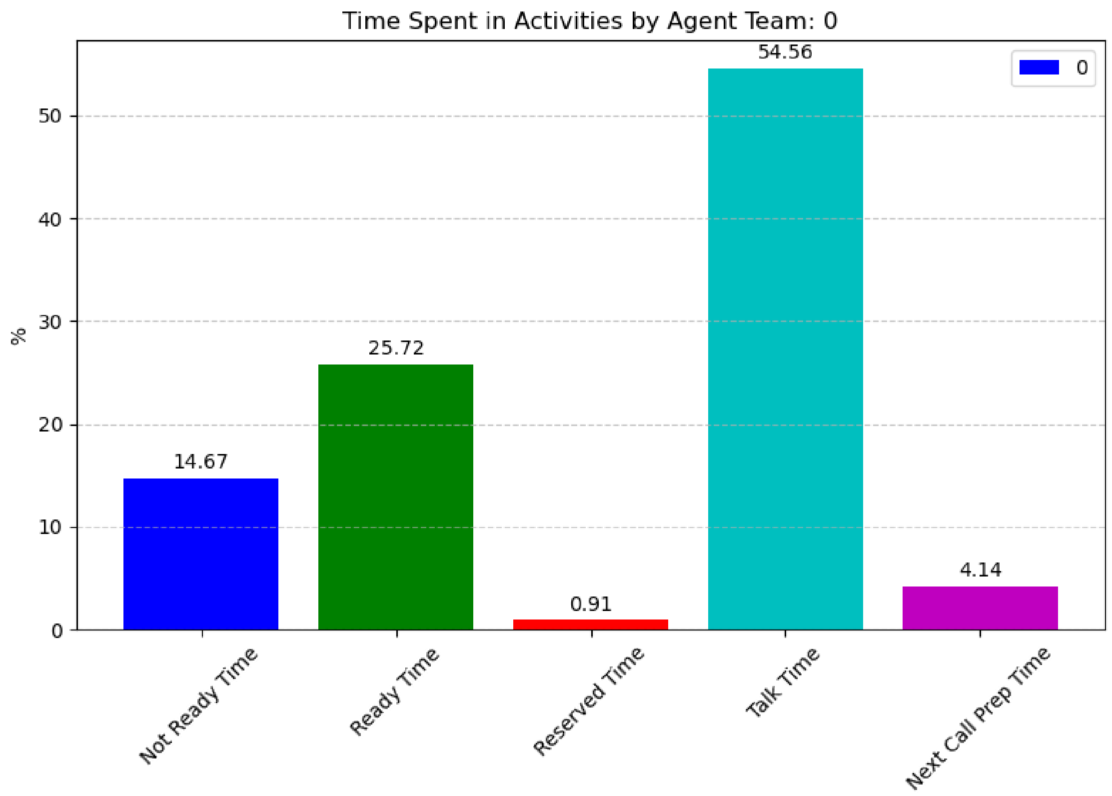

Agent Team: 3
Next Call Prep Time
5.2%
Not Ready Time
15.4%
72.9%
Talk Time
5.3%
1.3%
Ready Time
Reserved Time

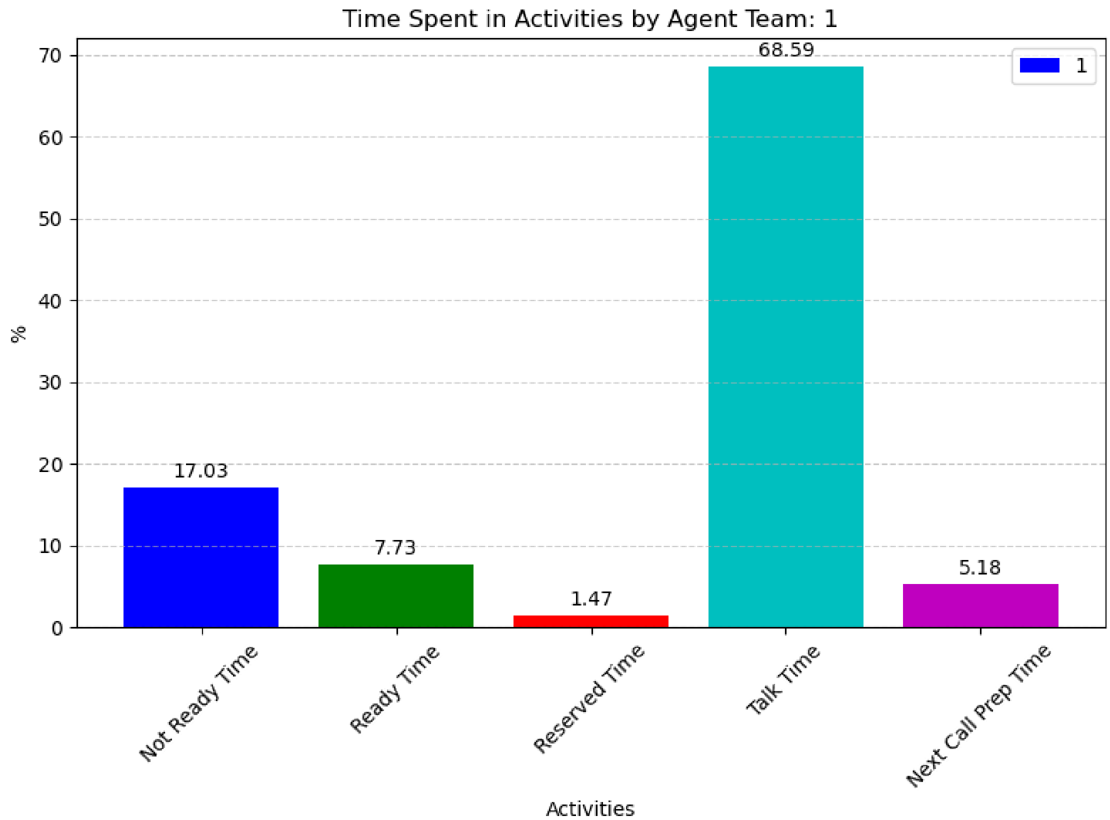

Agent Team: 4
Next Call Prep Time
Not Ready Time
Ready Time
Reserved Time
Talk Time
4.5%
16.0%
10.1%
1.3%
68.1%

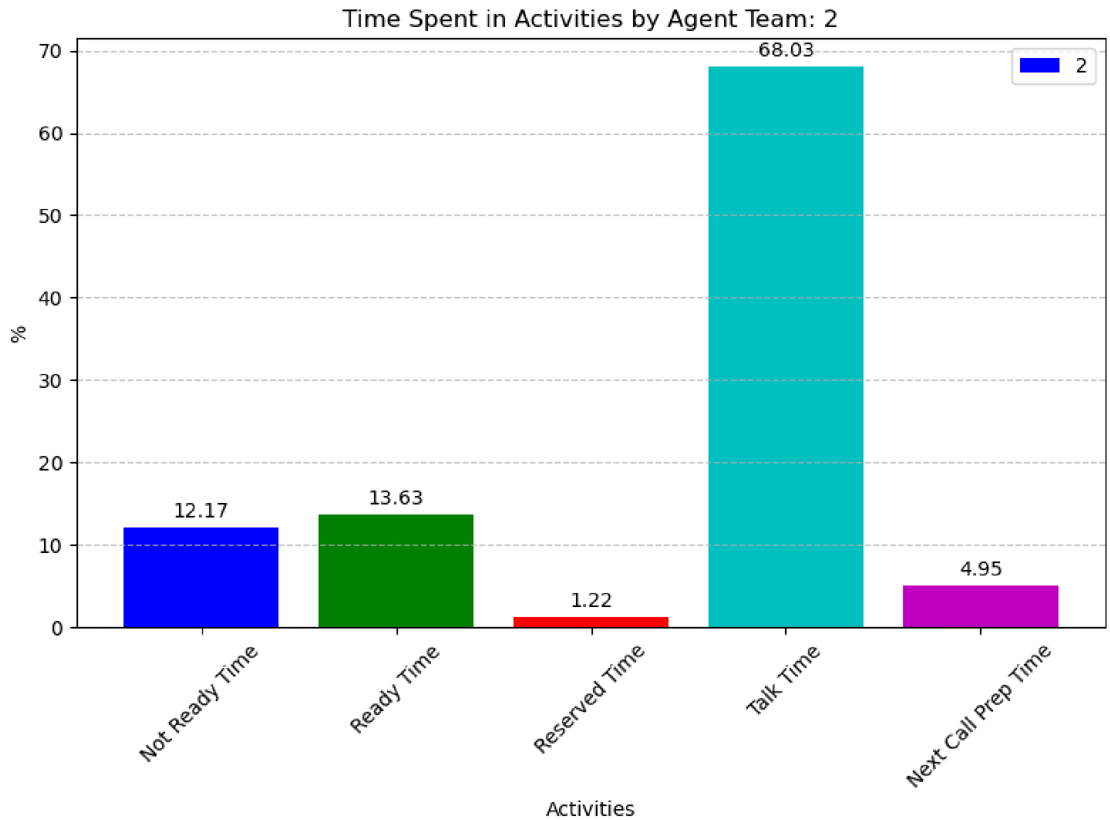


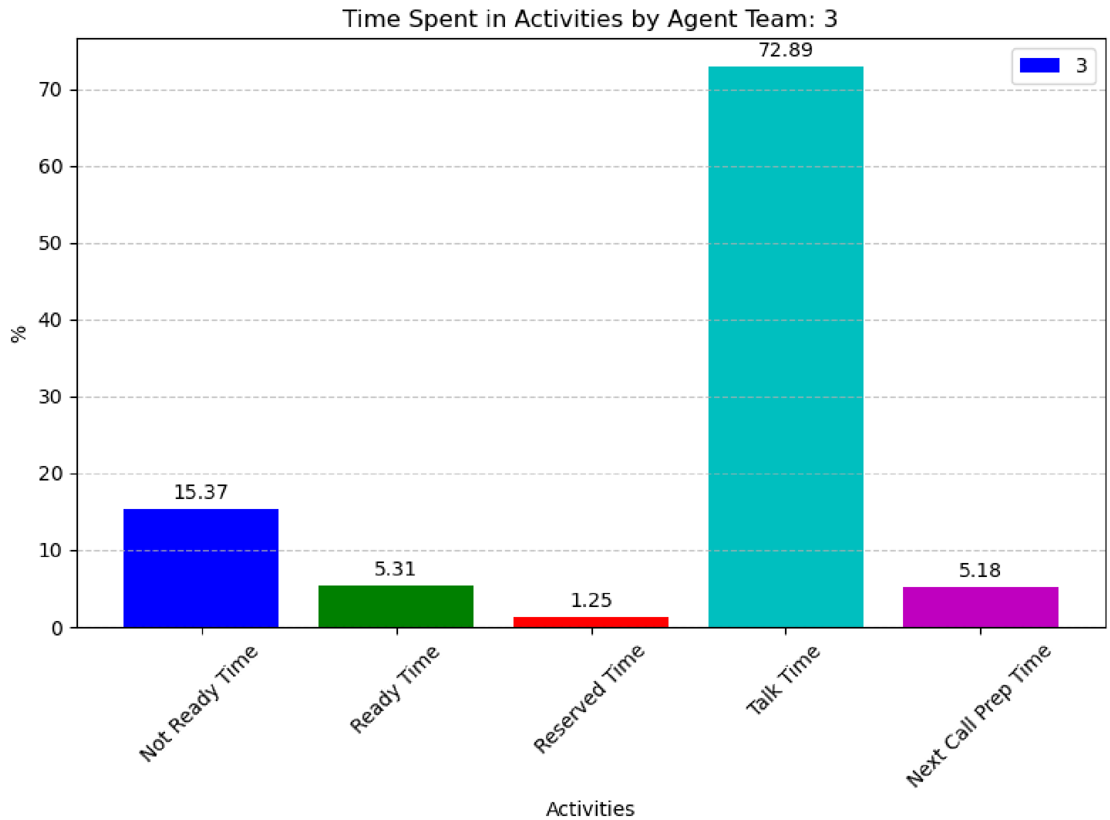
[33]:
```python
# Create a bar chart for each agent team with customizations
for team in team_activity_totals.index:
    team_data = team_activity_totals.loc[team, activities]
    plt.figure(figsize=(8, 6))

    # Set custom colors for bars
    colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']

    ax = plt.bar(activities, team_data, label=team, color=colors)
    plt.title(f'Time Spent in Activities by Agent Team: {team}')
    plt.xlabel('Activities')
    plt.ylabel('%')
    plt.legend()

    # Customize gridlines
    plt.grid(axis='y', linestyle='--', alpha=0.7)

    plt.xticks(rotation=45)

    # Annotate each bar with its respective data
```

```python
for p in ax:
    plt.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2.,␣
↪p.get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
↪xytext=(0, 5), textcoords='offset points')

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

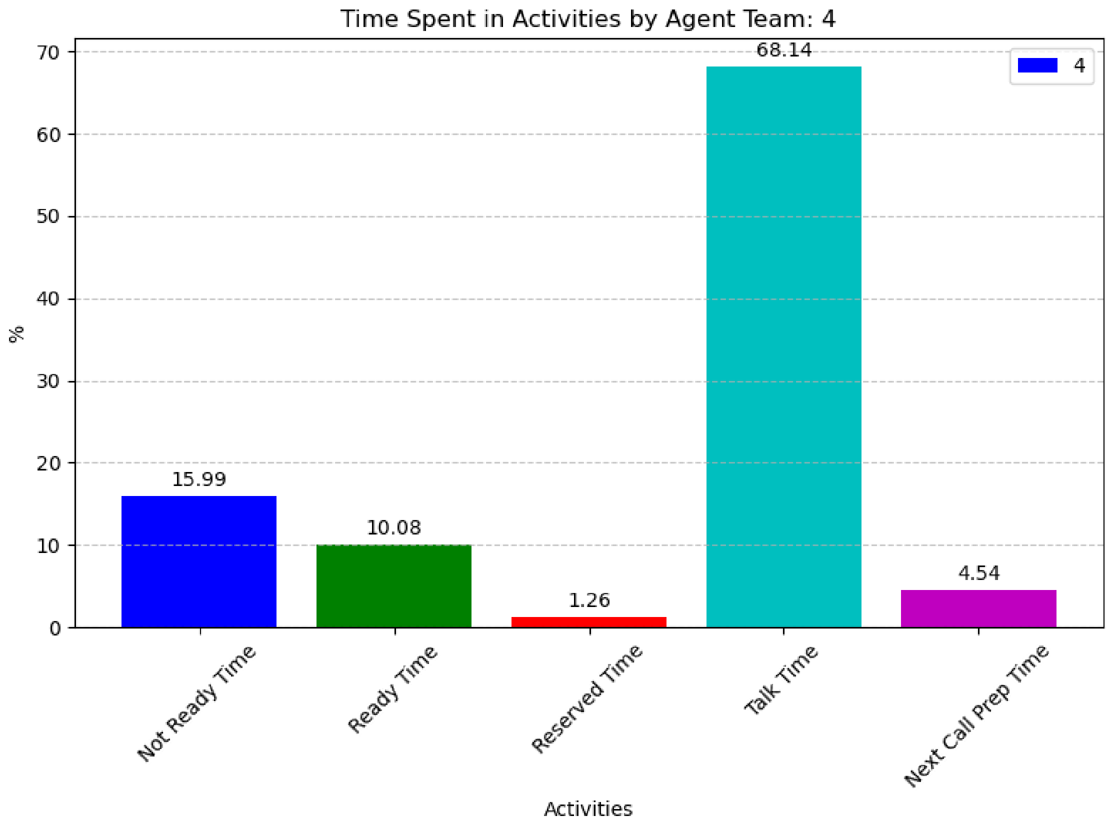


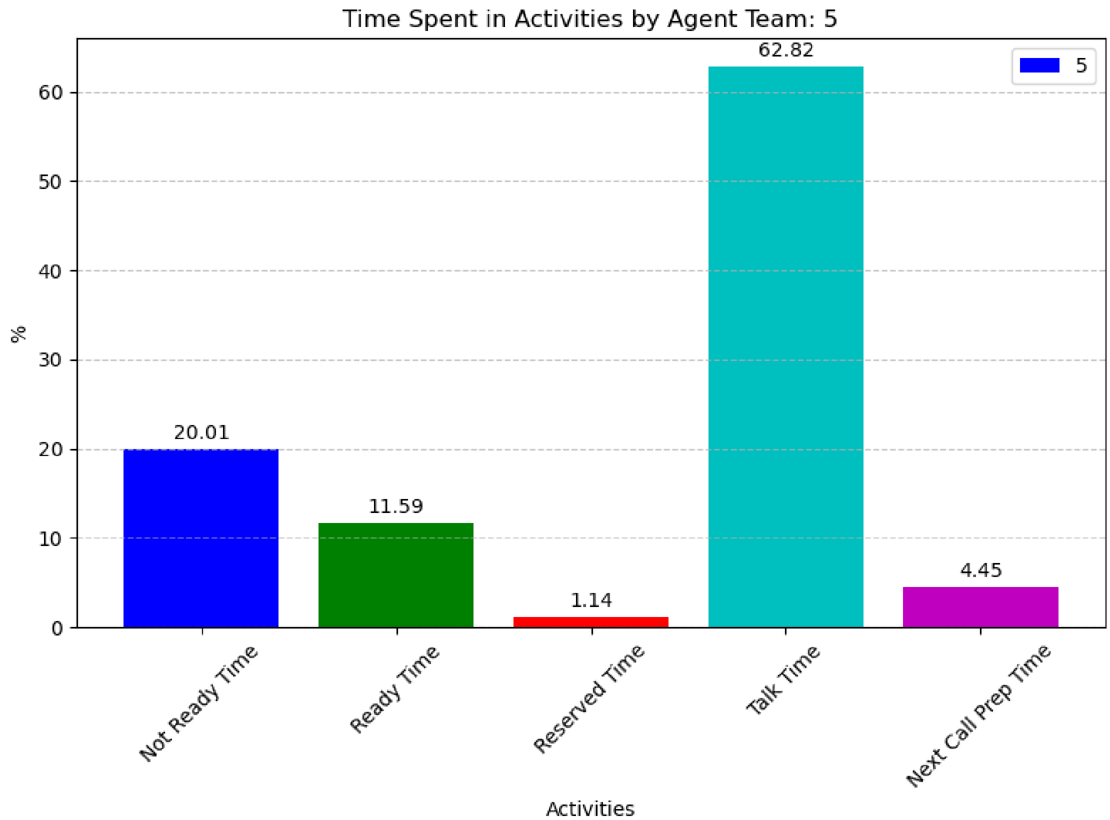

Time Spent in Activities by Agent Team: 1
%
70
60
50
40
30
20
10
0
17.03
7.73
1.47
68.59
5.18
1
Not Ready Time
Ready Time
Reserved Time
Talk Time
Next Call Prep Time
Activities


Time Spent in Activities by Agent Team: 2
%
70
60
50
40
30
20
10
0
12.17
13.63
1.22
68.03
4.95
2
Not Ready Time
Ready Time
Reserved Time
Talk Time
Next Call Prep Time
Activities



Time Spent in Activities by Agent Team: 3
72.89
3
70
60
50
40
30
20
10
0
%
15.37
5.31
1.25
5.18
Not Ready Time
Ready Time
Reserved Time
Talk Time
Next Call Prep Time
Activities


Time Spent in Activities by Agent Team: 4
4
70
60
50
40
30
20
10
0
%
15.99
10.08
1.26
68.14
4.54
Not Ready Time
Ready Time
Reserved Time
Talk Time
Next Call Prep Time
Activities



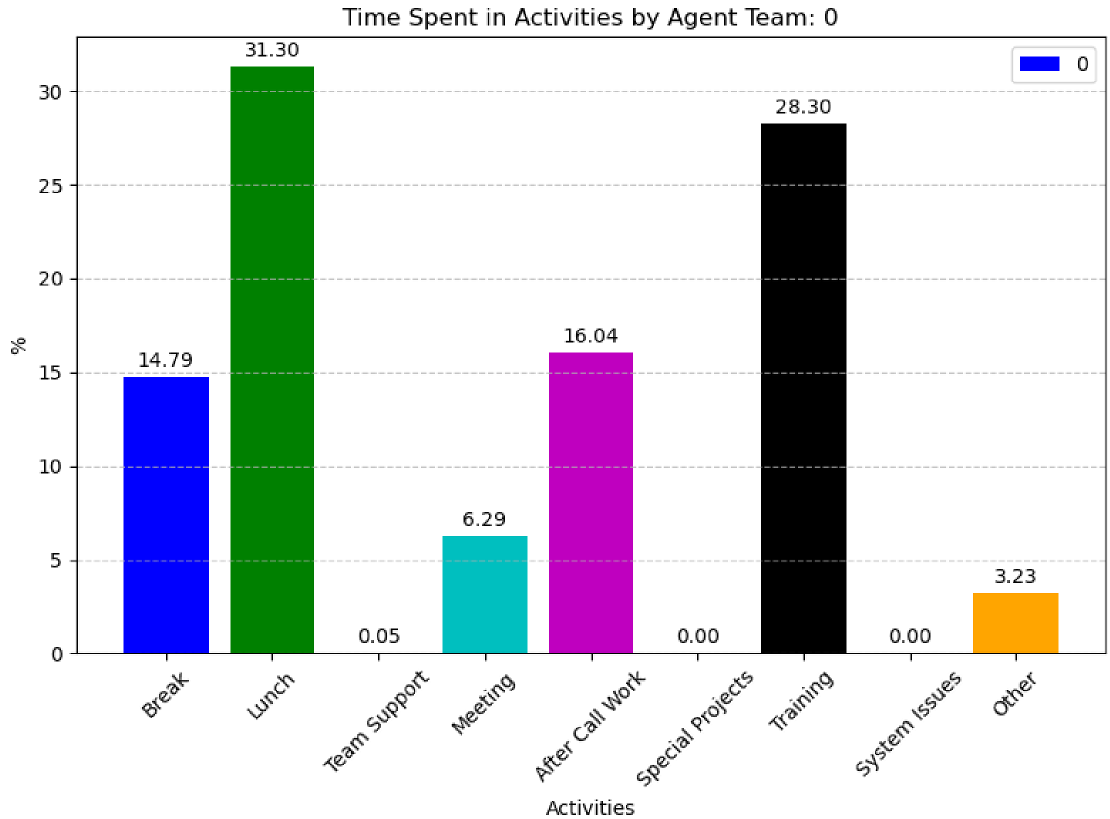
[34]:
```
# Specify the column names to copy
columns_to_copy = ["Agent Team"] + ["Not Ready Time"] + list(team_sorted2.
↪columns[-9:])

