DSC 640 Week 1-2

Introduction

The White House visitor log dataset provides a detailed record of appointments involving the President of the United States (POTUS), including scheduling dates, meeting timing, and attendance size. This analysis focuses specifically on POTUS-related meetings to examine workload distribution, scheduling efficiency, and periods of high demand. Visual analytics were used to identify trends across weekdays, months, and meeting sizes, as well as to assess whether increased meeting volume leads to scheduling backlogs. The findings support an operational review of scheduling performance and highlight opportunities to proactively manage workload during peak periods, with particular attention to January as a strategic planning window. Every dataset provided was used in my analysis, which covers approximately 2.5 years of data.

Primary Audience

The primary audience for this analysis is the White House scheduling and administrative staff responsible for coordinating POTUS meetings. Secondary audiences include operational leadership and policy advisors who rely on efficient scheduling to ensure the President's time is managed effectively. The analysis is designed to support decision-making by highlighting patterns in workload concentration and identifying opportunities to distribute meetings more evenly across time. Audience is familiar with the dataset and populates the data that the tool uses.

Purpose

The purpose of this analysis is twofold: first, to recognize and validate the effectiveness of current scheduling practices, and second, to identify data-driven opportunities for improvement. By examining meeting volume, lead time, and attendance size, the analysis aims to ensure that high-demand periods do not result in unnecessary strain on scheduling operations. Emphasis is placed on January as an ideal month for proactive workload planning before historical increases in meeting volume later in the year.

Medium

The findings are communicated through a short PowerPoint presentation supported by a series of visualizations, including bar charts, step charts, scatterplots and heatmaps. These visual tools allow complex scheduling patterns to be quickly interpreted by operational stakeholders. The accompanying written analysis provides additional context and supports the visuals with narrative explanations appropriate for an academic and professional audience. Not all the graphs generated were used in the presentation to avoid clutter.

Call to Action

The call to action includes spreading the workload across the weekdays and avoid weekends when possible. Continue to flag high volume meeting earlier to allow for flexibility. Preserve buffers ahead of peak periods/days as indicated in the heatmap diagram.

Design

The design prioritizes clarity, simplicity, and consistency. Visuals use clear labeling, minimal clutter, and intuitive layouts to emphasize trends rather than individual data points. Time-based charts are used to show workload distribution across days and months, while scatterplots illustrate scheduling efficiency relative to meeting size. The overall design supports quick comprehension while maintaining analytical rigor.

Ethical Considerations

Ethical considerations include responsible use of publicly available White House visitor log data and avoidance of sensitive interpretations. The analysis focuses on aggregate patterns rather than individual appointments or attendees, minimizing privacy concerns. The intent of the analysis is constructive and supportive, emphasizing process improvement rather than critique of individuals or institutions.

Managing POTUS Meeting Load: What’s Working & January Focus

RECOGNIZING STRONG SCHEDULING PERFORMANCE WHILE PREPARING FOR PEAK DEMAND

JANUARY OPERATIONAL REVIEW

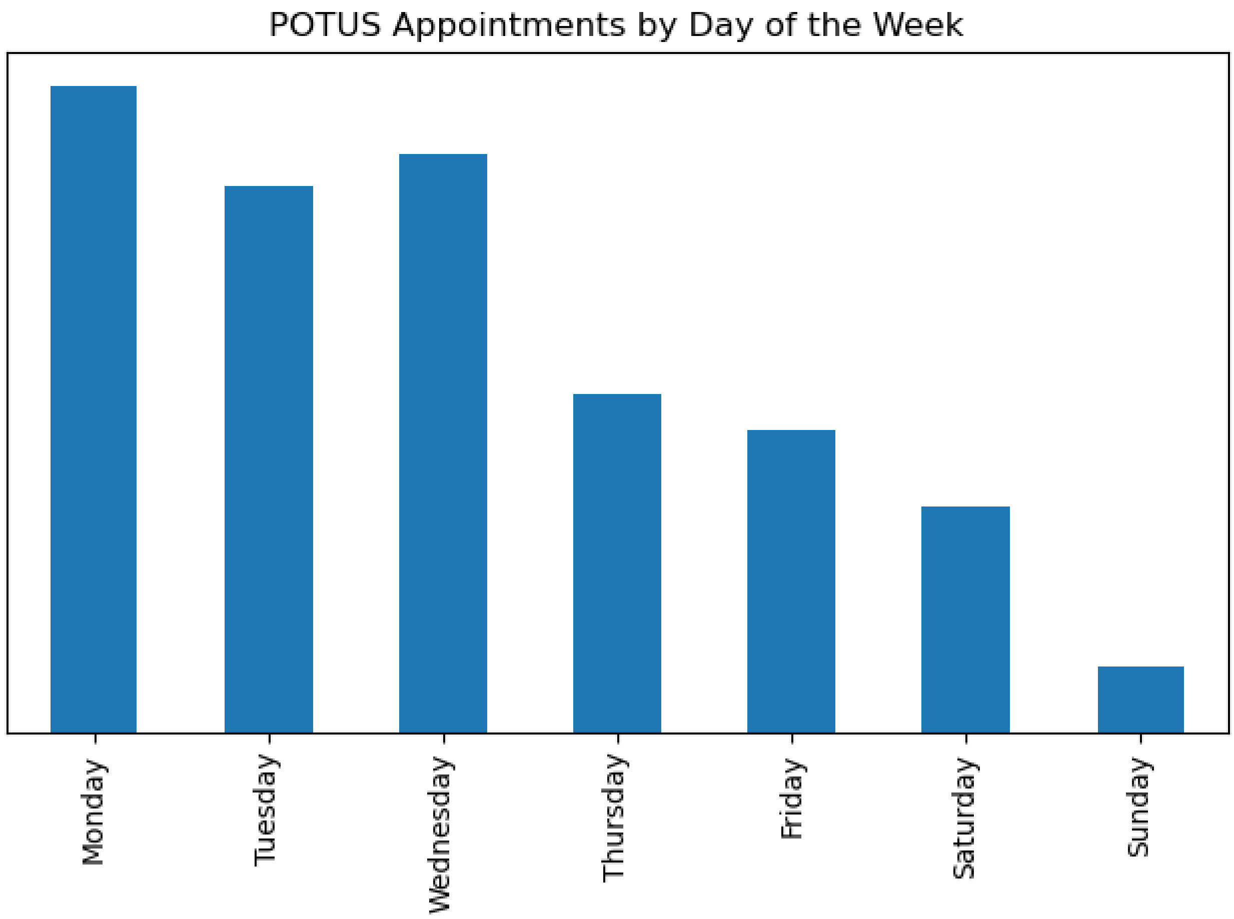
Strong Scheduling Performance

- HIGH-VOLUME POTUS MEETINGS ARE SCHEDULED WITH SHORT LEAD TIMES

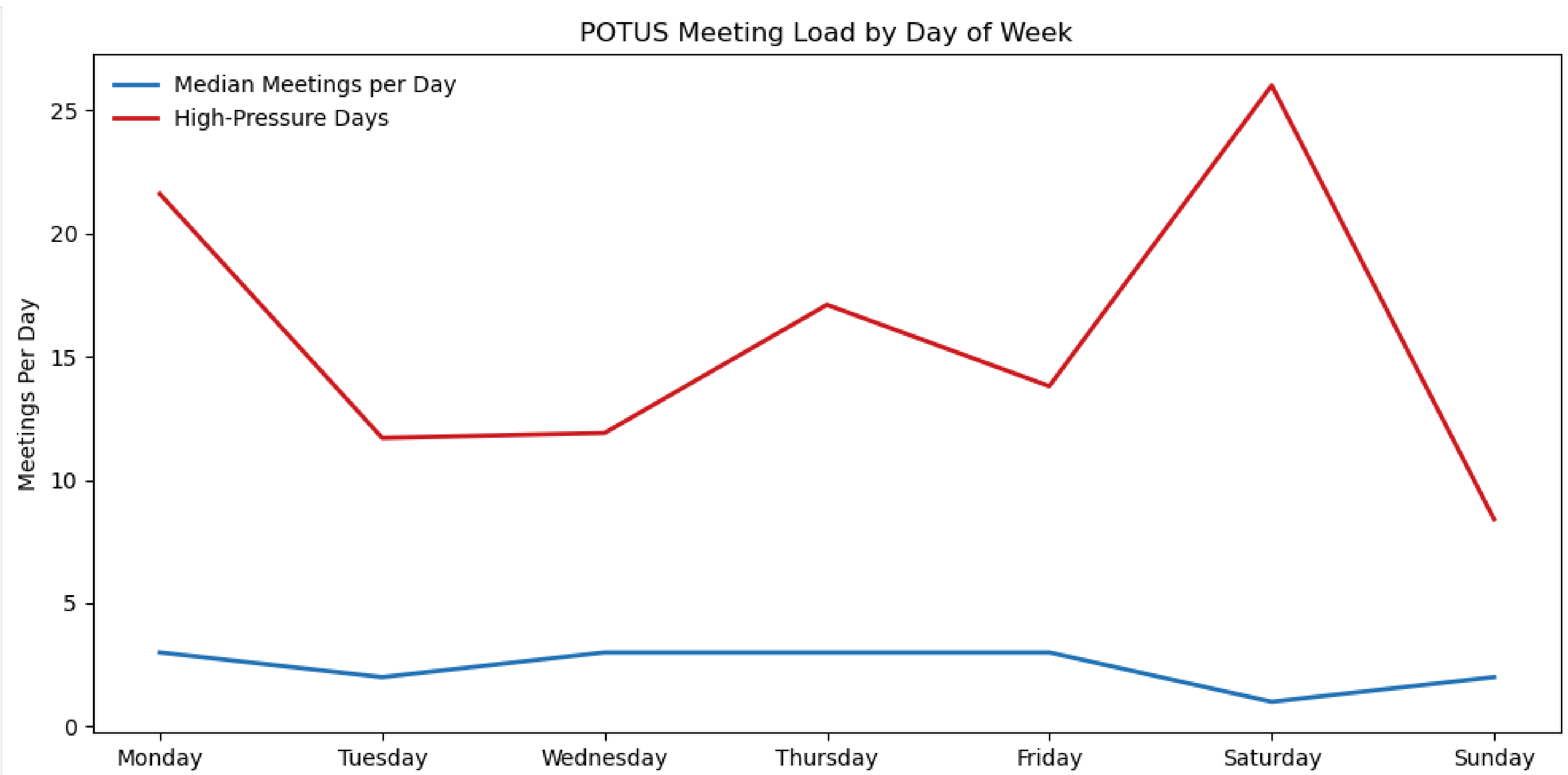
- LARGE MEETINGS DO NOT CREATE SIGNIFICANT BACKLOGS

