import numpy as np
import pandas as pd
import seaborn as sns
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import folium

Start coding or generate with AI.

df = pd.read_csv('/Users/mac/Desktop/-Health-Sales-Data-/PBJ_Daily_Nurse_Staffing_Q1_2024.csv',encoding='iso-8859-1',low_memory=False)

Start coding or generate with AI.

df.head()

→		PROVNUM	PROVNAME	CITY	STATE	COUNTY_NAME	COUNTY_FIPS	CY_Qtr	WorkDate	MDScensus	Hrs_RNDON	 Hrs_LPN_ctr	Hrs_CNA	Hrs_CNA_emp	Hrs_
	0	15009	BURNS NURSING HOME, INC.	RUSSELLVILLE	AL	Franklin	59	2024Q1	20240101	50	8.0	 0.0	156.34	156.34	
	1	15009	BURNS NURSING HOME, INC.	RUSSELLVILLE	AL	Franklin	59	2024Q1	20240102	49	8.0	 0.0	149.40	149.40	
	2	15009	BURNS NURSING HOME, INC.	RUSSELLVILLE	AL	Franklin	59	2024Q1	20240103	49	8.0	 0.0	147.15	147.15	
	3	15009	BURNS NURSING HOME, INC.	RUSSELLVILLE	AL	Franklin	59	2024Q1	20240104	50	8.0	 0.0	142.21	142.21	
	4	15009	BURNS NURSING HOME, INC.	RUSSELLVILLE	AL	Franklin	59	2024Q1	20240105	51	8.0	 0.0	149.40	149.40	

5 rows × 33 columns

```
# Convert 'WorkDate' column to datetime
df['WorkDate'] = pd.to_datetime(df['WorkDate'], format='%Y%m%d', errors='coerce')
Start coding or generate with AI.
#lets make sure the year Qtr are only for Q1
df['CY_Qtr'].value_counts()
→ CY_Qtr
    2024Q1
              1048575
    Name: count, dtype: int64
Start coding or generate with AI.
#check data null values has 0 missing values
df.isnull().sum()
→ PR0VNUM
                        0
                        0
    PROVNAME
    CITY
                        0
    STATE
                        0
    COUNTY_NAME
                        0
    COUNTY_FIPS
                        0
    CY_Qtr
                        0
                        0
    WorkDate
                        0
    MDScensus
                        0
    Hrs RNDON
    Hrs_RNDON_emp
                        0
    Hrs RNDON ctr
                        0
    Hrs_RNadmin
                        0
    Hrs RNadmin emp
                        0
                        0
    Hrs_RNadmin_ctr
    Hrs_RN
                        0
    Hrs_RN_emp
                        0
    Hrs_RN_ctr
                        0
    Hrs_LPNadmin
                        0
    Hrs_LPNadmin_emp
                        0
    Hrs LPNadmin ctr
                        0
    Hrs_LPN
                        0
                        0
    Hrs_LPN_emp
    Hrs_LPN_ctr
                        0
                        0
    Hrs CNA
    Hrs_CNA_emp
                        0
    Hrs_CNA_ctr
                        0
    Hrs NAtrn
                        0
    Hrs_NAtrn_emp
                        0
    Hrs NAtrn ctr
                        0
    Hrs MedAide
                        0
    Hrs MedAide emp
                        0
    Hrs_MedAide_ctr
                        0
    dtype: int64
```

load data set downloaded from website provided ('NH_provider_info') into dataframe for further analysis
df_provider=pd.read_csv('/Users/mac/Desktop/Health-Sales-Data-/NH_ProviderInfo_Sep2024.csv')

Start coding or generate with AI.

df_provider.head()

₹

	CMS Certification Number (CCN)	Provider Name	Provider Address	City/Town	State	ZIP Code	Telephone Number	Provider SSA County Code	County/Parish	Ownership Type		Number of Citations from Infection Control Inspections	Number of Fines	Tot Amou Fin Dolla
0	015009	BURNS NURSING HOME, INC.	701 MONROE STREET NW	RUSSELLVILLE	AL	35653	2563324110	290	Franklin	For profit - Corporation		NaN	1	2398
1	015010	COOSA VALLEY HEALTHCARE CENTER	260 WEST WALNUT STREET	SYLACAUGA	AL	35150	2562495604	600	Talladega	For profit - Corporation		0.0	0	
2	015012	HIGHLANDS HEALTH AND REHAB	380 WOODS COVE ROAD	SCOTTSBORO	AL	35768	2562183708	350	Jackson	Government - County	•••	NaN	0	
3	015014	EASTVIEW REHABILITATION & HEALTHCARE CENTER	7755 FOURTH AVENUE SOUTH	BIRMINGHAM	AL	35206	2058330146	360	Jefferson	For profit - Individual		0.0	0	
4	015015	PLANTATION MANOR NURSING HOME	6450 OLD TUSCALOOSA HIGHWAY	MC CALLA	AL	35111	2054776161	360	Jefferson	For profit - Individual		NaN	0	

5 rows × 103 columns

Start coding or generate with AI.

#Check Missing value and
df_provider.isnull().sum()

$\overline{\rightarrow}$	CMS Certification Nur	nber (CCN)	0
	Provider Name		0
	Provider Address		0
	City/Town		0
	State		0
	Location		0
	Latitude		0
	Longitude		0
	Geocoding Footnote		14020

```
Processing Date
Length: 103, dtype: int64
```

 $\begin{tabular}{ll} \#drop & note-geolocation & null all & missing & values & removed \\ df_provider=df_provider.dropna() & \end{tabular}$

```
# Melt the DataFrame to long format for easy exploring
hour_columns = [
    'Hrs_RNDON', 'Hrs_RNDON_emp', 'Hrs_RNDON_ctr',
    'Hrs_RNadmin', 'Hrs_RNadmin_emp', 'Hrs_RNadmin_ctr',
    'Hrs_RN', 'Hrs_RN_emp', 'Hrs_RN_ctr',
    'Hrs_LPNadmin', 'Hrs_LPNadmin_emp', 'Hrs_LPNadmin_ctr',
    'Hrs_LPN', 'Hrs_LPN_emp', 'Hrs_LPN_ctr',
    'Hrs_CNA', 'Hrs_CNA_emp', 'Hrs_CNA_ctr',
    'Hrs_NAtrn', 'Hrs_NAtrn_emp', 'Hrs_NAtrn_ctr',
    'Hrs_MedAide', 'Hrs_MedAide_emp', 'Hrs_MedAide_ctr']
```

Start coding or generate with AI.

df.head(1)

₹	PROVNUM	PROVNAME	CITY	STATE	COUNTY_NAME	COUNTY_FIPS	CY_Qtr	WorkDate	MDScensus	Hrs_RNDON	 Hrs_LPN_ctr	Hrs_CNA	Hrs_CNA_emp Hrs_
	0 15009	BURNS NURSING HOME, INC.	RUSSELLVILLE	AL	Franklin	59	2024Q1	20240101	50	8.0	 0.0	156.34	156.34

1 rows × 33 columns

df_melted.head(1)

₹	PROVNUM	PROVNAME	CITY	STATE	COUNTY_NAME	COUNTY_FIPS	CY_Qtr	WorkDate	MDScensus	Hour_Type	Hours	Day0fWeek	Employee_Hours
	0 15009	BURNS NURSING	RUSSELLVILLE	AL	Franklin	59	2024Q1	2024-01-	50	Hrs_RNDON	8.0	Monday	0.0

#lets check how the facilities are distributited in the STATES
Counting the number of unique providers by state
providers count by state = df melted.groupby('STATE')['PROVNAME'].nunique().reset index()

```
# Renaming the columns for clarity
providers_count_by_state.columns = ['STATE', 'Provider_Count']

# sorting the results
providers_count_by_state = providers_count_by_state.sort_values(by='Provider_Count', ascending=False)

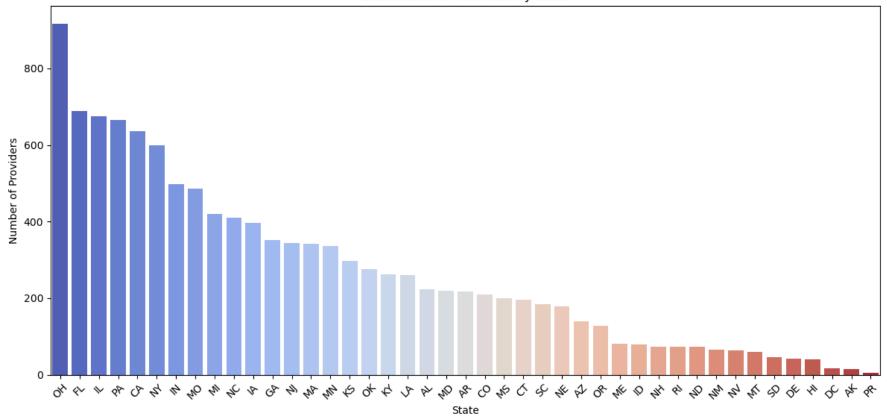
# Visualizing the distribution
plt.figure(figsize=(12, 6))
sns.barplot(data=providers_count_by_state, x='STATE', y='Provider_Count', palette='coolwarm')

plt.title('Distribution of Providers by State')
plt.xlabel('State')
plt.ylabel('Number of Providers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig("chart1.1.png")
plt.show()
```

/var/folders/gk/537qy50d4ls5vppc09_8xb0r0000gn/T/ipykernel_818/2052363222.py:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for 1 sns.barplot(data=providers_count_by_state, x='STATE', y='Provider_Count', palette='coolwarm')





Start coding or generate with AI.

#lets find out how many provider we have in the dataset and most of these fciltiles are in OH
unique_providers_count = df_melted['PROVNAME'].nunique()
print("Unique Providers Count:", unique_providers_count)

→ Unique Providers Count: 11405

#check total hours by each provider to checkout where are the most hours espending and by which provider ?
#lets find out how many provider we have in the dataset and most of these fciltiles are in OH
total_hours_by_provider = df_melted.groupby(['PROVNAME','CITY'])['Hours'].sum().reset_index()
print(total hours by provider)

	0	PROVNAME 15 CRAIGSIDE	CITY HONOLULU	Hours 39242.30
	1	24TH PLACE	NORMAN	33903.84
	2	60 WEST	ROCKY HILL	71594.88
	3	A GRACE SUB ACUTE & SKILLED CARE	SAN JOSE	63282.50
	4	A HOLLY PATTERSON EXTENDED CARE FACILITY	UNIONDALE	275118.90
		• • • • • • • • • • • • • • • • • • • •		
	11513	ZEBULON PARK HEALTH AND REHABILITATION	MACON	38963.98
	11514	ZEBULON REHABILITATION CENTER	ZEBULON	34571.50
	11515	ZERBE SISTERS NURSING CENTER,	NARVON	58651.56
	11516	ZIONSVILLE MEADOWS	ZIONSVILLE	42663.34
	11517	ZUMBROTA CARE CENTER	ZUMBROTA	23962.82

[11518 rows x 3 columns]

sorted_total_hours_by_provider = total_hours_by_provider.sort_values(by='Hours', ascending=False)

sorted_total_hours_by_provider.head(10)

₹		PROVNAME	CITY	Hours
	5060	ISABELLA GERIATRIC CENTER INC	NEW YORK	404400.24
	2366	COLER REHABILITATION AND NURSING CARE CENTER	ROOSEVELT ISLAND	402659.82
	5278	KINGS HARBOR MULTICARE CENTER	BRONX	389573.14
	5938	LORETTO HEALTH AND REHABILITATION CENTER	SYRACUSE	378463.24
	8750	RUTLAND NURSING HOME, INC	BROOKLYN	369114.52
	10203	THE PLAZA REHAB AND NURSING CENTER	BRONX	367224.00
	2362	COLD SPRING HILLS CENTER FOR NURSING AND REHAB	WOODBURY	355681.78
	2018	CEDARBROOK SENIOR CARE AND REHABILITATION	ALLENTOWN	355351.90
	6589	MIAMI JEWISH HEALTH SYSTEMS, INC	MIAMI	347356.58
	1420	BORO PARK CENTER FOR REHABILITATION AND HEALTH	BROOKLYN	339746.18

Start coding or generate with AI.

Start coding or generate with AI.

##check the total hours for top 10 facilities across states
total_hours_per_state = df_melted.groupby(['PROVNAME','STATE'])['Hours'].sum().reset_index()

print(total_hours_per_state)

₹	0 1 2 3	PROVNAME 15 CRAIGSIDE 24TH PLACE 60 WEST A GRACE SUB ACUTE & SKILLED CARE	HI OK CT CA	Hours 39242.30 33903.84 71594.88 63282.50
	4	A HOLLY PATTERSON EXTENDED CARE FACILITY	NY	275118.90
	11494	ZEBULON PARK HEALTH AND REHABILITATION	GA	38963.98
	11495	ZEBULON REHABILITATION CENTER	NC	34571.50
	11496	ZERBE SISTERS NURSING CENTER,	PA	58651.56
	11497	ZIONSVILLE MEADOWS	IN	42663.34
	11498	ZUMBROTA CARE CENTER	MN	23962.82

[11499 rows x 3 columns]

Start coding or generate with AI.

##sorte the total hours for top 10 facilities across states
sorted_total_hours_per_state = total_hours_per_state.sort_values(by='Hours', ascending=False)

sorted_total_hours_per_state.head(10)

→		PROVNAME	STATE	Hours
	6630	MILLER'S MERRY MANOR	IN	483607.50
	5053	ISABELLA GERIATRIC CENTER INC	NY	404400.24
	2362	COLER REHABILITATION AND NURSING CARE CENTER	NY	402659.82
	5272	KINGS HARBOR MULTICARE CENTER	NY	389573.14
	5932	LORETTO HEALTH AND REHABILITATION CENTER	NY	378463.24
	8731	RUTLAND NURSING HOME, INC	NY	369114.52
	9475	ST ANNS COMMUNITY	NY	368358.54
	10185	THE PLAZA REHAB AND NURSING CENTER	NY	367224.00
	2358	COLD SPRING HILLS CENTER FOR NURSING AND REHAB	NY	355681.78
	2016	CEDARBROOK SENIOR CARE AND REHABILITATION	PA	355351.90

Start coding or generate with AI.

Recommendation 1 Leverage High Staffing Demand in New York City

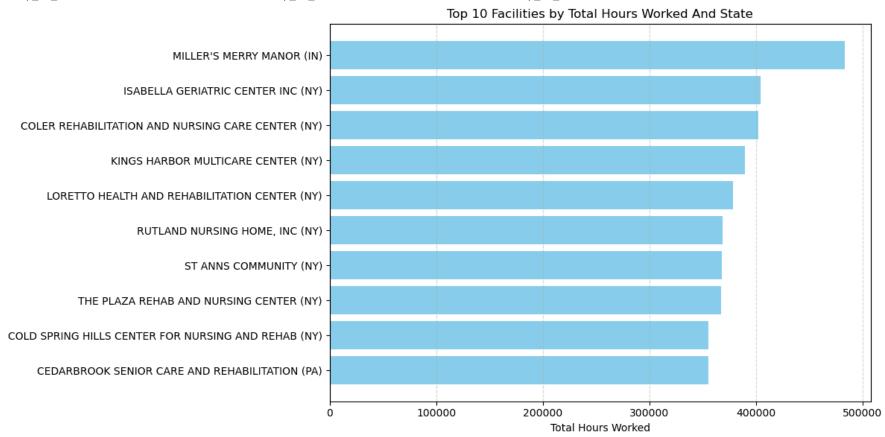
While most facilities are located in Ohio (OH), the city with the highest demand for staffing (total hours) is New York City (NYC), not Ohio. This suggests that although Ohio has more facilities, the individual facilities in NYC require more staffing hours on average. The App is attractive solution for facilities facing staffing challenges, especially in densely populated areas.

```
Start coding or generate with AI.
top_10_facilities = sorted_total_hours_per_state.head(10)
# Combine provider names with their state information
top_10_facilities['ProviderWithState'] = top_10_facilities['PROVNAME'] + " (" + top_10_facilities['STATE'] + ")"
# Extracting the names and hours for the top 10
facilities = top_10_facilities['ProviderWithState'].values
total_hours = top_10_facilities['Hours'].values
# Create the bar chart
plt.figure(figsize=(12, 6))
plt.barh(facilities, total hours, color='skyblue')
plt.title("Top 10 Facilities by Total Hours Worked And State")
plt.xlabel("Total Hours Worked")
plt.gca().invert_yaxis() # To ensure the facility with the highest hours is at the top
plt.grid(axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.savefig("Chart1.2.png")
plt.show()
```

/var/folders/gk/537qy50d4ls5vppc09_8xb0r0000gn/T/ipykernel_818/1185297253.py:4: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy top_10_facilities['ProviderWithState'] = top_10_facilities['PROVNAME'] + " (" + top_10_facilities['STATE'] + ")"



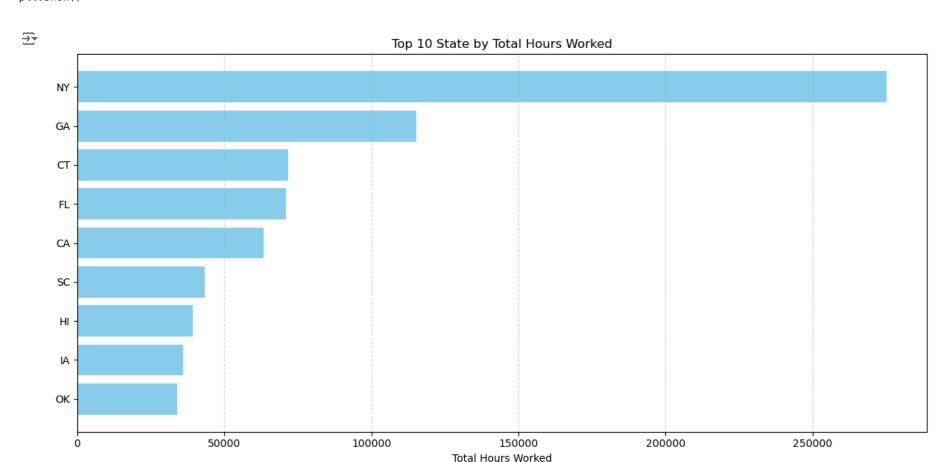
```
Start coding or generate with AI.

#visulaizing the top 1
top_10_provider_location = total_hours_per_state.head(15).sort_values(by='Hours', ascending=False)

# Extracting the names and hours for the top 10
facilities = top_10_provider_location['STATE'].values
total_hours = top_10_provider_location['Hours'].values

# Create the bar chart
```

```
plt.figure(figsize=(12, 6))
plt.barh(facilities, total_hours, color='skyblue')
plt.title("Top 10 State by Total Hours Worked")
plt.xlabel("Total Hours Worked")
plt.gca().invert_yaxis() # To ensure the facility with the highest hours is at the top
plt.grid(axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.savefig("Chart1.3.png")
plt.show()
```



Start coding or generate with AI.

- # Analyze the occupancy data ("MDScensus") to understand its distribution and trends over time
- # Basic statistics for occupancy the working hours in each day
 occupancy_stats = df_melted['MDScensus'].describe()
- # Check the trend of occupancy over time (grouping by 'WorkDate')

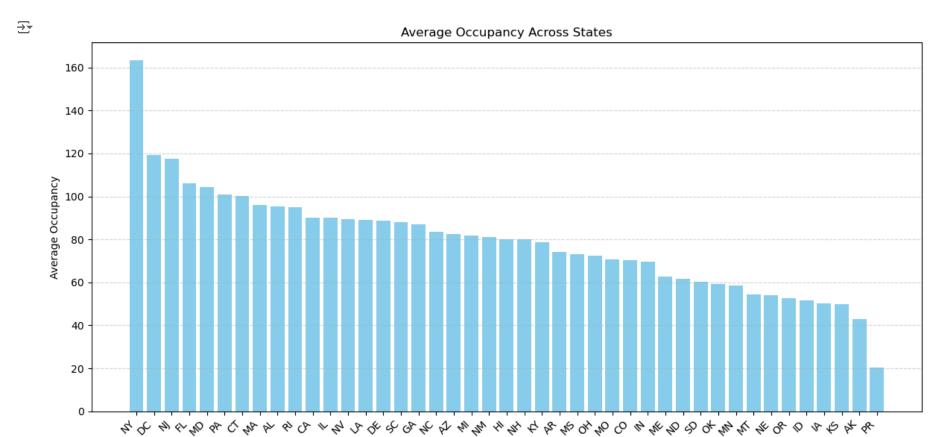
```
occupancy_trend = df_melted.groupby('WorkDate')['MDScensus'].mean()
# Display the statistics and trend overview
occupancy stats, occupancy trend.head()
              2.516580e+07
    (count
              8.578537e+01
     mean
     std
              5.153744e+01
     min
              0.000000e+00
     25%
              5.200000e+01
              7.800000e+01
     50%
     75%
              1.070000e+02
              7.430000e+02
     Name: MDScensus, dtype: float64,
     WorkDate
     2024-01-01
                   83.927189
                    84.072377
     2024-01-02
     2024-01-03
                   84.356678
     2024-01-04
                   84.690272
     2024-01-05
                   84.896294
     Name: MDScensus, dtype: float64)
Start coding or generate with AI.
Start coding or generate with AI.
```

findings

Minimum: 0 residents — This indicates that there were times when facilities recorded no residents, possibly reflecting temporary closures or extreme low-occupancy days. Maximum: 743 residents — The maximum number suggests some facilities have high capacities, which could be larger centers with higher demands.

```
# Group the data by 'STATE' and calculate key statistics for occupancy across states
state_occupancy_stats = df.groupby('STATE')['MDScensus'].agg(['mean', 'std', 'min', 'max', 'count']).reset_index()
# Rename columns for clarity
state_occupancy_stats.columns = [
    'State', 'Average_Occupancy', 'Occupancy_Variability', 'Min_Occupancy', 'Max_Occupancy', 'Count'
]
# Sort by Average Occupancy before plotting
state_occupancy_stats_sorted = state_occupancy_stats.sort_values(by='Average_Occupancy', ascending=False)
```

```
# Create a bar chart with the sorted data
plt.figure(figsize=(12, 6))
plt.bar(state_occupancy_stats_sorted['State'], state_occupancy_stats_sorted['Average_Occupancy'], color='skyblue')
plt.title("Average Occupancy Across States")
plt.xlabel("State")
plt.ylabel("Average Occupancy")
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.savefig("Chart1.4.png")
# Show the plot
plt.show()
```



Start coding or generate with AI.

Recomendation 2: Promote the App during Peak Bed Utilization Periods

During the first two weeks of January, the data shows a steady increase in the number of active beds (MDScensus). To address this trend, the app should be promoted as a solution that guarantees high availability of staff, making it a reliable choice for facilities that need dependable support during busy periods."

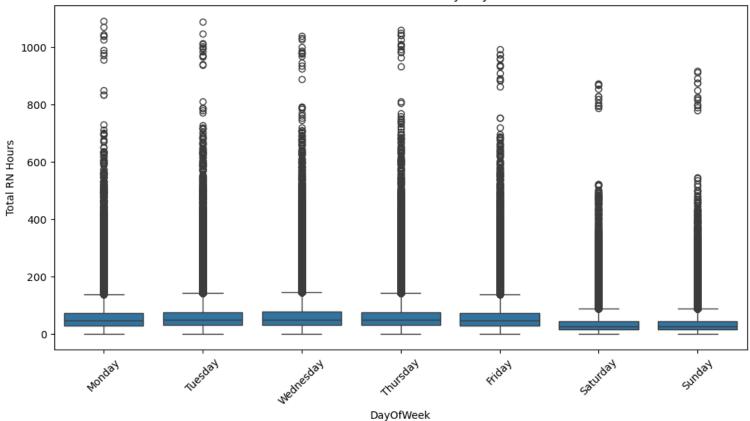
```
# Weekend Staffing Levels Analysis
# Calculate total RN hours
df['Total_RN_Hours'] = df['Hrs_RNDON'] + df['Hrs_RNadmin'] + df['Hrs_RN']

# Create a column for day of week
df['DayOfWeek'] = df['WorkDate'].dt.day_name()

# Plot RN hours by day of week
plt.figure(figsize=(12, 6))
sns.boxplot(x='DayOfWeek', y='Total_RN_Hours', data=df)
plt.title('Distribution of Total RN Hours by Day of Week')
plt.ylabel('Total RN Hours')
plt.xticks(rotation=45)
plt.savefig("Distribution of Total RN Hours by Day of Week.png")
plt.show()
```



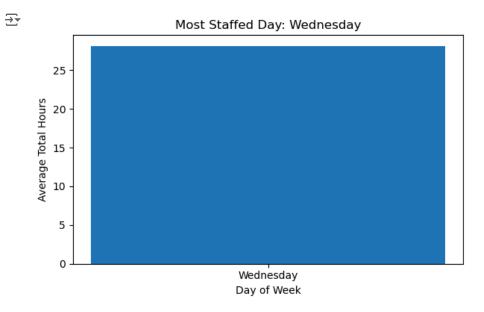
Distribution of Total RN Hours by Day of Week



#lets check which is the Most day that have the highest working hours
avg staffing by day = df melted.groupby('DayOfWeek')['Hours'].mean().sort values(ascending=False)

```
# Group by DayOfWeek and calculate the mean of Hours
avg_staffing_by_day = df_melted.groupby('DayOfWeek')['Hours'].mean()
# Find the day with the maximum average hours
max_day = avg_staffing_by_day.idxmax()
max_hours = avg_staffing_by_day.max()
# Filter to show only the day with the maximum hours
plt.figure(figsize=(6, 4))
plt.bar(max_day, max_hours)
plt.title(f'Most Staffed Day: {max_day}')
plt.xlabel('Day of Week')
```

```
plt.ylabel('Average Total Hours')
plt.tight_layout()
plt.show()
```

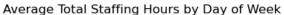


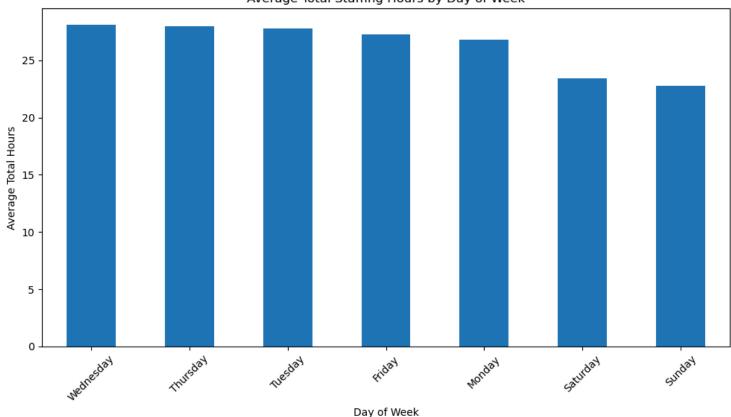
```
Start coding or generate with AI.

# Data-Driven Staffing Solutions
# Example: Predict staffing needs based on day of week
avg_staffing_by_day = df_melted.groupby('DayOfWeek')['Hours'].mean().sort_values(ascending=False)

plt.figure(figsize=(10, 6))
avg_staffing_by_day.plot(kind='bar')
plt.title('Average Total Staffing Hours by Day of Week')
plt.xlabel('Day of Week')
plt.xlabel('Day of Week')
plt.xlabel('Average Total Hours')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```







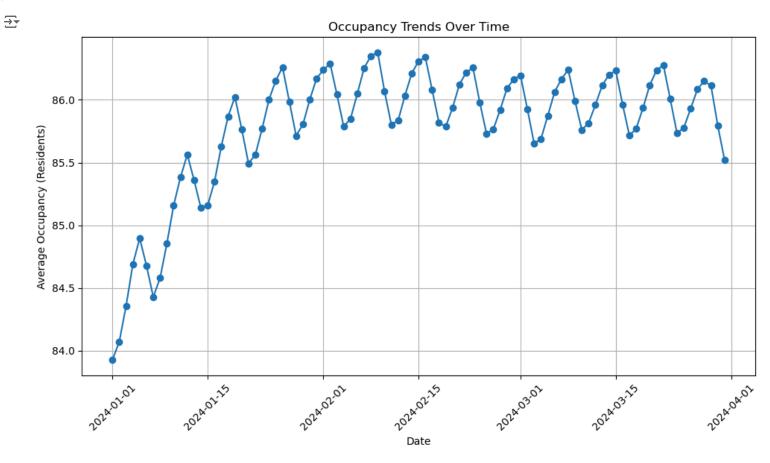
```
Start coding or generate with AI.

Start coding or generate with AI.

# Group the data by 'WorkDate' to calculate the mean occupancy per day occupancy_trend = df_melted.groupby('WorkDate')['MDScensus'].mean()

# Plot the occupancy trend over time plt.figure(figsize=(10, 6)) plt.plot(occupancy_trend.index, occupancy_trend.values, marker='o', linestyle='-') plt.title("Occupancy Trends Over Time") plt.xlabel("Date") plt.ylabel("Average Occupancy (Residents)") plt.xticks(rotation=45)
```

```
plt.grid(True)
plt.tight_layout()
plt.savefig('Chart2.1.png')
plt.show()
```



```
Start coding or <u>generate</u> with AI.

Start coding or <u>generate</u> with AI.

Start coding or <u>generate</u> with AI.

df_melted.head()
```

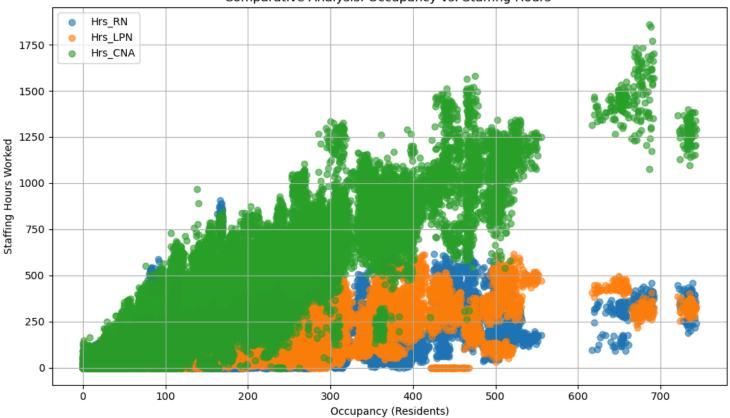
Recommendation 3: Market the App as a Real-Time Staffing Optimization Tool

The app should be marketed as a solution that helps facilities fine-tune their staffing, ensuring that they have the right balance of CNAs, RNs, and LPNs at all times. Facilities can use the app to monitor demand in real-time and adjust staffing levels accordingly, thereby avoiding excess costs due to overstaffing or the risks associated with understaffing.

Start coding or generate with AI. # Create a comparative analysis for different hour types (e.g., RN, LPN, CNA) versus occupancy # Select a few key hour types from the dataset to compare (e.g., Hrs_RNDON, Hrs_LPN, Hrs_CNA) hour_types = ['Hrs_RN', 'Hrs_LPN', 'Hrs_CNA'] # Plot each hour type against occupancy in a comparative scatter plot plt.figure(figsize=(10, 6)) for hour type in hour types: plt.scatter(df['MDScensus'],df[hour_type], alpha=0.6, label=hour_type) plt.title("Comparative Analysis: Occupancy vs. Staffing Hours ") plt.xlabel("Occupancy (Residents)") plt.ylabel("Staffing Hours Worked") plt.legend() plt.grid(True) plt.tight_layout() plt.savefig('Chart3.png') plt.show()







Start coding or generate with AI.

Recommendation 4: Prioritize CNA and LPN Recruitment to Meet Demand Peak

Most significant Targets are CNA Certified Nurse Assisstant with over 54% according to the working hours among all. suggeset the highest demand as the second target would be LPN licensce Practice Nurse. Focus efforts on recruiting and onboarding more CNAs and LPN ensure steady supply specially during the peak

```
Start coding or generate with AI.

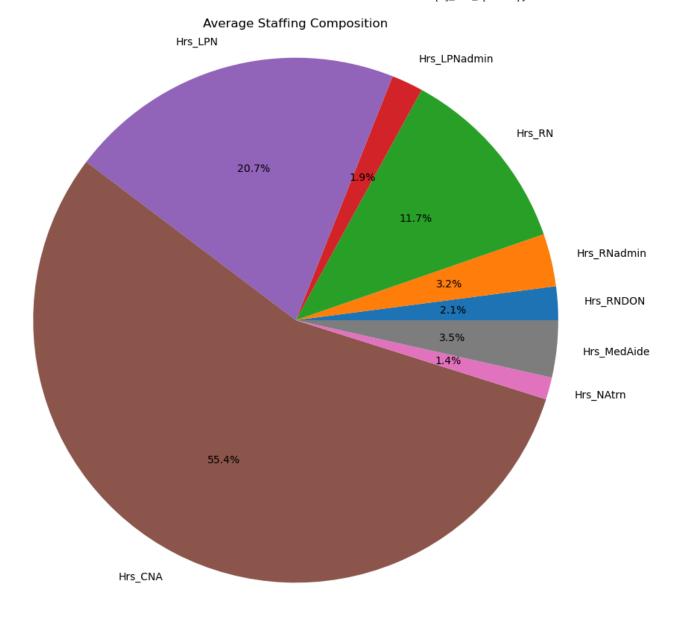
# Staffing Composition Analysis
staffing_categories = ['Hrs_RNDON', 'Hrs_RNadmin', 'Hrs_RN', 'Hrs_LPNadmin', 'Hrs_LPN', 'Hrs_CNA', 'Hrs_NAtrn', 'Hrs_MedAide']

df['Total_Hours'] = df[staffing_categories].sum(axis=1)
```

```
# Calculate percentage for each category
for category in staffing_categories:
    df[f'{category}_Percentage'] = df[category] / df['Total_Hours'] * 100

# Plot average staffing composition
avg_composition = df[[f'{category}_Percentage' for category in staffing_categories]].mean()

plt.figure(figsize=(10, 10))
plt.pie(avg_composition, labels=staffing_categories, autopct='%1.1f%*')
plt.title('Average Staffing Composition')
plt.axis('equal')
plt.savefig('Chart4.png')
plt.show()
```



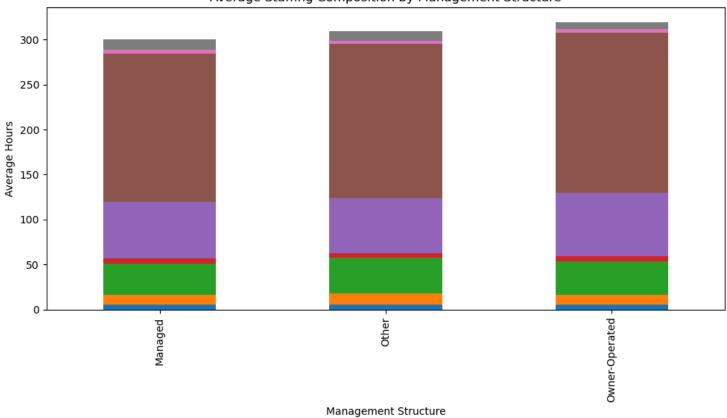
Start coding or generate with AI.

Load and prepare the ownership data
ownership_df = pd.read_csv('/Users/mac/Desktop/-Health-Sales-Data-/NH_Ownership_Sep2024.csv')

```
# Remove since from the date column
ownership_df['Association Date'] = ownership_df['Association Date'].str.replace('since ', '')
# Convert Association Date to datetime
ownership df['Association Date'] = pd.to datetime(ownership df['Association Date'], format='%m/%d/%Y', errors='coerce')
# Merge two data sets PBJ_Daily_nursing_staff with Owenrship Data set to analyze if the managemnt type effect staffing
merged df = pd.merge(df, ownership df, left on='PROVNUM', right on='CMS Certification Number (CCN)', how='inner')
print(f"Number of facilities after merge: {merged df['PROVNUM'].nunique()}")
Number of facilities after merge: 9783
Start coding or generate with AI.
# Create fucntion to simplify Role played in facility by mapping role to Ownership , Managed , other
def simplify_role(role):
   if 'OWNERSHIP' in role:
        return 'Owner-Operated'
   elif 'OPERATIONAL/MANAGERIAL' in role:
        return 'Managed'
   else:
        return 'Other'
Start coding or generate with AI.
merged_df['Management_Structure'] = merged_df['Role played by Owner or Manager in Facility'].apply(simplify_role)
# Calculate average staffing composition for each management structure
staffing composition = merged df.groupby('Management Structure')[staffing categories].mean()
# Plot the staffing composition
staffing composition.plot(kind='bar', stacked=True, figsize=(12, 6))
plt.title('Average Staffing Composition by Management Structure')
plt.xlabel('Management Structure')
plt.ylabel('Average Hours')
plt.legend(title='Staffing Category', bbox to anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.savefig("Average Staffing Composition by Management Structure.png")
plt.show()
```







Staffing Category

Hrs_RNDON

Hrs_RNadmin

Hrs_RN

Hrs_LPNadmin

Hrs_LPN

Hrs_CNA

Hrs_NAtrn

Hrs_MedAide

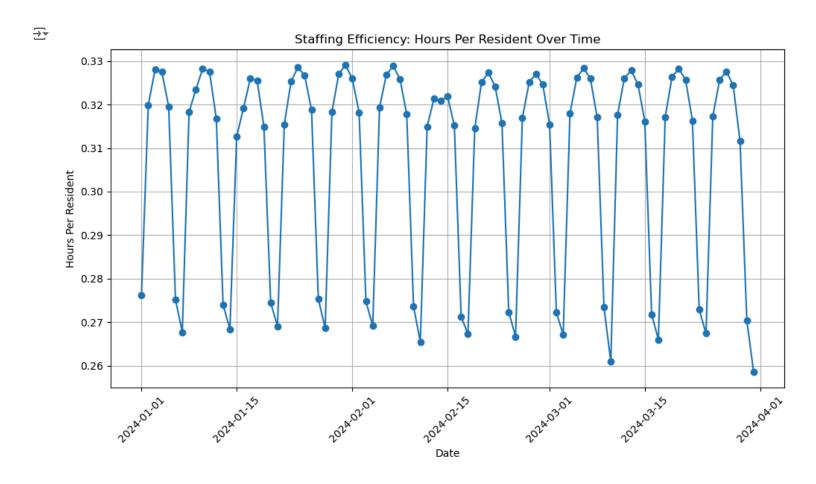
```
# Calculate the staffing efficiency: Hours per Resident (total hours worked / occupancy)
# We'll use columns for different types of staff hours and calculate the total staffing efficiency

# Ensure required columns are present in the dataset
required_columns = ['MDScensus', 'Hours', 'Hour_Type', 'WorkDate']
if all(col in df_melted.columns for col in required_columns):
    # Calculate total hours per day and divide by occupancy to get hours per resident
    daily_efficiency = df_melted.groupby(['WorkDate']).apply(
        lambda x: x['Hours'].sum() / x['MDScensus'].sum() if x['MDScensus'].sum() > 0 else 0
    ).reset_index(name='Hours_Per_Resident')

# Plot the staffing efficiency trend over time
    plt.figure(figsize=(10, 6))
    plt.plot(daily_efficiency['WorkDate'], daily_efficiency['Hours_Per_Resident'], marker='o', linestyle='-')
    plt.title("Staffing Efficiency: Hours Per Resident Over Time")
    plt.xlabel("Date")
```

```
plt.ylabel("Hours Per Resident")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.savefig('Chart5.2.png')
plt.show()

else:
    print("The dataset does not contain the required columns for this analysis.")
```



Start coding or generate with AI.

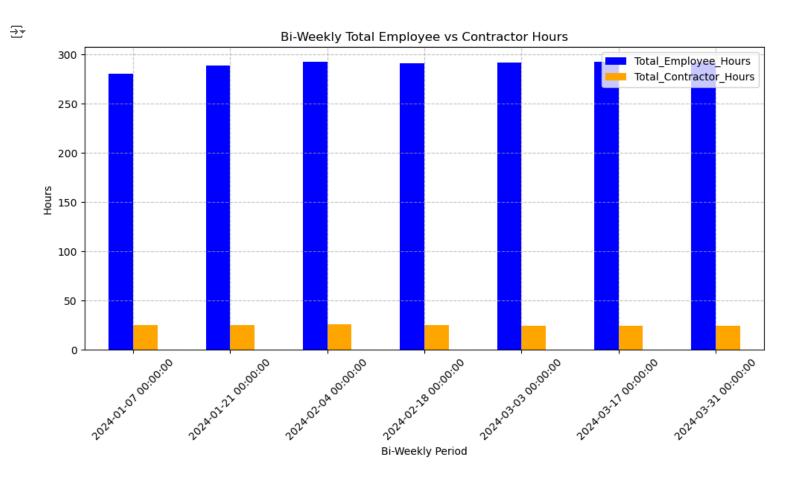
Recomendation 5 Target Facilities Needing Flexible and Consistent Staffing Solutions by checking the effect of employee to contractors in avarage of working hours as long

with management type if its After merage data set downloaded from the CMS webside "NH_Ownership_Sep2024" and NH_Ino_providers to analyzing the management effect on potinal matching

Organization-owned and shorter ownership tenures facilities(less than 10 years) tend to have higher variability in staffing hours this may face unexpected peaks in staffing needs and require more adaptable, flexible staffing solutions to manage changes, fast sloution for additional staff matching during peaks moreover, longer tenure facilities are more stable but can still benefit from efficient management tools by trageting each group by spesicfic sloution At management level to runs the facility, they always rely heavily on CNAs, with a balanced mix of LPNs and RNs regardless of it istructure

```
df extracted = pd.read csv('extract.csv')
# Convert 'WorkDate' to datetime
df_extracted['WorkDate'] = pd.to_datetime(df_extracted['WorkDate'])
# Calculate correlation between Employee and Contractor hours
correlation = df_extracted['Total_Employee_Hours'].corr(df_extracted['Total_Contractor_Hours'])
print(f"Correlation between Employee Hours and Contractor Hours: {correlation}")
→ Correlation between Employee Hours and Contractor Hours: 0.15657296535559065
Start coding or generate with AI.
# Set WorkDate as the index
df_extracted.set_index('WorkDate', inplace=True)
Start coding or generate with AI.
# Resample bi-weekly ('2W') and sum the employee and contractor hours
df biweekly = df extracted.resample('2W').mean() # Resample every 2 weeks
# Plot the bi-weekly totals for Employee and Contractor Hours
df_biweekly[['Total_Employee_Hours', 'Total_Contractor_Hours']].plot(kind='bar', figsize=(10, 6), color=['blue', 'orange'])
# Add title and labels
plt.title('Bi-Weekly Total Employee vs Contractor Hours')
plt.ylabel('Hours')
plt.xlabel('Bi-Weekly Period')
plt.xticks(rotation=45)
plt.grid(True, linestyle='--', alpha=0.7)
# Adjust layout and display the plot
```

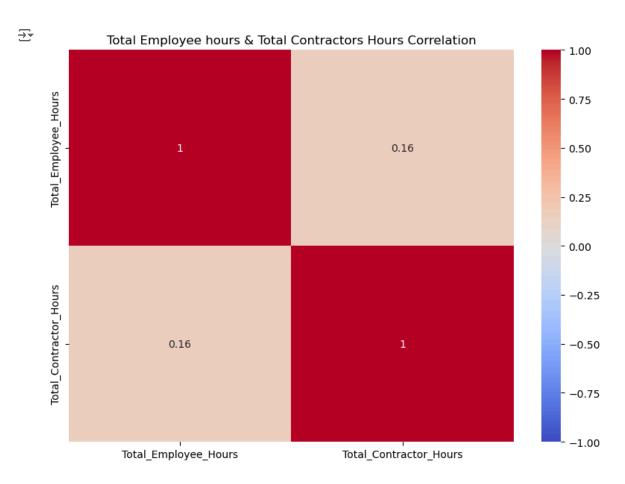
```
plt.tight_layout()
plt.savefig('Chart5.1.png')
plt.show()
```



```
# Select only the numerical columns (exclude 'WorkDate')
numerical_df = df_extracted[['Total_Employee_Hours', 'Total_Contractor_Hours']]
# Create a correlation matrix
corr_matrix = numerical_df.corr()
# Plot the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
# Add title
plt.title('Total Employee hours & Total Contractors Hours Correlation')
```

```
# Adjust layout for better appearance
plt.tight_layout()
```

Show the plot
plt.savefig('Chart5.2.png')
plt.show()



Start coding or generate with AI.

Start coding or generate with AI.

Start coding or generate with AI.

Load and prepare the provider_info data
provider_info_df = pd.read_csv('/Users/mac/Desktop/-Health-Sales-Data-/NH_ProviderInfo_Sep2024.csv')

```
Start coding or generate with AI.
# merge the provider_info data and nursing data provided for more insights for facilitites type
merged_df_info = pd.merge(df_melted, provider_info_df, left_on='PROVNUM', right_on='CMS Certification Number (CCN)', how='inner')
Start coding or generate with AI.
#check for the value for of owner of the facilitites
merged df info['Ownership Type'].unique()
⇒ array(['Non profit - Church related', 'For profit - Partnership',
            'Government - County', 'Government - State',
            'For profit - Corporation',
            'For profit - Limited Liability company',
            'For profit - Individual', 'Non profit - Corporation',
            'Government - Hospital district', 'Non profit - Other',
            'Government - Federal', 'Government - City',
            'Government - City/county'], dtype=object)
#Rename column for avioding spelling error retreving
merged df info.rename(columns={'Ownership Type': 'OwnershipType'}, inplace=True)
#Change the Ownership to to 3 categories Government , Profit , Non Profit by create function for easy insights
def categorize ownership(value):
    if 'Government' in value:
        return 'Government'
    elif 'For profit' in value:
        return 'For profit'
    elif 'Non profit' in value:
        return 'Non profit'
    else:
        return 'Other' # In case there are values that do not match the expected patterns
# Apply the function to the 'OwnershipType' column and categorized for analyize ploting
merged_df_info['ownership_category'] = merged_df_info['OwnershipType'].apply(categorize_ownership)
Start coding or generate with AI.
#check for column names
for col in merged df info.columns:
    print(col)
```

PROVNUM
PROVNAME
CITY
STATE

COUNTY_NAME COUNTY_FIPS CY_Qtr

WorkDate MDScensus Hour_Type

Hours DayOfWeek

CMS Certification Number (CCN)

Provider Name Provider Address City/Town State

ZIP Code

Telephone Number

Provider SSA County Code

County/Parish OwnershipType

Number of Certified Beds

Average Number of Residents per Day

Average Number of Residents per Day Footnote

Provider Type

Provider Resides in Hospital

Legal Business Name

Date First Approved to Provide Medicare and Medicaid Services

Affiliated Entity Name Affiliated Entity ID

Continuing Care Retirement Community

Special Focus Status

Abuse Icon

Most Recent Health Inspection More Than 2 Years Ago

Provider Changed Ownership in Last 12 Months

With a Resident and Family Council

Automatic Sprinkler Systems in All Required Areas

Overall Rating

Overall Rating Footnote

Health Inspection Rating

Health Inspection Rating Footnote

QM Rating

QM Rating Footnote

Long-Stay QM Rating

Long-Stay QM Rating Footnote

Short-Stay QM Rating

Short-Stay QM Rating Footnote

Staffing Rating

Staffing Rating Footnote

Reported Staffing Footnote

Physical Therapist Staffing Footnote

Reported Nurse Aide Staffing Hours per Resident per Day

Reported LPN Staffing Hours per Resident per Day

Reported RN Staffing Hours per Resident per Day

Reported Licensed Staffing Hours per Resident per Day

```
Reported Total Nurse Staffing Hours per Resident per Day
```

```
Start coding or generate with AI.
```

```
# Ownership Type and Staffing Levels
# Calculate average total hours per day for each facility
facility_avg_hours = merged_df_info.groupby('PROVNUM')['Hours'].mean().reset_index()

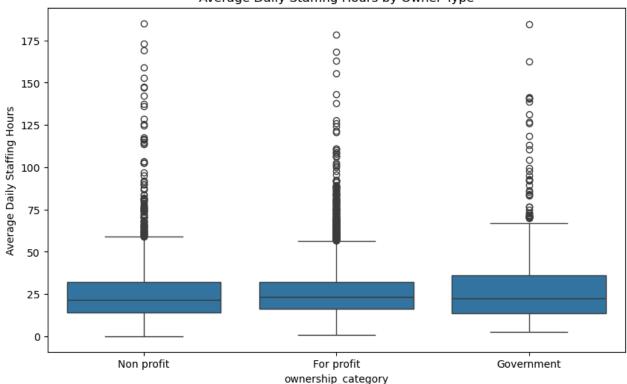
# Get the primary owner type for each facility
facility_owner_type = merged_df_info.groupby('PROVNUM')['ownership_category'].first().reset_index()

# Merge the two
facility_data = pd.merge(facility_avg_hours, facility_owner_type, on='PROVNUM')

plt.figure(figsize=(10, 6))
sns.boxplot(x='ownership_category', y='Hours', data=facility_data)
plt.title('Average Daily Staffing Hours by Owner Type')
plt.ylabel('Average Daily Staffing Hours')
plt.savefig('Average Daily Staffing Hours by Owner Type Chart5.1.png')
plt.show()
```



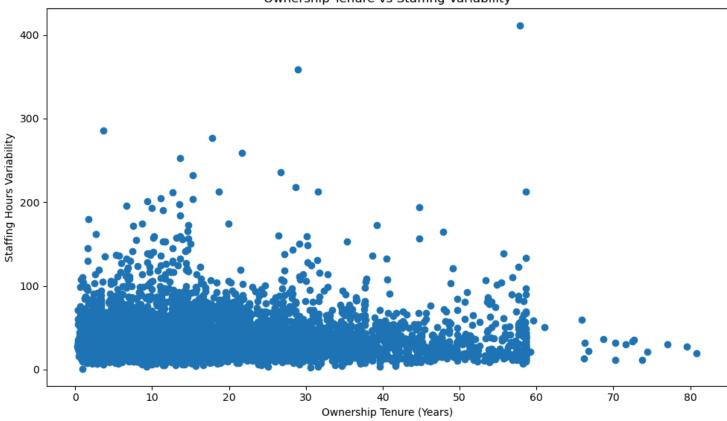




```
merged df.rename(columns={'Association Date': 'AssociationDate'}, inplace=True)
Start coding or generate with AI.
# Ownership Tenure and Staffing Stability
# Calculate ownership tenure
merged_df['Ownership_Tenure'] = (pd.to_datetime('2024-09-01') - merged_df['Association Date']).dt.days / 365.25
# Calculate staffing hour variability for each facility
staffing variability = merged df.groupby('PROVNUM')['Total Hours'].std().reset index()
staffing variability = staffing variability.rename(columns={'Total Hours': 'Staffing Variability'})
# Get the maximum tenure for each facility (assuming the longest-tenured owner)
max_tenure = merged_df.groupby('PROVNUM')['Ownership_Tenure'].max().reset_index()
# Merge tenure and variability data
tenure variability = pd.merge(max tenure, staffing variability, on='PROVNUM')
plt.figure(figsize=(10, 6))
plt.scatter(tenure_variability['Ownership_Tenure'], tenure_variability['Staffing_Variability'])
plt.title('Ownership Tenure vs Staffing Variability')
plt.xlabel('Ownership Tenure (Years)')
plt.ylabel('Staffing Hours Variability')
plt.savefig('Chart5.3.png')
plt.tight_layout()
plt.show()
```



Ownership Tenure vs Staffing Variability



Start coding or generate with AI.

merged_df.rename(columns={'Role played by Owner or Manager in Facility': 'RolePlayedByManageOrOwner'}, inplace=True)
merged_df['Management_Structure'] = merged_df['Role played by Owner or Manager in Facility'].apply(simplify_role)
merged_df.head(2)



	PROVNUM	PROVNAME	CITY	STATE	COUNTY_NAME	COUNTY_FIPS	CY_Qtr	WorkDate	MDScensus	Hrs_RNDON	 ZIP Code	Role played by Owner or Manager in Facility	Owner Type	Owner Name	Owne Perce
0	01A193	FATHER PURCELL MEMORIAL EXCEPTIONAL	MONTGOMERY	AL	Montgomery	101	2024Q1	2024-01- 01	44	0.0	 36108	Ownership Data Not Available	NaN	NaN	