# Create a new DataFrame with the selected columns
team_sorted23 = team_sorted2[columns_to_copy].copy()

# Exclude 'Agent Team' and 'Not Ready Time'
activity_columns2 = team_sorted23.columns[2:]
for activity in activity_columns2:
    team_sorted23[activity] = (team_sorted23[activity] / team_sorted23['Not␣
↪Ready Time']) * 100

# Rename the column
team_sorted23 = team_sorted23.drop(['Not Ready Time'], axis = 1)

# Display the result
team_sorted23.reset_index()
```

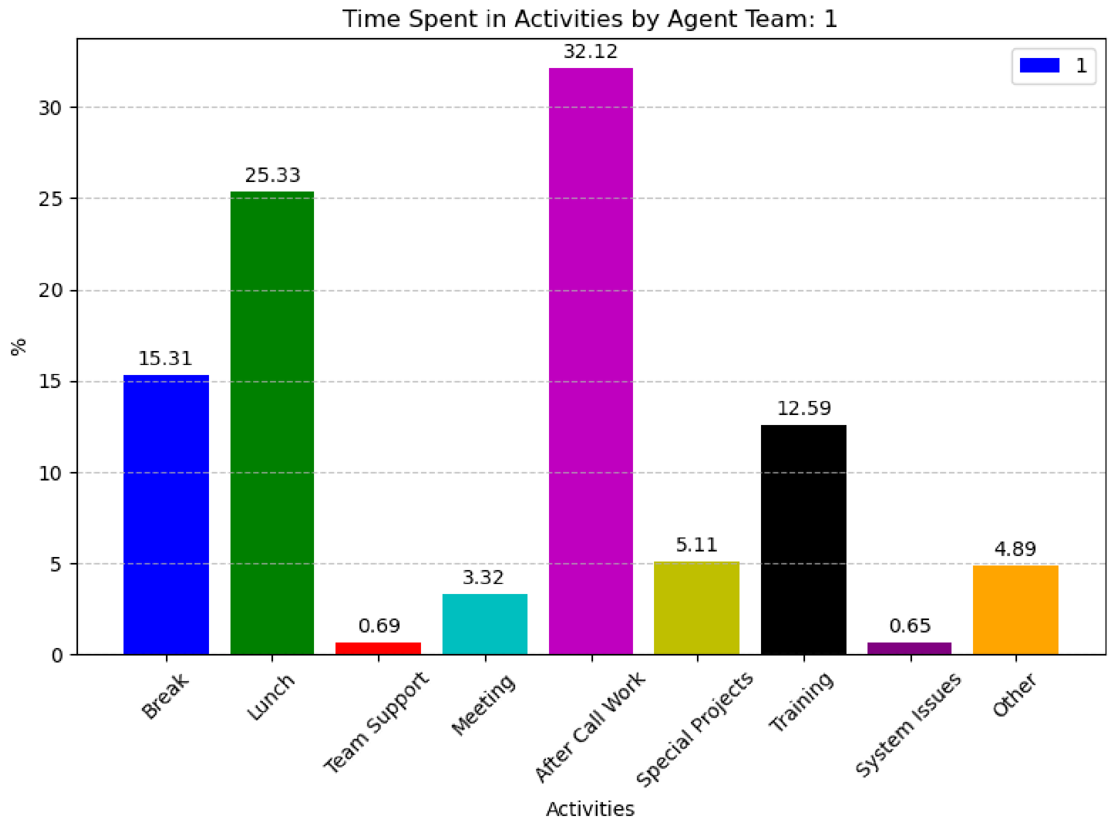
```
[34]:    index Agent Team      Break      Lunch  Team Support   Meeting  \
      0      0     team_0  14.791011  31.304497      0.053560  6.285751
      1      1     team_1  15.307842  25.327383      0.692097  3.318847
      2      2     team_2  18.578741  36.069798      0.185332  0.984610
      3      3     team_3  19.056520  28.257306      0.219668  1.771407
      4      4     team_4  18.588003  27.678751      0.040225  5.250413
      5      5     team_5  19.171457  23.749660      0.311491  3.004915

         After Call Work  Special Projects   Training  System Issues     Other
      0        16.040020          0.000000  28.296591       0.000000  3.228571
      1        32.124069          5.108158  12.588173       0.647084  4.886347
      2        21.574318          2.999177  14.182656       1.047062  4.378306
      3        25.999005          3.692091  15.090693       2.005135  3.908173
      4        32.733635          2.600122   8.557262       1.085530  3.466060
      5        28.853932          1.428960  18.304315       0.437238  4.738032
```

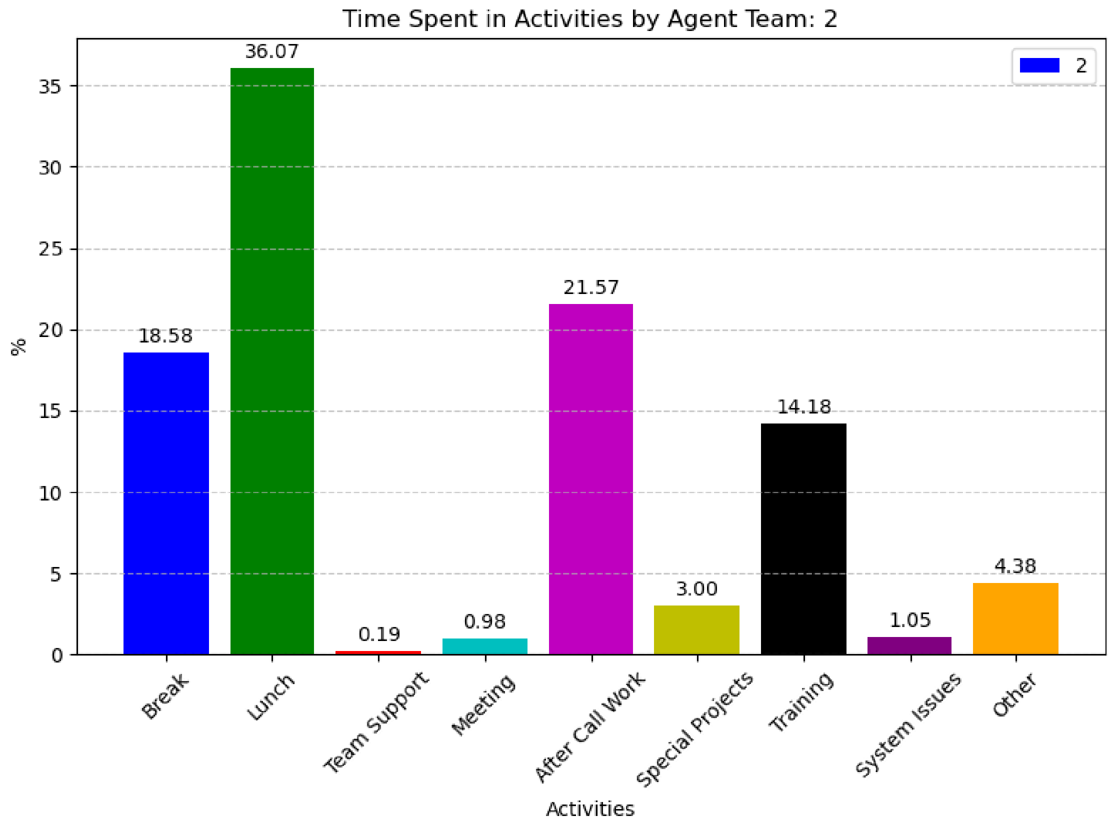
[35]:

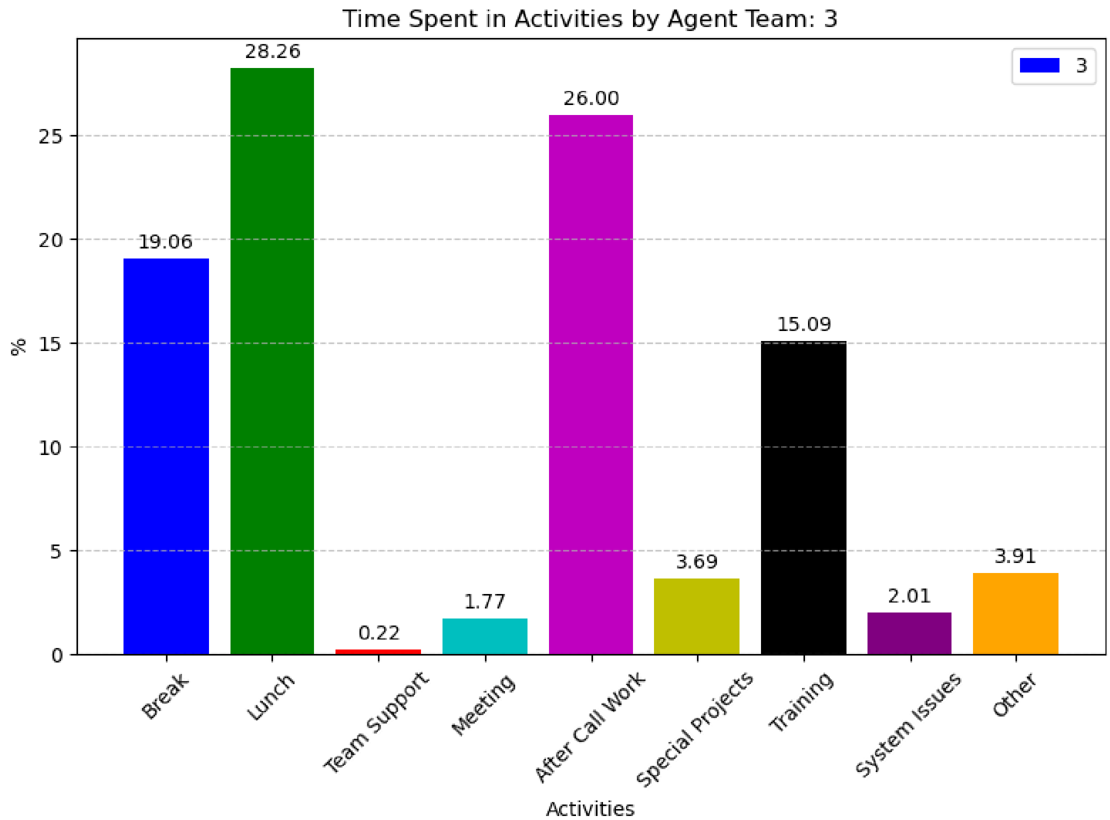
```python
# Group the data by 'Agent Team' and sum the time spent in each activity
team_activity_totals2 = team_sorted23.groupby('Agent Team').sum().reset_index()

# List of activities (excluding 'Agent Team' column)
activities2 = team_activity_totals2.columns[1:]


# Create a bar chart for each agent team with customizations
for team in team_activity_totals2.index:
    team_data2 = team_activity_totals2.loc[team, activities2]
    plt.figure(figsize=(8, 6))

    # Set custom colors for bars
    colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'purple', 'orange']

    ax = plt.bar(activities2, team_data2, label=team, color=colors)
    plt.title(f'Time Spent in Activities by Agent Team: {team}')
    plt.xlabel('Activities')
    plt.ylabel('%')
    plt.legend()

    # Customize gridlines
    plt.grid(axis='y', linestyle='--', alpha=0.7)

    plt.xticks(rotation=45)
    # Annotate each bar with its respective data
    for p in ax:
        plt.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2.,␣
 ↪p.get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
 ↪xytext=(0, 5), textcoords='offset points')
```

```
plt.tight_layout()