- PERFORMANCE REMAINS STRONG DESPITE RISING VOLUME

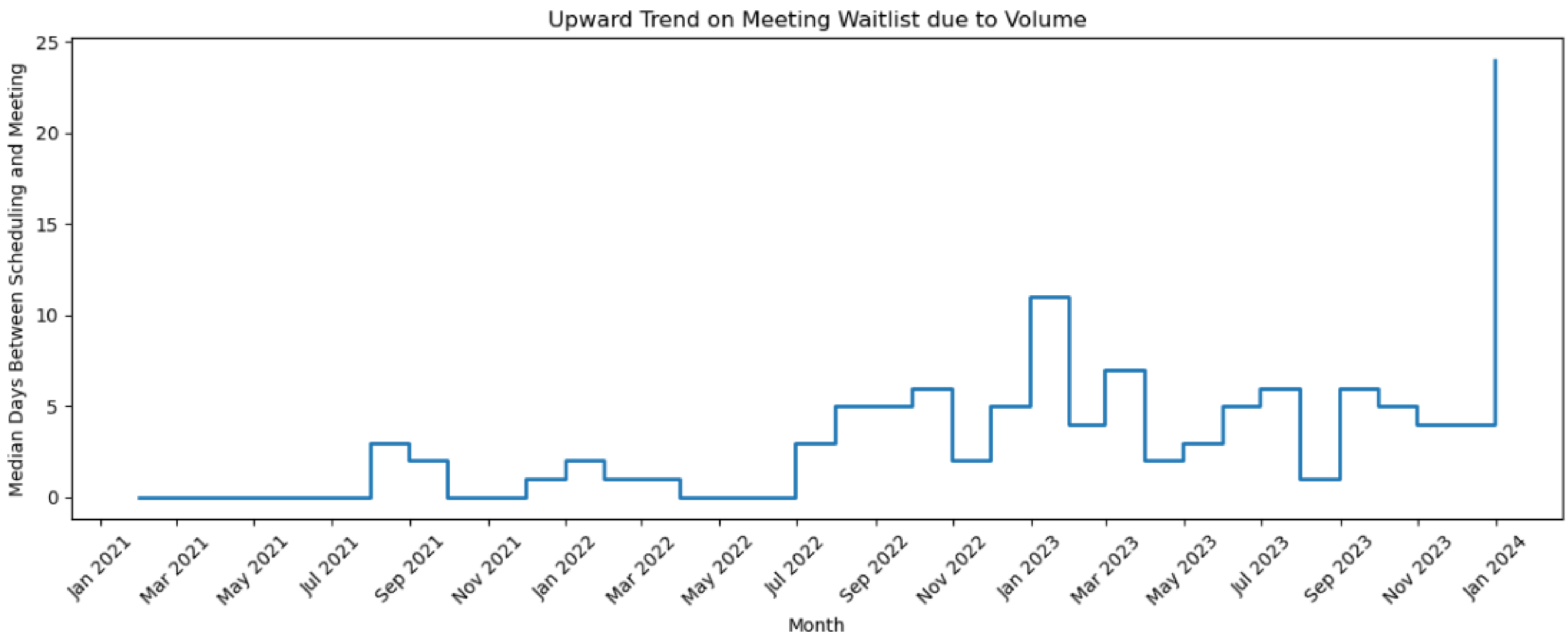
Keep Weekdays Available -> Be Prepared for High Volume Changes



POTUS Meeting Load by Day of the Week



Wait Times are Trending Up with Volumes



Where Pressure Concentrates

- Mondays–Wednesdays carry the highest meeting load

- Saturdays see occasional spikes

- Sundays remain intentionally low-volume

Predictable patterns enable proactive planning

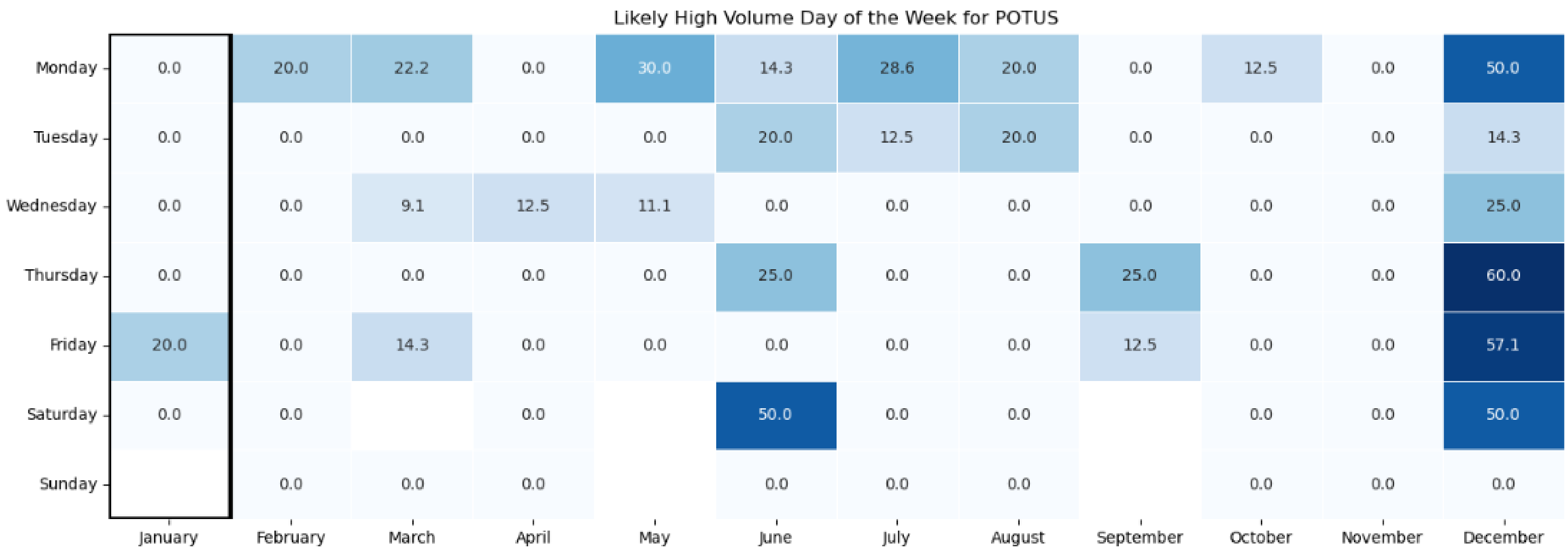
January Is a Strategic Opportunity

Volume increases mid-year and year-end

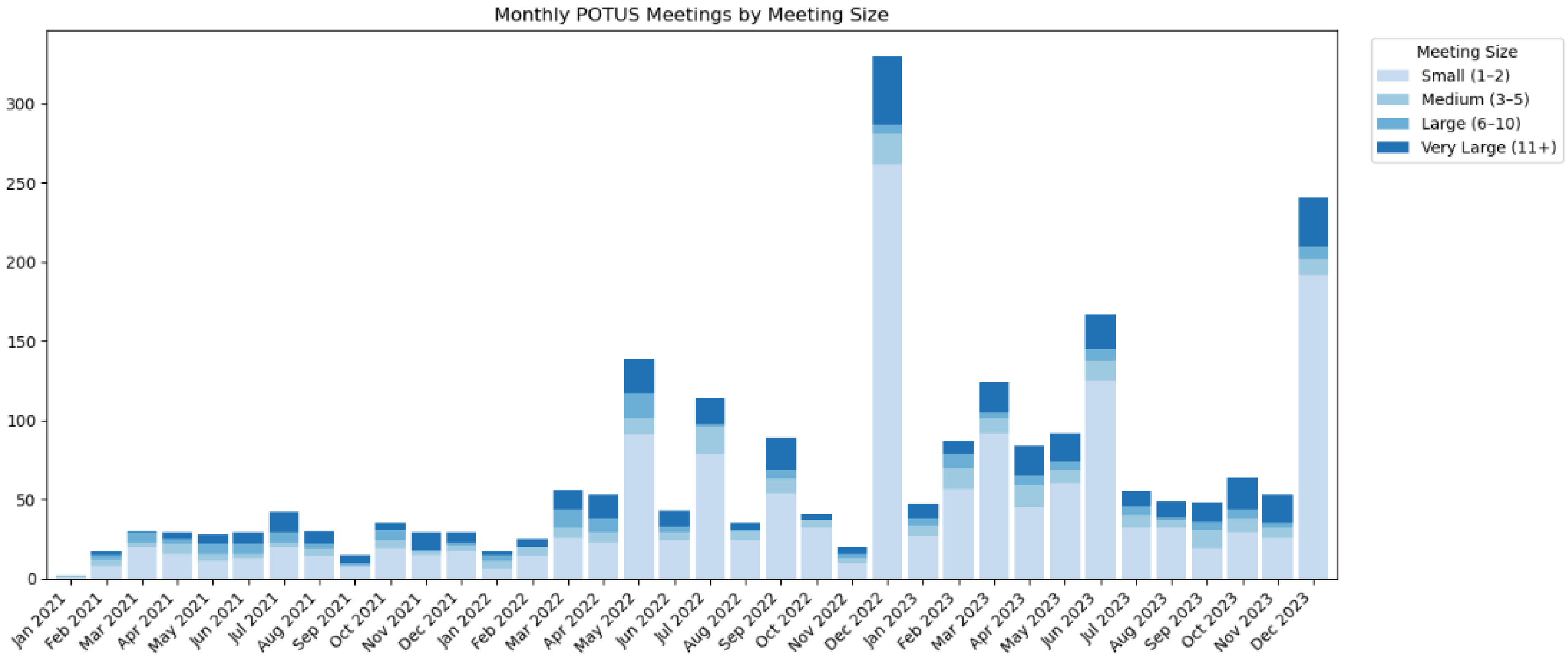
January starts lighter but ramps quickly