plt.show()
```

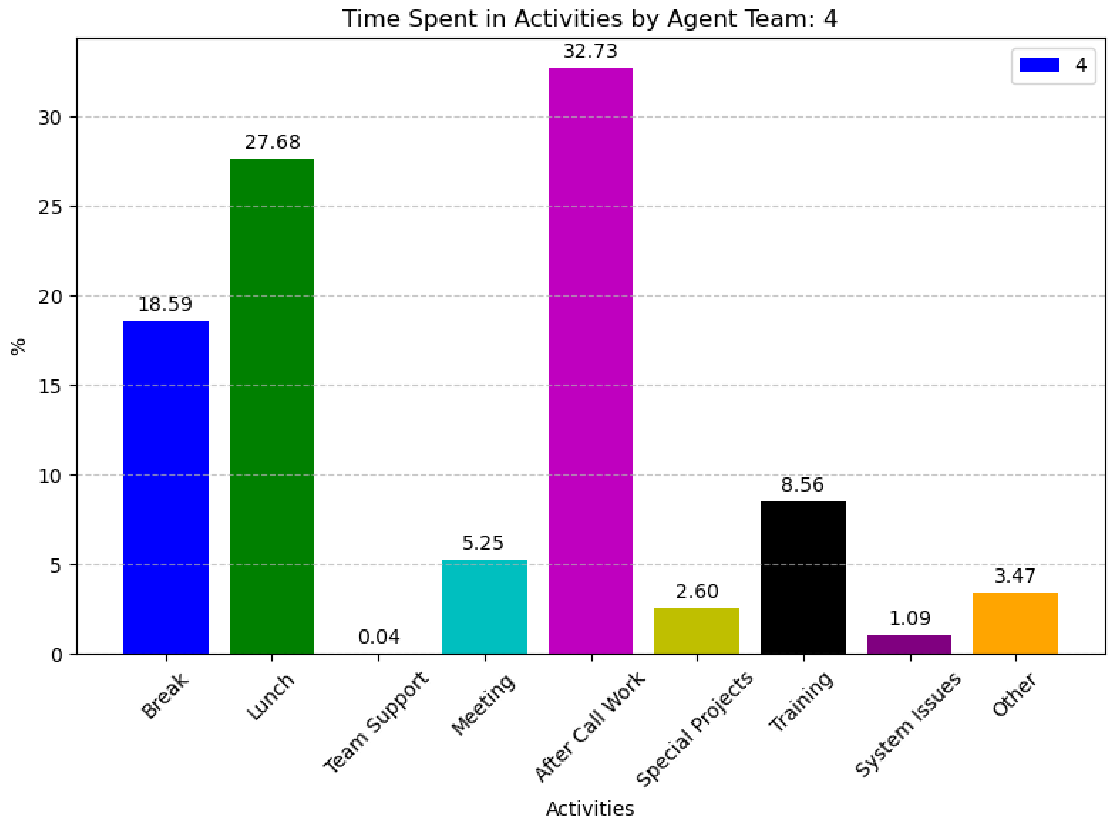


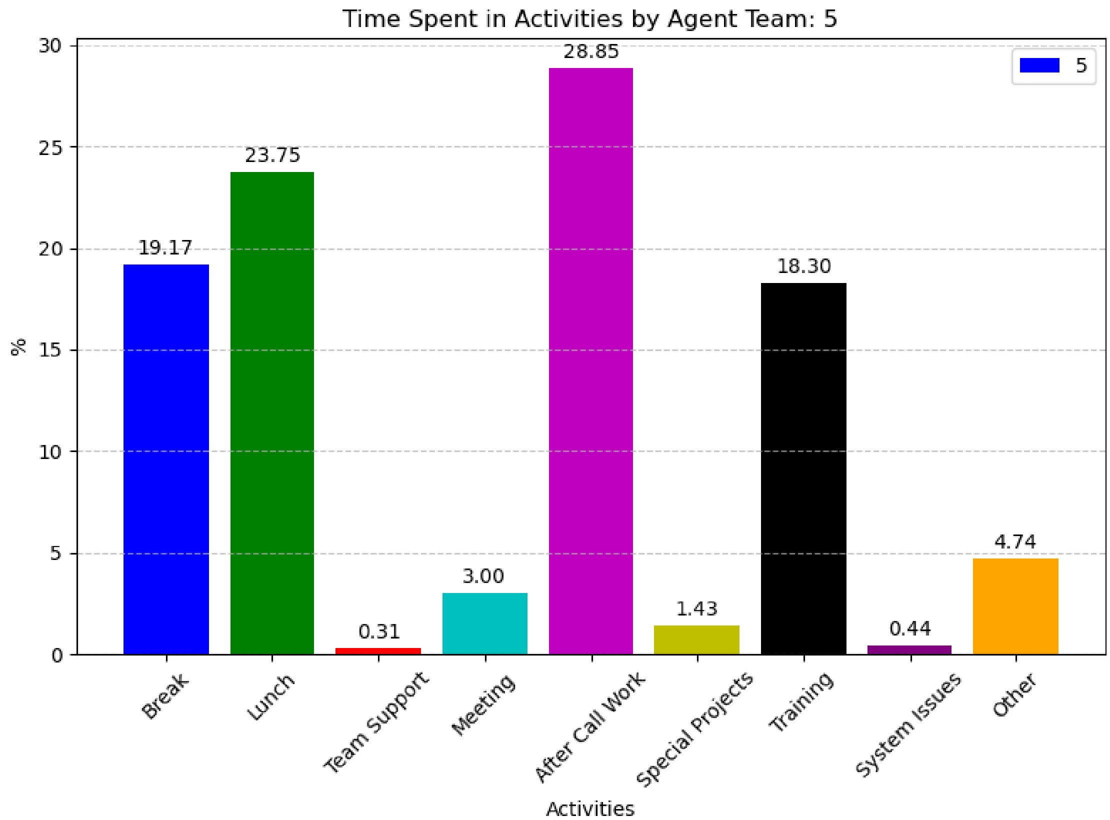

Time Spent in Activities by Agent Team: 1
1
32.12
25.33
15.31
12.59
5.11
4.89
3.32
0.69
0.65
30
25
20
15
10
5
0
%
Break
Lunch
Team Support
Meeting
After Call Work
Special Projects
Training
System Issues
Other
Activities


Time Spent in Activities by Agent Team: 2
2
%
Activities
0
5
10
15
20
25
30
35
18.58
36.07
0.19
0.98
21.57
3.00
14.18
1.05
4.38
Break
Lunch
Team Support
Meeting
After Call Work
Special Projects
Training
System Issues
Other



Time Spent in Activities by Agent Team: 3
3
%
0
5
10
15
20
25
19.06
28.26
0.22
1.77
26.00
3.69
15.09
2.01
3.91
Break
Lunch
Team Support
Meeting
After Call Work
Special Projects
Training
System Issues
Other
Activities


Time Spent in Activities by Agent Team: 4
4
%
0
5
10
15
20
25
30
18.59
27.68
0.04
5.25
32.73
2.60
8.56
1.09
3.47
Break
Lunch
Team Support
Meeting
After Call Work
Special Projects
Training
System Issues
Other
Activities



What is agents/teams utilization rate (on daily basis)? How about non-utilized time?

[36]:
```
copied_df = hcc_df.copy()

for col in time_related_columns:
    copied_df[col] = copied_df[col].dt.total_seconds() / (3600 * 24)

copied_df
```

[36]:
```
         Agent ID Agent Team       Date Interval Start Time   Interval End Time  \
0         Agent 1     team_1 2022-08-01 2022-08-01 08:00:00 2022-08-01 08:30:00
1         Agent 1     team_1 2022-08-01 2022-08-01 08:30:00 2022-08-01 09:00:00
2         Agent 1     team_1 2022-08-01 2022-08-01 09:00:00 2022-08-01 09:30:00
3         Agent 1     team_1 2022-08-01 2022-08-01 09:30:00 2022-08-01 10:00:00
4         Agent 1     team_1 2022-08-01 2022-08-01 10:00:00 2022-08-01 10:30:00
…           …          …          …                  …                    …
24907   Agent 97     team_3 2022-08-26 2022-08-26 14:30:00 2022-08-26 15:00:00
24908   Agent 97     team_3 2022-08-26 2022-08-26 15:00:00 2022-08-26 15:30:00
24909   Agent 97     team_3 2022-08-26 2022-08-26 15:30:00 2022-08-26 16:00:00
24910   Agent 97     team_3 2022-08-26 2022-08-26 16:00:00 2022-08-26 16:30:00
24911   Agent 97     team_3 2022-08-26 2022-08-26 16:30:00 2022-08-26 17:00:00
```

```
       Total Logged In Time  Not Ready Time  Ready Time  Reserved Time  \
0                  0.018773        0.002384    0.000081       0.000255
1                  0.020833        0.001076    0.001296       0.000382
2                  0.020833        0.002963    0.000000       0.000428
3                  0.020833        0.004329    0.000000       0.000174
4                  0.020833        0.001262    0.000000       0.000174
…                       …              …           …             …
24907              0.020833        0.000000    0.002859       0.000255
24908              0.020833        0.000000    0.010127       0.000231
24909              0.020833        0.003113    0.013252       0.000104
24910              0.020833        0.000000    0.004641       0.000150
24911              0.001366        0.000127    0.000000       0.000000

       Talk Time  Next Call Prep Time     Break  Lunch  Team Support  Meeting  \
0       0.015174             0.000880  0.000000    0.0           0.0      0.0
1       0.017002             0.001076  0.000000    0.0           0.0      0.0
2       0.015984             0.001458  0.000012    0.0           0.0      0.0
3       0.015544             0.000787  0.004329    0.0           0.0      0.0
4       0.018715             0.000683  0.000000    0.0           0.0      0.0
…           …                    …        …     …           …        …
24907   0.016563             0.001157  0.000000    0.0           0.0      0.0
24908   0.009780             0.000694  0.000000    0.0           0.0      0.0
24909   0.003669             0.000694  0.003113    0.0           0.0      0.0
24910   0.015579             0.000463  0.000000    0.0           0.0      0.0
24911   0.001157             0.000081  0.000000    0.0           0.0      0.0

       After Call Work  Special Projects  Training  System Issues     Other
0             0.002350               0.0  0.000000            0.0  0.000035
1             0.001076               0.0  0.000000            0.0  0.000000
2             0.002951               0.0  0.000000            0.0  0.000000
3             0.000000               0.0  0.000000            0.0  0.000000
4             0.001262               0.0  0.000000            0.0  0.000000
…                  …                …        …             …         …
24907         0.000000               0.0  0.000000            0.0  0.000000
24908         0.000000               0.0  0.000000            0.0  0.000000
24909         0.000000               0.0  0.000000            0.0  0.000000
24910         0.000000               0.0  0.000000            0.0  0.000000
24911         0.000000               0.0  0.000127            0.0  0.000000

[24912 rows x 20 columns]
```

[37]:
```python
# Group data by day and calculate metrics
daily_metrics = copied_df.resample('D', on='Date').agg({
    'Agent ID': 'nunique',
    'Agent Team': 'nunique',
    'Total Logged In Time': 'sum',
```

```
    'Talk Time': 'sum',
    'Reserved Time': 'sum',
    'Ready Time': 'sum',
    'Not Ready Time': 'sum'
    # Count unique agents per day
}).reset_index()
```

[38]:
```
daily_metrics
```

[38]:
```
          Date  Agent ID  Agent Team  Total Logged In Time  Talk Time  \
0   2022-08-01        72           6             22.497778  16.891944
1   2022-08-02        70           6             18.478287  13.524988
2   2022-08-03        76           6             21.292801  13.740868
3   2022-08-04        73           6             19.299444  12.501030
4   2022-08-05        65           6             17.548275  10.786806
5   2022-08-06         0           0              0.000000   0.000000
6   2022-08-07         0           0              0.000000   0.000000
7   2022-08-08        76           6             25.178576  17.300139
8   2022-08-09        74           6             21.129942  13.998750
9   2022-08-10        74           6             20.431238  12.692361
10  2022-08-11        70           6             18.688819  12.156539
11  2022-08-12        60           5             16.096632  10.913530
12  2022-08-13         0           0              0.000000   0.000000
13  2022-08-14         0           0              0.000000   0.000000
14  2022-08-15        66           6             20.715914  15.470359
15  2022-08-16        67           6             19.318831  13.662639
16  2022-08-17        67           6             18.630799  12.926655
17  2022-08-18        71           6             19.512106  12.465220
18  2022-08-19        63           6             17.587118  11.214699
19  2022-08-20         0           0              0.000000   0.000000
20  2022-08-21         0           0              0.000000   0.000000
21  2022-08-22        77           5             25.329861  17.434664
22  2022-08-23        70           5             20.517870  14.519931
23  2022-08-24        69           5             18.978657  13.161956
24  2022-08-25        64           5             17.072141  12.220648
25  2022-08-26        60           5             15.866713  10.839861

    Reserved Time  Ready Time  Not Ready Time
0        0.266319    0.638623        3.631736
1        0.259549    1.044062        2.724259
2        0.276806    2.852882        3.432037
3        0.248403    2.086516        3.550139
4        0.211725    2.886794        2.861366
5        0.000000    0.000000        0.000000
6        0.000000    0.000000        0.000000
7        0.302558    2.840532        3.557419
8        0.270428    2.601551        3.217431
```

```
9         0.262870    2.879653         3.633553
10        0.224375    2.393310         3.045046
11        0.200440    1.614734         2.574722
12        0.000000    0.000000         0.000000
13        0.000000    0.000000         0.000000
14        0.254618    0.877454         3.094780
15        0.255833    1.322859         3.104005
16        0.244352    1.701910         2.826736
17        0.239815    2.568322         3.325787
18        0.218519    2.565370         2.779502
19        0.000000    0.000000         0.000000
20        0.000000    0.000000         0.000000
21        0.336597    2.388032         3.897743
22        0.263889    1.293368         3.374757
23        0.247176    1.527650         3.043877
24        0.209502    1.155058         2.637894
25        0.191030    1.555475         2.507731
```

[39]:

```python
# Define a function to calculate utilization rate
def calculate_utilization_rate(copied_df):
    utilization_time = copied_df['Ready Time'] + copied_df['Talk Time'] +␣
 ↪copied_df['Reserved Time']
    utilization_rate = utilization_time / copied_df['Total Logged In Time']
    return utilization_rate

# Define a function to calculate non-utilized time
def calculate_non_utilized_rate(copied_df):
    non_utilized_rate = copied_df['Not Ready Time'] / copied_df['Total Logged␣
 ↪In Time']
    return non_utilized_rate

# Calculate utilization rate and non-utilized time
daily_metrics['Utilization Rate'] = calculate_utilization_rate(daily_metrics)
daily_metrics['Non-Utilized Rate'] = calculate_non_utilized_rate(daily_metrics)

# Print the weekly metrics
daily_metrics.reset_index()
```

[39]:

```
    index        Date  Agent ID  Agent Team  Total Logged In Time  Talk Time  \
0       0  2022-08-01        72           6             22.497778  16.891944
1       1  2022-08-02        70           6             18.478287  13.524988
2       2  2022-08-03        76           6             21.292801  13.740868
3       3  2022-08-04        73           6             19.299444  12.501030
4       4  2022-08-05        65           6             17.548275  10.786806
5       5  2022-08-06         0           0              0.000000   0.000000
6       6  2022-08-07         0           0              0.000000   0.000000
7       7  2022-08-08        76           6             25.178576  17.300139
```

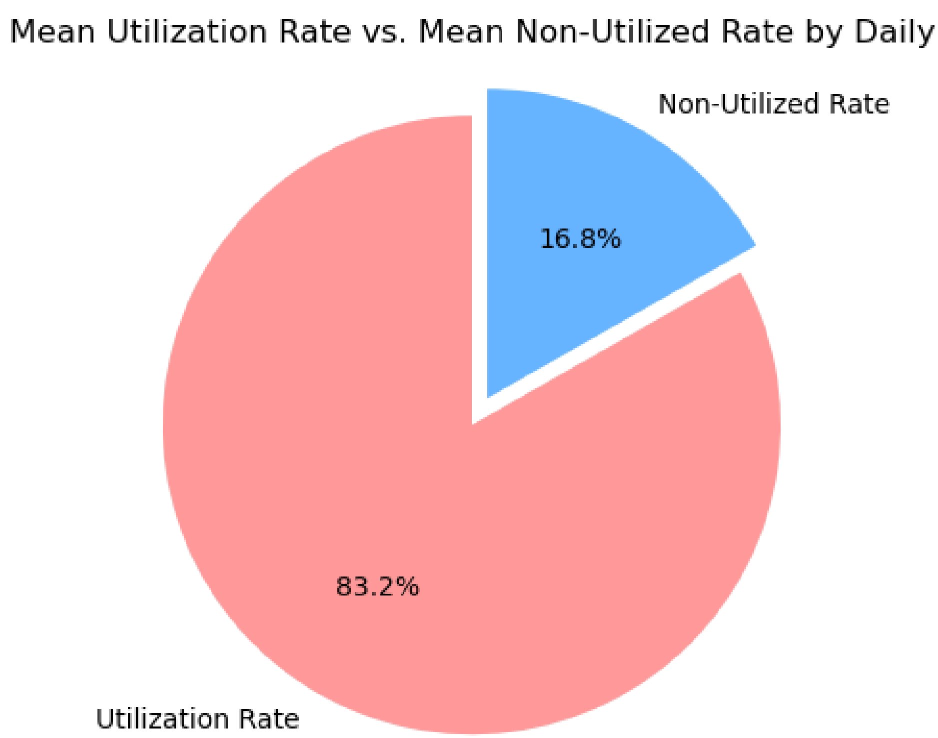
8	8	2022-08-09	74	6	21.129942	13.998750
9	9	2022-08-10	74	6	20.431238	12.692361
10	10	2022-08-11	70	6	18.688819	12.156539
11	11	2022-08-12	60	5	16.096632	10.913530
12	12	2022-08-13	0	0	0.000000	0.000000
13	13	2022-08-14	0	0	0.000000	0.000000
14	14	2022-08-15	66	6	20.715914	15.470359
15	15	2022-08-16	67	6	19.318831	13.662639
16	16	2022-08-17	67	6	18.630799	12.926655
17	17	2022-08-18	71	6	19.512106	12.465220
18	18	2022-08-19	63	6	17.587118	11.214699
19	19	2022-08-20	0	0	0.000000	0.000000
20	20	2022-08-21	0	0	0.000000	0.000000
21	21	2022-08-22	77	5	25.329861	17.434664
22	22	2022-08-23	70	5	20.517870	14.519931
23	23	2022-08-24	69	5	18.978657	13.161956
24	24	2022-08-25	64	5	17.072141	12.220648
25	25	2022-08-26	60	5	15.866713	10.839861

	Reserved Time	Ready Time	Not Ready Time	Utilization Rate	\
0	0.266319	0.638623	3.631736	0.791051	
1	0.259549	1.044062	2.724259	0.802488	
2	0.276806	2.852882	3.432037	0.792313	
3	0.248403	2.086516	3.550139	0.768724	
4	0.211725	2.886794	2.861366	0.791264	
5	0.000000	0.000000	0.000000	NaN	
6	0.000000	0.000000	0.000000	NaN	
7	0.302558	2.840532	3.557419	0.811930	
8	0.270428	2.601551	3.217431	0.798428	
9	0.262870	2.879653	3.633553	0.775033	
10	0.224375	2.393310	3.045046	0.790538	
11	0.200440	1.614734	2.574722	0.790768	
12	0.000000	0.000000	0.000000	NaN	
13	0.000000	0.000000	0.000000	NaN	
14	0.254618	0.877454	3.094780	0.801434	
15	0.255833	1.322859	3.104005	0.788937	
16	0.244352	1.701910	2.826736	0.798297	
17	0.239815	2.568322	3.325787	0.782763	
18	0.218519	2.565370	2.779502	0.795957	
19	0.000000	0.000000	0.000000	NaN	
20	0.000000	0.000000	0.000000	NaN	
21	0.336597	2.388032	3.897743	0.795871	
22	0.263889	1.293368	3.374757	0.783570	
23	0.247176	1.527650	3.043877	0.787031	
24	0.209502	1.155058	2.637894	0.795753	
25	0.191030	1.555475	2.507731	0.793256	

```
    Non-Utilized Rate
0           0.161426
1           0.147430
2           0.161183
3           0.183950
4           0.163057
5                NaN
6                NaN
7           0.141288
8           0.152269
9           0.177843
10          0.162934
11          0.159954
12               NaN
13               NaN
14          0.149391
15          0.160672
16          0.151724
17          0.170447
18          0.158042
19               NaN
20               NaN
21          0.153879
22          0.164479
23          0.160384
24          0.154515
25          0.158050
```

[40]:

```
# Calculate the mean utilization rate and non-utilization rate
mean_utilization_rate = daily_metrics['Utilization Rate'].mean()
mean_non_utilization_rate = daily_metrics['Non-Utilized Rate'].mean()

# Create a pie chart
labels = ['Utilization Rate', 'Non-Utilized Rate']
sizes = [mean_utilization_rate, mean_non_utilization_rate]
colors = ['#ff9999', '#66b3ff']
explode = (0.1, 0)

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=90,␣
↪explode=explode)
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

# Display the pie chart
plt.title('Mean Utilization Rate vs. Mean Non-Utilized Rate by Daily')
plt.show()
```



What is agents/teams utilization rate (on weekly basis)? How about non-utilized time?

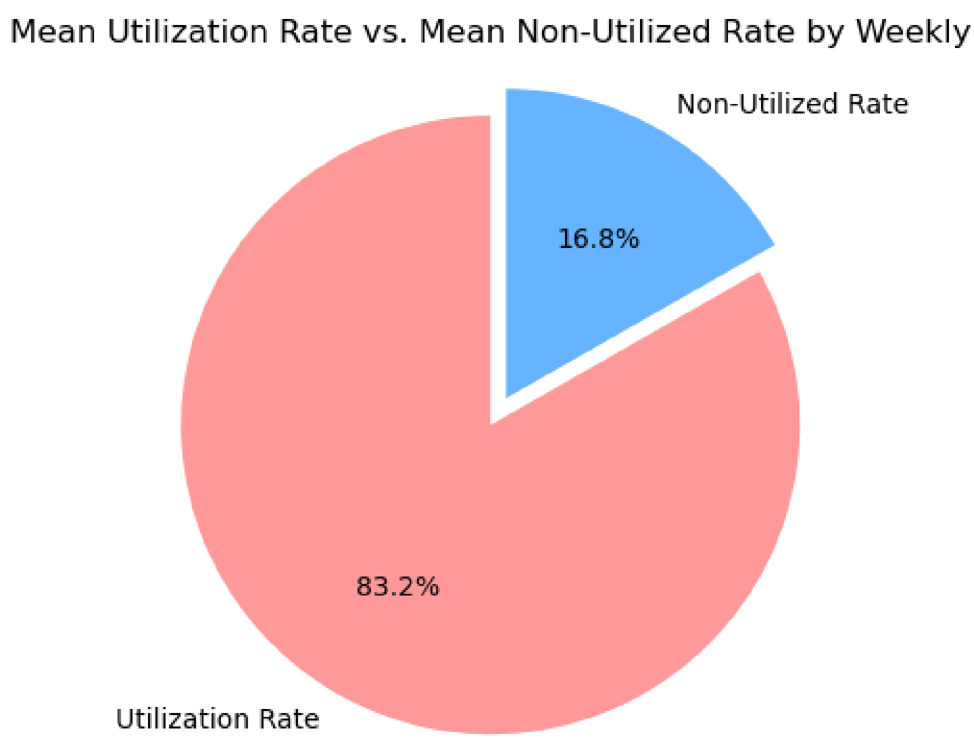
[41]:
```
# Group data by week and calculate metrics
weekly_metrics = copied_df.resample('W', on='Date').agg({
    'Agent ID': 'nunique',
    'Agent Team': 'nunique',
    'Total Logged In Time': 'sum',
    'Talk Time': 'sum',
    'Reserved Time': 'sum',
    'Ready Time': 'sum',
    'Not Ready Time': 'sum'
    # Count unique agents per week
}).reset_index()
```

[42]:
```
# Calculate utilization rate and non-utilized time
weekly_metrics['Utilization Rate'] = calculate_utilization_rate(weekly_metrics)
weekly_metrics['Non-Utilized Rate'] =␣
 ↪calculate_non_utilized_rate(weekly_metrics)

weekly_metrics.rename(columns={'Date': 'Week'}, inplace=True)
```

```python
# Print the weekly metrics
weekly_metrics.reset_index()
```

[42]:
```
   index       Week  Agent ID  Agent Team  Total Logged In Time  Talk Time  \
0      0 2022-08-07        90           6             99.116586  67.445637
1      1 2022-08-14        87           6            101.525208  67.061319
2      2 2022-08-21        89           6             95.764769  65.739572
3      3 2022-08-28        88           5             97.765243  68.177060

   Reserved Time  Ready Time  Not Ready Time  Utilization Rate  \
0       1.262801    9.508877       16.199537          0.789145
1       1.260671   12.329780       16.028171          0.794401
2       1.213137    9.035914       15.130810          0.793492
3       1.248194    7.919583       15.462002          0.791128

   Non-Utilized Rate
0           0.163439
1           0.157874
2           0.158000
3           0.158154
```

[43]:
```python
# Calculate the mean utilization rate and non-utilization rate
mean_utilization_rate2 = weekly_metrics['Utilization Rate'].mean()
mean_non_utilization_rate2 = weekly_metrics['Non-Utilized Rate'].mean()

# Create a pie chart
labels = ['Utilization Rate', 'Non-Utilized Rate']
sizes = [mean_utilization_rate2, mean_non_utilization_rate2]
colors = ['#ff9999', '#66b3ff']
explode = (0.1, 0)

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=90,␣
 ↪explode=explode)
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

# Display the pie chart
plt.title('Mean Utilization Rate vs. Mean Non-Utilized Rate by Weekly')
plt.show()
```



[44]:

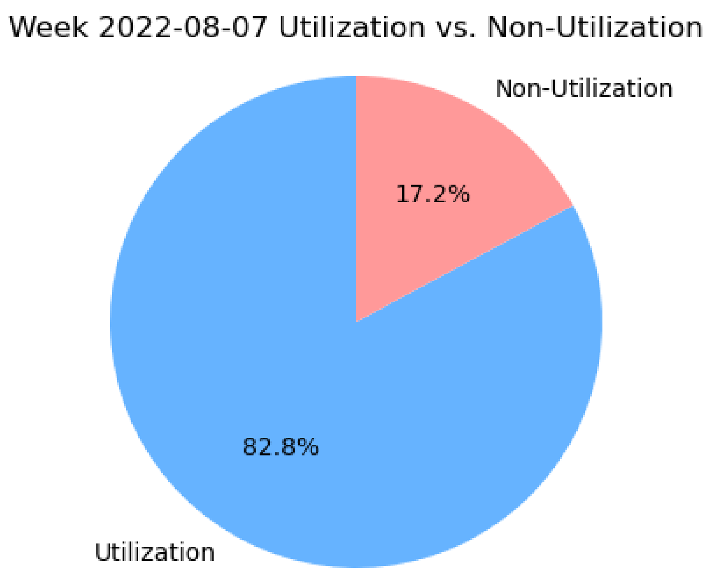
```
weekly_metrics.info()
```

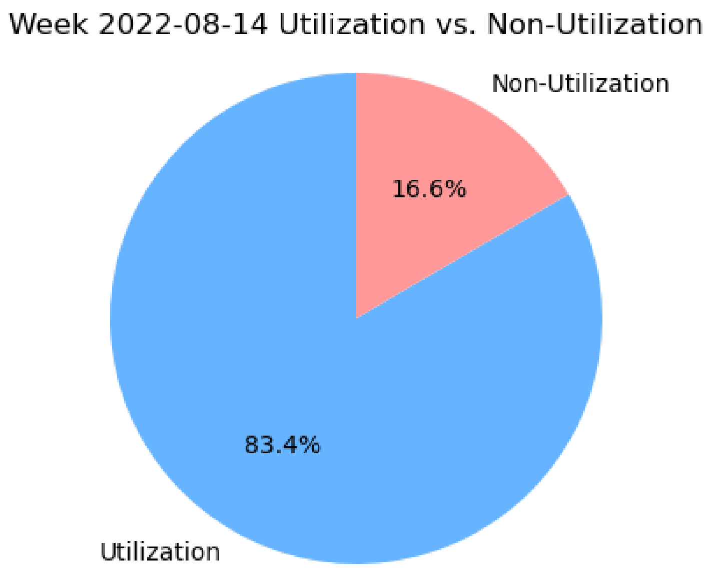
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Week                4 non-null      datetime64[ns]
 1   Agent ID            4 non-null      int64
 2   Agent Team          4 non-null      int64
 3   Total Logged In Time  4 non-null    float64
 4   Talk Time           4 non-null      float64
 5   Reserved Time       4 non-null      float64
 6   Ready Time          4 non-null      float64
 7   Not Ready Time      4 non-null      float64
 8   Utilization Rate    4 non-null      float64
 9   Non-Utilized Rate   4 non-null      float64
dtypes: datetime64[ns](1), float64(7), int64(2)
memory usage: 448.0 bytes
```

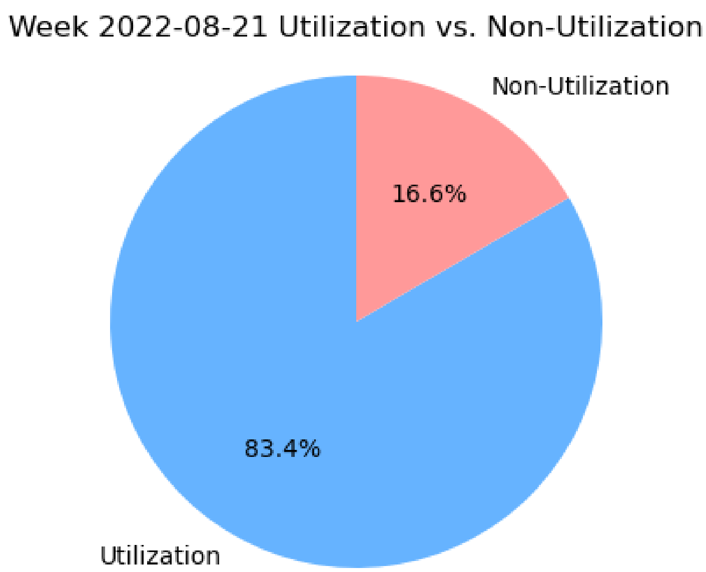
[45]:

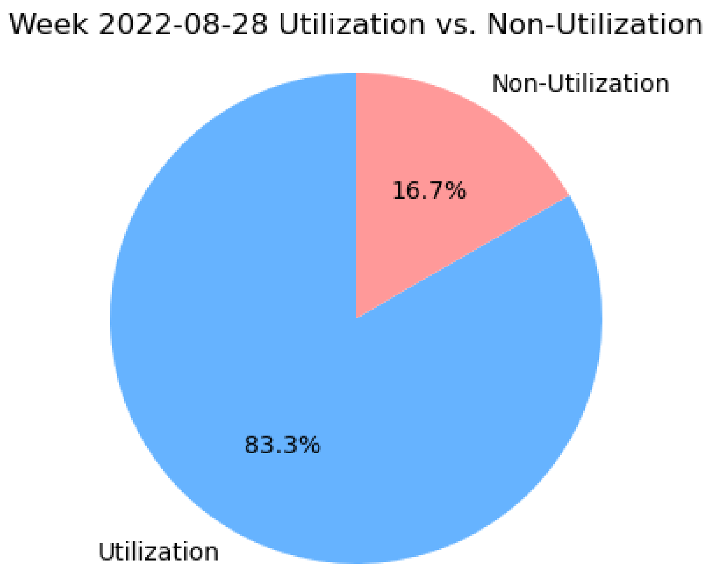
```
# Extract the relevant data for visualization
weeks = weekly_metrics['Week'].tolist()
```

```
utilization_rates = weekly_metrics['Utilization Rate'].tolist()
non_utilization_rates = weekly_metrics['Non-Utilized Rate'].tolist()

# Create pie charts for each week
for week, utilization_rate, non_utilization_rate in zip(weeks,␣
↪utilization_rates, non_utilization_rates):
    plt.figure(figsize=(8, 4))
    labels = ['Utilization', 'Non-Utilization']
    sizes = [utilization_rate, non_utilization_rate]
    colors = ['#66b3ff', '#ff9999']  # Blue for utilization, red for␣
↪non-utilization
    plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%',␣
↪startangle=90)
    plt.title(f'Week {week.strftime("%Y-%m-%d")} Utilization vs.␣
↪Non-Utilization')
    plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a␣
↪circle
    plt.show()
```




Week 2022-08-14 Utilization vs. Non-Utilization
Non-Utilization
16.6%
83.4%
Utilization

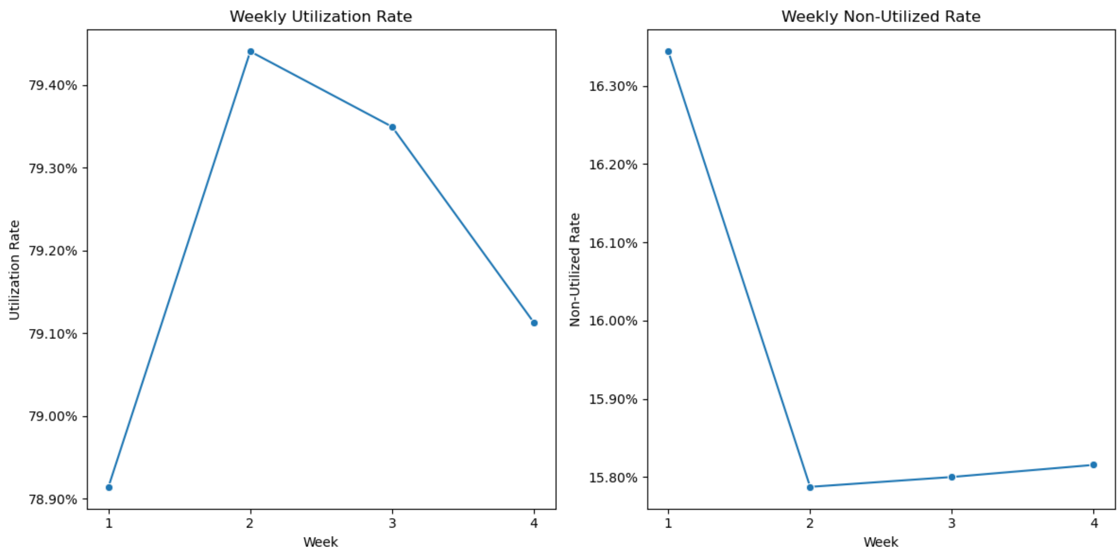

Week 2022-08-21 Utilization vs. Non-Utilization
Non-Utilization
16.6%
83.4%
Utilization



[46]:
```
weekly_metrics2 = weekly_metrics.copy()

# Initialize a counter
counter = 1

# Create a dictionary to store the mapping of old values to new values
week_mapping = {}

# Iterate through the unique values in the 'Week' column
for week in weekly_metrics2['Week'].unique():
    week_mapping[week] = str(counter)
    counter += 1

# Replace the values in the 'Week' column using the mapping
weekly_metrics2['Week'] = weekly_metrics2['Week'].map(week_mapping)
```

[47]:
```
import matplotlib.ticker as mtick  # Import the necessary module for formatting␣
↪y-axis as percentages

plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
sns.lineplot(x='Week', y='Utilization Rate', data=weekly_metrics2, marker='o')
plt.title("Weekly Utilization Rate")
plt.xlabel("Week")
plt.ylabel("Utilization Rate")
```

```
plt.gca().yaxis.set_major_formatter(mtick.PercentFormatter(1.0))  # Format␣
↪y-axis as percentages

plt.subplot(1, 2, 2)
sns.lineplot(x='Week', y='Non-Utilized Rate', data=weekly_metrics2, marker='o')
plt.title("Weekly Non-Utilized Rate")
plt.xlabel("Week")
plt.ylabel("Non-Utilized Rate")
plt.gca().yaxis.set_major_formatter(mtick.PercentFormatter(1.0))  # Format␣
↪y-axis as percentages

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



[48]:
```
# Calculate the number of FTEs (assuming a 40-hour workweek)
weekly_metrics2['FTEs'] = (weekly_metrics2['Utilization Rate'] * 40) / (60 * 5)␣
↪ # 60 minutes per hour, 5 workdays per week

# Print the weekly metrics
weekly_metrics2.reset_index()
```

[48]:
```
   index  Week  Agent ID  Agent Team  Total Logged In Time  Talk Time  \
0      0     1        90           6             99.116586  67.445637
1      1     2        87           6            101.525208  67.061319
2      2     3        89           6             95.764769  65.739572
3      3     4        88           5             97.765243  68.177060

   Reserved Time  Ready Time  Not Ready Time  Utilization Rate  \
```

```
0       1.262801    9.508877       16.199537          0.789145
1       1.260671   12.329780       16.028171          0.794401
2       1.213137    9.035914       15.130810          0.793492
3       1.248194    7.919583       15.462002          0.791128

   Non-Utilized Rate      FTEs
0           0.163439  0.105219
1           0.157874  0.105920
2           0.158000  0.105799
3           0.158154  0.105484
```

[49]:
```python
# Group data by team and calculate average talk time per call
team_avg_talk_time = hcc_df.groupby('Agent Team')['Talk Time'].mean()
highest_avg_talk_time_team = team_avg_talk_time.idxmax()
lowest_avg_talk_time_team = team_avg_talk_time.idxmin()
```

[50]:
```python
highest_avg_talk_time_team
```

[50]:
```
'team_3'
```

[51]:
```python
lowest_avg_talk_time_team
```

[51]:
```
'team_0'
```

How does the number of handled calls vary by specialty (Agent Team) on a weekly basis?

[52]:
```python
# Merge sheet3 with merged_df on 'Agent ID' and 'Date'
hcc_df2 = pd.merge(sheet3, sheet4, on=['Agent ID'])
hcc_df2
```

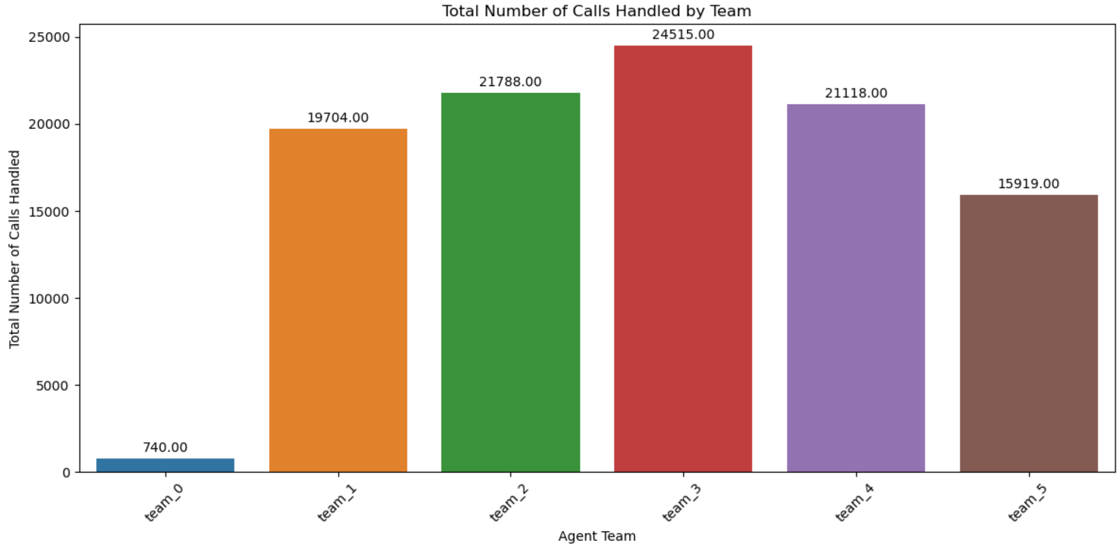
[52]:
```
      Agent ID       Date  Number of Calls Handled Average Handle Time  \
0      Agent 1 2022-08-01                      94            00:04:40
1      Agent 1 2022-08-02                      80            00:04:42
2      Agent 1 2022-08-03                      81            00:04:34
3      Agent 1 2022-08-04                      73            00:05:12
4      Agent 1 2022-08-05                      75            00:04:51
…          …          …                      …                    …
1914  Agent 72 2022-08-22                       0            00:00:00
1915  Agent 72 2022-08-23                       0            00:00:00
1916  Agent 72 2022-08-24                       0            00:00:00
1917  Agent 72 2022-08-25                       0            00:00:00
1918  Agent 72 2022-08-26                       0            00:00:00