Early workload balancing prevents future bottlenecks

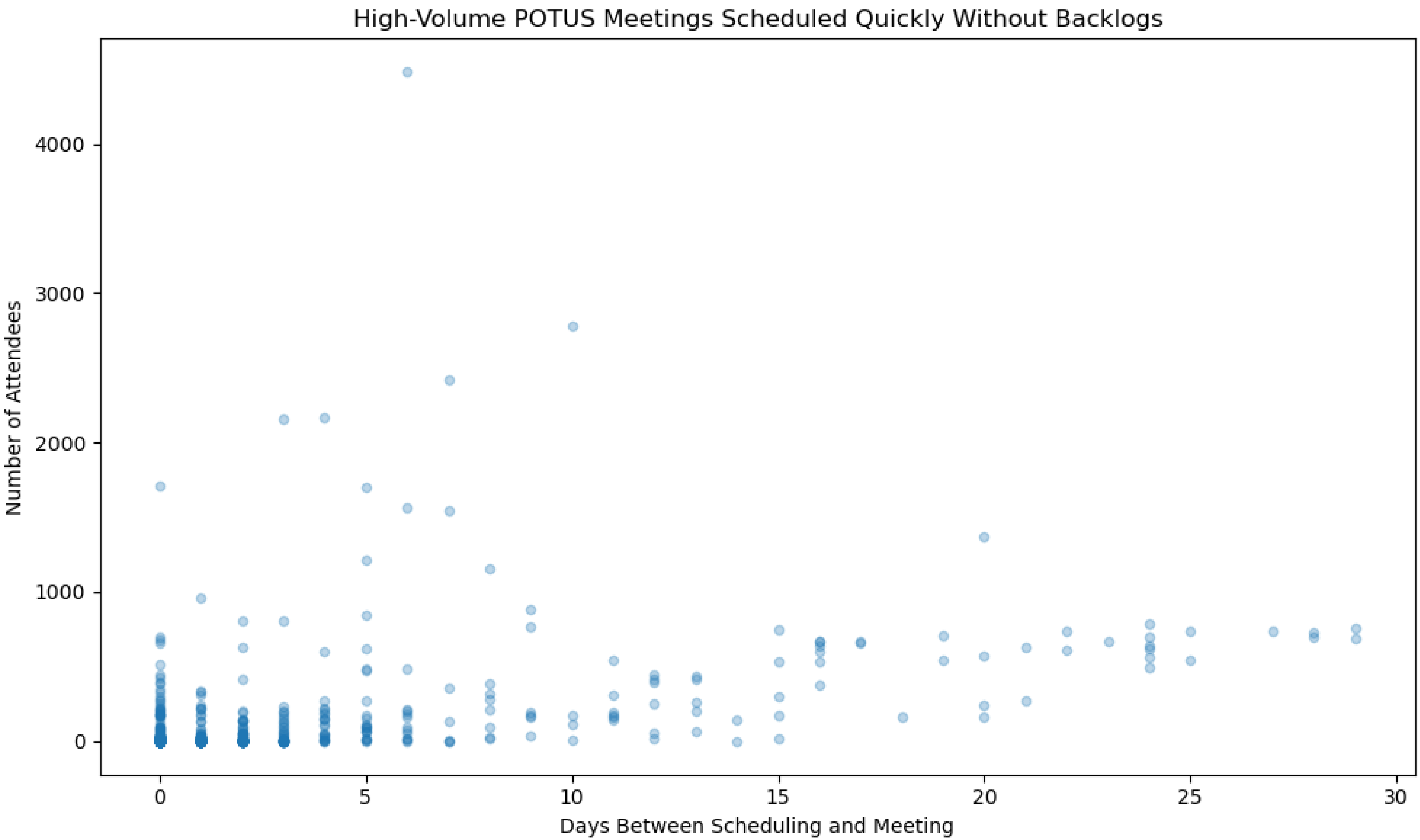
January Is a Strategic Opportunity



More Smaller Meetings = More Volume to Manage



Great Job Meeting Demands with Little Backlog



Call to Action

- Spread flexible meetings across weekdays
- Flag high-volume meetings earlier
- Preserve buffers ahead of peak periods
- Continue effective prioritization practices

Strong performance today enables sustainable success

4 of your 6 required visualizations must be from this list of types of visual:

Bar & Column Charts

Stacked Bars with Time

Scatterplots with Time

Line Charts

Step Charts

In [1]:

```
import pandas as pd
import glob
import os

# Folder path
folder_path = r"C:\Users\samkl"

# Grab all the files with Wave Access in the name
files = glob.glob(os.path.join(folder_path, "*WAVES-ACCESS-RECORDS*.csv"))

# Read, fix dtypes, and combine
WhiteHouse = pd.concat(
    [
        pd.read_csv(
            file,
            dtype=str,
            low_memory=False
        ).assign(source_file=os.path.basename(file))
        for file in files
    ],
    ignore_index=True
)

#Check file
WhiteHouse.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1207458 entries, 0 to 1207457
Data columns (total 32 columns):
 #   Column                   Non-Null Count    Dtype 
---  ------                   --------------    ----- 
 0   Last Name                1207385 non-null  object
 1   First Name               1207448 non-null  object
 2   Middle Initial           1206944 non-null  object
 3   UIN                      1206944 non-null  object
 4   BDGNBR                   173716 non-null   object
 5   Access Type              1207458 non-null  object
 6   TOA                      844689 non-null   object
 7   POA                      20916 non-null    object
 8   TOD                      12820 non-null    object
 9   POD                      124359 non-null   object
 10  Appointment Made Date    1207455 non-null  object
 11  Appointment Start Date   1207458 non-null  object
 12  Appointment End Date     1207458 non-null  object
 13  Appointment Cancel Date  815 non-null      object
 14  Total People             1206901 non-null  object
 15  Last Updated By          1207424 non-null  object
 16  POST                     1207458 non-null  object
 17  Last Entry Date          1207458 non-null  object
 18  Terminal Suffix          1207424 non-null  object
 19  Visitee Last Name        1193624 non-null  object
 20  Visitee First Name       1104896 non-null  object
 21  Meeting Location         1207458 non-null  object
 22  Meeting Room             1207445 non-null  object
 23  Caller Last Name         1207458 non-null  object
 24  Caller First Name        1207458 non-null  object
 25  Caller Room              0 non-null        object
 26  Release Date             847318 non-null   object
 27  source_file              1207458 non-null  object
 28  Unnamed: 27              381 non-null      object
 29  Unnamed: 28              378 non-null      object
 30  CALLER_ROOM              0 non-null        object
 31  RELEASEDATE              360138 non-null   object
dtypes: object(32)
memory usage: 294.8+ MB
```

In [2]:

```
import pandas as pd

# List of all columns (excluding your helper)
cols = [c for c in WhiteHouse.columns if c != "source_file"]

# Build a presence matrix: rows=files, cols=column names, values=True/False
presence = (
    pd.DataFrame({"source_file": WhiteHouse["source_file"]})
    .assign(dummy=1)
    .groupby("source_file")["dummy"]
    .size()
    .to_frame("row_count")
)

# For each file, compute which columns are non-null at least once
file_col_presence = (
```

```
    WhiteHouse.groupby("source_file")[cols]
    .apply(lambda df: df.notna().any(axis=0))
)

# Combine counts + presence
summary = presence.join(file_col_presence)

# Save to Excel so you can filter/sort and manually inspect and change the files th
summary.to_excel("whitehouse_column_presence_by_file.xlsx")

print("Saved: whitehouse_column_presence_by_file.xlsx")
summary.head()
```

```
Saved: whitehouse_column_presence_by_file.xlsx
```

Out[2]:

source_file	row_count	Last Name	First Name	Middle Initial	UIN	BDGNBR	Access Type	TOA	POA	T
2021_WAVES-ACCESS-RECORDS White House.csv	41412	True	True	True	True	True	True	True	True	T
2022.01_WAVES-ACCESS-RECORDS.csv	1185	True	True	True	True	True	True	True	True	T
2022.02_WAVES-ACCESS-RECORDS.csv	2155	True	True	True	True	True	True	True	True	T
2022.03_WAVES-ACCESS-RECORDS-.csv	6065	True	True	True	True	True	True	True	True	F
2022.04_WAVES-ACCESS-RECORDS.csv	13524	True	True	True	True	True	True	True	False	F

5 rows × 32 columns

In [3]:

```
# Identify unnamed columns
unnamed_cols = [c for c in WhiteHouse.columns if str(c).startswith("Unnamed")]

for col in unnamed_cols:
    print(f"\n===== Inspecting {col} =====")

    # Find rows where this column has data
    bad_rows = WhiteHouse[WhiteHouse[col].notna()]

    print(f"Rows with data in {col}: {len(bad_rows)}")

    # Show sample rows and their source file
```

```
    display(
        bad_rows[
            ["source_file", col]
        ].head(10)
    )
```

```
===== Inspecting Unnamed: 27 =====
Rows with data in Unnamed: 27: 381
```

	source_file	Unnamed: 27
50436	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50437	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50438	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50439	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50440	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50441	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50442	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50443	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50444	2022.03_WAVES-ACCESS-RECORDS-.csv	RL
50445	2022.03_WAVES-ACCESS-RECORDS-.csv	FPG

```
===== Inspecting Unnamed: 28 =====
Rows with data in Unnamed: 28: 378
```

	source_file	Unnamed: 28
50436	2022.03_WAVES-ACCESS-RECORDS-.csv	ashley.n.grove@whmo.mil
50437	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50438	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50439	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50440	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50441	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50442	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50443	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50444	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov
50445	2022.03_WAVES-ACCESS-RECORDS-.csv	david.w.nelson@ovp.eop.gov