     Agent Team
0        team_1
1        team_1
2        team_1
```

```
3        team_1
4        team_1
…         …
1914     team_5
1915     team_5
1916     team_5
1917     team_5
1918     team_5

[1919 rows x 5 columns]
```

[53]:
```python
# Group data by team and date, then calculate the number of handled calls
team_handled_calls = hcc_df2.groupby(['Agent Team'])['Number of Calls Handled'].
↪sum().reset_index()
team_handled_calls
```

[53]:
```
  Agent Team  Number of Calls Handled
0     team_0                      740
1     team_1                    19704
2     team_2                    21788
3     team_3                    24515
4     team_4                    21118
5     team_5                    15919
```

[54]:
```python
# Create a bar plot of Total Logged In Time by Team in days
plt.figure(figsize=(12, 6))
ax = sns.barplot(x='Agent Team', y='Number of Calls Handled',␣
↪data=team_handled_calls)
plt.title('Total Number of Calls Handled by Team')
plt.xlabel('Agent Team')
plt.ylabel('Total Number of Calls Handled')
plt.xticks(rotation=45)

# Annotate each bar with its respective data
for p in ax.patches:
    plt.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2., p.
↪get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
↪xytext=(0, 5), textcoords='offset points')

plt.tight_layout()

plt.show()
```



[55]:
```python
# Group by 'Agent Team' and the week of the 'Date'
team_weekly_handled_calls = hcc_df2.groupby(['Agent Team', hcc_df2['Date'].dt.
↪strftime('%U-%Y')])['Number of Calls Handled'].sum().reset_index()

# Rename the columns for clarity
team_weekly_handled_calls.columns = ['Agent Team', 'Week', 'Total Calls␣
↪Handled']

# Sort the data by 'Agent Team' and 'Week'
team_weekly_handled_calls = team_weekly_handled_calls.sort_values(by=['Agent␣
↪Team', 'Week'])

# Remove the first character from the 'Week' column
team_weekly_handled_calls['Week'] = team_weekly_handled_calls['Week'].str[1:]

team_weekly_handled_calls.reset_index()
```

[55]:

	index	Agent Team	Week	Total Calls Handled
0	0	team_0	1-2022	217
1	1	team_0	2-2022	168
2	2	team_0	3-2022	355
3	3	team_0	4-2022	0
4	4	team_1	1-2022	4742
5	5	team_1	2-2022	4889
6	6	team_1	3-2022	5113
7	7	team_1	4-2022	4960
8	8	team_2	1-2022	5592
9	9	team_2	2-2022	5064

```
10     10     team_2   3-2022                 5356
11     11     team_2   4-2022                 5776
12     12     team_3   1-2022                 5091
13     13     team_3   2-2022                 6687
14     14     team_3   3-2022                 6021
15     15     team_3   4-2022                 6716
16     16     team_4   1-2022                 5549
17     17     team_4   2-2022                 4989
18     18     team_4   3-2022                 4642
19     19     team_4   4-2022                 5938
20     20     team_5   1-2022                 4212
21     21     team_5   2-2022                 4088
22     22     team_5   3-2022                 3544
23     23     team_5   4-2022                 4075
```

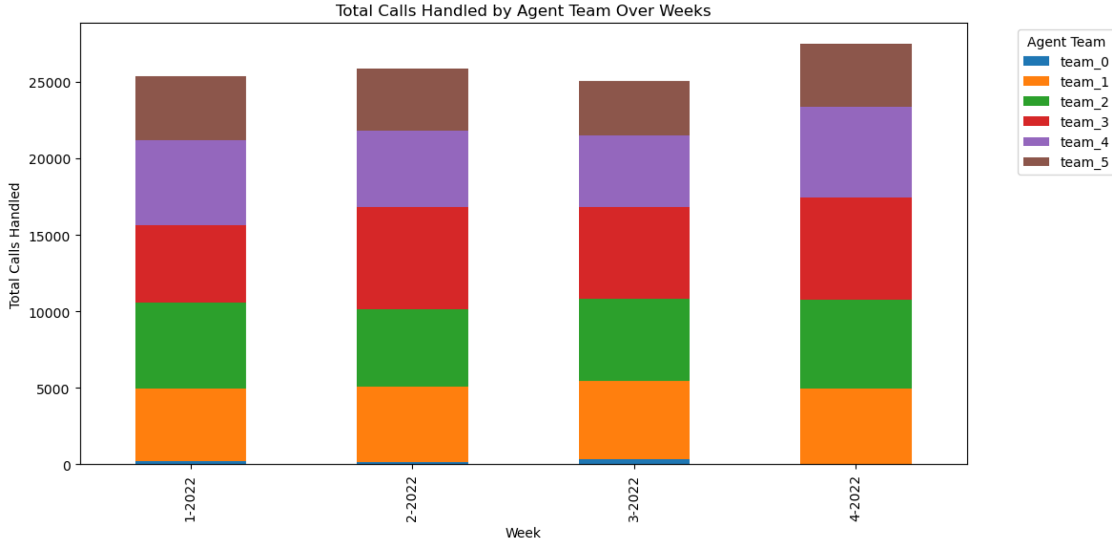
[56]:

```
team_weekly_handled_calls.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24 entries, 0 to 23
Data columns (total 3 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Agent Team            24 non-null     object
 1   Week                  24 non-null     object
 2   Total Calls Handled   24 non-null     int64
dtypes: int64(1), object(2)
memory usage: 768.0+ bytes
```

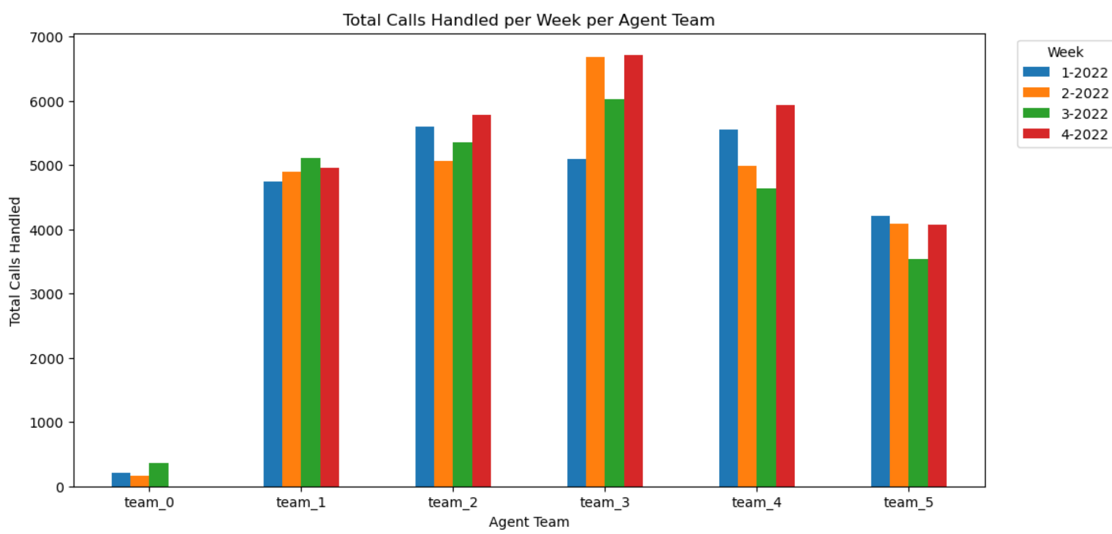
[57]:

```
# Pivot the DataFrame to prepare it for a stacked bar chart
pivot_df = team_weekly_handled_calls.pivot(index='Week', columns='Agent Team',␣
 ↪values='Total Calls Handled')

# Create a stacked bar chart
ax = pivot_df.plot(kind='bar', stacked=True, figsize=(12, 6))

# Add labels and title
plt.xlabel('Week')
plt.ylabel('Total Calls Handled')
plt.title('Total Calls Handled by Agent Team Over Weeks')

# Show the legend
plt.legend(title='Agent Team', bbox_to_anchor=(1.05, 1), loc='upper left')

# Show the chart
plt.show()
```



[58]:

```python
# Create a pivot table to reshape the data for plotting
pivot_table = team_weekly_handled_calls.pivot(index='Agent Team',␣
 ↪columns='Week', values='Total Calls Handled')

# Plot the data as a bar chart
ax = pivot_table.plot(kind='bar', figsize=(12, 6))
plt.title('Total Calls Handled per Week per Agent Team')
plt.xlabel('Agent Team')
plt.ylabel('Total Calls Handled')
plt.legend(title='Week', loc='upper right', bbox_to_anchor=(1.15, 1))
plt.xticks(rotation=0)  # Rotate x-axis labels for better readability

plt.show()
```



1.1.1 c) By Agent:

[59]:
```
agent_sorted = hcc_df.groupby(['Agent ID'])[time_related_columns].sum().
    ↪reset_index()
agent_sorted
```

[59]:
```
   Agent ID Total Logged In Time  Not Ready Time      Ready Time  \
0   Agent 1      6 days 15:33:03 0 days 23:27:09 0 days 11:27:15
1  Agent 10      3 days 10:20:55 0 days 07:05:56 1 days 11:21:54
2  Agent 11      3 days 12:03:39 0 days 17:56:24 0 days 05:30:23
3  Agent 12      3 days 21:27:28 0 days 06:01:56 0 days 06:46:27
4  Agent 13      3 days 14:33:26 0 days 12:52:46 0 days 21:41:38
..      …                  …               …               …
92 Agent 93      0 days 16:19:24 0 days 03:32:43 0 days 02:21:59
93 Agent 94      0 days 14:20:04 0 days 01:26:29 0 days 06:17:13
94 Agent 95      2 days 10:31:16 0 days 09:37:32 0 days 20:53:14
95 Agent 96      1 days 04:51:38 0 days 04:05:40 0 days 13:07:34
96 Agent 97      1 days 16:57:17 0 days 06:48:41 0 days 16:50:43

     Reserved Time       Talk Time Next Call Prep Time           Break  \
0  0 days 01:58:01 4 days 19:53:35     0 days 06:47:03 0 days 04:16:51
1  0 days 01:19:18 1 days 10:15:09     0 days 04:18:38 0 days 02:56:14
2  0 days 00:42:36 2 days 09:35:14     0 days 02:19:02 0 days 02:05:22
3  0 days 01:19:14 3 days 02:36:32     0 days 04:43:19 0 days 02:04:31
4  0 days 00:46:19 1 days 23:39:18     0 days 03:33:25 0 days 01:50:43
..             …               …                   …               …
92 0 days 00:07:22 0 days 09:40:56     0 days 00:36:24 0 days 00:15:16
93 0 days 00:17:45 0 days 05:45:26     0 days 00:33:11 0 days 00:21:09
94 0 days 00:37:54 1 days 01:26:33     0 days 01:56:03 0 days 01:53:09
95 0 days 00:26:25 0 days 10:20:09     0 days 00:51:50 0 days 00:43:20
96 0 days 00:41:40 0 days 14:58:08     0 days 01:38:05 0 days 02:14:12

             Lunch    Team Support         Meeting After Call Work  \
0  0 days 09:00:44 0 days 00:00:00 0 days 00:28:08 0 days 06:40:34
1  0 days 04:01:06 0 days 00:00:00 0 days 00:00:00 0 days 00:00:26
2  0 days 04:00:52 0 days 00:00:00 0 days 02:22:34 0 days 09:00:47
3  0 days 00:29:05 0 days 00:17:33 0 days 00:03:10 0 days 02:01:24
4  0 days 04:03:32 0 days 00:00:25 0 days 00:48:54 0 days 02:04:34
..               …               …               …               …
92 0 days 00:30:57 0 days 00:00:00 0 days 00:00:00 0 days 01:51:44
93 0 days 00:34:18 0 days 00:00:00 0 days 00:00:00 0 days 00:00:00
94 0 days 03:23:03 0 days 00:01:08 0 days 00:01:01 0 days 00:00:00
95 0 days 00:59:13 0 days 00:00:00 0 days 00:00:00 0 days 00:00:00
96 0 days 01:28:30 0 days 00:00:00 0 days 00:00:00 0 days 00:00:00
```

```
   Special Projects          Training    System Issues             Other
0    0 days 01:30:26 0 days 01:09:44 0 days 00:13:20 0 days 00:07:22
1    0 days 00:00:00 0 days 00:00:00 0 days 00:02:53 0 days 00:05:17
2    0 days 00:00:00 0 days 00:22:24 0 days 00:00:00 0 days 00:04:25
3    0 days 00:43:13 0 days 00:06:55 0 days 00:00:00 0 days 00:16:05
4    0 days 00:00:00 0 days 03:40:08 0 days 00:00:00 0 days 00:24:30
..                …               …               …               …
92   0 days 00:00:00 0 days 00:48:21 0 days 00:00:05 0 days 00:06:20
93   0 days 00:00:00 0 days 00:16:07 0 days 00:00:17 0 days 00:14:38
94   0 days 00:00:00 0 days 04:07:56 0 days 00:03:27 0 days 00:07:48
95   0 days 00:00:00 0 days 01:08:06 0 days 00:00:00 0 days 01:15:01
96   0 days 00:00:00 0 days 02:26:05 0 days 00:03:12 0 days 00:36:42

[97 rows x 16 columns]
```

[60]:
```
agent_sorted.describe()
```

[60]:
```
              Total Logged In Time              Not Ready Time  \
count                           97                          97
mean     4 days 01:31:37.360824742  0 days 15:32:35.597938144
std      1 days 18:10:18.923891820  0 days 09:13:50.914340245
min                0 days 01:50:37             0 days 00:05:11
25%                3 days 01:20:07             0 days 08:52:32
50%                3 days 21:27:28             0 days 14:48:45
75%                5 days 13:54:33             0 days 19:59:59
max                7 days 02:55:44             2 days 00:44:19

                        Ready Time               Reserved Time  \
count                           97                          97
mean     0 days 09:35:54.793814432  0 days 01:14:00.072164948
std      0 days 10:01:11.383552252  0 days 00:39:56.581829082
min                0 days 00:21:53             0 days 00:02:05
25%                0 days 03:08:47             0 days 00:44:23
50%                0 days 06:17:13             0 days 01:09:36
75%                0 days 12:17:01             0 days 01:37:22
max                2 days 10:07:26             0 days 02:54:20

                         Talk Time         Next Call Prep Time  \
count                           97                          97
mean     2 days 18:24:50.701030927  0 days 04:44:16.195876288
std      1 days 07:54:36.092407044  0 days 02:51:00.754656334
min                0 days 00:34:31             0 days 00:06:20
25%                1 days 22:39:40             0 days 02:46:49
50%                2 days 17:52:03             0 days 04:11:59
75%                3 days 17:22:45             0 days 06:04:05
max                5 days 10:53:50             0 days 12:35:03
```

```
                    Break                     Lunch  \
count                  97                        97
mean   0 days 02:48:51.154639175  0 days 04:19:42.948453608
std    0 days 02:05:54.771206744  0 days 03:13:09.557273657
min              0 days 00:00:00            0 days 00:00:00
25%              0 days 01:29:00            0 days 01:28:30
50%              0 days 02:28:51            0 days 04:01:05
75%              0 days 03:50:19            0 days 07:06:24
max              0 days 14:10:11            0 days 09:54:22

                    Team Support                Meeting  \
count                  97                        97
mean   0 days 00:02:43.381443298  0 days 00:27:53.855670103
std    0 days 00:11:19.561262312  0 days 00:42:57.453066941
min              0 days 00:00:00            0 days 00:00:00
25%              0 days 00:00:00            0 days 00:00:00
50%              0 days 00:00:00            0 days 00:10:22
75%              0 days 00:00:03            0 days 00:35:05
max              0 days 01:43:11            0 days 03:22:35

                  After Call Work          Special Projects  \
count                  97                        97
mean   0 days 04:25:28.298969072  0 days 00:28:59.432989690
std    0 days 04:27:08.830119613  0 days 01:00:13.213648965
min              0 days 00:00:00            0 days 00:00:00
25%              0 days 01:31:39            0 days 00:00:00
50%              0 days 03:00:45            0 days 00:00:00
75%              0 days 06:18:16            0 days 00:16:48
max              1 days 02:17:17            0 days 04:41:22

                         Training             System Issues  \
count                  97                        97
mean   0 days 02:09:38.051546391  0 days 00:09:28.927835051
std    0 days 02:46:17.749854228  0 days 00:22:02.217867254
min              0 days 00:00:00            0 days 00:00:00
25%              0 days 00:16:07            0 days 00:00:00
50%              0 days 01:09:07            0 days 00:02:49
75%              0 days 02:51:24            0 days 00:12:16
max              0 days 16:48:18            0 days 03:09:09

                            Other
count                          97
mean   0 days 00:39:49.546391752
std    0 days 00:49:37.711219140
min              0 days 00:00:37
25%              0 days 00:08:40
```

```
50%              0 days 00:22:26
75%              0 days 00:50:43
max              0 days 05:41:26
```

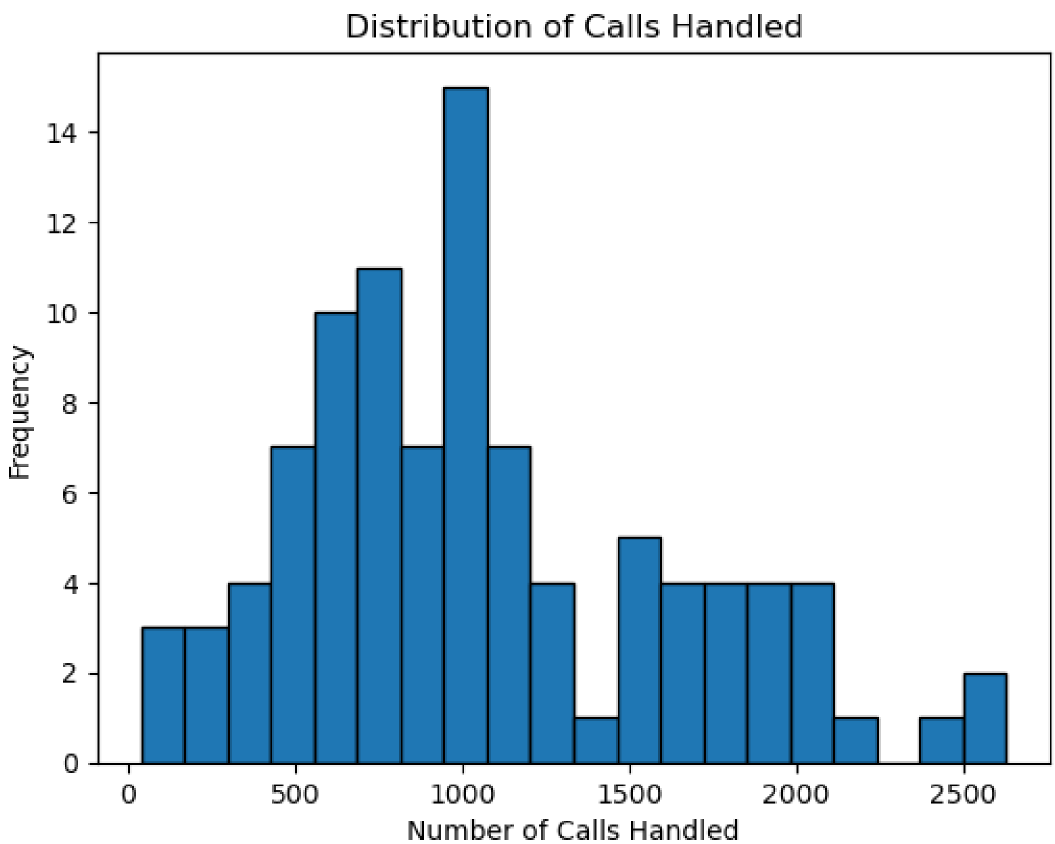
[61]:
```
total_performance = sheet3.groupby(['Agent ID']).sum(numeric_only=True)
total_performance.reset_index(inplace=True)
total_performance
```

[61]:
```
    Agent ID  Number of Calls Handled
0    Agent 1                     1696
1   Agent 10                     1547
2   Agent 11                      608
3   Agent 12                     1209
4   Agent 13                      702
..       …                       …
92  Agent 93                      126
93  Agent 94                      201
94  Agent 95                      520
95  Agent 96                      284
96  Agent 97                      525

[97 rows x 2 columns]
```

[62]:
```
# Assuming your data is in a DataFrame called df
mean_calls = total_performance['Number of Calls Handled'].mean()
median_calls = total_performance['Number of Calls Handled'].median()
min_calls = total_performance['Number of Calls Handled'].min()
max_calls = total_performance['Number of Calls Handled'].max()

print(f"Mean Calls Handled: {mean_calls}")
print(f"Median Calls Handled: {median_calls}")
print(f"Minimum Calls Handled: {min_calls}")
print(f"Maximum Calls Handled: {max_calls}")
```

```
Mean Calls Handled: 1069.9381443298969
Median Calls Handled: 968.0
Minimum Calls Handled: 38
Maximum Calls Handled: 2632
```

[63]:
```
# Create a histogram
plt.hist(total_performance['Number of Calls Handled'], bins=20, edgecolor='k')
plt.xlabel('Number of Calls Handled')
plt.ylabel('Frequency')
plt.title('Distribution of Calls Handled')
plt.show()
```



[64]:
```python
top_agents = total_performance.nlargest(5, 'Number of Calls Handled')
top_agents.reset_index()
```

[64]:

	index	Agent ID	Number of Calls Handled
0	24	Agent 31	2632
1	50	Agent 55	2594
2	12	Agent 20	2409
3	29	Agent 36	2167
4	11	Agent 2	2069

[65]:
```python
bottom_agents = total_performance.nsmallest(5, 'Number of Calls Handled')
bottom_agents.reset_index()
```

[65]:

	index	Agent ID	Number of Calls Handled
0	79	Agent 81	38
1	37	Agent 43	102
2	92	Agent 93	126
3	6	Agent 15	189
4	93	Agent 94	201

1.1.2 d) Staffing Plan:

[66]:
```
daily_metrics2 = daily_metrics.copy()
daily_metrics2['Day of Week'] = daily_metrics2['Date'].dt.strftime('%A')

# Calculate the number of FTEs (assuming a 40-hour workweek)
daily_metrics2['FTEs'] = (daily_metrics2['Utilization Rate'] * 40) / 60  # 60␣
↪minutes per hour

# Print the weekly metrics
daily_metrics2.reset_index()
daily_metrics2
```

[66]:
```
          Date  Agent ID  Agent Team  Total Logged In Time  Talk Time  \
0   2022-08-01        72           6             22.497778  16.891944
1   2022-08-02        70           6             18.478287  13.524988
2   2022-08-03        76           6             21.292801  13.740868
3   2022-08-04        73           6             19.299444  12.501030
4   2022-08-05        65           6             17.548275  10.786806
5   2022-08-06         0           0              0.000000   0.000000
6   2022-08-07         0           0              0.000000   0.000000
7   2022-08-08        76           6             25.178576  17.300139
8   2022-08-09        74           6             21.129942  13.998750
9   2022-08-10        74           6             20.431238  12.692361
10  2022-08-11        70           6             18.688819  12.156539
11  2022-08-12        60           5             16.096632  10.913530
12  2022-08-13         0           0              0.000000   0.000000
13  2022-08-14         0           0              0.000000   0.000000
14  2022-08-15        66           6             20.715914  15.470359
15  2022-08-16        67           6             19.318831  13.662639
16  2022-08-17        67           6             18.630799  12.926655
17  2022-08-18        71           6             19.512106  12.465220
18  2022-08-19        63           6             17.587118  11.214699
19  2022-08-20         0           0              0.000000   0.000000
20  2022-08-21         0           0              0.000000   0.000000
21  2022-08-22        77           5             25.329861  17.434664
22  2022-08-23        70           5             20.517870  14.519931
23  2022-08-24        69           5             18.978657  13.161956
24  2022-08-25        64           5             17.072141  12.220648
25  2022-08-26        60           5             15.866713  10.839861

    Reserved Time  Ready Time  Not Ready Time  Utilization Rate  \
0        0.266319    0.638623        3.631736          0.791051
1        0.259549    1.044062        2.724259          0.802488
2        0.276806    2.852882        3.432037          0.792313
3        0.248403    2.086516        3.550139          0.768724
4        0.211725    2.886794        2.861366          0.791264
```

5	0.000000	0.000000	0.000000	NaN
6	0.000000	0.000000	0.000000	NaN
7	0.302558	2.840532	3.557419	0.811930
8	0.270428	2.601551	3.217431	0.798428
9	0.262870	2.879653	3.633553	0.775033
10	0.224375	2.393310	3.045046	0.790538
11	0.200440	1.614734	2.574722	0.790768
12	0.000000	0.000000	0.000000	NaN
13	0.000000	0.000000	0.000000	NaN
14	0.254618	0.877454	3.094780	0.801434
15	0.255833	1.322859	3.104005	0.788937
16	0.244352	1.701910	2.826736	0.798297
17	0.239815	2.568322	3.325787	0.782763
18	0.218519	2.565370	2.779502	0.795957
19	0.000000	0.000000	0.000000	NaN
20	0.000000	0.000000	0.000000	NaN
21	0.336597	2.388032	3.897743	0.795871
22	0.263889	1.293368	3.374757	0.783570
23	0.247176	1.527650	3.043877	0.787031
24	0.209502	1.155058	2.637894	0.795753
25	0.191030	1.555475	2.507731	0.793256

	Non-Utilized Rate	Day of Week	FTEs
0	0.161426	Monday	0.527367
1	0.147430	Tuesday	0.534992
2	0.161183	Wednesday	0.528208
3	0.183950	Thursday	0.512483
4	0.163057	Friday	0.527510
5	NaN	Saturday	NaN
6	NaN	Sunday	NaN
7	0.141288	Monday	0.541286
8	0.152269	Tuesday	0.532285
9	0.177843	Wednesday	0.516689
10	0.162934	Thursday	0.527025
11	0.159954	Friday	0.527179
12	NaN	Saturday	NaN
13	NaN	Sunday	NaN
14	0.149391	Monday	0.534289
15	0.160672	Tuesday	0.525958
16	0.151724	Wednesday	0.532198
17	0.170447	Thursday	0.521842
18	0.158042	Friday	0.530638
19	NaN	Saturday	NaN
20	NaN	Sunday	NaN
21	0.153879	Monday	0.530580
22	0.164479	Tuesday	0.522380
23	0.160384	Wednesday	0.524687

```
24           0.154515    Thursday  0.530502
25           0.158050      Friday  0.528837
```

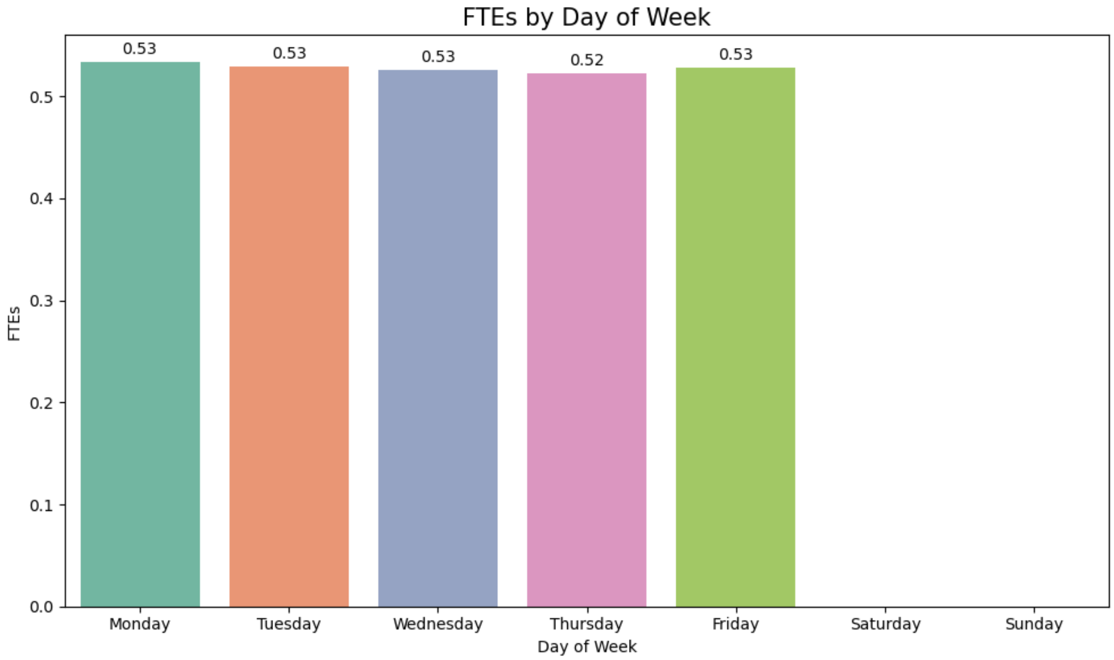
[67]:
```
fte_mean_by_day = daily_metrics2.groupby('Day of Week')['FTEs'].mean().
 ↪reset_index()

# Create a custom sorting order for the days of the week
custom_order = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
 ↪"Saturday", "Sunday"]

# Convert the "Day of Week" column to a categorical data type with the custom␣
 ↪sorting order
fte_mean_by_day["Day of Week"] = pd.Categorical(fte_mean_by_day["Day of Week"],␣
 ↪categories=custom_order, ordered=True)

# Sort the DataFrame by the custom order
fte_mean_by_day = fte_mean_by_day.sort_values(by="Day of Week")

# Reset the index if needed
fte_mean_by_day.reset_index(drop=True, inplace=True)

fte_mean_by_day
```

[67]:

	Day of Week	FTEs
0	Monday	0.533381
1	Tuesday	0.528904
2	Wednesday	0.525446
3	Thursday	0.522963
4	Friday	0.528541
5	Saturday	NaN
6	Sunday	NaN

[68]:
```
# Create a bar chart
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='Day of Week', y='FTEs', data=fte_mean_by_day,palette='Set2')
plt.title('FTEs by Day of Week',fontsize=15)
plt.xlabel('Day of Week')
plt.ylabel('FTEs')

# Annotate each bar with its respective productivity score
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2., p.
 ↪get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
 ↪xytext=(0, 5), textcoords='offset points')

plt.tight_layout()
```

```
plt.show()
```



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3 - Define a model for productivity using the provided variables:

Defining a model for productivity in a call center context typically involves using key performance metrics to assess how efficiently agents and teams are handling calls. In this case, you can consider a simple model for productivity by combining metrics like utilization rate, efficiency (average handle time), and the number of handled calls.

Model for Productivity:

Utilization Rate (UR): This measures the percentage of time agents are actively engaged in productive tasks (e.g., taking calls). Higher utilization rates generally indicate better productivity.

Efficiency (EFF): Efficiency is often measured by the average handle time (AHT) per call. Lower AHT suggests more efficient call handling.

Number of Handled Calls (NHC): The total number of calls handled by an agent or team can also be an indicator of productivity.

To create a composite productivity score, we can use a weighted combination of these metrics based on their relative importance to the call center's goals. For example:

Productivity Score (PS) = w1 * UR + w2 * (1 - EFF) + w3 * NHC

Where:

w1, w2, w3 are weights assigned to each metric, reflecting their importance. These weights can be adjusted based on the call center's priorities.

[69]:
```python
# Define a function to calculate efficiency
def calculate_efficiency(copied_df2):
    efficiency = copied_df2['Talk Time'] / copied_df2['Total Logged In Time']
    return efficiency
```

[70]:
```python
copied_df2 = copied_df.copy()
```

[71]:
```python
# Calculate utilization rate and non-utilized time
copied_df2['Utilization Rate'] = calculate_utilization_rate(copied_df2)
copied_df2['Non-Utilized Rate'] = calculate_non_utilized_rate(copied_df2)
copied_df2['Efficiency'] = calculate_efficiency(copied_df2)
```

[72]:
```python
copied_df2.head()
```

[72]:
```
  Agent ID Agent Team       Date Interval Start Time   Interval End Time  \
0  Agent 1     team_1 2022-08-01 2022-08-01 08:00:00 2022-08-01 08:30:00
1  Agent 1     team_1 2022-08-01 2022-08-01 08:30:00 2022-08-01 09:00:00
2  Agent 1     team_1 2022-08-01 2022-08-01 09:00:00 2022-08-01 09:30:00
3  Agent 1     team_1 2022-08-01 2022-08-01 09:30:00 2022-08-01 10:00:00
4  Agent 1     team_1 2022-08-01 2022-08-01 10:00:00 2022-08-01 10:30:00

   Total Logged In Time  Not Ready Time  Ready Time  Reserved Time  Talk Time  \
0              0.018773        0.002384    0.000081       0.000255   0.015174
1              0.020833        0.001076    0.001296       0.000382   0.017002
2              0.020833        0.002963    0.000000       0.000428   0.015984
3              0.020833        0.004329    0.000000       0.000174   0.015544
4              0.020833        0.001262    0.000000       0.000174   0.018715

   …  Team Support  Meeting  After Call Work  Special Projects  Training  \
0  …           0.0      0.0         0.002350               0.0       0.0
1  …           0.0      0.0         0.001076               0.0       0.0
2  …           0.0      0.0         0.002951               0.0       0.0
3  …           0.0      0.0         0.000000               0.0       0.0
4  …           0.0      0.0         0.001262               0.0       0.0

   System Issues     Other  Utilization Rate  Non-Utilized Rate  Efficiency
0            0.0  0.000035          0.826141           0.127004    0.808261
1            0.0  0.000000          0.896667           0.051667    0.816111
2            0.0  0.000000          0.787778           0.142222    0.767222
```

```
3            0.0  0.000000          0.754444           0.207778     0.746111
4            0.0  0.000000          0.906667           0.060556     0.898333

[5 rows x 23 columns]
```

a) Productivity by team:

[73]:
```python
# Calculate team-level productivity
team_productivity = copied_df2.groupby('Agent Team')[['Efficiency',␣
 ↪'Utilization Rate', 'Non-Utilized Rate']].mean()

#  Display the team-level productivity metrics
team_productivity.reset_index()
```

[73]:
```
  Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate
0     team_0    0.541065          0.795201           0.163201
1     team_1    0.669305          0.760131           0.188256
2     team_2    0.657391          0.804826           0.146117
3     team_3    0.714895          0.779054           0.167481
4     team_4    0.660812          0.772761           0.181879
5     team_5    0.614152          0.740468           0.215216
```

[74]:
```python
# Merge team_productivity with team_handled_calls on 'Agent Team'
team_model = pd.merge(team_productivity, team_handled_calls, on=['Agent Team'])
team_model
```

[74]:
```
  Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
0     team_0    0.541065          0.795201           0.163201
1     team_1    0.669305          0.760131           0.188256
2     team_2    0.657391          0.804826           0.146117
3     team_3    0.714895          0.779054           0.167481
4     team_4    0.660812          0.772761           0.181879
5     team_5    0.614152          0.740468           0.215216

   Number of Calls Handled
0                      740
1                    19704
2                    21788
3                    24515
4                    21118
5                    15919
```

[75]:
```python
# Define weights for each metric (you can adjust these)
w1 = 0.4
w2 = 0.3
w3 = 0.3

# Calculate the productivity score (PS)
```

```
team_model['Productivity Score'] = w1 * team_model['Utilization Rate'] + w2 *␣
↪(1 - team_model['Efficiency']) + w3 * team_model['Number of Calls Handled']

# Sort the data by productivity score to identify top-performing and␣
↪low-performing agents/teams
team_sorted_data = team_model.sort_values(by='Productivity Score',␣
↪ascending=False)

team_sorted_data
```

[75]:

```
  Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
3     team_3    0.714895          0.779054           0.167481
2     team_2    0.657391          0.804826           0.146117
4     team_4    0.660812          0.772761           0.181879
1     team_1    0.669305          0.760131           0.188256
5     team_5    0.614152          0.740468           0.215216
0     team_0    0.541065          0.795201           0.163201