In [4]:

```
#drop unnamed columns
if unnamed_cols:
    WhiteHouse.drop(columns=unnamed_cols, inplace=True)
    print(f"\n🗑️ Dropped unnamed columns: {unnamed_cols}")
```

```python
else:
    print("\nNo unnamed columns to drop.")
```

```
🗑️ Dropped unnamed columns: ['Unnamed: 27', 'Unnamed: 28']
```

In [5]:
```python
list(WhiteHouse.columns)
```

Out[5]:
```
['Last Name',
 'First Name',
 'Middle Initial',
 'UIN',
 'BDGNBR',
 'Access Type',
 'TOA',
 'POA',
 'TOD',
 'POD',
 'Appointment Made Date',
 'Appointment Start Date',
 'Appointment End Date',
 'Appointment Cancel Date',
 'Total People',
 'Last Updated By',
 'POST',
 'Last Entry Date',
 'Terminal Suffix',
 'Visitee Last Name',
 'Visitee First Name',
 'Meeting Location',
 'Meeting Room',
 'Caller Last Name',
 'Caller First Name',
 'Caller Room',
 'Release Date',
 'source_file',
 'CALLER_ROOM',
 'RELEASEDATE']
```

In [6]:
```python
WhiteHouse["source_file"].unique()
#ensure all my files loaded into the larger df I made
```

```
Out[6]: array(['2021_WAVES-ACCESS-RECORDS White House.csv',
               '2022.01_WAVES-ACCESS-RECORDS.csv',
               '2022.02_WAVES-ACCESS-RECORDS.csv',
               '2022.03_WAVES-ACCESS-RECORDS-.csv',
               '2022.04_WAVES-ACCESS-RECORDS.csv',
               '2022.05-WAVES-ACCESS-RECORDS.csv',
               '2022.06_WAVES-ACCESS-RECORDS.csv',
               '2022.07_WAVES-ACCESS-RECORDS.csv',
               '2022.08_WAVES-ACCESS-RECORDS.csv',
               '2022.09_WAVES-ACCESS-RECORDS.csv',
               '2022.10_WAVES-ACCESS-RECORDS.csv',
               '2022.11_WAVES-ACCESS-RECORDS.csv',
               '2022.12_WAVES-ACCESS-RECORDS.csv',
               '2023.01_WAVES-ACCESS-RECORDS.csv',
               '2023.02_WAVES-ACCESS-RECORDS.csv',
               '2023.03_WAVES-ACCESS-RECORDS.csv',
               '2023.04_WAVES-ACCESS-RECORDS.csv',
               '2023.05_WAVES-ACCESS-RECORDS.csv',
               '2023.06_WAVES-ACCESS-RECORDS.csv',
               '2023.07_WAVES-ACCESS-RECORDS.csv',
               '2023.08_WAVES-ACCESS-RECORDS.csv',
               '2023.09_WAVES-ACCESS-RECORDS.csv',
               '2023.10_WAVES-ACCESS-RECORDS.csv',
               '2023.11_WAVES-ACCESS-RECORDS.csv',
               '2023.12_WAVES-ACCESS-RECORDS.csv'], dtype=object)
```

```
In [7]: WhiteHouse.head()
```

Out[7]:

	Last Name	First Name	Middle Initial	UIN	BDGNBR	Access Type	TOA	POA	TOD	POD
0	AAKHUU	BOLORMAA	N	U38116	NaN	VA	NaN	NaN	NaN	NaN
1	AASSAR	MIA	L	U37794	NaN	VA	12/17/2021 12:23	NaN	NaN	NaN
2	ABALOS	JANILA	L	U38186	NaN	VA	NaN	NaN	NaN	NaN
3	ABARCAR	KARA	N	U37879	NaN	VA	12/19/2021 17:25	NaN	NaN	NaN
4	ABBOTT	NICOLAS	P	U36630	NaN	VA	NaN	NaN	NaN	NaN

5 rows × 30 columns

In [8]:

```
WhiteHouse.dtypes
```

```
Out[8]: Last Name                   object
First Name                  object
Middle Initial              object
UIN                         object
BDGNBR                      object
Access Type                 object
TOA                         object
POA                         object
TOD                         object
POD                         object
Appointment Made Date       object
Appointment Start Date      object
Appointment End Date        object
Appointment Cancel Date     object
Total People                object
Last Updated By             object
POST                        object
Last Entry Date             object
Terminal Suffix             object
Visitee Last Name           object
Visitee First Name          object
Meeting Location            object
Meeting Room                object
Caller Last Name            object
Caller First Name           object
Caller Room                 object
Release Date                object
source_file                 object
CALLER_ROOM                 object
RELEASEDATE                 object
dtype: object
```

In [9]:

```
# --- RAW missingness check for Appointment Start Date (BEFORE any parsing/coalesci

import pandas as pd

total_rows = len(WhiteHouse)

# True nulls (NaN)
null_count = WhiteHouse["Appointment Start Date"].isna().sum()

# Blank / whitespace-only values
blank_count = (
    WhiteHouse["Appointment Start Date"]
    .astype(str)
    .str.strip()
    .eq("")
    .sum()
)

# Combined missing (null OR blank)
missing_mask = (
    WhiteHouse["Appointment Start Date"].isna()
    | WhiteHouse["Appointment Start Date"].astype(str).str.strip().eq("")
)
```

```python
print("TOTAL ROWS:", total_rows)
print("NULL COUNT:", null_count)
print("BLANK COUNT:", blank_count)
print("TOTAL MISSING (NULL + BLANK):", missing_mask.sum())
print("MISSING PERCENT:", round(missing_mask.mean() * 100, 2), "%")

# Optional: missingness by source file (to see if 2023 differs)
print("\nMissing % by source_file:")
print(
    WhiteHouse.assign(is_missing_start_date=missing_mask)
    .groupby("source_file")["is_missing_start_date"]
    .mean()
    .mul(100)
    .round(2)
    .sort_values(ascending=False)
)
```

```
TOTAL ROWS: 1207458
NULL COUNT: 0
BLANK COUNT: 0
TOTAL MISSING (NULL + BLANK): 0
MISSING PERCENT: 0.0 %

Missing % by source_file:
source_file
2021_WAVES-ACCESS-RECORDS White House.csv    0.0
2022.01_WAVES-ACCESS-RECORDS.csv             0.0
2022.02_WAVES-ACCESS-RECORDS.csv             0.0
2022.03_WAVES-ACCESS-RECORDS-.csv            0.0
2022.04_WAVES-ACCESS-RECORDS.csv             0.0
2022.05-WAVES-ACCESS-RECORDS.csv             0.0
2022.06_WAVES-ACCESS-RECORDS.csv             0.0
2022.07_WAVES-ACCESS-RECORDS.csv             0.0
2022.08_WAVES-ACCESS-RECORDS.csv             0.0
2022.09_WAVES-ACCESS-RECORDS.csv             0.0
2022.10_WAVES-ACCESS-RECORDS.csv             0.0
2022.11_WAVES-ACCESS-RECORDS.csv             0.0
2022.12_WAVES-ACCESS-RECORDS.csv             0.0
2023.01_WAVES-ACCESS-RECORDS.csv             0.0
2023.02_WAVES-ACCESS-RECORDS.csv             0.0
2023.03_WAVES-ACCESS-RECORDS.csv             0.0
2023.04_WAVES-ACCESS-RECORDS.csv             0.0
2023.05_WAVES-ACCESS-RECORDS.csv             0.0
2023.06_WAVES-ACCESS-RECORDS.csv             0.0
2023.07_WAVES-ACCESS-RECORDS.csv             0.0
2023.08_WAVES-ACCESS-RECORDS.csv             0.0
2023.09_WAVES-ACCESS-RECORDS.csv             0.0
2023.10_WAVES-ACCESS-RECORDS.csv             0.0
2023.11_WAVES-ACCESS-RECORDS.csv             0.0
2023.12_WAVES-ACCESS-RECORDS.csv             0.0
Name: is_missing_start_date, dtype: float64
```

In [10]:

```python
import pandas as pd

col = "Appointment Start Date"
```

```python
# 1) Clean invisible/control characters that break parsing but don't show in prints
s = (WhiteHouse[col].astype(str)
     .str.replace("\u00A0", " ", regex=False)                         # NBSP
     .str.replace(r"[\u200B-\u200F\u202A-\u202E\u2060\uFEFF]", "", regex=True)  # z
     .str.replace("\x00", "", regex=False)                            # null byte
     .str.strip()
)

# 2) Parse with explicit formats first (fast + reliable)
parsed = pd.to_datetime(s, format="%m/%d/%Y %H:%M", errors="coerce")

# 3) Fallback: sometimes seconds appear
mask = parsed.isna()
if mask.any():
    parsed.loc[mask] = pd.to_datetime(s.loc[mask], format="%m/%d/%Y %H:%M:%S", erro

# 4) Final fallback: let pandas/dateutil try remaining oddballs
mask = parsed.isna()
if mask.any():
    parsed.loc[mask] = pd.to_datetime(s.loc[mask], errors="coerce")

# 5) Assign back IN PLACE
WhiteHouse[col] = parsed

# 6) Quick proof
print("NaT count after parse:", int(WhiteHouse[col].isna().sum()))
print("Max parsed date:", WhiteHouse[col].max())
print("Year counts:")
print(WhiteHouse[col].dt.year.value_counts(dropna=False).sort_index())
```

```
NaT count after parse: 0
Max parsed date: 2023-12-31 10:00:00
Year counts:
Appointment Start Date
2021     41412
2022    322830
2023    843216
Name: count, dtype: int64
```