   Number of Calls Handled  Productivity Score
3                    24515         7354.897153
2                    21788         6536.824713
4                    21118         6335.810861
1                    19704         5911.603261
5                    15919         4776.111942
0                      740          222.455761
```

[76]:

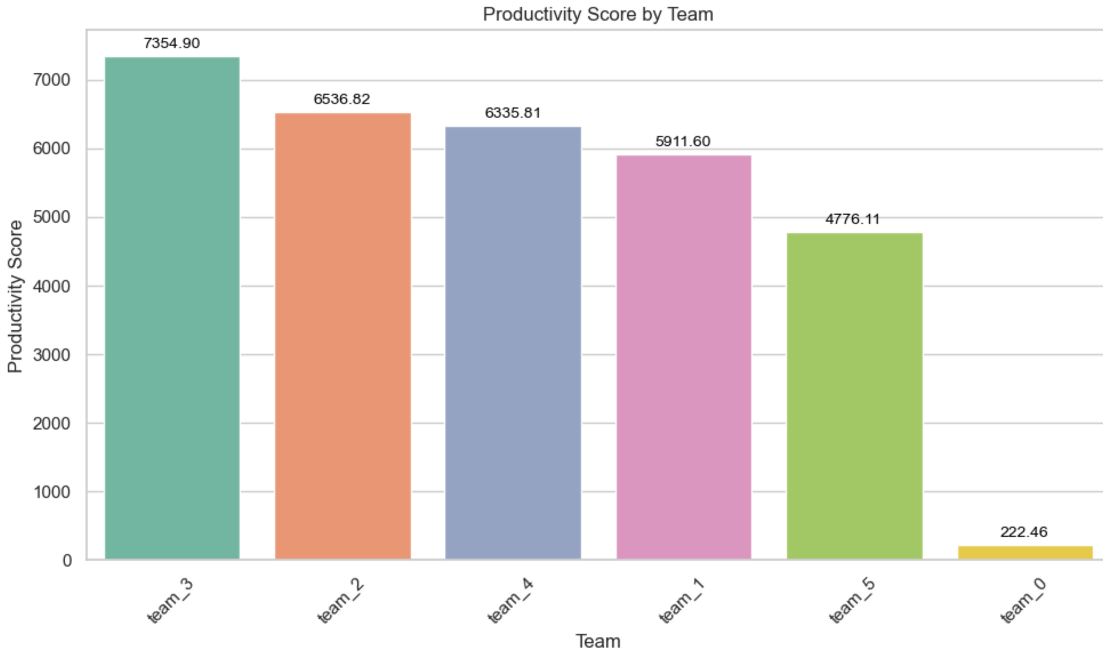
```
# Set Seaborn style and color palette
sns.set(style="whitegrid")
sns.set_palette("pastel")

plt.figure(figsize=(10, 6))
ax = sns.barplot(x='Agent Team', y='Productivity Score', data=team_sorted_data,␣
↪palette="Set2")
plt.xlabel('Team')
plt.ylabel('Productivity Score')
plt.title('Productivity Score by Team')
plt.xticks(rotation=45)

# Annotate each bar with its respective productivity score
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}', (p.get_x() + p.get_width() / 2., p.
↪get_height()), ha='center', va='baseline', fontsize=10, color='black',␣
↪xytext=(0, 5), textcoords='offset points')

plt.tight_layout()

plt.show()
```



a1) Productivity by team dashboard:

[77]:
```
# Create a figure for the dashboard
fig = go.Figure()

# Add a bar chart for Efficiency
fig.add_trace(go.Bar(
    x=team_model['Agent Team'],
    y=team_model['Efficiency'],
    name='Efficiency',
    marker_color='royalblue'
))

# Add a bar chart for Utilization Rate
fig.add_trace(go.Bar(
    x=team_model['Agent Team'],
    y=team_model['Utilization Rate'],
    name='Utilization Rate',
    marker_color='limegreen'
))

# Add a bar chart for Non-Utilization Rate
fig.add_trace(go.Bar(
    x=team_model['Agent Team'],
    y=team_model['Non-Utilized Rate'],
    name='Non-Utilization Rate',
```

```
    marker_color='tomato'
))

# Add a line chart for Number of Calls Handled
fig.add_trace(go.Scatter(
    x=team_model['Agent Team'],
    y=team_model['Number of Calls Handled'],
    name='Number of Calls Handled',
    mode='lines+markers',
    yaxis='y2',  # Use a secondary y-axis for this
    line=dict(color='purple', width=2)
))

# Define layout for the dashboard
fig.update_layout(
    title='Call Center Productivity Dashboard',
    xaxis=dict(title='Agent Team'),
    yaxis=dict(title='Metrics', titlefont=dict(color='black')),
    yaxis2=dict(title='Number of Calls Handled', titlefont=dict(color='black'),␣
 ↪overlaying='y', side='right'),
    barmode='group',  # Group bars for efficiency, utilization rate, and␣
 ↪non-utilization rate
    legend=dict(x=0.7, y=1),
    height=600
)

# Add interactive capabilities like hovering over data points
fig.update_traces(hoverinfo='x+y')

# Show the dashboard
fig.show()
```

a2) Productivity by team dashboard by Week:

[78]:
```
# Calculate team-level productivity
team_productivity2 = copied_df2.groupby(['Agent Team', copied_df2['Date'].dt.
 ↪strftime('%U-%Y')])[['Efficiency', 'Utilization Rate', 'Non-Utilized Rate']].
 ↪mean().reset_index()

# Rename the 'Week' column
team_productivity2 = team_productivity2.rename(columns={'Date': 'Week'})

# Remove the first character from the 'Week' column
team_productivity2['Week'] = team_productivity2['Week'].str[1:]

# Display the team-level productivity metrics
team_productivity2.reset_index()
```

[78]:

	index	Agent Team	Week	Efficiency	Utilization Rate	Non-Utilized Rate
0	0	team_0	1-2022	0.507913	0.741335	0.221776
1	1	team_0	2-2022	0.443652	0.757487	0.207552
2	2	team_0	3-2022	0.631269	0.860384	0.090065
3	3	team_1	1-2022	0.678400	0.754960	0.194882
4	4	team_1	2-2022	0.626941	0.758971	0.190856
5	5	team_1	3-2022	0.681052	0.773890	0.172329
6	6	team_1	4-2022	0.691941	0.752789	0.194813
7	7	team_2	1-2022	0.663027	0.818042	0.131895
8	8	team_2	2-2022	0.624935	0.805327	0.148386
9	9	team_2	3-2022	0.645016	0.790971	0.161665
10	10	team_2	4-2022	0.697684	0.804525	0.142879
11	11	team_3	1-2022	0.732942	0.772688	0.173584
12	12	team_3	2-2022	0.733684	0.787440	0.154493
13	13	team_3	3-2022	0.716085	0.780422	0.166203
14	14	team_3	4-2022	0.682137	0.775098	0.175847
15	15	team_4	1-2022	0.640802	0.755209	0.202320
16	16	team_4	2-2022	0.650691	0.784647	0.170366
17	17	team_4	3-2022	0.671755	0.766459	0.189110
18	18	team_4	4-2022	0.683204	0.786106	0.164049
19	19	team_5	1-2022	0.611765	0.735289	0.221305
20	20	team_5	2-2022	0.577980	0.731382	0.228279
21	21	team_5	3-2022	0.629172	0.752116	0.203249
22	22	team_5	4-2022	0.645941	0.746068	0.204088

b) Productivity by agent:

[79]:
```python
# Calculate agent-level productivity
agent_productivity = copied_df2.groupby(['Agent ID','Agent Team'])[['Efficiency', 'Utilization Rate', 'Non-Utilized Rate']].mean()

# Display the agent-level productivity metrics
agent_productivity.reset_index(inplace=True)
agent_productivity
```

[79]:

	Agent ID	Agent Team	Efficiency	Utilization Rate	Non-Utilized Rate
0	Agent 1	team_1	0.723987	0.808010	0.148564
1	Agent 10	team_4	0.401055	0.826329	0.122138
2	Agent 11	team_4	0.687236	0.759750	0.211629
3	Agent 12	team_2	0.751821	0.829167	0.120584
4	Agent 13	team_0	0.548810	0.793844	0.164659
..	…	…	…	…	…
92	Agent 93	team_4	0.584128	0.736218	0.225475
93	Agent 94	team_3	0.391485	0.854785	0.105329
94	Agent 95	team_3	0.432688	0.793343	0.173640
95	Agent 96	team_2	0.332503	0.774287	0.197326
96	Agent 97	team_3	0.376880	0.795153	0.163986

```
[97 rows x 5 columns]
```

[80]:
```python
# Merge agent_productivity with total_performance on 'Agent ID'
agent_model = pd.merge(agent_productivity, total_performance, on=['Agent ID'])
agent_model
```

[80]:
```
    Agent ID Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
0    Agent 1     team_1    0.723987          0.808010           0.148564
1   Agent 10     team_4    0.401055          0.826329           0.122138
2   Agent 11     team_4    0.687236          0.759750           0.211629
3   Agent 12     team_2    0.751821          0.829167           0.120584
4   Agent 13     team_0    0.548810          0.793844           0.164659
..       ...        ...         ...               ...                ...
92  Agent 93     team_4    0.584128          0.736218           0.225475
93  Agent 94     team_3    0.391485          0.854785           0.105329
94  Agent 95     team_3    0.432688          0.793343           0.173640
95  Agent 96     team_2    0.332503          0.774287           0.197326
96  Agent 97     team_3    0.376880          0.795153           0.163986

    Number of Calls Handled
0                      1696
1                      1547
2                       608
3                      1209
4                       702
..                      ...
92                      126
93                      201
94                      520
95                      284
96                      525

[97 rows x 6 columns]
```

[81]:
```python
# Define weights for each metric (you can adjust these)
w1 = 0.4
w2 = 0.3
w3 = 0.3

# Calculate the productivity score (PS)
agent_model['Productivity Score'] = w1 * agent_model['Utilization Rate'] + w2 *␣
↪(1 - agent_model['Efficiency']) + w3 * agent_model['Number of Calls Handled']

# Sort the data by productivity score to identify top-performing and␣
↪low-performing agents/teams
agent_sorted_data = agent_model.sort_values(by='Productivity Score',␣
↪ascending=False)
```

```
agent_sorted_data
```

[81]:

```
     Agent ID Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
24   Agent 31     team_2    0.701059          0.792421           0.145182
50   Agent 55     team_3    0.730204          0.750964           0.176208
12   Agent 20     team_2    0.673734          0.771363           0.160972
29   Agent 36     team_4    0.620405          0.812553           0.125120
11    Agent 2     team_3    0.632228          0.657759           0.287839
..        …          …          …                 …                 …
93   Agent 94     team_3    0.391485          0.854785           0.105329
6    Agent 15     team_3    0.708972          0.752618           0.181351
92   Agent 93     team_4    0.584128          0.736218           0.225475
37   Agent 43     team_4    0.587481          0.623204           0.363461
79   Agent 81     team_0    0.249877          0.846207           0.108362

    Number of Calls Handled  Productivity Score
24                     2632          790.006651
50                     2594          778.581324
12                     2409          723.106425
29                     2167          650.538900
11                     2069          621.073435
..                       …                  …
93                      201           60.824469
6                       189           57.088355
92                      126           38.219249
37                      102           30.973037
79                       38           11.963520

[97 rows x 7 columns]
```

[82]:

```
#Top 5 agents have highest PS
agent_sorted_data.nlargest(5, 'Productivity Score')
```

[82]:

```
     Agent ID Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
24   Agent 31     team_2    0.701059          0.792421           0.145182
50   Agent 55     team_3    0.730204          0.750964           0.176208
12   Agent 20     team_2    0.673734          0.771363           0.160972
29   Agent 36     team_4    0.620405          0.812553           0.125120
11    Agent 2     team_3    0.632228          0.657759           0.287839

    Number of Calls Handled  Productivity Score
24                     2632          790.006651
50                     2594          778.581324
12                     2409          723.106425
29                     2167          650.538900
11                     2069          621.073435
```

[83]:
```
#Top 5 agents have lowest PS
agent_sorted_data.nsmallest(5, 'Productivity Score')
```

[83]:
```
    Agent ID Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
79  Agent 81     team_0    0.249877          0.846207           0.108362
37  Agent 43     team_4    0.587481          0.623204           0.363461
92  Agent 93     team_4    0.584128          0.736218           0.225475
6   Agent 15     team_3    0.708972          0.752618           0.181351
93  Agent 94     team_3    0.391485          0.854785           0.105329

    Number of Calls Handled  Productivity Score
79                       38           11.963520
37                      102           30.973037
92                      126           38.219249
6                       189           57.088355
93                      201           60.824469
```

b1) Productivity by agent dashboard:

[84]:
```
# Extract the numerical part of 'Agent ID' and convert it to integers
agent_model['Agent ID Numeric'] = agent_model['Agent ID'].str.extract('(\d+)').
↪astype(int)

# Sort the DataFrame by 'Agent ID Numeric' and 'Week'
df_sorted1 = agent_model.sort_values(by=['Agent ID Numeric'])

# Drop the 'Agent ID Numeric' column if you don't need it anymore
df_sorted1 = df_sorted1.drop(columns=['Agent ID Numeric'])

# Reset the index after sorting
df_sorted1.reset_index(drop=True)
```

[84]:
```
    Agent ID Agent Team  Efficiency  Utilization Rate  Non-Utilized Rate  \
0    Agent 1     team_1    0.723987          0.808010           0.148564
1    Agent 2     team_3    0.632228          0.657759           0.287839
2    Agent 3     team_3    0.771184          0.796351           0.187739
3    Agent 4     team_4    0.653282          0.747824           0.196428
4    Agent 5     team_4    0.791097          0.835344           0.123427
..       …          …          …                …                  …
92  Agent 93     team_4    0.584128          0.736218           0.225475
93  Agent 94     team_3    0.391485          0.854785           0.105329
94  Agent 95     team_3    0.432688          0.793343           0.173640
95  Agent 96     team_2    0.332503          0.774287           0.197326
96  Agent 97     team_3    0.376880          0.795153           0.163986

    Number of Calls Handled  Productivity Score
0                      1696          509.206008
1                      2069          621.073435
```

```
2                        1591         477.687185
3                        1987         596.503145
4                        1469         441.096808
..                         …              …
92                        126          38.219249
93                        201          60.824469
94                        520         156.487531
95                        284          85.709964
96                        525         158.004997

[97 rows x 7 columns]
```

[85]:
```python
# Create a figure for the dashboard
fig = go.Figure()

# Add a bar chart for Efficiency
fig.add_trace(go.Bar(
    x=df_sorted1['Agent ID'],
    y=df_sorted1['Efficiency'],
    name='Efficiency',
    marker_color='royalblue'
))

# Add a bar chart for Utilization Rate
fig.add_trace(go.Bar(
    x=df_sorted1['Agent ID'],
    y=df_sorted1['Utilization Rate'],
    name='Utilization Rate',
    marker_color='limegreen'
))

# Add a bar chart for Non-Utilization Rate
fig.add_trace(go.Bar(
    x=df_sorted1['Agent ID'],
    y=df_sorted1['Non-Utilized Rate'],
    name='Non-Utilization Rate',
    marker_color='tomato'
))

# Add a line chart for Number of Calls Handled
fig.add_trace(go.Scatter(
    x=df_sorted1['Agent ID'],
    y=df_sorted1['Number of Calls Handled'],
    name='Number of Calls Handled',
    mode='lines+markers',
    yaxis='y2',  # Use a secondary y-axis for this
    line=dict(color='purple', width=2)
```

```
))

# Define layout for the dashboard
fig.update_layout(
    title='Call Center Productivity Dashboard',
    xaxis=dict(title='Agent ID'),
    yaxis=dict(title='Metrics', titlefont=dict(color='black')),
    yaxis2=dict(title='Number of Calls Handled', titlefont=dict(color='black'),␣
 ↪overlaying='y', side='right'),
    barmode='group',  # Group bars for efficiency, utilization rate, and␣
 ↪non-utilization rate
    legend=dict(x=0.7, y=1),
    height=600
)

# Add interactive capabilities like hovering over data points
fig.update_traces(hoverinfo='x+y')

# Show the dashboard
fig.show()
```

b2) Productivity by agent by Week dashboard:

[86]:
```
# Group and calculate the mean values
agent_productivity2 = copied_df2.groupby(['Agent ID', copied_df2['Date'].dt.
 ↪strftime('%U-%Y')])[['Efficiency', 'Utilization Rate', 'Non-Utilized Rate']].
 ↪mean()

# Reset the index to make the group keys ('Agent ID' and 'Date') as columns
agent_productivity2 = agent_productivity2.reset_index()

# Now, 'agent_productivity2' contains the desired columns and data
agent_productivity2
```

[86]:

	Agent ID	Date	Efficiency	Utilization Rate	Non-Utilized Rate
0	Agent 1	31-2022	0.749320	0.806607	0.156315
1	Agent 1	32-2022	0.684445	0.792085	0.156787
2	Agent 1	33-2022	0.715627	0.831178	0.123587
3	Agent 1	34-2022	0.745317	0.806940	0.152490
4	Agent 10	31-2022	0.437121	0.791412	0.153175
..	…	…	…	…	…
349	Agent 95	33-2022	0.277538	0.783322	0.183379
350	Agent 95	34-2022	0.498399	0.797587	0.169515
351	Agent 96	33-2022	0.219706	0.750255	0.229811
352	Agent 96	34-2022	0.370855	0.782458	0.186281
353	Agent 97	34-2022	0.376880	0.795153	0.163986

```
[354 rows x 5 columns]
```

[87]:
```python
agent_productivity2 = agent_productivity2.rename(columns={'Date': 'Week'})

# Remove the first character from the 'Week' column
agent_productivity2['Week'] = agent_productivity2['Week'].str[1:]

# Display the agent-level productivity metrics
agent_productivity2.reset_index()
```

[87]:
```
     index  Agent ID    Week  Efficiency  Utilization Rate  Non-Utilized Rate
0        0   Agent 1  1-2022    0.749320          0.806607           0.156315
1        1   Agent 1  2-2022    0.684445          0.792085           0.156787
2        2   Agent 1  3-2022    0.715627          0.831178           0.123587
3        3   Agent 1  4-2022    0.745317          0.806940           0.152490
4        4  Agent 10  1-2022    0.437121          0.791412           0.153175
..     …         …     …          …                 …                  …
349    349  Agent 95  3-2022    0.277538          0.783322           0.183379
350    350  Agent 95  4-2022    0.498399          0.797587           0.169515
351    351  Agent 96  3-2022    0.219706          0.750255           0.229811
352    352  Agent 96  4-2022    0.370855          0.782458           0.186281
353    353  Agent 97  4-2022    0.376880          0.795153           0.163986

[354 rows x 6 columns]
```

[88]:
```python
# Extract the numerical part of 'Agent ID' and convert it to integers
agent_productivity2['Agent ID Numeric'] = agent_productivity2['Agent ID'].str.
 ↪extract('(\d+)').astype(int)

# Sort the DataFrame by 'Agent ID Numeric' and 'Week'
df_sorted2 = agent_productivity2.sort_values(by=['Agent ID Numeric', 'Week'])

# Drop the 'Agent ID Numeric' column if you don't need it anymore
df_sorted2 = df_sorted2.drop(columns=['Agent ID Numeric'])

# Reset the index after sorting
df_sorted2.reset_index(drop=True)
```

[88]:
```
     Agent ID    Week  Efficiency  Utilization Rate  Non-Utilized Rate
0     Agent 1  1-2022    0.749320          0.806607           0.156315
1     Agent 1  2-2022    0.684445          0.792085           0.156787
2     Agent 1  3-2022    0.715627          0.831178           0.123587
3     Agent 1  4-2022    0.745317          0.806940           0.152490
4     Agent 2  1-2022    0.632997          0.653751           0.290204
..        …       …           …                 …                  …
349  Agent 95  3-2022    0.277538          0.783322           0.183379
350  Agent 95  4-2022    0.498399          0.797587           0.169515
```

```
351  Agent 96  3-2022    0.219706            0.750255              0.229811
352  Agent 96  4-2022    0.370855            0.782458              0.186281
353  Agent 97  4-2022    0.376880            0.795153              0.163986

[354 rows x 5 columns]
```

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4 - Productivity Prediction Model:

1) Data Preprocessing: - Import the necessary libraries for data manipulation and machine learning. - Load the dataset into a pandas DataFrame. - Check for missing values and handle them if necessary.

2) Data Splitting: - Split the dataset into a training set and a testing set. This is typically done to evaluate the model's performance.

3) Feature Selection: - Decide which features to use for prediction. In this case, you can use 'Efficiency,' 'Utilization Rate,' 'Non-Utilized Rate,' and 'Number of Calls Handled' as your input features. - Productivity Score will be transformed into binary variables (1 for scores higher than the mean and 0 for scores lower than or equal to the mean), to predict Higher Productivity staff and Lower Productivity staff.

4) Select a Machine Learning Model: - Choose a regression model since you want to predict Productivity. In this case, we will use Logistic Regression and Decision Tree.

5) Train the Model: - Fit the chosen model on the training data, using the selected features as inputs and 'Productivity Score' as the target variable.

6) Model Evaluation: - Evaluate the model's performance on the testing set using appropriate metrics (e.g., Mean Absolute Error, Mean Squared Error, R-squared).

7) Make Predictions: - Once you are satisfied with the model's performance, you can use it to make predictions on new data.

Build model

[89]:
```
from sklearn.model_selection import cross_validate,train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn import metrics
# Encode categorical variables
agent_model2 = agent_model.drop(['Agent Team', 'Agent ID Numeric'], axis = 1)
```

[90]:
```
# Calculate the mean of 'Productivity Score'
mean_score = agent_model2['Productivity Score'].mean()
```

```
# Create a new column 'Binary Productivity' and assign 1 to scores greater than␣
↪the mean, and 0 otherwise
agent_model2['Productivity'] = (agent_model2['Productivity Score'] >␣
↪mean_score).astype(int)

# Drop the original 'Productivity Score' column if you don't need it anymore
agent_model2.drop('Productivity Score', axis=1, inplace=True)

# Display the modified DataFrame
agent_model2
```

[90]:

```
     Agent ID  Efficiency  Utilization Rate  Non-Utilized Rate  \
0     Agent 1    0.723987          0.808010           0.148564
1    Agent 10    0.401055          0.826329           0.122138
2    Agent 11    0.687236          0.759750           0.211629
3    Agent 12    0.751821          0.829167           0.120584
4    Agent 13    0.548810          0.793844           0.164659
..        …           …               …                  …
92   Agent 93    0.584128          0.736218           0.225475
93   Agent 94    0.391485          0.854785           0.105329
94   Agent 95    0.432688          0.793343           0.173640
95   Agent 96    0.332503          0.774287           0.197326
96   Agent 97    0.376880          0.795153           0.163986

    Number of Calls Handled  Productivity
0                      1696             1
1                      1547             1
2                       608             0
3                      1209             1
4                       702             0
..                        …           …
92                      126             0
93                      201             0
94                      520             0
95                      284             0
96                      525             0

[97 rows x 6 columns]
```

[91]:

```
# Select features and target variable
X = agent_model2[['Efficiency', 'Utilization Rate', 'Non-Utilized Rate',␣
↪'Number of Calls Handled']]
y = agent_model2['Productivity']
```

[92]:

```
# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[93]:
```python
print("X_train shape: {}".format(X_train.shape))
print("X_test shape: {}".format(X_test.shape))
print("y_train shape: {}".format(y_train.shape))
print("y_test shape: {}".format(y_test.shape))
```

```
X_train shape: (77, 4)
X_test shape: (20, 4)
y_train shape: (77,)
y_test shape: (20,)
```

Logistic Regression Model

[94]:
```python
# Create and train a Logistic Regression model
model = LogisticRegression(C=100,max_iter = 2000)
model.fit(X_train,y_train)
pred_val = model.predict(X_test)
```

[95]:
```python
X_new1=[[0.72,0.8,0.2,1500]]

def Predict_for_new_agent(X_new):
    pred_val = model.predict(X_new)
    print("Prediction for new value = ", pred_val)

    if pred_val == 1:
        pred_valstr = "Higher tier"
    elif pred_val == 0:
        pred_valstr = "Lower tier"

    return pred_valstr

print("Predicted value for New Agent = ", Predict_for_new_agent(X_new1))
print("Predicted probability of class 1 (Productivity = 1) = ", model.
 ↪predict_proba(X_new1)[:, 1])
```

```
Prediction for new value =  [1]
Predicted value for New Agent =  Higher tier
Predicted probability of class 1 (Productivity = 1) =  [1.]
```

```
/Users/yangyang/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:450:
UserWarning:

X does not have valid feature names, but LogisticRegression was fitted with
feature names

/Users/yangyang/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:450:
UserWarning:

X does not have valid feature names, but LogisticRegression was fitted with
feature names
```

[96]:
```
print ("Accuracy = %.2f" % (metrics.accuracy_score(y_test, pred_val)))
```

```
Accuracy = 1.00
```

[97]:
```
from sklearn.metrics import make_scorer,mean_absolute_error,␣
↪mean_squared_error, r2_score

# Evaluate the model
mae = mean_absolute_error(y_test, pred_val)
mse = mean_squared_error(y_test, pred_val)
r2 = r2_score(y_test, pred_val)

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

```
Mean Absolute Error: 0.0
Mean Squared Error: 0.0
R-squared: 1.0
```

A Mean Absolute Error (MAE) of 0.0, Mean Squared Error (MSE) of 0.0, and an R-squared (R2) of 1.0 indicate that the regression model is performing perfectly on the test data. Here's what these metrics mean:

1. **Mean Absolute Error (MAE):** An MAE of 0.0 means that, on average, the model's predictions are exactly equal to the actual 'Productivity Score' values in the test set. In other words, the model is making perfect predictions with no errors.
2. **Mean Squared Error (MSE):** An MSE of 0.0 means that the squared differences between the model's predictions and the actual values are all zero. Again, this indicates perfect predictions with no errors.
3. **R-squared (R2):** An R2 score of 1.0 indicates that the model explains 100% of the variance in the 'Productivity Score' in the test set. In simpler terms, the model is an excellent fit for the data and makes predictions that match the data perfectly.

While these results may seem ideal, it's essential to consider the possibility of overfitting.

To ensure that the model's performance is genuinely this good and not due to overfitting, it's a good practice to validate the model on a separate dataset or use cross-validation during the training process.

[98]:
```
# Define scoring metrics
scoring = {
    'MAE': make_scorer(mean_absolute_error),
    'MSE': make_scorer(mean_squared_error),
    'R2': make_scorer(r2_score)
}
```

```python
# Perform cross-validation
cv_results = cross_validate(model, X_train, y_train, cv=5, scoring=scoring)

# Print cross-validation results
print(f'Mean MAE: {cv_results["test_MAE"].mean()}')
print(f'Mean MSE: {cv_results["test_MSE"].mean()}')
print(f'Mean R2: {cv_results["test_R2"].mean()}')
```

```
Mean MAE: 0.0125
Mean MSE: 0.0125
Mean R2: 0.9466666666666667
```

Decision Tree Model

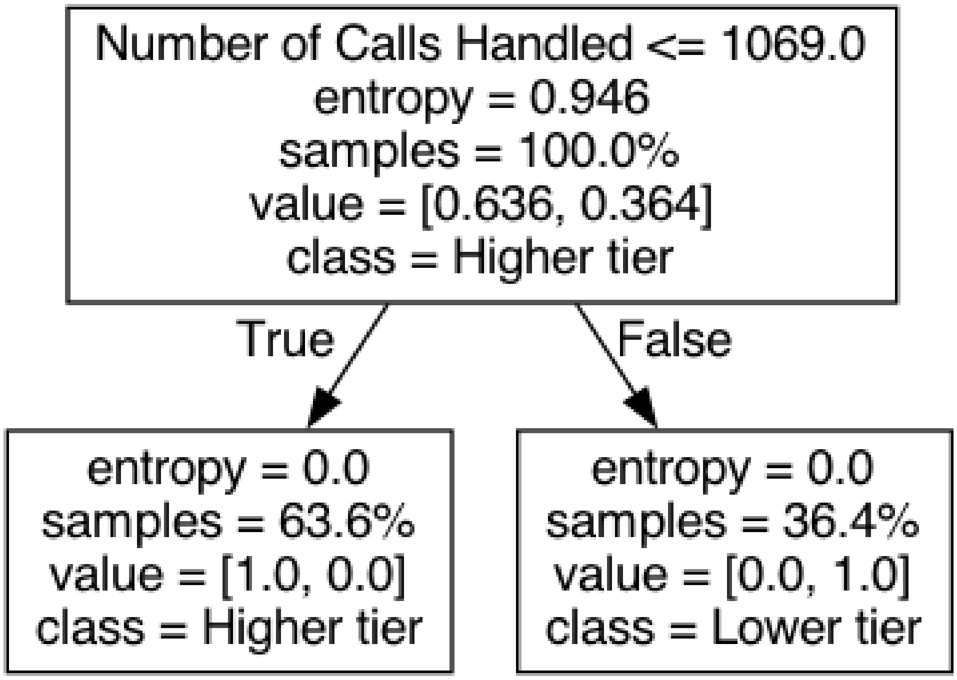
[99]:
```python
predictor_cols = ['Efficiency', 'Utilization Rate', 'Non-Utilized Rate',␣
↪'Number of Calls Handled']

from sklearn.tree import DecisionTreeClassifier
# Let's define the model (tree)
decision_tree = DecisionTreeClassifier(max_depth=6,␣
↪criterion="entropy",max_leaf_nodes = 12, min_samples_leaf = 1)
# Let's tell the model what is the data
decision_tree.fit(X_train, y_train)
```

[99]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=6, max_leaf_nodes=12)
```

[100]:
```python
import os
from IPython.display import Image
from sklearn.tree import export_graphviz

def visualize_tree(decision_tree, feature_names, class_names, directory="./
↪images", name="tree2", proportion=True):
    # Export the decision tree to graphviz format
    directory1 = directory[2:]
    os.makedirs(directory1, exist_ok=True)  # Create the directory if it␣
↪doesn't exist
    dot_name = "%s/%s.dot" % (directory, name)
    dot_file = export_graphviz(
        decision_tree, out_file=dot_name, feature_names=feature_names,␣
↪class_names=class_names, proportion=proportion
    )

    # Call Graphviz to make an image file from the decision tree
    image_name = "%s/%s.png" % (directory, name)
    os.system("dot -Tpng %s -o %s" % (dot_name, image_name))

    # Return the .png image so we can see it
    return Image(filename=image_name)
```

```python
# Define your class names (replace with actual class names)
class_names = ["Higher tier", "Lower tier"]

visualize_tree(decision_tree, predictor_cols, ["Higher tier", "Lower tier"])
```

[100]:



[101]:

```python
X_new1=[[0.72,0.8,0.2,1500]]

def Predict_for_New_Value2(X_new):
    prediction = decision_tree.predict(X_new)
    print("Prediction: {}".format(prediction))
    if(prediction == 1):
        return("Higher tier")
    elif(prediction == 0):
        return("Lower tier")
    else:
        return("UNKNOWN STATUS..")

predicted_status = Predict_for_New_Value2(X_new1)
print("Predicted value for new record is %", predicted_status)
```

```
Prediction: [1]
Predicted value for new record is % Higher tier
```

```
/Users/yangyang/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:450:
UserWarning:
```

```
X does not have valid feature names, but DecisionTreeClassifier was fitted with
feature names
```

[102]:
```python
prediction = decision_tree.predict(X_test)

print ( "Accuracy = %.3f" % (metrics.accuracy_score(y_test,prediction)))
```

```
Accuracy = 1.000
```

[103]:
```python
# Define scoring metrics
scoring = {
    'MAE': make_scorer(mean_absolute_error),
    'MSE': make_scorer(mean_squared_error),
    'R2': make_scorer(r2_score)
}

# Perform cross-validation
cv_results = cross_validate(decision_tree, X_train, y_train, cv=5,␣
 ↪scoring=scoring)

# Print cross-validation results
print(f'Mean MAE: {cv_results["test_MAE"].mean()}')
print(f'Mean MSE: {cv_results["test_MSE"].mean()}')
print(f'Mean R2: {cv_results["test_R2"].mean()}')
```

```
Mean MAE: 0.0125
Mean MSE: 0.0125
Mean R2: 0.9466666666666667
```

[104]:
```python
# Evaluate the model
mae = mean_absolute_error(y_test, prediction)
mse = mean_squared_error(y_test, prediction)
r2 = r2_score(y_test, prediction)

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

```
Mean Absolute Error: 0.0
Mean Squared Error: 0.0
R-squared: 1.0
```

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5 - Productivity Dashboard:

[105]:
```
# Import necessary libraries
from plotly.subplots import make_subplots
import plotly.graph_objs as go

# Create a Dash app
app = dash.Dash(__name__)

# Assuming you have a DataFrame called team_productivity2
# Initialize the layout of the combined dashboard
app.layout = html.Div([
    html.H1("Call Center Performance Dashboard by Team"),

    # Dropdown to select team for the first dashboard
    dcc.Dropdown(
        id='team-dropdown',
        options=[{'label': team, 'value': team} for team in␣
↪team_productivity2['Agent Team'].unique()],
        value=team_productivity2['Agent Team'].iloc[0],  # Set the initial value
        multi=False
    ),

    # Line chart for Efficiency and Utilization Rate for the first dashboard
    dcc.Graph(id='efficiency-utilization-line-chart'),

    # Pie chart for Time-Utilization Rate for the first dashboard
    dcc.Graph(id='time-utilization-pie-chart'),

    html.H2("Call Center Performance Dashboard by Agent"),

    # Dropdown to select agent for the second dashboard
    dcc.Dropdown(
        id='agent-dropdown',
        options=[{'label': agent, 'value': agent} for agent in␣
↪df_sorted2['Agent ID'].unique()],
        value=df_sorted2['Agent ID'].iloc[0],  # Set the initial value
        multi=False
    ),

    # Line chart for weekly utilization rate for the second dashboard
    dcc.Graph(id='utilization-line-chart'),

    # Pie chart for weekly non-utilization rate for the second dashboard
    dcc.Graph(id='time-utilization-pie-chart-2'),
])
```

```
# Define callback functions to update charts based on user input for the first␣
↪dashboard
@app.callback(
    [Output('efficiency-utilization-line-chart', 'figure'),
     Output('time-utilization-pie-chart', 'figure')],
    [Input('team-dropdown', 'value')]
)
def update_charts(selected_team):
    filtered_data = team_productivity2[team_productivity2['Agent Team'] ==␣
↪selected_team]

    # Create a subplot with two line charts (Efficiency and Utilization Rate)
    fig = make_subplots(rows=1, cols=2, subplot_titles=("Efficiency",␣
↪"Utilization Rate"))

    # Line chart for Efficiency
    efficiency_trace = go.Scatter(
        x=filtered_data['Week'],
        y=filtered_data['Efficiency'],
        mode='lines',
        name='Efficiency'
    )
    fig.add_trace(efficiency_trace, row=1, col=1)

    # Line chart for Utilization Rate
    utilization_trace = go.Scatter(
        x=filtered_data['Week'],
        y=filtered_data['Utilization Rate'],
        mode='lines',
        name='Utilization Rate'
    )
    fig.add_trace(utilization_trace, row=1, col=2)

    # Update layout for the subplot
    fig.update_layout(title=f'Efficiency and Utilization Rate for␣
↪{selected_team}')

    # Pie chart for Time-Utilization Rate
    time_utilization_fig = px.pie(
        names=['Utilization', 'Non-Utilization'],
        values=[filtered_data['Utilization Rate'].mean(),␣
↪filtered_data['Non-Utilized Rate'].mean()],
        title=f'Time-Utilization Breakdown for {selected_team}'
    )

    return fig, time_utilization_fig
```

```python
# Define callback functions to update charts based on user input for the second␣
↪dashboard
@app.callback(
    [Output('utilization-line-chart', 'figure'),
     Output('time-utilization-pie-chart-2', 'figure')],
    [Input('agent-dropdown', 'value')]
)
def update_charts(selected_agent):
    filtered_data2 = df_sorted2[df_sorted2['Agent ID'] == selected_agent]

    # Line chart for weekly utilization rate
    utilization_fig2 = px.line(
        filtered_data2,
        x='Week',
        y='Utilization Rate',
        title=f'Weekly Utilization Rate for {selected_agent}'
    )

    # Pie chart for weekly non-utilization rate
    time_utilization_fig2 = px.pie(
        names=['Utilization', 'Non-Utilization'],
        values=[filtered_data2['Utilization Rate'].mean(),␣
↪filtered_data2['Non-Utilized Rate'].mean()],
        title=f'Time-Utilization Breakdown for {selected_agent}'
    )

    return utilization_fig2, time_utilization_fig2

# Run the combined app
if __name__ == '__main__':
    app.run_server(debug=True)
```

```
<IPython.lib.display.IFrame at 0x7f7f33df7340>
```

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