In [11]:

```python
import pandas as pd

# Date columns to validate
date_cols = [
    "Appointment Made Date",
    "Appointment Start Date",
    "Appointment End Date",
    "Appointment Cancel Date",
    "Last Entry Date",
    "Release Date",
]

# Keep only columns that exist
date_cols = [c for c in date_cols if c in WhiteHouse.columns]

# Force datetime conversion (this fixes the error)
for col in date_cols:
```

```
    WhiteHouse[col] = pd.to_datetime(WhiteHouse[col], errors="coerce")

# Year-range bounds
CURRENT_YEAR = 2025
MIN_YEAR = 2021

# Completeness + year checks
date_summary = pd.DataFrame({
    "MISSING_COUNT": WhiteHouse[date_cols].isna().sum(),
    "MISSING_PCT": (WhiteHouse[date_cols].isna().mean() * 100).round(2),
    "MIN_YEAR": WhiteHouse[date_cols].apply(lambda s: s.dt.year.min()),
    "MAX_YEAR": WhiteHouse[date_cols].apply(lambda s: s.dt.year.max()),
}, index=date_cols)

# Out-of-range year counts
date_summary["OUT_OF_RANGE_COUNT"] = [
    (
        WhiteHouse[col].notna()
        & (
            (WhiteHouse[col].dt.year < MIN_YEAR)
            | (WhiteHouse[col].dt.year > CURRENT_YEAR)
        )
    ).sum()
    for col in date_cols
]

print("=== DATE SUMMARY (date boundaries) ===")
print(date_summary.sort_values("MISSING_PCT", ascending=False).to_string())
```

```
=== DATE SUMMARY (date boundaries) ===
                         MISSING_COUNT  MISSING_PCT  MIN_YEAR  MAX_YEAR  OUT_OF_RANG
E_COUNT
Appointment Cancel Date        1206646        99.93    1900.0    2023.0
12
Release Date                    360140        29.83    2021.0    2024.0
0
Last Entry Date                   7280         0.60    2021.0    2023.0
0
Appointment Made Date                3         0.00    2021.0    2023.0
0
Appointment Start Date               0         0.00    2021.0    2023.0
0
Appointment End Date                 0         0.00    2021.0    2023.0
0
```

In [12]:

```
#evaluted the files at the source and all those are data entry errors, removing the

mask_cancel_oor = (
    WhiteHouse["Appointment Cancel Date"].notna()
    & (
        (WhiteHouse["Appointment Cancel Date"].dt.year < MIN_YEAR)
        | (WhiteHouse["Appointment Cancel Date"].dt.year > CURRENT_YEAR)
    )
)

print("Out-of-range Appointment Cancel Date rows:", mask_cancel_oor.sum())
```

```python
# Clear the bad values (keep rows)
WhiteHouse.loc[mask_cancel_oor, "Appointment Cancel Date"] = pd.NA
WhiteHouse.loc[mask_cancel_oor, "Appointment Cancel Date"] = pd.NaT
```

```
Out-of-range Appointment Cancel Date rows: 12
```

In [13]:
```python
WhiteHouse["booking_lead_time_days"] = (
    WhiteHouse["Appointment Start Date"] - WhiteHouse["Appointment Made Date"]
).dt.days
#calculate how long it takes from booking to your appointment
```

In [14]:
```python
#look at Cancelled appointments
WhiteHouse["was_cancelled"] = WhiteHouse["Appointment Cancel Date"].notna()
cancelled_count = WhiteHouse["was_cancelled"].sum()
total_appointments = len(WhiteHouse)
cancelled_pct = (cancelled_count / total_appointments) * 100

print(f"Cancelled appointments: {cancelled_count}")
print(f"Total appointments: {total_appointments}")
print(f"Percent cancelled: {cancelled_pct:.4f}%")
```

```
Cancelled appointments: 800
Total appointments: 1207458
Percent cancelled: 0.0663%
```

Fewer than 0.1% of appointments contained a cancellation record, indicating that cancellation data are sparse and were not analyzed further.

In [15]:
```python
WhiteHouse["booking_lead_time_days"].describe()
```

Out[15]:
```
count    1.207455e+06
mean     4.080757e+00
std      4.167098e+00
min     -9.100000e+01
25%      1.000000e+00
50%      2.000000e+00
75%      7.000000e+00
max      3.200000e+01
Name: booking_lead_time_days, dtype: float64
```

In [16]:
```python
WhiteHouse.loc[
    WhiteHouse["booking_lead_time_days"] < 0,
    "booking_lead_time_days"
] = pd.NA
```

In [17]:
```python
WhiteHouse["booking_lead_time_days"].describe()
#clean up negatives due to rounding
```

Out[17]:

```
count    1.188490e+06
mean     4.166300e+00
std      4.095736e+00
min      0.000000e+00
25%      1.000000e+00
50%      3.000000e+00
75%      7.000000e+00
max      3.200000e+01
Name: booking_lead_time_days, dtype: float64
```

In [18]:

```python
#create visitor and vistiee full name columns for analysis

WhiteHouse["visitor_full_name"] = (
    WhiteHouse["First Name"].fillna("") + " " +
    WhiteHouse["Middle Initial"].fillna("") + " " +
    WhiteHouse["Last Name"].fillna("")
).str.replace(r"\s+", " ", regex=True).str.strip()

WhiteHouse["visitee_full_name"] = (
    WhiteHouse["Visitee First Name"].fillna("") + " " +
    WhiteHouse["Visitee Last Name"].fillna("")
).str.replace(r"\s+", " ", regex=True).str.strip()

# Replace empty strings with NA (no chained assignment)
WhiteHouse["visitor_full_name"] = WhiteHouse["visitor_full_name"].replace("", pd.NA
WhiteHouse["visitee_full_name"] = WhiteHouse["visitee_full_name"].replace("", pd.NA
```

In [19]:

```python
#See who was a repeat visitor (same person)

# Group visitor -> visitee and count visits
visit_counts = (
    WhiteHouse
    .dropna(subset=["visitor_full_name", "visitee_full_name"])
    .groupby(["visitor_full_name", "visitee_full_name"])
    .size()
    .reset_index(name="visit_count")
)

# Sort by most frequent repeat visits
visit_counts_sorted = visit_counts.sort_values(
    "visit_count", ascending=False
)

# Show top 25 repeat visitor-visitee pairs
visit_counts_sorted.head(25)
```

Out[19]:

	visitor_full_name	visitee_full_name	visit_count
324785	FERN E SATO	Dan Via	97
130737	BRIAN C TURNMIRE	Dan Via	83
831025	RUSSELL A WILSON	Dan Via	79
19724	ALAN C PRATHER	Dan Via	77
189926	CHRISTOPHER E SCHMITT	Dan Via	77
859	AARON D CLAY	Dan Via	65
328643	FRANCIS C SHIEH	Dan Via	64
939370	TIFFANY J RAMSEYER	Craig Guyton	63
414190	JAMES W LEVINGS	Kolakowski	63
304933	ERIC D SABO	Dan Via	60
488508	JOSHUA A COLLINS	LEVI REED	59
760074	PATRICIA A DONILON	Jing Qu	56
478268	JORDAN C BOOTH	Ed Teleky	55
240779	DAVID P MCCABE	Ed Teleky	55
902614	STEPHEN T KOEHLER	Jon Finer	55
754820	OWEN M HOSLER	Ed Teleky	54
904378	STEVEN J BUSSELL	Ed Teleky	54
407451	JAMES C VAUGHN	Dan Via	53
415933	JAMILLAH A FULLER	Ed Teleky	53
478927	JORDAN M HUPPERT	Ed Teleky	52
338789	GAVIN K CORNELIUS	Ed Teleky	52
392259	ISOBEL D COLEMAN	Jon Finer	52
555936	KOMLANVI I AKOHOUEGNON	Ed Teleky	52
904842	STEVEN L OWEN	Dan Via	52
693182	MICHAEL N HERZOG	Brett McGurk	51

In [20]:

```
# Count how many visits each visitee received
visitee_counts = (
    WhiteHouse
    .dropna(subset=["visitee_full_name"])
    .groupby("visitee_full_name")
    .size()
    .reset_index(name="visit_count")
    .sort_values("visit_count", ascending=False)
```

```
)

# Show top 25 visitees by number of visits
visitee_counts.head(25)
```

Out[20]:

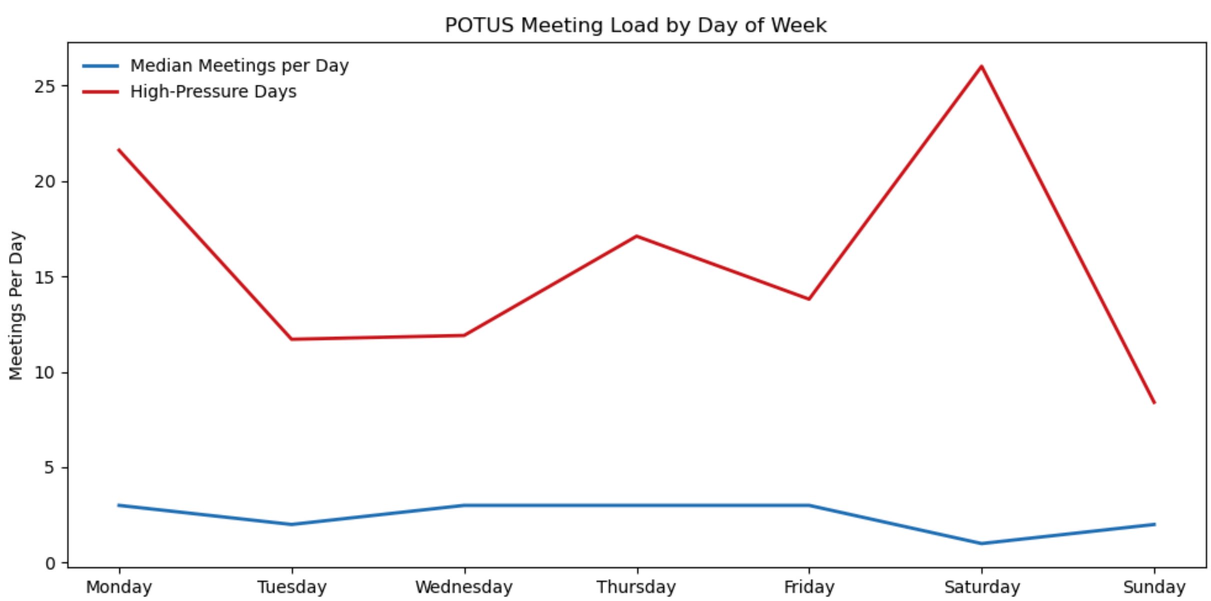
	visitee_full_name	visit_count
6437	Visitors Office	698518
4997	POTUS	96274
1964	Ed Teleky	20733
6354	VPOTUS	11649
2359	Gionelly Mills	10625
1552	Dan Via	7158
334	Amanda Trocola	6607
4014	Lydia Hecmanczuk	6036
2343	Gianna Juarez	5615
3618	Kevin Ballen	4914
5453	Room 1	4639
5123	Peyton Schwartz	4223
2206	FLOTUS	4188
2266	GIONELLY MILLS	3361
6107	Tarun Chhabra	2544
522	Anne Neuberger	2192
3135	Jon Finer	2108
1373	Claudia Marconi	1839
247	Alia Schechter	1826
6388	Venus Johnson	1723
1955	EVA KNIGHT	1673
6346	VENUS JOHNSON	1649
3004	Jessika Vallejo	1626
4619	Mitch Landrieu	1501
5849	Shelley Greenspan	1437

sorted(

```
    WhiteHouse["Meeting Room"]
    .dropna()
    .astype(str)
    .str.strip()
    .unique()

)
```

In [21]:
```
import pandas as pd
import matplotlib.pyplot as plt

# --- 1) Filter to POTUS only ---
potus = WhiteHouse.loc[
    WhiteHouse["visitee_full_name"].astype(str).str.strip().str.upper() == "POTUS"
].copy()

# --- 2) Convert required columns ---
potus["Appointment Start Date"] = pd.to_datetime(
    potus["Appointment Start Date"], errors="coerce"
)

# --- 3) Drop rows missing meeting-defining info ---
potus = potus.dropna(
    subset=["Appointment Start Date", "Meeting Location", "Meeting Room"]
)

# --- 4) Deduplicate to ONE row per meeting ---
meetings = potus.drop_duplicates(
    subset=[
        "Appointment Start Date",
        "Appointment End Date",
        "Meeting Location",
        "Meeting Room"
    ]
)

# --- 5) Count meetings per DAY ---
daily_counts = (
    meetings
    .assign(
        day=meetings["Appointment Start Date"].dt.normalize(),
        weekday=meetings["Appointment Start Date"].dt.day_name()
    )
    .groupby(["day", "weekday"])
    .size()
    .rename("meetings_per_day")
    .reset_index()
)

# --- 6) Aggregate by weekday ---
weekday_stats = (
    daily_counts
    .groupby("weekday")["meetings_per_day"]
    .agg(
        median="median",
```

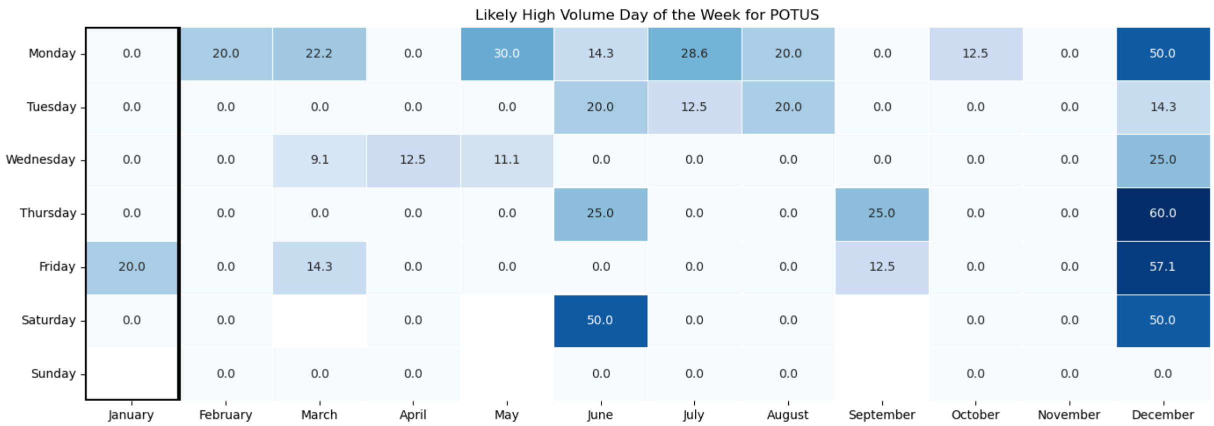
```
        p90=lambda x: x.quantile(0.90)
    )
)

# Ensure correct weekday order
weekday_order = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday"
weekday_stats = weekday_stats.reindex(weekday_order).dropna()

# --- 7) Plot ---
plt.figure(figsize=(10, 5))

plt.plot(
    weekday_stats.index,
    weekday_stats["median"],
    marker="",
    linewidth=2,
    color="#2171b5",
    label="Median Meetings per Day"
)

plt.plot(
    weekday_stats.index,
    weekday_stats["p90"],
    marker="",
    linewidth=2,
    color="#cb181d",
    label="High-Pressure Days"
)

plt.title("POTUS Meeting Load by Day of Week")
plt.xlabel("")
plt.ylabel("Meetings Per Day")
plt.legend(frameon=False)

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



In [22]:

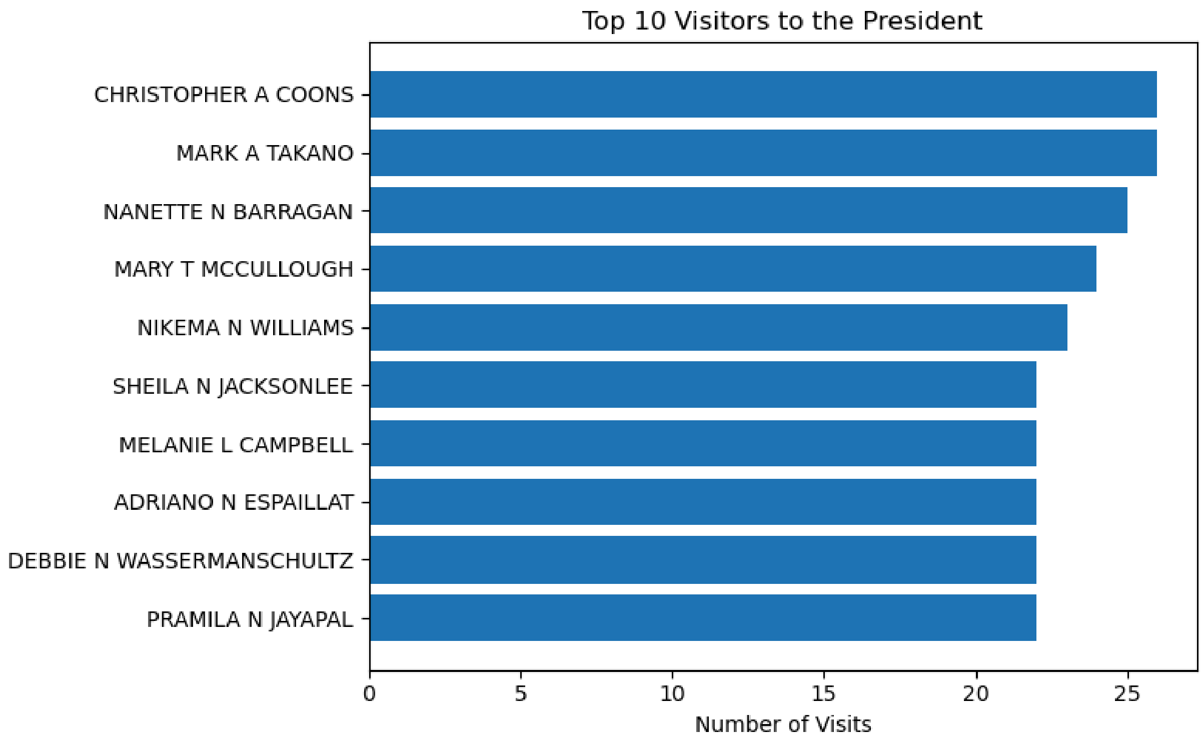
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.patches import Rectangle

# --- 1) Filter to POTUS only ---
potus = WhiteHouse.loc[
    WhiteHouse["visitee_full_name"].astype(str).str.strip().str.upper() == "POTUS"
].copy()

# --- 2) Convert date ---
potus["Appointment Start Date"] = pd.to_datetime(
    potus["Appointment Start Date"], errors="coerce"
)

# --- 3) Drop rows missing meeting-defining info ---
potus = potus.dropna(
    subset=["Appointment Start Date", "Meeting Location", "Meeting Room"]
)

# --- 4) Deduplicate to ONE row per meeting ---
meetings = potus.drop_duplicates(
    subset=[
        "Appointment Start Date",
        "Appointment End Date",
        "Meeting Location",
        "Meeting Room"
    ]
)

# --- 5) Count meetings per day ---
daily = (
    meetings
    .assign(
        day=meetings["Appointment Start Date"].dt.normalize(),
        weekday=meetings["Appointment Start Date"].dt.day_name(),
        month=meetings["Appointment Start Date"].dt.month_name()
    )
    .groupby(["day", "weekday", "month"])
    .size()
    .rename("meetings_per_day")
    .reset_index()
)

# --- 6) High-pressure threshold (90th percentile) ---
p90_threshold = daily["meetings_per_day"].quantile(0.90)
daily["is_high_pressure"] = daily["meetings_per_day"] >= p90_threshold

# --- 7) % of high-pressure days by Month × Weekday ---
risk = (
    daily
    .groupby(["month", "weekday"])["is_high_pressure"]
    .mean()
    .mul(100)
    .reset_index(name="pct_high_pressure")
```

```python
)

month_order = [
    "January","February","March","April","May","June",
    "July","August","September","October","November","December"
]
weekday_order = ["Monday","Tuesday","Wednesday","Thursday","Friday","Saturday","Sun

risk["month"] = pd.Categorical(risk["month"], month_order, ordered=True)
risk["weekday"] = pd.Categorical(risk["weekday"], weekday_order, ordered=True)

pivot = risk.pivot(index="weekday", columns="month", values="pct_high_pressure")

# --- 8) Plot heatmap (NO colorbar) ---
plt.figure(figsize=(14, 5))
ax = sns.heatmap(
    pivot,
    cmap="Blues",
    annot=True,
    fmt=".1f",
    linewidths=0.5,
    cbar=False   # <-- removes legend
)

# --- 9) Highlight January column ---
jan_col_index = pivot.columns.get_loc("January")

rect = Rectangle(
    (jan_col_index, 0),
    width=1,
    height=pivot.shape[0],
    fill=False,
    edgecolor="black",
    linewidth=3
)

ax.add_patch(rect)

plt.title("Likely High Volume Day of the Week for POTUS")
plt.xlabel("")
plt.ylabel("")
plt.tight_layout()
plt.show()
```



In [23]:

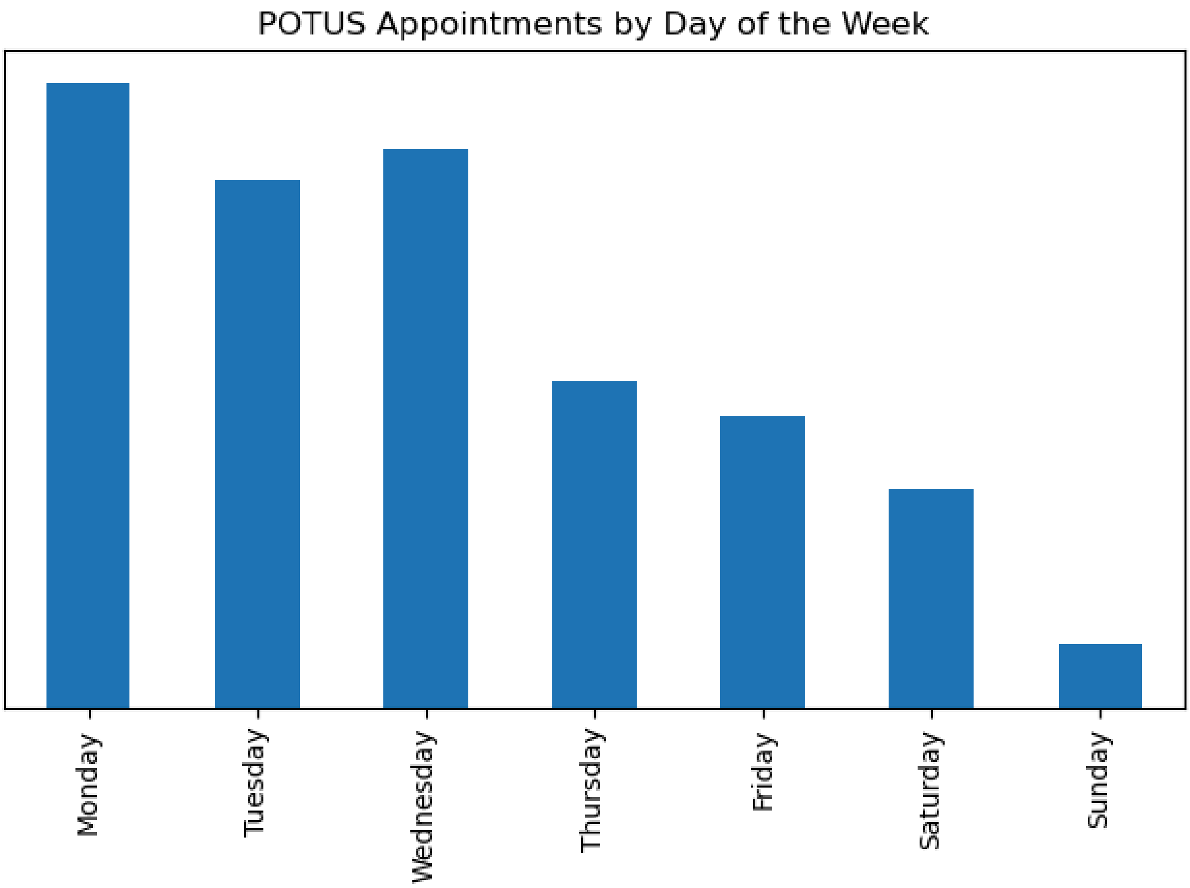
```python
# Filter to POTUS appointments only
potus_visits = (
    WhiteHouse
    .dropna(subset=["visitee_full_name", "visitor_full_name"])
    .loc[WhiteHouse["visitee_full_name"] == "POTUS"]
)

# Count visits per visitor
top_10_visitors = (
    potus_visits["visitor_full_name"]
    .value_counts()
    .head(10)
    .reset_index()
)

top_10_visitors.columns = ["Visitor", "Number of Visits"]

top_10_visitors


import matplotlib.pyplot as plt

plt.figure(figsize=(8, 5))
plt.barh(
    top_10_visitors["Visitor"],
    top_10_visitors["Number of Visits"],
    color="#1f77b4"
)

plt.title("Top 10 Visitors to the President")
plt.xlabel("Number of Visits")
plt.ylabel("")

plt.gca().invert_yaxis()  # highest at top
plt.tight_layout()
plt.show()
```



In [24]:

```
import matplotlib.pyplot as plt
import pandas as pd

# Prepare data (POTUS ONLY)
dow_data = (
    WhiteHouse
    .loc[WhiteHouse["visitee_full_name"] == "POTUS"]
    .dropna(subset=["Appointment Start Date"])
    .assign(day_of_week=lambda df: df["Appointment Start Date"].dt.day_name())
)

day_order = [
    "Monday", "Tuesday", "Wednesday",
    "Thursday", "Friday", "Saturday", "Sunday"
]

dow_counts = (
    dow_data["day_of_week"]
    .value_counts()
    .reindex(day_order)
)

# Plot
plt.figure()
ax = dow_counts.plot(kind="bar")

plt.title("POTUS Appointments by Day of the Week")
plt.xlabel("")
plt.ylabel("")

# Remove ALL y-axis elements
ax.set_yticks([])
ax.yaxis.set_visible(False)
```

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



In [25]:
```
# --- Filter POTUS visits only ---
potus_visits = (
    WhiteHouse
    .dropna(subset=["visitee_full_name", "visitor_full_name"])
    .loc[WhiteHouse["visitee_full_name"] == "POTUS"]
)

# --- Manual role classification (transparent + auditable) ---
role_map = {
    "CHRISTOPHER A COONS": "Congress",
    "MARK A TAKANO": "Congress",
    "NANETTE N BARRAGAN": "Congress",
    "PRAMILA N JAYAPAL": "Congress",
    "NIKEMA N WILLIAMS": "Congress",
    "DEBBIE N WASSERMANSCHULTZ": "Congress",
    "SHEILA N JACKSONLEE": "Congress",
    "ADRIANO N ESPAILLAT": "Congress",

    "MARY T MCCULLOUGH": "Executive Branch",
    "MELANIE L CAMPBELL": "Political Party Leadership",
}

# --- Apply roles ---
potus_visits["visitor_role"] = (
```

```python
    potus_visits["visitor_full_name"]
    .map(role_map)
    .fillna("Other / Unknown")
)

# --- Aggregate by role ---
role_counts = (
    potus_visits
    .groupby("visitor_role")
    .size()
    .sort_values(ascending=False)
    .reset_index(name="Number of Visits")
)

role_counts
```

Out[25]:

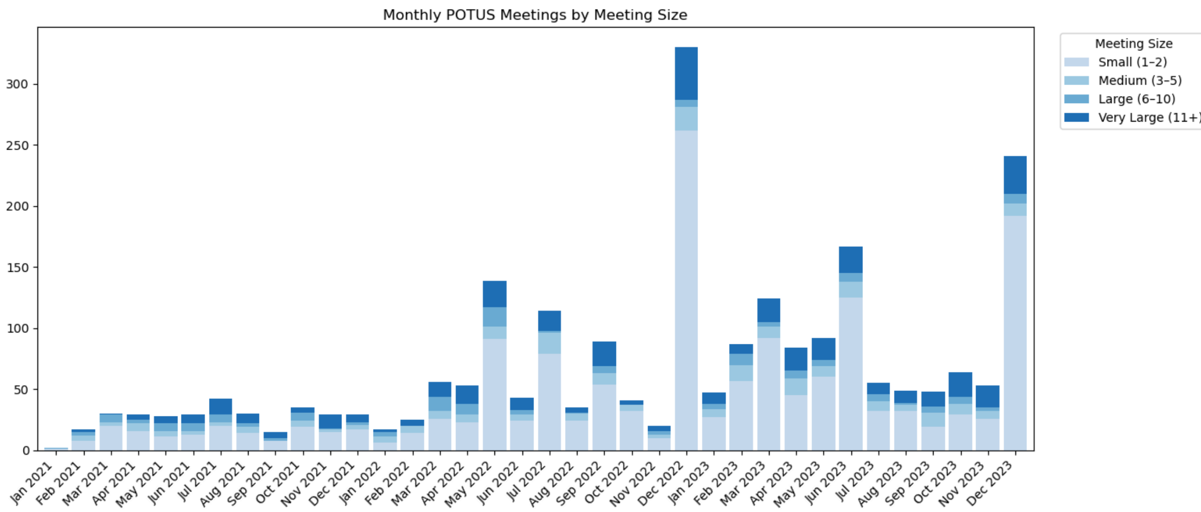
	visitor_role	Number of Visits
0	Other / Unknown	96040
1	Congress	188
2	Executive Branch	24
3	Political Party Leadership	22

In [26]:

```python
import pandas as pd
import matplotlib.pyplot as plt

# --- 1) Filter to POTUS meetings ONLY ---
potus = WhiteHouse.loc[
    WhiteHouse["visitee_full_name"] == "POTUS"
].copy()

# --- 2) Convert required columns ---
potus["Appointment Start Date"] = pd.to_datetime(potus["Appointment Start Date"], e
potus["Appointment End Date"]   = pd.to_datetime(potus["Appointment End Date"], err
potus["Total People"] = pd.to_numeric(potus["Total People"], errors="coerce")

# --- 3) Drop rows missing meeting-defining info (needed for dedupe) ---
potus = potus.dropna(subset=["Appointment Start Date", "Meeting Location", "Meeting

# --- 4) Define meeting size buckets ---
potus["meeting_size"] = pd.cut(
    potus["Total People"],
    bins=[0, 2, 5, 10, float("inf")],
    labels=["Small (1–2)", "Medium (3–5)", "Large (6–10)", "Very Large (11+)"],
    right=True
)

# --- 5) Deduplicate to ONE row per meeting ---
# (This prevents counting one meeting many times due to multiple attendee rows.)
meetings = potus.drop_duplicates(
    subset=["Appointment Start Date", "Appointment End Date", "Meeting Location", "
)
```

```python
# --- 6) Aggregate monthly meeting counts by size ---
monthly = (
    meetings
    .groupby([pd.Grouper(key="Appointment Start Date", freq="ME"), "meeting_size"])
    .size()
    .unstack(fill_value=0)
)

# Ensure consistent stack order
size_order = ["Small (1–2)", "Medium (3–5)", "Large (6–10)", "Very Large (11+)"]
monthly = monthly.reindex(columns=size_order).fillna(0)

# --- 7) FIX THE 1970 X-AXIS PROBLEM FOR BAR CHARTS ---
# Bar charts treat the x-axis as categories; convert datetime index to readable str
monthly.index = monthly.index.strftime("%b %Y")

# --- 8) Plot stacked bars (blue hues) ---
colors = [
    "#c6dbef",  # Small (1–2)
    "#9ecae1",  # Medium (3–5)
    "#6baed6",  # Large (6–10)
    "#2171b5"   # Very Large (11+)
]

ax = monthly.plot(kind="bar", stacked=True, figsize=(14, 6), color=colors, width=0.

plt.title("Monthly POTUS Meetings by Meeting Size")
plt.xlabel("")
plt.ylabel("")
plt.xticks(rotation=45, ha="right")
plt.legend(title="Meeting Size", bbox_to_anchor=(1.02, 1), loc="upper left")



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

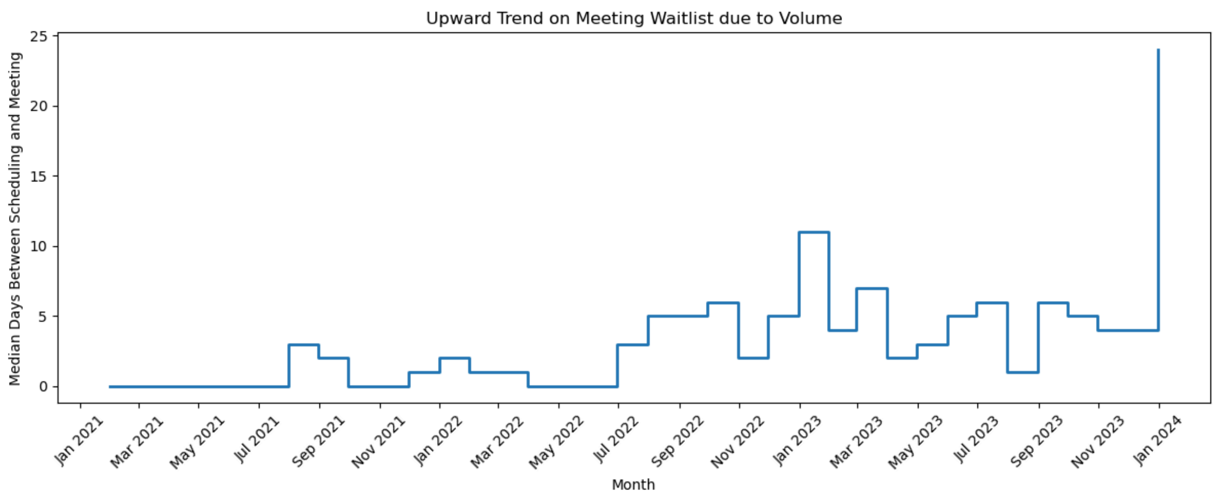
```
C:\Users\samkl\AppData\Local\Temp\ipykernel_45680\2242003769.py:34: FutureWarning: T
he default of observed=False is deprecated and will be changed to True in a future v
ersion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  .groupby([pd.Grouper(key="Appointment Start Date", freq="ME"), "meeting_size"])
```



In [27]:

```python
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# Build plotting-only dataframe
plot_df = WhiteHouse[
    ["Appointment Made Date", "Appointment Start Date"]
].copy()

plot_df = WhiteHouse.loc[
    WhiteHouse["visitee_full_name"] == "POTUS"
].copy()


# Ensure datetime
plot_df["Appointment Made Date"] = pd.to_datetime(plot_df["Appointment Made Date"],
plot_df["Appointment Start Date"] = pd.to_datetime(plot_df["Appointment Start Date"

# Compute booking lead time (days)
plot_df["booking_lead_time_days"] = (
    plot_df["Appointment Start Date"] - plot_df["Appointment Made Date"]
).dt.days

# Remove invalid values (visualization only)
plot_df = plot_df[
    (plot_df["booking_lead_time_days"] >= 0) &
    (plot_df["booking_lead_time_days"] <= 180)
]

# Aggregate to monthly median (Month-End)
monthly = (
    plot_df
    .set_index("Appointment Start Date")
    .resample("ME")["booking_lead_time_days"]
    .median()
)

# Step chart (single color)
plt.figure(figsize=(12, 5))
plt.step(
```

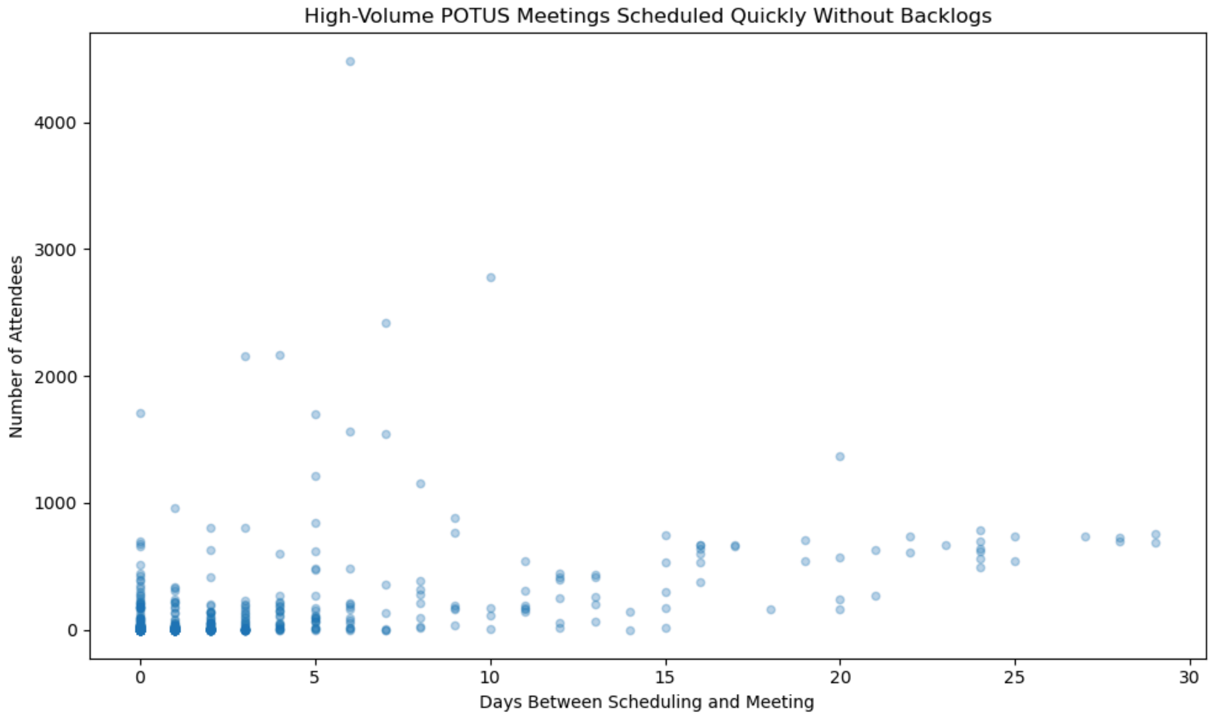
```
    monthly.index,
    monthly.values,
    where="post",
    linewidth=2
)

plt.title("Upward Trend on Meeting Waitlist due to Volume")
plt.xlabel("Month")
plt.ylabel("Median Days Between Scheduling and Meeting")

# Force month labels
ax = plt.gca()
ax.xaxis.set_major_locator(mdates.MonthLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter("%b %Y"))
plt.xticks(rotation=45)

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



In [28]:

```
import pandas as pd
import matplotlib.pyplot as plt

# --- 1) Filter to POTUS meetings only ---
potus = WhiteHouse.loc[
    WhiteHouse["visitee_full_name"] == "POTUS"
].copy()

# --- 2) Convert needed columns ---
potus["Appointment Made Date"] = pd.to_datetime(potus["Appointment Made Date"], err
potus["Appointment Start Date"] = pd.to_datetime(potus["Appointment Start Date"], e
potus["Total People"] = pd.to_numeric(potus["Total People"], errors="coerce")

# --- 3) Drop rows missing essentials ---
potus = potus.dropna(subset=[
    "Appointment Made Date",
    "Appointment Start Date",
    "Total People",
    "Meeting Location",
    "Meeting Room"
])
```

```python
# --- 4) Calculate booking lead time (days) ---
potus["booking_lead_time_days"] = (
    potus["Appointment Start Date"] - potus["Appointment Made Date"]
).dt.days

# Remove obvious bad values (negative or extreme)
potus = potus.loc[
    (potus["booking_lead_time_days"] >= 0) &
    (potus["booking_lead_time_days"] <= 60)
]

# --- 5) Deduplicate to ONE row per meeting ---
meetings = potus.drop_duplicates(
    subset=[
        "Appointment Start Date",
        "Appointment End Date",
        "Meeting Location",
        "Meeting Room"
    ]
)

# --- 6) Scatterplot ---
plt.figure(figsize=(10, 6))
plt.scatter(
    meetings["booking_lead_time_days"],
    meetings["Total People"],
    alpha=0.3,
    s=20
)

plt.title("High-Volume POTUS Meetings Scheduled Quickly Without Backlogs")
plt.xlabel("Days Between Scheduling and Meeting")
plt.ylabel("Number of Attendees")

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



High-Volume POTUS Meetings Scheduled Quickly Without Backlogs
Number of Attendees
0
1000
2000
3000
4000
0
5
10
15
20
25
30
Days Between Scheduling and Meeting

In [ ]: