In [22]:
```
import pandas as pd
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.impute import SimpleImputer
import os
from scipy import stats
from sklearn.ensemble import IsolationForest

os.environ['OMP_NUM_THREADS'] = '1'

file_path = "Janitza Reading.xlsx"
janitza_data = pd.read_excel(file_path,engine='openpyxl')  # Load all sheets
print(janitza_data .iloc[:10, 5])
```

```
0    362627
1    103336
2    102709
3     13057
4     12093
5      1536
6     14070
7     36843
8     27265
9     25092
Name: 2022-04-01 00:00:00, dtype: object
```

In [24]:
```
import pandas as pd
import numpy as np

# Read the Excel file
df = pd.read_excel('Janitza Reading.xlsx', sheet_name='Janitza data', skiprows=0

# Rename columns
months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct',
years = range(2022, 2025)
new_columns = ['Meter_location'] + [f'{month}_{year}' for year in years for mont
df.columns = new_columns
df_base = df

# Replace missing values and NULL with 0
df = df.fillna(0)

# Convert all columns except 'Meter_location' to numeric
for col in df.columns[1:]:
    df[col] = pd.to_numeric(df[col], errors='coerce').fillna(0)

# Perform seasonal imputation
for year in range(2022, 2024):
    for month in months:
        current_col = f'{month}_{year}'
        prev_year_col = f'{month}_{year-1}' if year > 2022 else None
        next_year_col = f'{month}_{year+1}'

        if prev_year_col:
```

```
            mask = (df[current_col] == 0) & ((df[prev_year_col] != 0) | (df[next
            df.loc[mask, current_col] = df.loc[mask, [prev_year_col, next_year_c
        else:
            mask = (df[current_col] == 0) & (df[next_year_col] != 0)
            df.loc[mask, current_col] = df.loc[mask, next_year_col]

# Round off values to 2 decimal points
df.iloc[:, 1:] = df.iloc[:, 1:].round(2)

# Export cleaned data to CSV
df.to_csv('Jantiza_Med_Data_Cleaned.csv', index=False)

print("Data processing complete. Check the output file 'Jantiza_Med_Data_Cleaned
```

```
Data processing complete. Check the output file 'Jantiza_Med_Data_Cleaned.csv'.
```

```
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\389344157.py:33: FutureWarning:
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '[1307.82]' has dtype incompatible with int64, pl
ease explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\389344157.py:33: FutureWarning:
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '[1487.83]' has dtype incompatible with int64, pl
ease explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\389344157.py:33: FutureWarning:
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '[150.77]' has dtype incompatible with int64, ple
ase explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
```

In [3]:

```
import pandas as pd
import numpy as np

def process_table(df, table_name):
    # Rename columns
    months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oc
    years = range(2022, 2025)
    new_columns = ['Meter_location'] + [f'{month}_{year}' for year in years for
    df.columns = new_columns

    # Remove rows with null Meter_location
    df = df.dropna(subset=['Meter_location'])

    # Replace missing values and NULL with 0
    df = df.fillna(0)

    # Convert all columns except 'Meter_location' to numeric
    for col in df.columns[1:]:
        df[col] = pd.to_numeric(df[col], errors='coerce').fillna(0)

    # Perform seasonal imputation
    for year in range(2022, 2024):
        for month in months:
            current_col = f'{month}_{year}'
            prev_year_col = f'{month}_{year-1}' if year > 2022 else None
            next_year_col = f'{month}_{year+1}'

            if prev_year_col:
                mask = (df[current_col] == 0) & ((df[prev_year_col] != 0) | (df[
```

```
                df.loc[mask, current_col] = df.loc[mask, [prev_year_col, next_ye
            else:
                mask = (df[current_col] == 0) & (df[next_year_col] != 0)
                df.loc[mask, current_col] = df.loc[mask, next_year_col]

    # Round off values to 2 decimal points
    df.iloc[:, 1:] = df.iloc[:, 1:].round(2)

    # Export cleaned data to CSV
    df.to_csv(f'{table_name}_Cleaned.csv', index=False)

    print(f"Data processing complete for {table_name}. Check the output file '{t

    return df

# Read and process each table
file_path = 'Janitza Reading.xlsx'

tables = [
    {'name': 'Janitza_Med_Data', 'skiprows': 0, 'nrows': 72},
    {'name': 'Janitza_Freezer_Room_LFB', 'skiprows': 73, 'nrows': 3},
    {'name': 'Janitza_UO_D4_F6', 'skiprows': 79, 'nrows': 227},
    {'name': 'Janitza_UO_F8_X', 'skiprows': 307, 'nrows': 196},
    {'name': 'Janitza_Manual_Meters', 'skiprows': 504, 'nrows': 37},
    {'name': 'Janitza_Calculated_Consumption', 'skiprows': 549, 'nrows': 51}
]

all_data = {}

for table in tables:
    df = pd.read_excel(file_path, sheet_name='Janitza data', skiprows=table['ski
    all_data[table['name']] = process_table(df, table['name'])

# Combine all cleaned data into a single DataFrame
combined_df = pd.concat(all_data.values(), keys=all_data.keys())

# Export combined data to CSV
combined_df.to_csv('Combined_Cleaned_Data.csv')

print("All data processing complete. Check the individual CSV files and the 'Com
```

```
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\253832063.py:33: FutureWarning:
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '[1307.82]' has dtype incompatible with int64, pl
ease explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\253832063.py:33: FutureWarning:
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '[1487.83]' has dtype incompatible with int64, pl
ease explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\253832063.py:33: FutureWarning:
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '[150.77]' has dtype incompatible with int64, ple
ase explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
```

```
Data processing complete for Janitza_Med_Data. Check the output file 'Janitza_Med
_Data_Cleaned.csv'.
Data processing complete for Janitza_Freezer_Room_LFB. Check the output file 'Jan
itza_Freezer_Room_LFB_Cleaned.csv'.
Data processing complete for Janitza_UO_D4_F6. Check the output file 'Janitza_UO_
D4_F6_Cleaned.csv'.
Data processing complete for Janitza_UO_F8_X. Check the output file 'Janitza_UO_F
8_X_Cleaned.csv'.
Data processing complete for Janitza_Manual_Meters. Check the output file 'Janitz
a_Manual_Meters_Cleaned.csv'.
Data processing complete for Janitza_Calculated_Consumption. Check the output fil
e 'Janitza_Calculated_Consumption_Cleaned.csv'.
All data processing complete. Check the individual CSV files and the 'Combined_Cl
eaned_Data.csv' file.
```

In [4]:

```
import pandas as pd
import numpy as np

def process_table(df, table_name):
    # Rename columns
    months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oc
    years = range(2022, 2025)
    new_columns = ['Meter_location'] + [f'{month}_{year}' for year in years for
    df.columns = new_columns

    # Remove rows with null Meter_location
    df = df.dropna(subset=['Meter_location'])

    # Replace missing values, NULL, and negative values with 0
    df = df.fillna(0)
    for col in df.columns[1:]:
        df[col] = pd.to_numeric(df[col], errors='coerce').fillna(0)
        df[col] = df[col].clip(lower=0)  # This replaces negative values with 0

    # Perform seasonal imputation
    for year in range(2022, 2024):
        for month in months:
            current_col = f'{month}_{year}'
            prev_year_col = f'{month}_{year-1}' if year > 2022 else None
            next_year_col = f'{month}_{year+1}'

            if prev_year_col:
                mask = (df[current_col] == 0) & ((df[prev_year_col] != 0) | (df[
                df.loc[mask, current_col] = df.loc[mask, [prev_year_col, next_ye
            else:
                mask = (df[current_col] == 0) & (df[next_year_col] != 0)
                df.loc[mask, current_col] = df.loc[mask, next_year_col]

    # Round off values to 2 decimal points
    df.iloc[:, 1:] = df.iloc[:, 1:].round(2)

    # Export cleaned data to CSV
    df.to_csv(f'{table_name}_Cleaned.csv', index=False)

    print(f"Data processing complete for {table_name}. Check the output file '{t

    return df

# Read and process each table
file_path = 'Janitza Reading.xlsx'
```

```
tables = [
    {'name': 'Janitza_Med_Data', 'skiprows': 0, 'nrows': 72},
    {'name': 'Janitza_Freezer_Room_LFB', 'skiprows': 73, 'nrows': 3},
    {'name': 'Janitza_UO_D4_F6', 'skiprows': 79, 'nrows': 227},
    {'name': 'Janitza_UO_F8_X', 'skiprows': 307, 'nrows': 196},
    {'name': 'Janitza_Manual_Meters', 'skiprows': 504, 'nrows': 37},
    {'name': 'Janitza_Calculated_Consumption', 'skiprows': 549, 'nrows': 51}
]

all_data = {}

for table in tables:
    df = pd.read_excel(file_path, sheet_name='Janitza data', skiprows=table['ski
    all_data[table['name']] = process_table(df, table['name'])

# Combine all cleaned data into a single DataFrame
combined_df = pd.concat(all_data.values(), keys=all_data.keys())

# Export combined data to CSV
combined_df.to_csv('Combined_Cleaned_Data.csv')

print("All data processing complete. Check the individual CSV files and the 'Com
```

```
Data processing complete for Janitza_Med_Data. Check the output file 'Janitza_Med
_Data_Cleaned.csv'.
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\4043187958.py:32: FutureWarnin
g: Setting an item of incompatible dtype is deprecated and will raise an error in
a future version of pandas. Value '[1307.82]' has dtype incompatible with int64,
please explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\4043187958.py:32: FutureWarnin
g: Setting an item of incompatible dtype is deprecated and will raise an error in
a future version of pandas. Value '[1487.83]' has dtype incompatible with int64,
please explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\4043187958.py:32: FutureWarnin
g: Setting an item of incompatible dtype is deprecated and will raise an error in
a future version of pandas. Value '[150.77]' has dtype incompatible with int64, p
lease explicitly cast to a compatible dtype first.
  df.loc[mask, current_col] = df.loc[mask, next_year_col]
Data processing complete for Janitza_Freezer_Room_LFB. Check the output file 'Jan
itza_Freezer_Room_LFB_Cleaned.csv'.
Data processing complete for Janitza_UO_D4_F6. Check the output file 'Janitza_UO_
D4_F6_Cleaned.csv'.
Data processing complete for Janitza_UO_F8_X. Check the output file 'Janitza_UO_F
8_X_Cleaned.csv'.
Data processing complete for Janitza_Manual_Meters. Check the output file 'Janitz
a_Manual_Meters_Cleaned.csv'.
Data processing complete for Janitza_Calculated_Consumption. Check the output fil
e 'Janitza_Calculated_Consumption_Cleaned.csv'.
All data processing complete. Check the individual CSV files and the 'Combined_Cl
eaned_Data.csv' file.
```

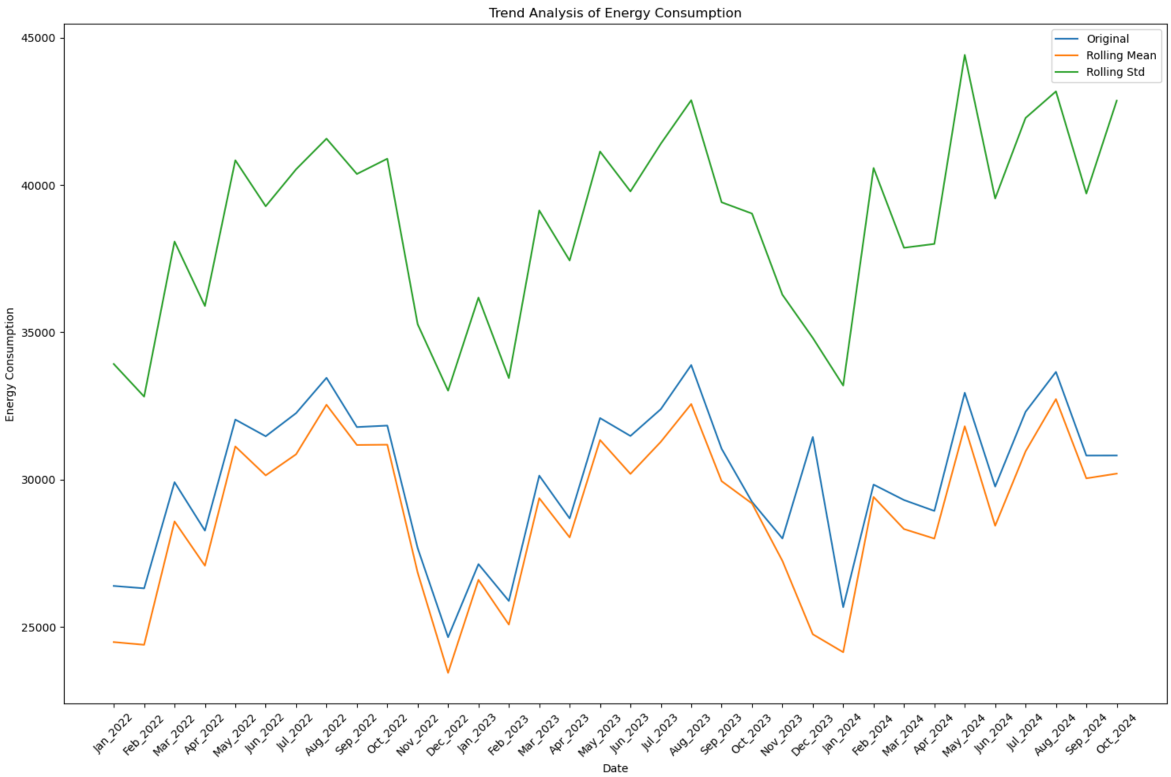
In [5]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

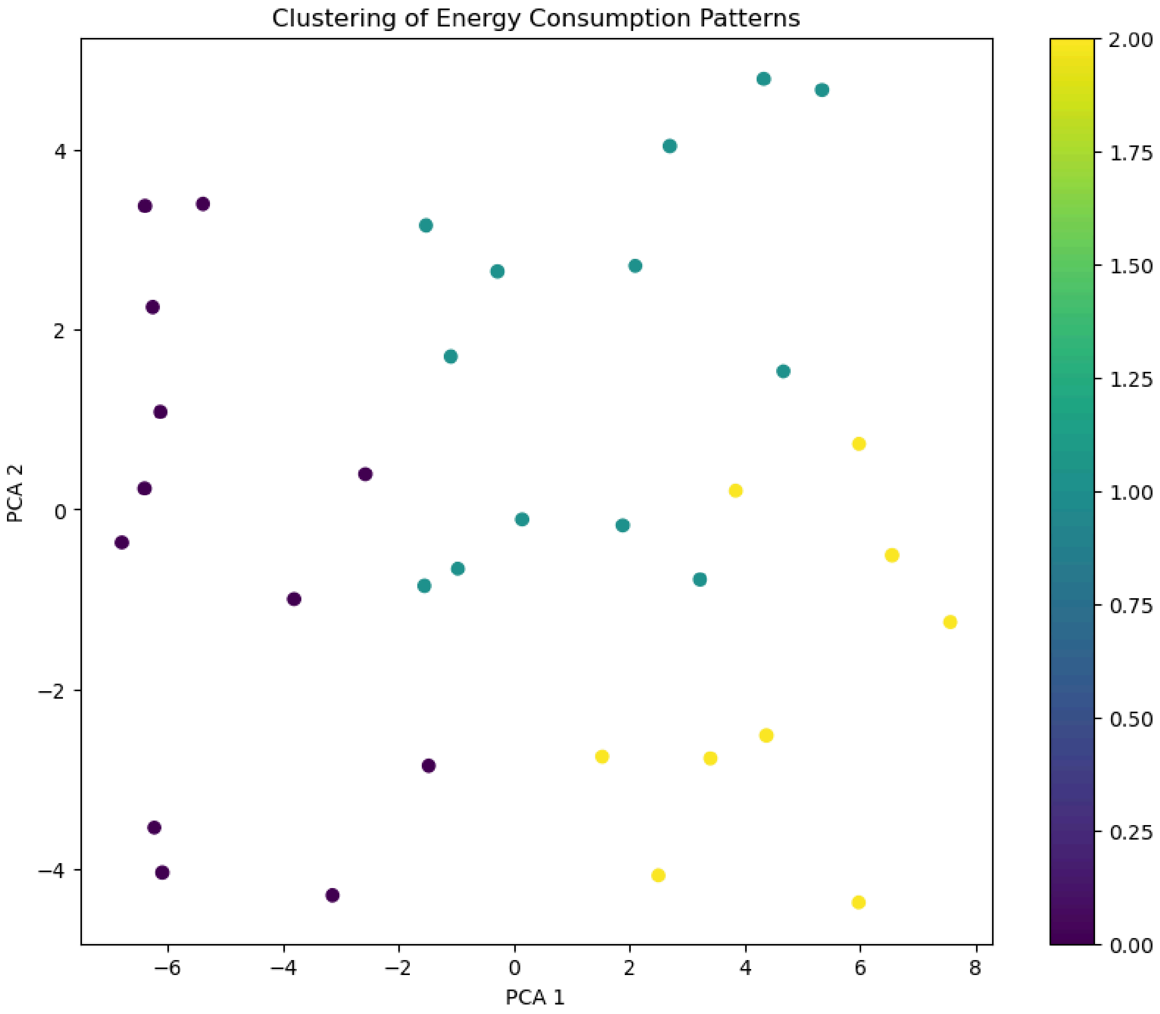
```
from sklearn.decomposition import PCA
from statsmodels.tsa.seasonal import seasonal_decompose

# Load the data
df = pd.read_csv('Janitza_Calculated_Consumption_Cleaned.csv')

# Set Meter_location as index
df.set_index('Meter_location', inplace=True)

# Remove Nov_2024 and Dec_2024 columns
df = df.drop(columns=['Nov_2024', 'Dec_2024'])

# Extreme Data Analysis
def extreme_data_analysis(df):
    print("Extreme Data Analysis:")
    print(df.describe())

    # Identify outliers using IQR method
    Q1 = df.quantile(0.25)
    Q3 = df.quantile(0.75)
    IQR = Q3 - Q1
    outliers = ((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum()
    print("\nNumber of outliers in each column:")
    print(outliers)

# Trend Analysis
def trend_analysis(df):
    # Calculate rolling mean and standard deviation
    rolling_mean = df.rolling(window=12).mean()
    rolling_std = df.rolling(window=12).std()

    # Plot trend
    plt.figure(figsize=(15, 10))
    plt.plot(df.columns, df.mean(), label='Original')
    plt.plot(rolling_mean.columns, rolling_mean.mean(), label='Rolling Mean')
    plt.plot(rolling_std.columns, rolling_std.mean(), label='Rolling Std')
    plt.title('Trend Analysis of Energy Consumption')
    plt.xlabel('Date')
    plt.ylabel('Energy Consumption')
    plt.legend()
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

# Clustering
def clustering_analysis(df):
    # Prepare data for clustering
    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(df.T)

    # Perform K-means clustering
    kmeans = KMeans(n_clusters=3, random_state=42)
    cluster_labels = kmeans.fit_predict(scaled_data)

    # Visualize clusters
    pca = PCA(n_components=2)
    pca_result = pca.fit_transform(scaled_data)

    plt.figure(figsize=(10, 8))
    scatter = plt.scatter(pca_result[:, 0], pca_result[:, 1], c=cluster_labels,
```

```
    plt.title('Clustering of Energy Consumption Patterns')
    plt.xlabel('PCA 1')
    plt.ylabel('PCA 2')
    plt.colorbar(scatter)
    plt.show()

    # Print cluster information
    for cluster in range(3):
        cluster_points = df.iloc[:, cluster_labels == cluster]
        print(f"\nCluster {cluster} Summary:")
        print(f"Number of points: {cluster_points.shape[1]}")
        print("Average consumption:")
        print(cluster_points.mean().mean())
        print("Top 5 highest consuming meters:")
        print(cluster_points.mean().nlargest(5))
        print("Top 5 lowest consuming meters:")
        print(cluster_points.mean().nsmallest(5))

# Seasonal Decomposition
def seasonal_decomposition(df):
    # Perform seasonal decomposition on the mean consumption
    mean_consumption = df.mean(axis=0)
    result = seasonal_decompose(mean_consumption, model='additive', period=12)

    # Plot the decomposition
    fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(15, 20))
    result.observed.plot(ax=ax1)
    ax1.set_title('Observed')
    result.trend.plot(ax=ax2)
    ax2.set_title('Trend')
    result.seasonal.plot(ax=ax3)
    ax3.set_title('Seasonal')
    result.resid.plot(ax=ax4)
    ax4.set_title('Residual')
    plt.tight_layout()
    plt.show()

# Heatmap
def create_heatmap(df):
    plt.figure(figsize=(20, 16))
    sns.heatmap(df.corr(), annot=False, cmap='coolwarm')
    plt.title('Correlation Heatmap of Energy Consumption')
    plt.tight_layout()
    plt.show()

# Run analyses
extreme_data_analysis(df)
trend_analysis(df)
clustering_analysis(df)
seasonal_decomposition(df)
create_heatmap(df)

print("Analysis complete.")
```

```
Extreme Data Analysis:
           Jan_2022       Feb_2022       Mar_2022       Apr_2022  \
count     50.000000      50.000000      50.000000      50.000000   
mean   26388.754200   26306.730200   29910.133800   28266.771200   
std    36802.059283   34796.348446   39440.464394   36867.131898   
min        0.000000       0.000000       0.000000       0.000000   
25%      756.500000     774.750000     699.000000    1370.500000   
50%     5534.505000    8715.500000    8796.955000    5875.615000   
75%    37251.750000   36566.987500   42277.315000   45804.000000   
max   127748.000000  117146.000000  134855.000000  129467.000000   

           May_2022       Jun_2022       Jul_2022       Aug_2022  \
count     50.000000      50.000000      50.000000      50.000000   
mean   32036.176600   31469.317000   32254.353400   33453.052400   
std    40982.143243   40253.422805   41214.260303   42037.026542   
min        0.000000       0.000000       0.000000       0.000000   
25%     1578.750000    1736.000000    2356.500000    2140.000000   
50%     6003.500000    6305.025000    7852.095000    7088.500000   
75%    57403.000000   61296.750000   59843.500000   64540.750000   
max   137229.000000  133950.000000  140486.000000  135071.000000   

           Sep_2022       Oct_2022  ...       Jan_2024       Feb_2024  \
count     50.000000      50.000000  ...      50.000000      50.000000   
mean   31782.229600   31831.482000  ...   25668.390800   29828.849600   
std    40143.568501   40771.102428  ...   35894.292931   39965.809403   
min        0.130000       0.140000  ...       0.000000       0.000000   
25%     1757.500000    1847.000000  ...     638.750000     781.500000   
50%     6145.000000    5934.000000  ...    7490.885000    9829.480000   
75%    56981.500000   54761.500000  ...   39622.655000   52096.392500   
max   127943.000000  135458.040000  ...  152384.770000  155640.000000   

           Mar_2024       Apr_2024       May_2024       Jun_2024  \
count     50.000000      50.000000      50.000000      50.000000   
mean   29304.781200   28934.851400   32947.032200   29761.675800   
std    38888.588523   38206.238348   43868.363359   39980.811025   
min        0.000000       0.000000       0.000000       0.000000   
25%      913.500000    1411.500000    1382.250000    1284.500000   
50%     5835.500000    5480.680000    7245.875000    5619.550000   
75%    47454.505000   47048.927500   62061.637500   56550.907500   
max   150091.000000  143823.110000  161285.130000  145358.590000   

           Jul_2024       Aug_2024       Sep_2024       Oct_2024  
count     50.000000      50.000000      50.000000      50.000000  
mean   32299.827200   33653.780400   30814.869000   30816.845400  
std    42810.980828   43330.650736   39883.303291   43851.960188  
min        0.000000       0.000000       0.000000       0.000000  
25%     1896.532500    1985.250000    1733.107500     449.590000  
50%     5545.115000    8564.310000    7799.570000    6996.500000  
75%    62397.787500   64541.375000   52549.472500   60562.667500  
max   153205.500000  152299.260000  146707.710000  168395.520000  

[8 rows x 34 columns]

Number of outliers in each column:
Jan_2022    5
Feb_2022    3
Mar_2022    3
Apr_2022    1
May_2022    0
Jun_2022    0
```

```
Jul_2022    0
Aug_2022    0
Sep_2022    0
Oct_2022    1
Nov_2022    2
Dec_2022    2
Jan_2023    3
Feb_2023    1
Mar_2023    1
Apr_2023    2
May_2023    1
Jun_2023    0
Jul_2023    0
Aug_2023    0
Sep_2023    1
Oct_2023    1
Nov_2023    2
Dec_2023    3
Jan_2024    2
Feb_2024    2
Mar_2024    2
Apr_2024    2
May_2024    1
Jun_2024    1
Jul_2024    1
Aug_2024    0
Sep_2024    1
Oct_2024    1
dtype: int64
```

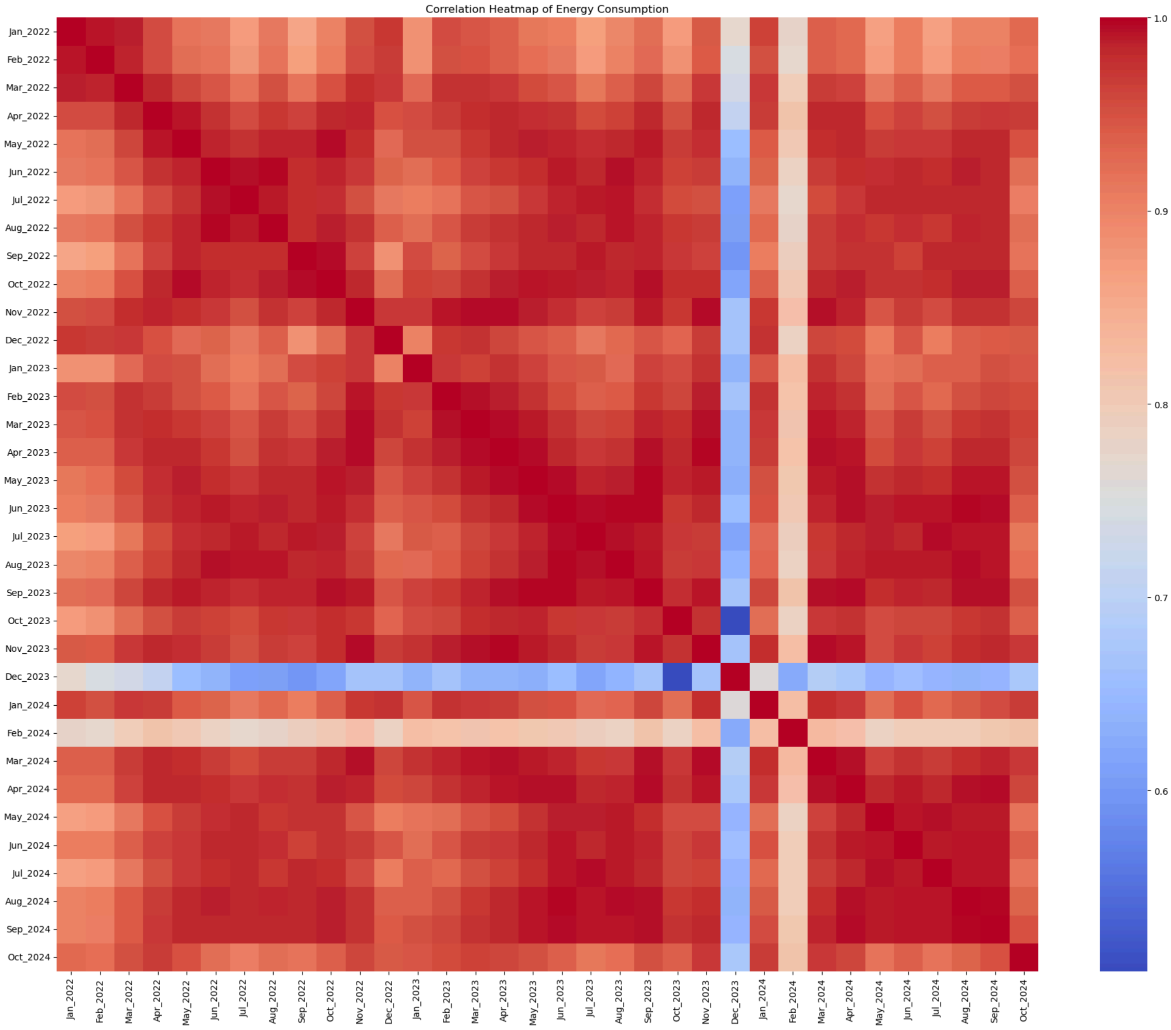




Clustering of Energy Consumption Patterns
PCA 1
PCA 2
−6
−4
−2
0
2
4
6
8
−4
−2
0
2
4
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

```
Cluster 0 Summary:
Number of points: 12
Average consumption:
27594.954616666666
Top 5 highest consuming meters:
Dec_2023    31443.9564
Mar_2022    29910.1338
Feb_2024    29828.8496
Apr_2022    28266.7712
Nov_2023    28000.4116
dtype: float64
Top 5 lowest consuming meters:
Dec_2022    24647.7150
Jan_2024    25668.3908
Feb_2023    25878.9814
Feb_2022    26306.7302
Jan_2022    26388.7542
dtype: float64

Cluster 1 Summary:
Number of points: 13
Average consumption:
30747.828846153843
Top 5 highest consuming meters:
Aug_2024    33653.7804
May_2024    32947.0322
Jul_2024    32299.8272
May_2023    32086.4022
Sep_2023    31044.9110
dtype: float64
Top 5 lowest consuming meters:
Apr_2023    28680.9670
Apr_2024    28934.8514
Oct_2023    29242.6674
Mar_2024    29304.7812
Jun_2024    29761.6758
dtype: float64

Cluster 2 Summary:
Number of points: 9
Average consumption:
32286.923066666666
Top 5 highest consuming meters:
Aug_2023    33886.6312
Aug_2022    33453.0524
Jul_2023    32389.6912
Jul_2022    32254.3534
May_2022    32036.1766
dtype: float64
Top 5 lowest consuming meters:
Jun_2022    31469.3170
Jun_2023    31479.3742
Sep_2022    31782.2296
Oct_2022    31831.4820
May_2022    32036.1766
dtype: float64
```

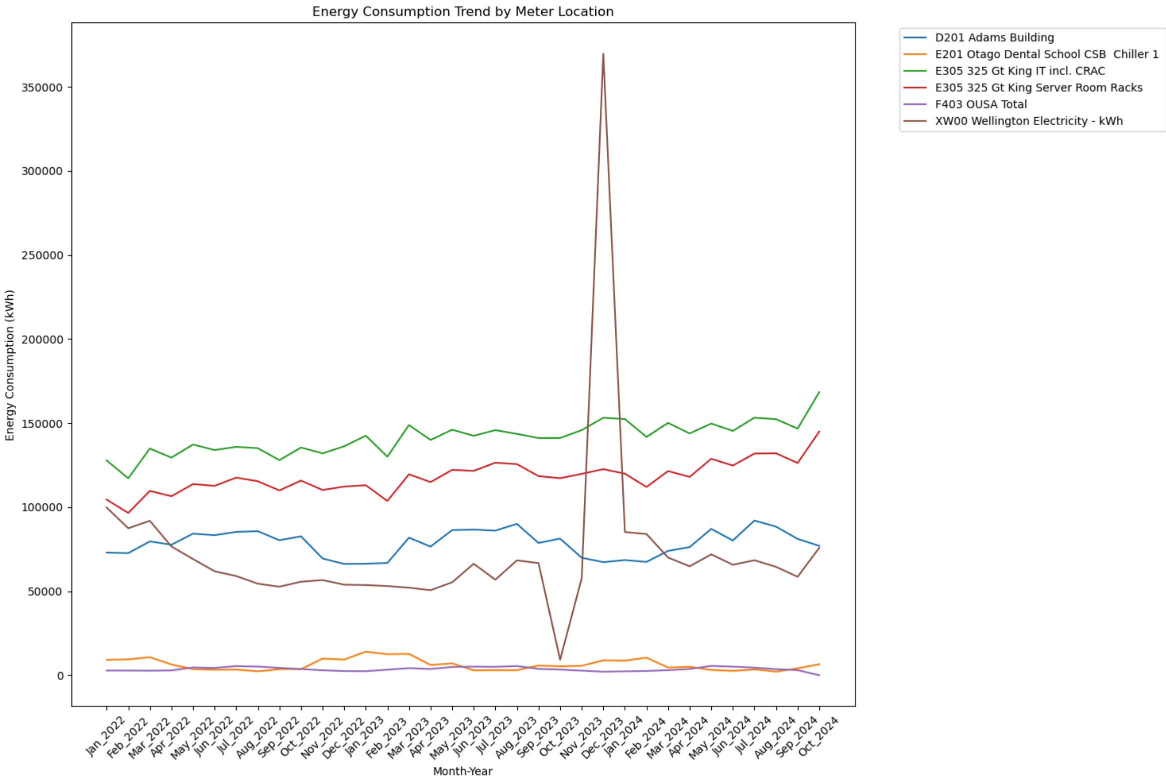

Observed
34000
32000
30000
28000
26000
Jan_2022
Jun_2022
Nov_2022
Apr_2023
Sep_2023
Feb_2024
Jul_2024
Trend
30300
30200
30100
30000
29900
29800
29700
29600
29500
Jun_2022
Nov_2022
Apr_2023
Sep_2023
Feb_2024
Seasonal
4000
3000
2000
1000
0
−1000
−2000
−3000
−4000
Jan_2022
Jun_2022
Nov_2022
Apr_2023
Sep_2023
Feb_2024
Jul_2024
Residual
3000
2000
1000
0
−1000
−2000
−3000
Jun_2022
Nov_2022
Apr_2023
Sep_2023
Feb_2024



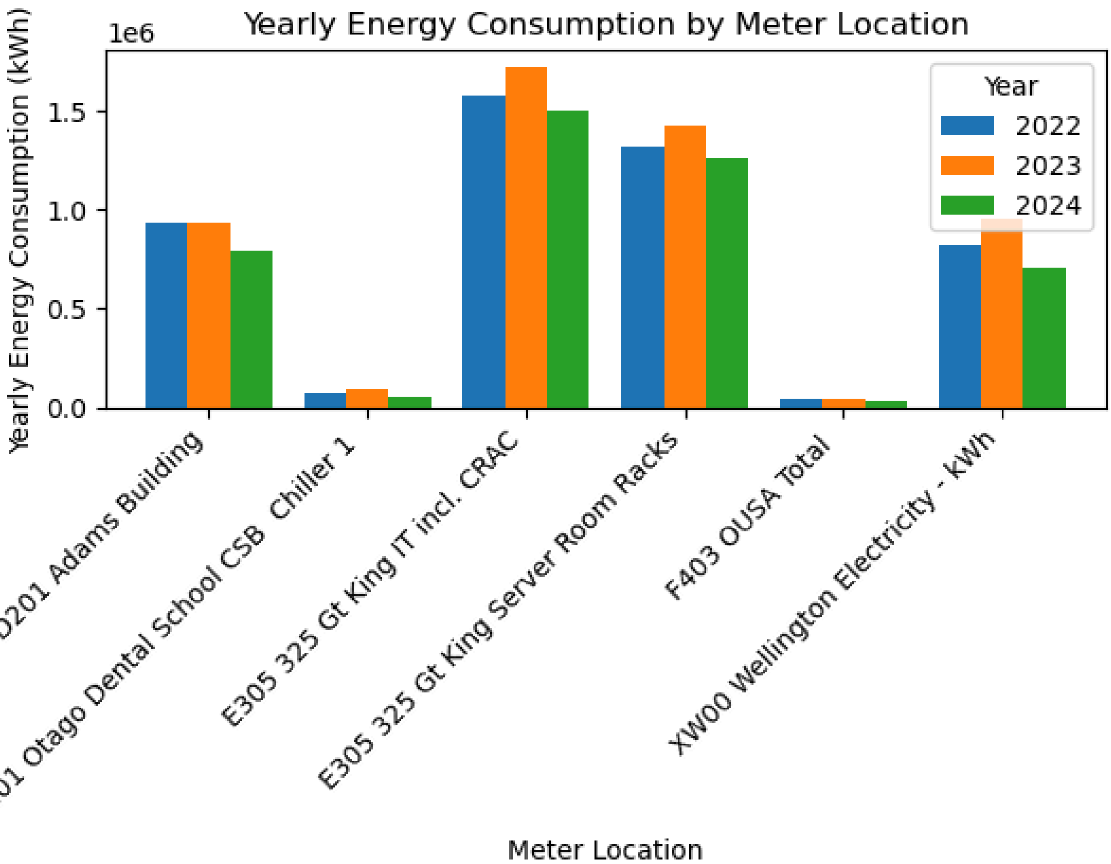
Analysis complete.

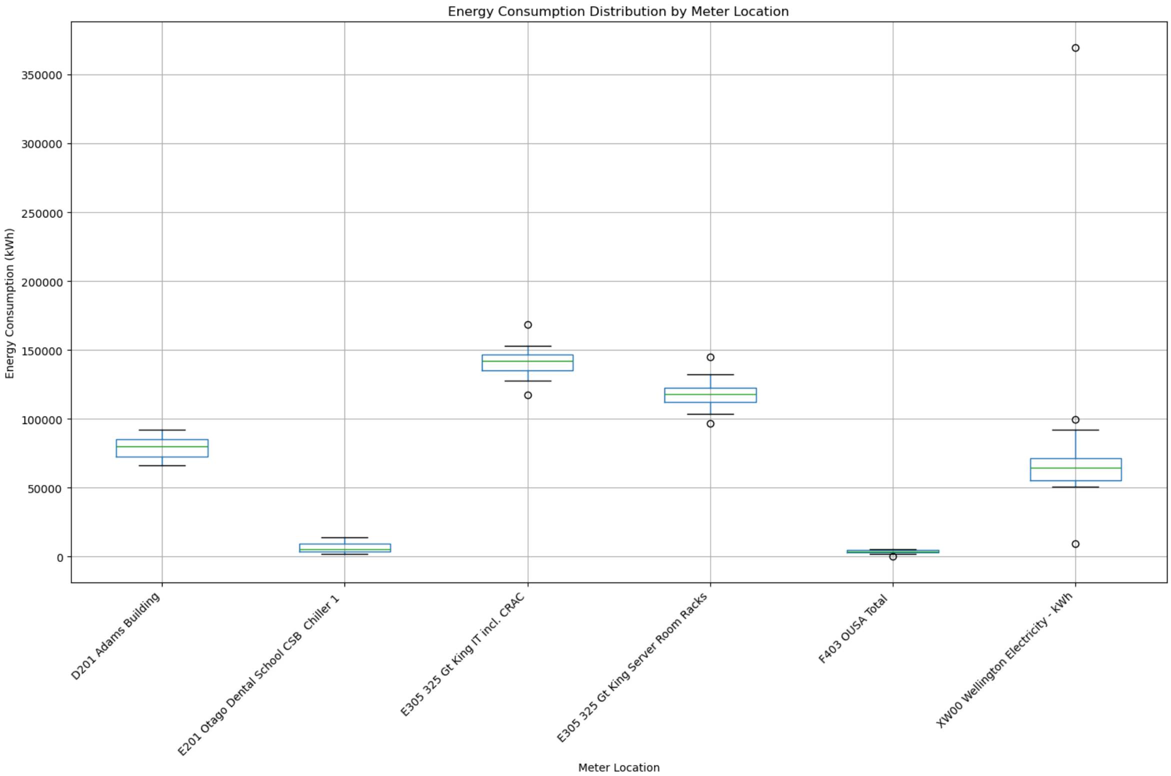
In [6]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

# Assuming df is your DataFrame
# If it's not loaded, load it first:
# df = pd.read_csv('Janitza_Calculated_Consumption_Cleaned.csv', index_col='Mete

locations = [
    'D201 Adams Building',
    'E201 Otago Dental School CSB  Chiller 1 ',
    'E305 325 Gt King IT incl. CRAC',
    'E305 325 Gt King Server Room Racks',
    'F403 OUSA Total ',
    'XW00 Wellington Electricity - kWh'
]

# Trend Analysis
plt.figure(figsize=(15, 10))
for location in locations:
    if location in df.index:
        plt.plot(df.columns, df.loc[location], label=location)
    else:
        print(f"Location '{location}' not found in the DataFrame")

plt.title('Energy Consumption Trend by Meter Location')
```

```
plt.xlabel('Month-Year')
plt.ylabel('Energy Consumption (kWh)')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Yearly Consumption Bar Chart
def get_yearly_consumption(df):
    yearly = {}
    for year in range(2022, 2025):
        yearly[year] = df[[col for col in df.columns if str(year) in col]].sum(a
    return pd.DataFrame(yearly)

yearly_consumption = get_yearly_consumption(df.loc[locations])

plt.figure(figsize=(15, 10))
yearly_consumption.plot(kind='bar', width=0.8)
plt.title('Yearly Energy Consumption by Meter Location')
plt.xlabel('Meter Location')
plt.ylabel('Yearly Energy Consumption (kWh)')
plt.legend(title='Year')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Comparison Between Locations (Box Plot)
plt.figure(figsize=(15, 10))
df.loc[locations].T.boxplot()
plt.title('Energy Consumption Distribution by Meter Location')
plt.xlabel('Meter Location')
plt.ylabel('Energy Consumption (kWh)')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Monthly Average Consumption
def get_month(col):
    return col[:3]

monthly_avg = df.loc[locations].groupby(get_month, axis=1).mean()

plt.figure(figsize=(15, 10))
sns.heatmap(monthly_avg, cmap='YlOrRd', annot=True, fmt='.0f')
plt.title('Average Monthly Energy Consumption by Meter Location')
plt.xlabel('Month')
plt.ylabel('Meter Location')
plt.tight_layout()
plt.show()
```

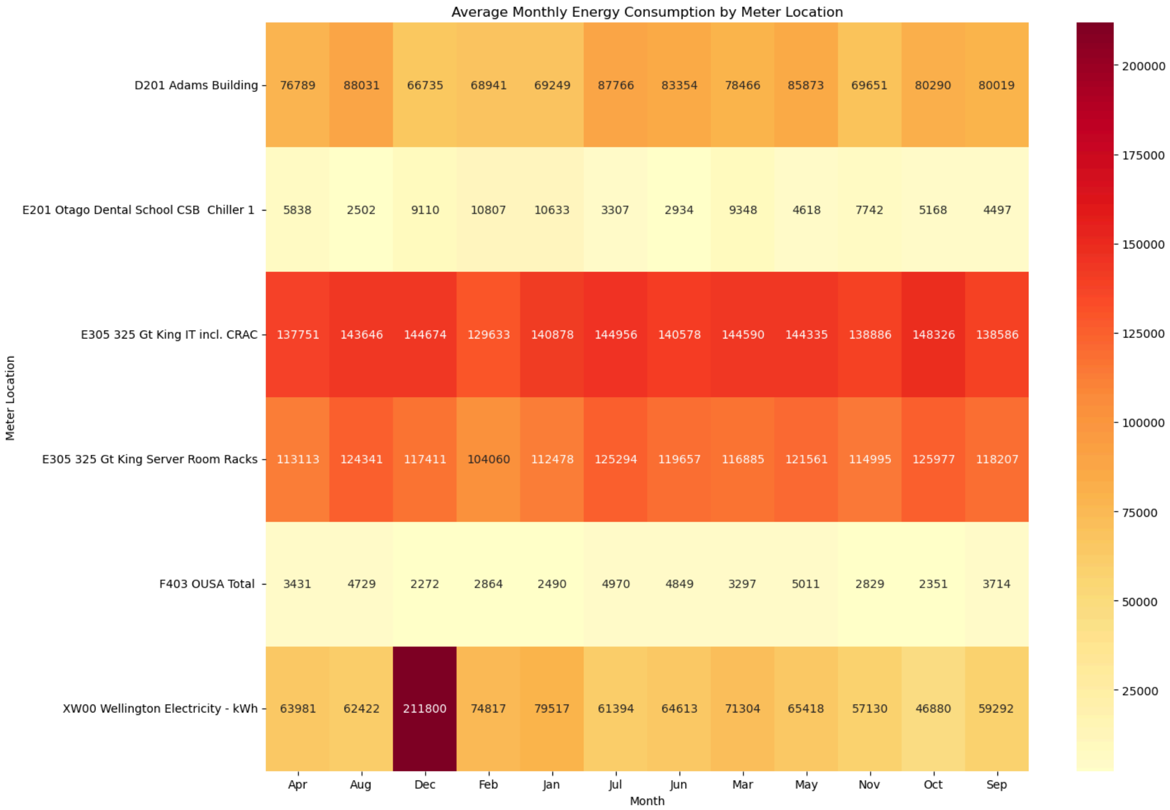


<Figure size 1500x1000 with 0 Axes>






```
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\93015222.py:68: FutureWarning:
DataFrame.groupby with axis=1 is deprecated. Do `frame.T.groupby(...)` without ax
is instead.
  monthly_avg = df.loc[locations].groupby(get_month, axis=1).mean()
```

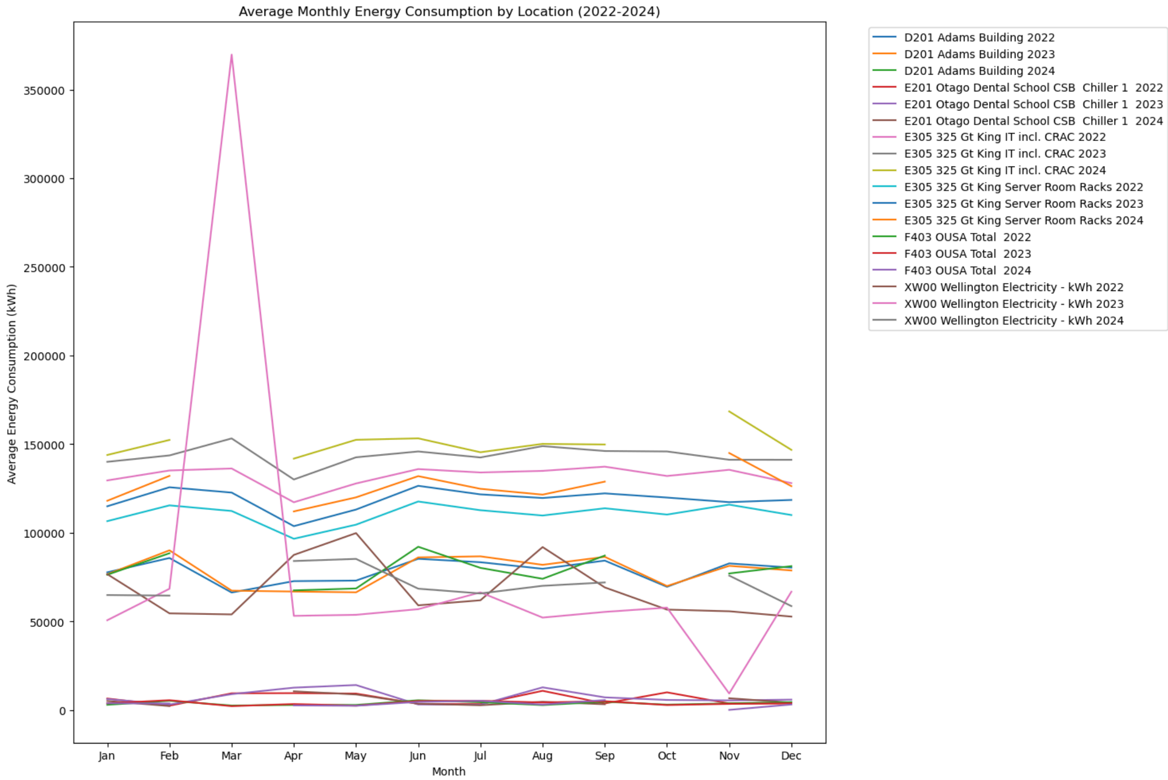


In [7]:

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

# Define the requested locations
locations = [
    'D201 Adams Building',
    'E201 Otago Dental School CSB  Chiller 1 ',
```

```
    'E305 325 Gt King IT incl. CRAC',
    'E305 325 Gt King Server Room Racks',
    'F403 OUSA Total ',
    'XW00 Wellington Electricity - kWh'
]

# Load the data (assuming the DataFrame is already loaded as df)
# If not, uncomment the following line:
# df = pd.read_csv('Janitza_Calculated_Consumption_Cleaned.csv', index_col='Mete

# Filter the DataFrame to include only the specified locations
df_filtered = df.loc[df.index.isin(locations)]

# Function to get month from column name
def get_month(col):
    return col.split('_')[0]

# Function to get year from column name
def get_year(col):
    return col.split('_')[1]

# Calculate monthly averages for each location and year
monthly_avg = df_filtered.T.groupby([get_year, get_month]).mean().T

# Reshape data for plotting
plot_data = monthly_avg.stack().unstack(level=1).T

# Plot
fig, ax = plt.subplots(figsize=(15, 10))

months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct',
x = range(len(months))

available_years = monthly_avg.columns.get_level_values(0).unique()

for location in locations:
    if location in plot_data.columns:
        for year in available_years:
            ax.plot(x, plot_data[location][year], label=f'{location} {year}')

ax.set_xticks(x)
ax.set_xticklabels(months)
ax.set_xlabel('Month')
ax.set_ylabel('Average Energy Consumption (kWh)')
ax.set_title('Average Monthly Energy Consumption by Location (2022-2024)')
ax.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

```
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\1809504946.py:33: FutureWarnin
g: The previous implementation of stack is deprecated and will be removed in a fu
ture version of pandas. See the What's New notes for pandas 2.1.0 for details. Sp
ecify future_stack=True to adopt the new implementation and silence this warning.
  plot_data = monthly_avg.stack().unstack(level=1).T
```

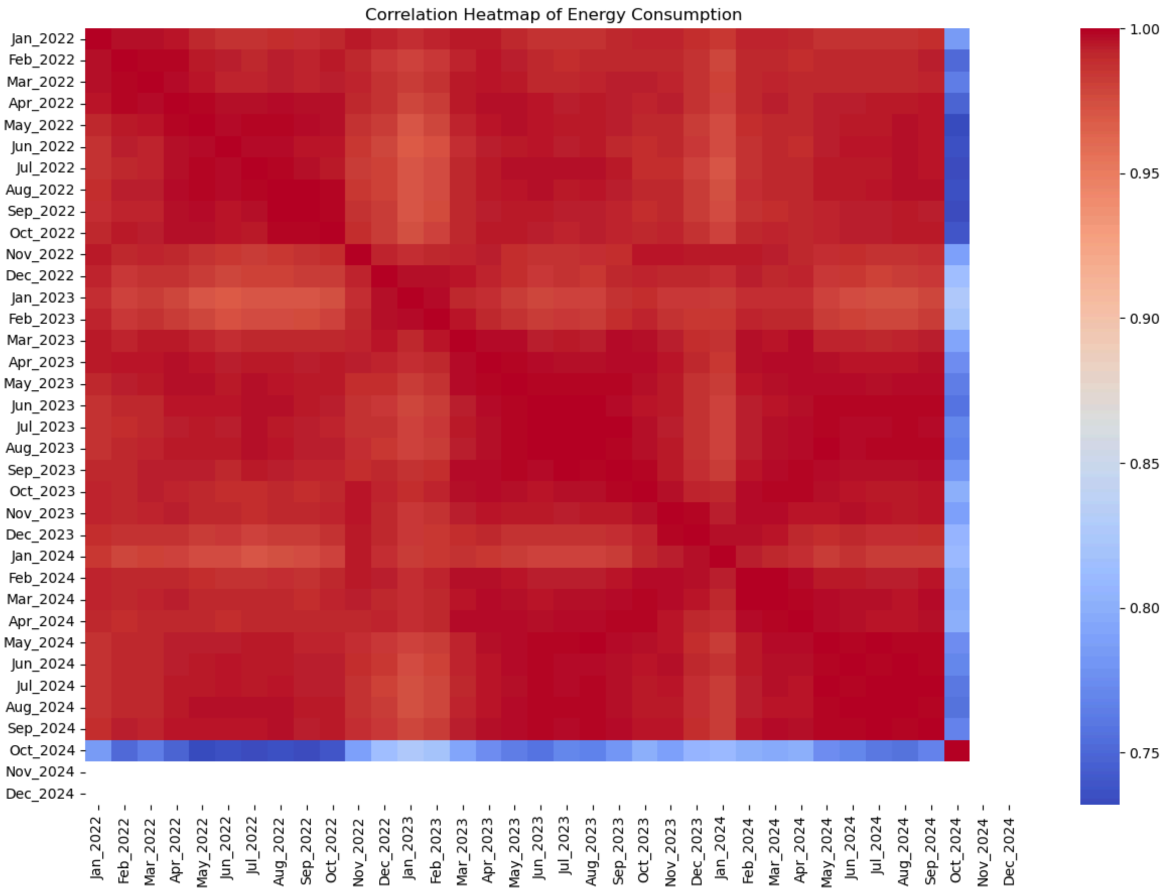


In [8]:
```
locations
```

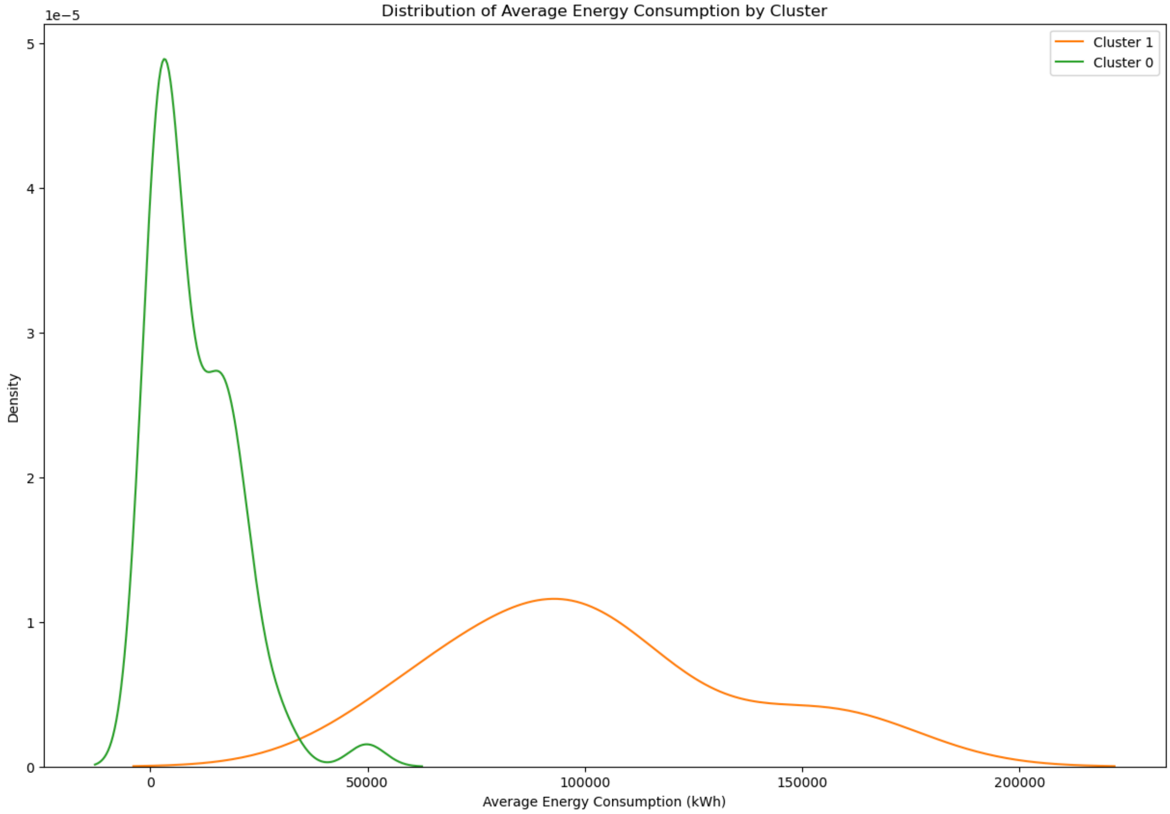
Out[8]:
```
['D201 Adams Building',
 'E201 Otago Dental School CSB  Chiller 1 ',
 'E305 325 Gt King IT incl. CRAC',
 'E305 325 Gt King Server Room Racks',
 'F403 OUSA Total ',
 'XW00 Wellington Electricity - kWh']
```

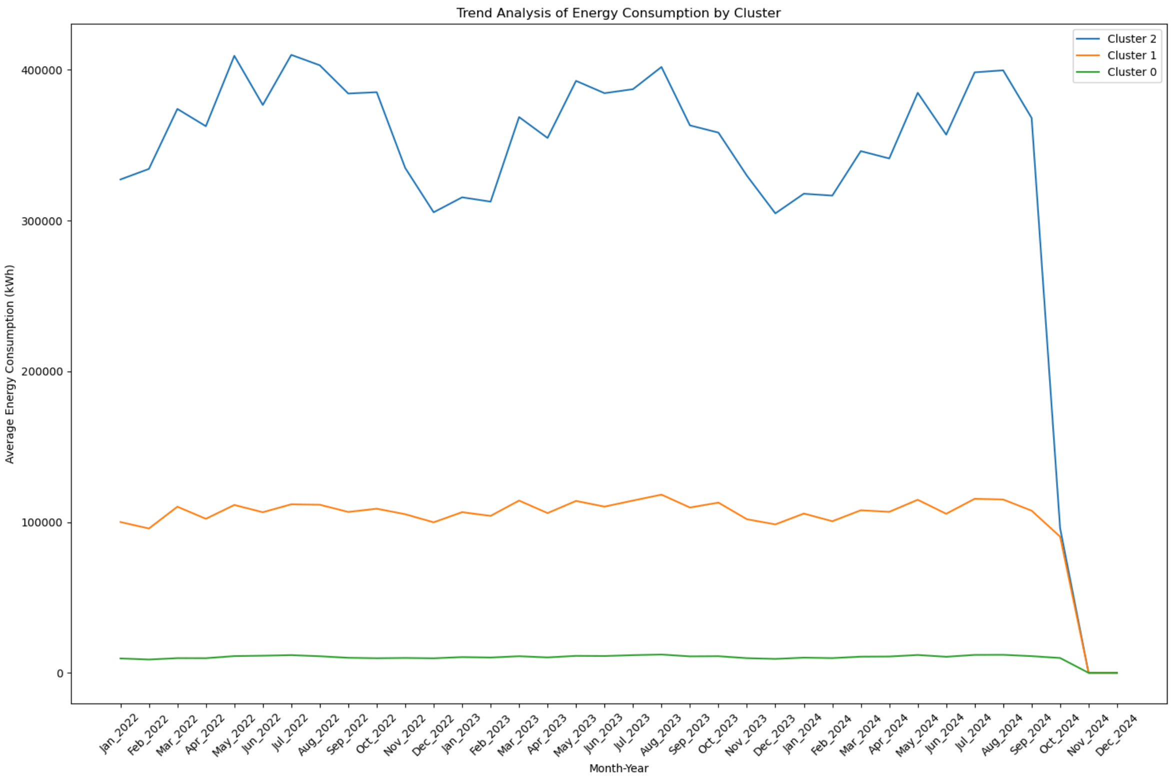
In [9]:
```
# Load the Janitza_Med_Data_Cleaned dataset
data_path = 'Janitza_Med_Data_Cleaned.csv'
janitza_med_data = pd.read_csv(data_path)

# Prepare the data for clustering (excluding the 'Meter_location' column)
data_for_clustering = janitza_med_data.iloc[:, 1:].fillna(0)

# Standardize the data
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data_for_clustering)

# Perform KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(data_scaled)

# Add cluster labels to the original dataset
janitza_med_data['Cluster'] = clusters

# Correlation heatmap
plt.figure(figsize=(15, 10))
sns.heatmap(data_for_clustering.corr(), annot=False, cmap='coolwarm')
plt.title('Correlation Heatmap of Energy Consumption')
plt.show()

# Distribution analysis by cluster
plt.figure(figsize=(15, 10))
for cluster in janitza_med_data['Cluster'].unique():
```

```
    sns.kdeplot(janitza_med_data[janitza_med_data['Cluster'] == cluster].iloc[:,
plt.title('Distribution of Average Energy Consumption by Cluster')
plt.xlabel('Average Energy Consumption (kWh)')
plt.ylabel('Density')
plt.legend()
plt.show()

# Trend analysis for clusters
plt.figure(figsize=(15, 10))
for cluster in janitza_med_data['Cluster'].unique():
    cluster_data = janitza_med_data[janitza_med_data['Cluster'] == cluster].iloc
    plt.plot(cluster_data.index, cluster_data.values, label=f'Cluster {cluster}'
plt.title('Trend Analysis of Energy Consumption by Cluster')
plt.xlabel('Month-Year')
plt.ylabel('Average Energy Consumption (kWh)')
plt.xticks(rotation=45)
plt.legend()
plt.tight_layout()
plt.show()

# Cluster summary
cluster_centers = scaler.inverse_transform(kmeans.cluster_centers_)
cluster_summary = pd.DataFrame(cluster_centers, columns=janitza_med_data.columns
print("Cluster Summary:")
print(cluster_summary)
```




```
C:\Users\sugan\AppData\Local\Temp\ipykernel_15636\1775354909.py:28: UserWarning:
Dataset has 0 variance; skipping density estimate. Pass `warn_singular=False` to
disable this warning.
  sns.kdeplot(janitza_med_data[janitza_med_data['Cluster'] == cluster].iloc[:, 1:
-1].mean(axis=1), label=f'Cluster {cluster}')
```


Distribution of Average Energy Consumption by Cluster
1e−5
Density
Average Energy Consumption (kWh)
0
50000
100000
150000
200000
Cluster 1
Cluster 0

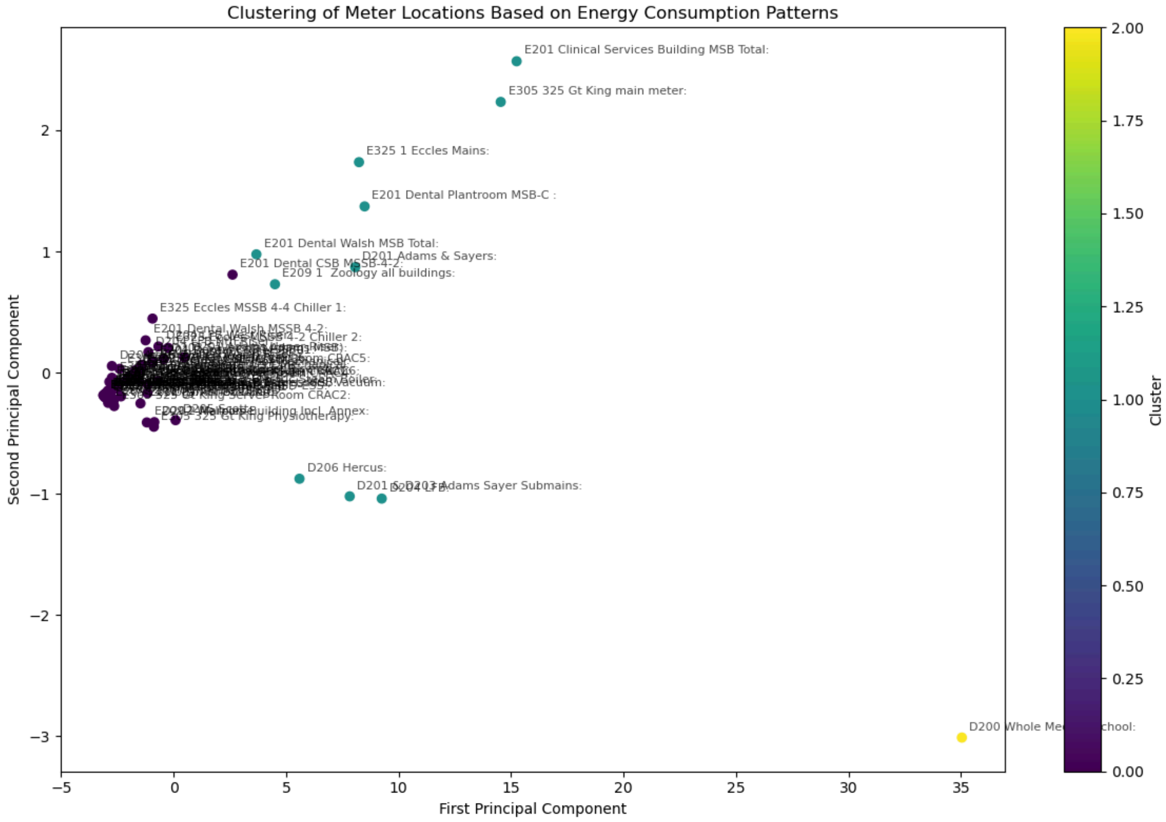

Trend Analysis of Energy Consumption by Cluster
Average Energy Consumption (kWh)
Month-Year
Cluster 2
Cluster 1
Cluster 0
0
100000
200000
300000
400000
Jan_2022 Feb_2022 Mar_2022 Apr_2022 May_2022 Jun_2022 Jul_2022 Aug_2022 Sep_2022 Oct_2022 Nov_2022 Dec_2022 Jan_2023 Feb_2023 Mar_2023 Apr_2023 May_2023 Jun_2023 Jul_2023 Aug_2023 Sep_2023 Oct_2023 Nov_2023 Dec_2023 Jan_2024 Feb_2024 Mar_2024 Apr_2024 May_2024 Jun_2024 Jul_2024 Aug_2024 Sep_2024 Oct_2024 Nov_2024 Dec_2024

```
Cluster Summary:
        Jan_2022       Feb_2022       Mar_2022       Apr_2022       May_2022  \
0    9572.786885    8821.606557    9758.491803    9720.622951   11104.459016
1  100047.700000   95755.900000  110217.300000  102194.300000  111373.800000
2  327299.000000  334299.000000  374104.000000  362627.000000  409346.000000

        Jun_2022       Jul_2022   Aug_2022       Sep_2022      Oct_2022  ...  \
0   11368.360656   11746.521639   11008.03    9981.406066    9697.31459  ...
1  106558.100000  111816.100000  111532.70  106748.600000  108894.04200  ...
2  376717.000000  409956.000000  403055.00  384319.000000  385204.22000  ...

       Mar_2024       Apr_2024       May_2024       Jun_2024       Jul_2024  \
0   10727.68918   10830.808525   11843.190984   10659.923607   11894.556393
1  107845.66000  106820.916000  114821.429000  105522.354000  115475.838000
2  346120.19000  341229.560000  384794.630000  357027.840000  398360.560000

        Aug_2024       Sep_2024      Oct_2024  Nov_2024  Dec_2024
0   11950.380984   11076.604426   9850.059672       0.0       0.0
1  115006.463000  107577.678000  90346.957000       0.0       0.0
2  399708.160000  368099.310000  95965.190000       0.0       0.0

[3 rows x 36 columns]
```

In [10]:

```python
data_path = 'Janitza_Med_Data_Cleaned.csv'
janitza_med_data = pd.read_csv(data_path)

# Prepare data for clustering (excluding the Meter_location column)
X = janitza_med_data.iloc[:, 1:].values
meter_locations = janitza_med_data['Meter_location']

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Reduce dimensionality to 2D for visualization using PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Perform KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Create scatter plot
plt.figure(figsize=(12, 8))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=clusters, cmap='viridis')
plt.xlabel('First Principal Component')
plt.ylabel('Second Principal Component')
plt.title('Clustering of Meter Locations Based on Energy Consumption Patterns')

# Add legend
plt.colorbar(scatter, label='Cluster')

# Add annotations for meter locations
for i, location in enumerate(meter_locations):
    plt.annotate(location, (X_pca[i, 0], X_pca[i, 1]),
                xytext=(5, 5), textcoords='offset points',
                fontsize=8, alpha=0.7)

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

```python
# Print cluster information
for cluster in range(3):
    print(f"\nCluster {cluster} locations:")
    print(meter_locations[clusters == cluster].values)
```

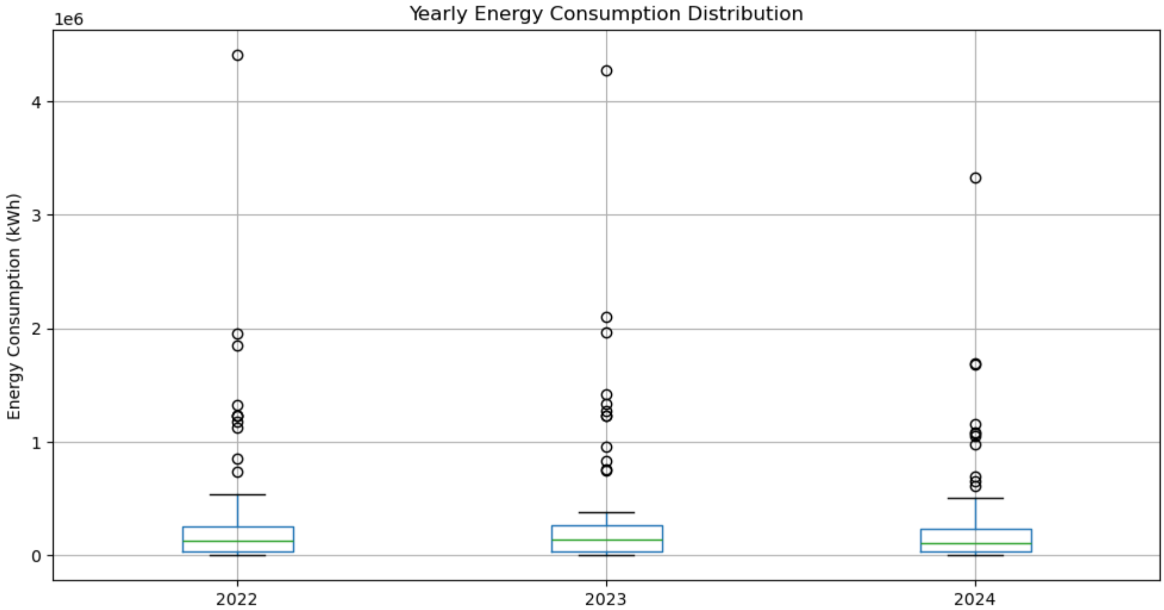


```
Cluster 0 locations:
['D201 Adams 7th Floor Mechanical:' 'D201 Adams Basement Mechanical:'
 'D201 Adams Lift:' 'D201 Adams Lower Riser:' 'D201 Adams Upper Riser:'
 'D202 Wellcome:' 'D203 Sayers (at Adams MSB):' 'D204 LFB Chiller:'
 'D204 LFB DBB1:' 'D204 LFB DBB2:' 'D204 LFB DBB4:' 'D204 LFB DBB5:'
 'D204 LFB Nth Riser:' 'D204 LFB Sth Riser:' 'D204 LFB West Riser:'
 'D205 Scott:' 'D207 Generator:' 'D207 Nitrogenplant:'
 'D207 Thermal Storage IT:' 'D207 Thermal Storage plant :'
 'E201 Busduct Riser 3:' 'E201 Dental CSB Busduct Riser 4:'
 'E201 Dental CSB DB-C-CSSD-ESS:' 'E201 Dental CSB DB-C-WS:'
 'E201 Dental CSB DB-CSSD:' 'E201 Dental CSB MSSB-4-2:'
 'E201 Dental CSB MSSB01:' 'E201 Dental CSB MSSD02:'
 'E201 Dental Walsh MSSB 0-3:' 'E201 Dental Walsh MSSB 1-1:'
 'E201 Dental Walsh MSSB 4-2:' 'E201 Dental Walsh MSSB 5-1:'
 'E201 Dental Walsh Riser 1:' 'E201 Dental Walsh Riser 2:'
 'E209 2 Marples Building Incl. Annex:' 'E209 Zoology Annex DBGC:'
 'E209 Zoology Annex DBGD:' 'E211 Parker Building:'
 'E305 325 Gt King Physiotherapy:' 'E305 325 Gt King Server Room CRAC1:'
 'E305 325 Gt King Server Room CRAC2:'
 'E305 325 Gt King Server Room CRAC4:'
 'E305 325 Gt King st Server Room CRAC5:'
 'E305 325 Gt King st Server Room CRAC6:' 'E315 71 Frederick Street, MSB:'
 'E325 2 Eccles Physio Building:' 'E325 3 Eccles Generator:'
 'E325 Eccles DB 1.1:' 'E325 Eccles DB 2.1:' 'E325 Eccles DB 3.1:'
 'E325 Eccles DB 3.2:' 'E325 Eccles DB 4.1:' 'E325 Eccles HSSB G1:'
 'E325 Eccles HSSB-4.1:' 'E325 Eccles MSSB 4-1 Compressors, Vacuum:'
 'E325 Eccles MSSB 4-2 Chiller 2:' 'E325 Eccles MSSB 4-3 Fans:'
 'E325 Eccles MSSB 4-4 Chiller 1:' 'E325 Eccles MSSB-G.1:'
 'E325 Eccles MSSB-G.2 Electric Steam Boiler:' 'E325 Eccles MSSB-G.3:']

Cluster 1 locations:
['D201 & D203 Adams Sayer Submains:' 'D201 Adams & Sayers:' 'D204 LFB:'
 'D206 Hercus:' 'E201 Clinical Services Building MSB Total:'
 'E201 Dental Plantroom MSB-C :' 'E201 Dental Walsh MSB Total:'
 'E209 1  Zoology all buildings:' 'E305 325 Gt King main meter:'
 'E325 1 Eccles Mains:']

Cluster 2 locations:
['D200 Whole Medical School:']
```

In [11]:

```python
# Load the data
df = pd.read_csv('Jantiza_Med_Data_Cleaned.csv')
df.set_index('Meter_location', inplace=True)

# 1. Year-over-Year Analysis
def yearly_analysis(df):
    # Calculate yearly totals
    yearly_consumption = {}
    for year in ['2022', '2023', '2024']:
        yearly_consumption[year] = df[[col for col in df.columns if year in col]

    yearly_df = pd.DataFrame(yearly_consumption)

    # Plot yearly comparison
    plt.figure(figsize=(12, 6))
    yearly_df.boxplot()
    plt.title('Yearly Energy Consumption Distribution')
    plt.ylabel('Energy Consumption (kWh)')
    plt.show()
```

```
    return yearly_df

# 2. Anomaly Detection using IsolationForest
def detect_anomalies(df):
    # Prepare data for anomaly detection
    scaler = StandardScaler()
    data_scaled = scaler.fit_transform(df)

    # Train IsolationForest
    iso_forest = IsolationForest(contamination=0.1, random_state=42)
    anomalies = iso_forest.fit_predict(data_scaled)

    # Get anomalous locations
    anomaly_indices = np.where(anomalies == -1)[0]
    anomalous_locations = df.index[anomaly_indices]

    return anomalous_locations

# 3. Statistical Analysis for Monthly Patterns
def monthly_pattern_analysis(df):
    # Calculate monthly averages
    monthly_avg = {}
    for month in ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                  'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']:
        monthly_avg[month] = df[[col for col in df.columns if col.startswith(mon

    monthly_df = pd.DataFrame(monthly_avg)

    # Plot heatmap of monthly patterns
    plt.figure(figsize=(15, 10))
    sns.heatmap(monthly_df, cmap='YlOrRd', annot=True)
    plt.title('Monthly Energy Consumption Patterns')
    plt.show()

    return monthly_df

# 4. Z-score based Anomaly Detection
def zscore_anomalies(df, threshold=3):
    z_scores = stats.zscore(df)
    anomalies = np.abs(z_scores) > threshold

    # Get locations with anomalous readings
    anomaly_locations = df.index[anomalies.any(axis=1)]
    return anomaly_locations

# Execute analyses
yearly_df = yearly_analysis(df)
anomalous_locations = detect_anomalies(df)
#monthly_patterns = monthly_pattern_analysis(df)
zscore_anomalies = zscore_anomalies(df)

# Print findings
print("Locations with Anomalous Consumption Patterns:")
print(anomalous_locations)
print("\nLocations with Statistical Anomalies (Z-score):")
print(zscore_anomalies)
```

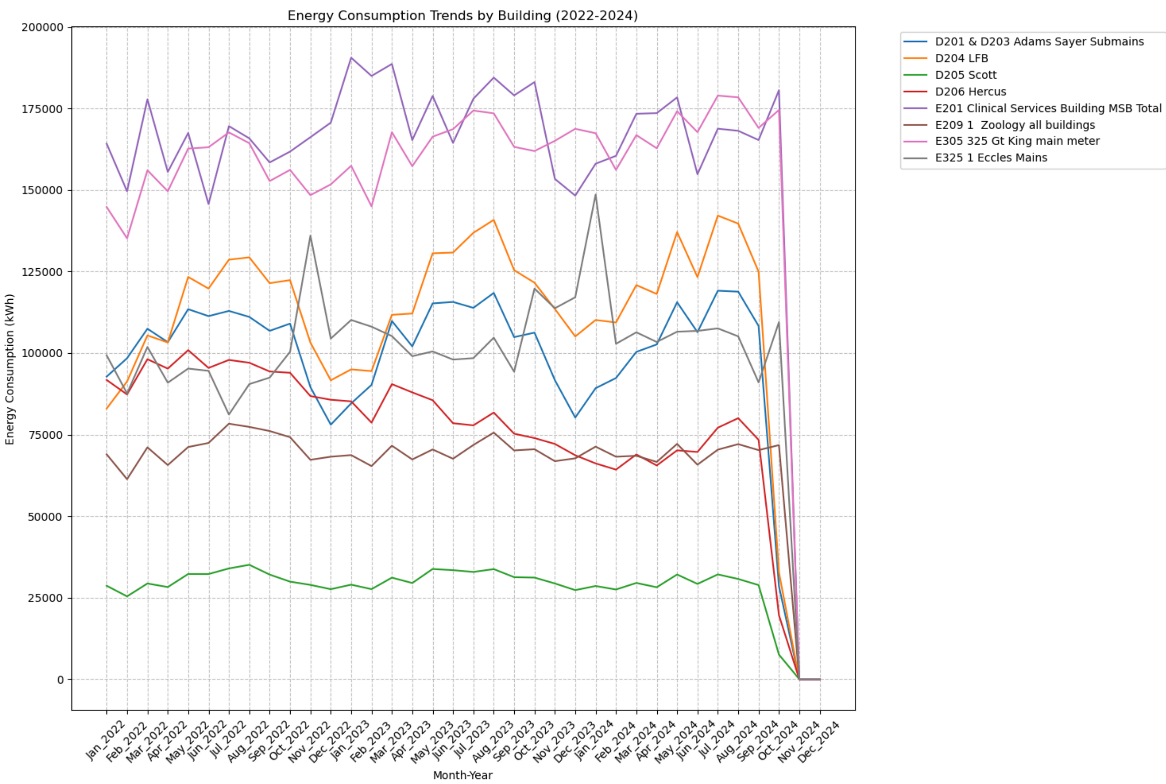



```
Locations with Anomalous Consumption Patterns:
Index(['D200 Whole Medical School:', 'D204 LFB:', 'D206 Hercus:',
       'E201 Clinical Services Building MSB Total:',
       'E201 Dental CSB MSSB-4-2:', 'E209 1  Zoology all buildings:',
       'E305 325 Gt King main meter:', 'E325 1 Eccles Mains:'],
      dtype='object', name='Meter_location')

Locations with Statistical Anomalies (Z-score):
Index(['D200 Whole Medical School:',
       'E201 Clinical Services Building MSB Total:',
       'E305 325 Gt King main meter:'],
      dtype='object', name='Meter_location')
```

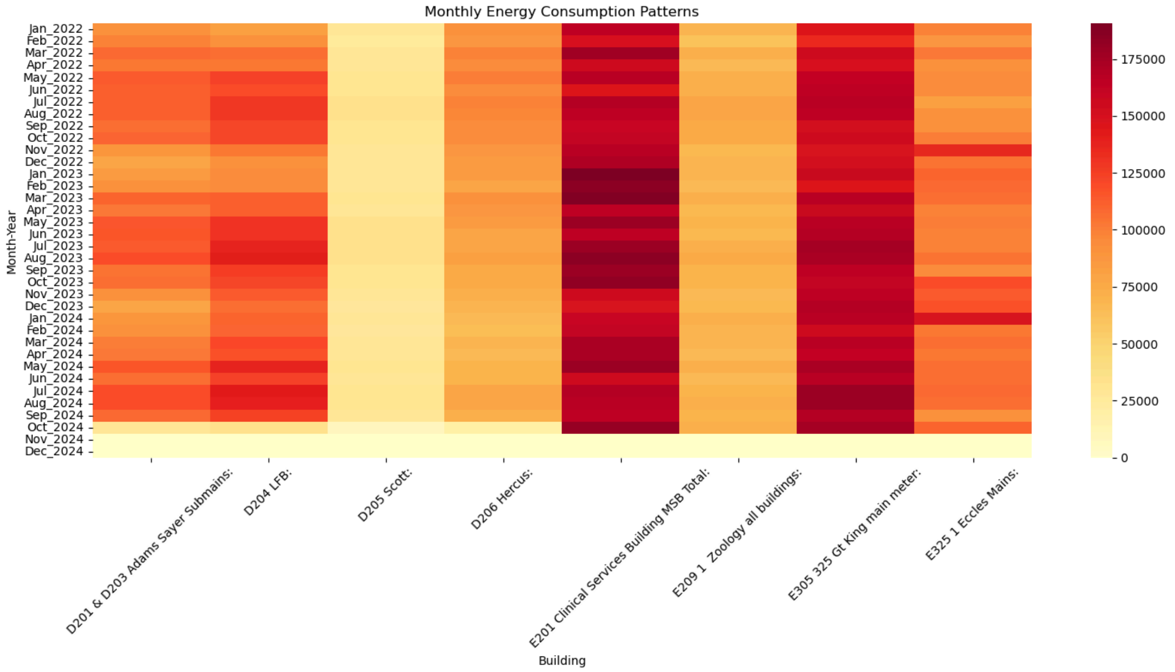
In [12]:

```python
# Specify the locations to analyze
locations = [
    'D201 & D203 Adams Sayer Submains:',
    'D204 LFB:',
    'D205 Scott:',
    'D206 Hercus:',
    'E201 Clinical Services Building MSB Total:',
    'E209 1  Zoology all buildings:',
    'E305 325 Gt King main meter:',
    'E325 1 Eccles Mains:'
]

# Create the plot
plt.figure(figsize=(15, 10))

# Plot trend for each location
for location in locations:
    plt.plot(df.columns, df.loc[location], label=location.replace(':', ''))

# Customize the plot
plt.title('Energy Consumption Trends by Building (2022-2024)')
plt.xlabel('Month-Year')
plt.ylabel('Energy Consumption (kWh)')
plt.xticks(rotation=45)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True, linestyle='--', alpha=0.7)

# Adjust layout to prevent label cutoff
```

```python
plt.tight_layout()

# Show the plot
plt.show()

# Calculate and display yearly averages
def calculate_yearly_averages(df, locations):
    yearly_avg = {}
    for year in ['2022', '2023', '2024']:
        year_cols = [col for col in df.columns if year in col]
        yearly_avg[year] = df.loc[locations, year_cols].mean(axis=1)

    return pd.DataFrame(yearly_avg)

# Calculate and display yearly averages
yearly_averages = calculate_yearly_averages(df, locations)
print("\nYearly Averages (kWh):")
print(yearly_averages.round(2))

# Create a heatmap of monthly patterns
plt.figure(figsize=(15, 8))
monthly_data = df.loc[locations].T
sns.heatmap(monthly_data, cmap='YlOrRd', xticklabels=True, yticklabels=True)
plt.title('Monthly Energy Consumption Patterns')
plt.xlabel('Building')
plt.ylabel('Month-Year')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



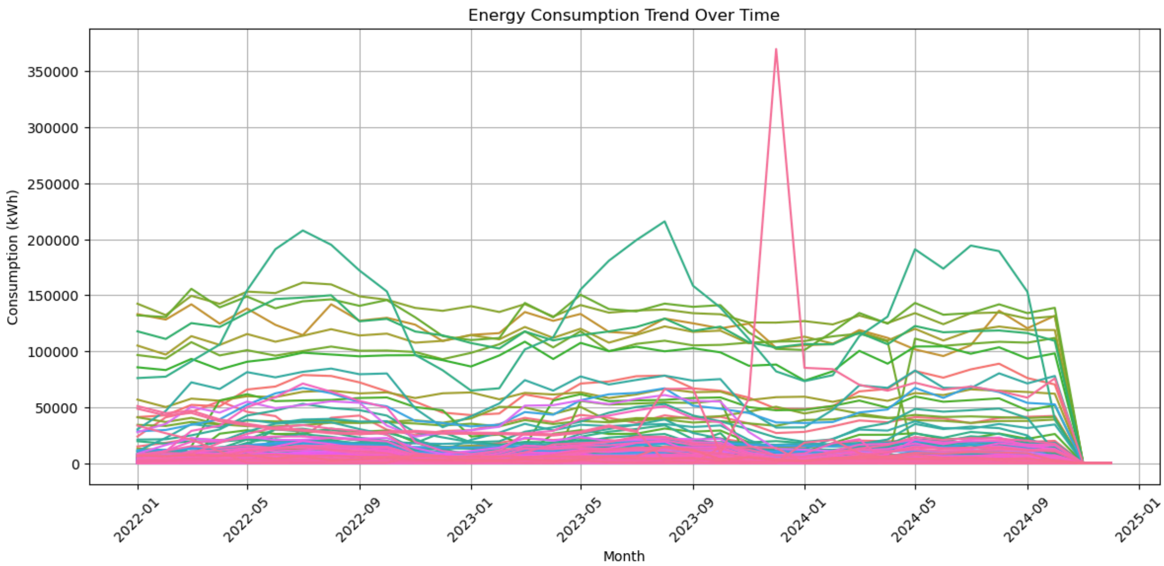
```
Yearly Averages (kWh):
                                                2022        2023        2024
Meter_location
D201 & D203 Adams Sayer Submains:          102849.51   102746.20    81778.60
D204 LFB:                                  110219.80   118167.47    96532.14
D205 Scott:                                 30306.71    30850.24    22863.02
D206 Hercus:                                93702.56    79659.09    54573.31
E201 Clinical Services Building MSB Total: 162727.49   174908.24   140124.12
E209 1  Zoology all buildings:              71008.97    69475.75    58085.12
E305 325 Gt King main meter:               154367.10   164101.97   141328.64
E325 1 Eccles Mains:                        97864.47   105751.77    90640.83
```

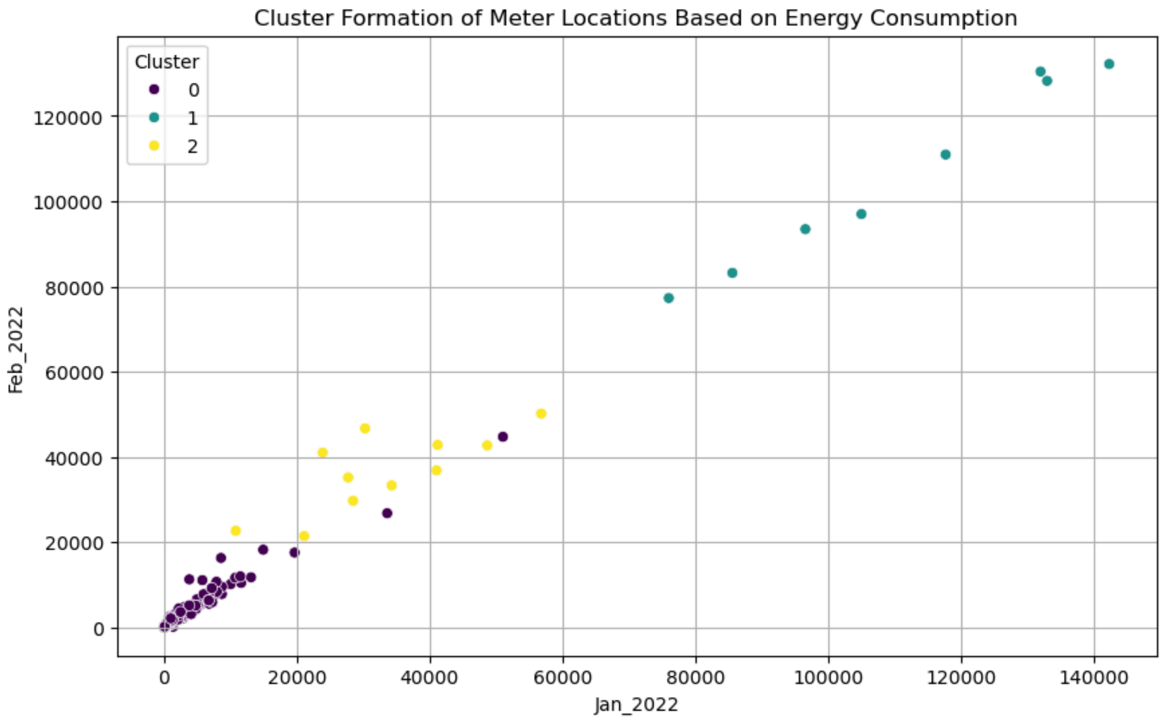


In [13]:

```
# Load the dataset
file_path = "Janitza_UO_F8_X_Cleaned.csv"
df = pd.read_csv(file_path)

# Reshape data for trend analysis
df_melted = df.melt(id_vars=["Meter_location"], var_name="Month", value_name="Cc

# Convert month names to datetime format
df_melted["Month"] = pd.to_datetime(df_melted["Month"], format="%b_%Y")

# Plot trend for selected meter locations
plt.figure(figsize=(14, 6))
sns.lineplot(data=df_melted, x="Month", y="Consumption", hue="Meter_location", l
plt.title("Energy Consumption Trend Over Time")
plt.xlabel("Month")
plt.ylabel("Consumption (kWh)")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()

# Prepare data for clustering
df_cluster = df.set_index("Meter_location")

# Standardize the data for clustering
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df_cluster)

# Apply K-means clustering
```

```
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
df_cluster["Cluster"] = kmeans.fit_predict(df_scaled)

# Visualize cluster formation
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_cluster, x=df_cluster.iloc[:, 0], y=df_cluster.iloc[:, 1
plt.title("Cluster Formation of Meter Locations Based on Energy Consumption")
plt.xlabel(df_cluster.columns[0])
plt.ylabel(df_cluster.columns[1])
plt.legend(title="Cluster")
plt.grid(True)
plt.show()

# Display clustered data
import ace_tools as tools
tools.display_dataframe_to_user(name="Clustered Meter Locations", dataframe=df_c
```





```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[13], line 43
     40 plt.show()
     42 # Display clustered data
---> 43 import ace_tools as tools
     44 tools.display_dataframe_to_user(name="Clustered Meter Locations", datafra
me=df_cluster)

ModuleNotFoundError: No module named 'ace_tools'
```

In [ ]:

```
# Reshape data for trend analysis
df_melted = df.melt(id_vars=["Meter_location"], var_name="Month", value_name="Co

# Convert month names to datetime format
df_melted["Month"] = pd.to_datetime(df_melted["Month"], format="%b_%Y")

# Plot trend for selected meter locations with labels
plt.figure(figsize=(14, 6))
ax = sns.lineplot(data=df_melted, x="Month", y="Consumption", hue="Meter_locatio

# Annotate some points with meter location names for clarity
selected_meters = df_melted["Meter_location"].unique()[:5]  # Select 5 sample lo
for meter in selected_meters:
    sub_df = df_melted[df_melted["Meter_location"] == meter]
    last_point = sub_df.iloc[-1]  # Get the last data point for labeling
    plt.text(last_point["Month"], last_point["Consumption"], meter, fontsize=9,

plt.title("Energy Consumption Trend Over Time")
plt.xlabel("Month")
plt.ylabel("Consumption (kWh)")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

In [ ]:

```
# Calculate the mean consumption for each month across all meters
df_mean = df.drop(columns=["Meter_location"]).mean()

# Convert to DataFrame for plotting
df_mean = pd.DataFrame(df_mean, columns=["Mean_Consumption"])
df_mean.index = pd.to_datetime(df_mean.index, format="%b_%Y")  # Convert index t
df_mean = df_mean.sort_index()  # Ensure chronological order

# Plot the mean energy consumption trend
plt.figure(figsize=(14, 6))
plt.plot(df_mean.index, df_mean["Mean_Consumption"], marker='o', linestyle='-',
plt.title("Mean Energy Consumption Trend Over Time")
plt.xlabel("Month")
plt.ylabel("Mean Consumption (kWh)")
plt.xticks(rotation=45)
plt.grid(True)

# Annotate each data point with its corresponding value
for i, txt in enumerate(df_mean["Mean_Consumption"]):
    plt.annotate(f'{txt:.2f}', (df_mean.index[i], df_mean["Mean_Consumption"][i]
                 textcoords="offset points", xytext=(0, 5), ha='center', fontsiz

plt.legend()
plt.show()
```

```
# Display the data in tabular form
df_mean_display = df_mean.reset_index().rename(columns={"index": "Month"})

# Show the data
import ace_tools as tools
tools.display_dataframe_to_user(name="Mean Energy Consumption Data", dataframe=d
```

In [ ]:
```
# Calculate the mean consumption for each meter location across all months
df_meter_mean = df.set_index("Meter_location").mean(axis=1)

# Convert to DataFrame for plotting
df_meter_mean = pd.DataFrame(df_meter_mean, columns=["Mean_Consumption"])

# Sort the data for better visualization
df_meter_mean = df_meter_mean.sort_values(by="Mean_Consumption", ascending=False

# Plot the mean consumption for each meter location
plt.figure(figsize=(14, 6))
colors = plt.cm.viridis(np.linspace(0, 1, len(df_meter_mean)))  # Generate uniqu
plt.bar(df_meter_mean.index, df_meter_mean["Mean_Consumption"], color=colors)

# Formatting the plot
plt.xticks(rotation=90, fontsize=8)  # Rotate meter locations for better readabi
plt.ylabel("Mean Consumption (kWh)")
plt.xlabel("Meter Location")
plt.title("Mean Energy Consumption Per Meter Location (Jan 2022 - Dec 2024)")
plt.grid(axis="y")

# Show the plot
plt.show()

# Display the mean consumption data for each meter location
import ace_tools as tools
tools.display_dataframe_to_user(name="Mean Consumption Per Meter Location", data
```

In [ ]:
```
# Calculate the mean consumption for each meter location across all months
df_meter_mean = df.set_index("Meter_location").mean(axis=1)

# Convert to DataFrame for plotting
df_meter_mean = pd.DataFrame(df_meter_mean, columns=["Mean_Consumption"])

# Sort the data for better visualization
df_meter_mean = df_meter_mean.sort_values(by="Mean_Consumption", ascending=False

# Define consumption ranges based on quantiles
high_threshold = df_meter_mean["Mean_Consumption"].quantile(0.67)  # Top 33% as
low_threshold = df_meter_mean["Mean_Consumption"].quantile(0.33)   # Bottom 33%

# Split data into three categories
high_consumption = df_meter_mean[df_meter_mean["Mean_Consumption"] >= high_thres
medium_consumption = df_meter_mean[(df_meter_mean["Mean_Consumption"] < high_thr
                                   (df_meter_mean["Mean_Consumption"] >= low_thr
low_consumption = df_meter_mean[df_meter_mean["Mean_Consumption"] < low_threshol

# Function to plot consumption categories with solid colors
def plot_consumption_solid(data, title, color):
    plt.figure(figsize=(14, 6))
    plt.bar(data.index, data["Mean_Consumption"], color=color)
```

```
    plt.xticks(rotation=90, fontsize=8)  # Rotate meter locations for better rea
    plt.ylabel("Mean Consumption (kWh)")
    plt.xlabel("Meter Location")
    plt.title(title)
    plt.grid(axis="y")

    plt.show()

# Plot each category separately with solid colors
plot_consumption_solid(high_consumption, "High Energy Consumption Meters", "red"
plot_consumption_solid(medium_consumption, "Medium Energy Consumption Meters", "
plot_consumption_solid(low_consumption, "Low Energy Consumption Meters", "green"

# Display the categorized data tables
import ace_tools as tools
tools.display_dataframe_to_user(name="High Consumption Meters", dataframe=high_c
tools.display_dataframe_to_user(name="Medium Consumption Meters", dataframe=medi
tools.display_dataframe_to_user(name="Low Consumption Meters", dataframe=low_con
```

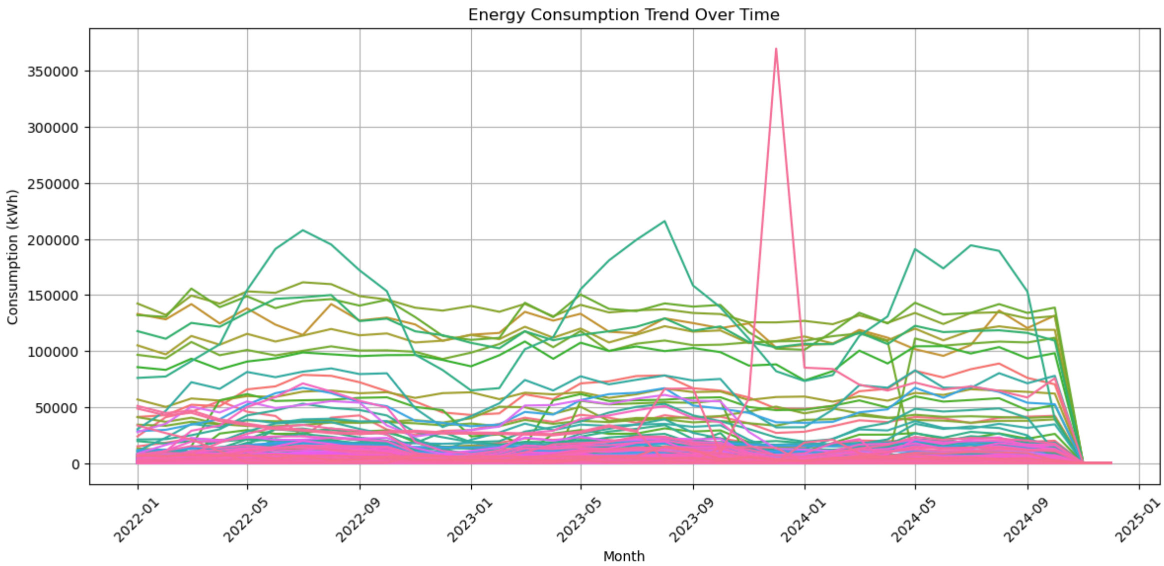
In [ ]:

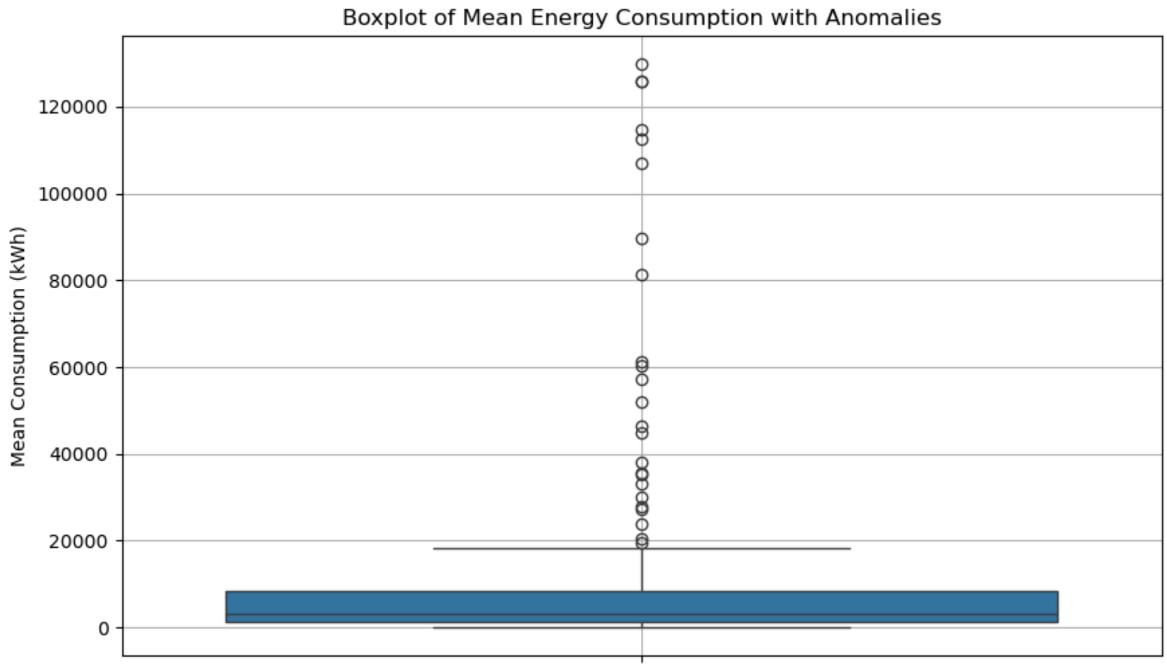
```
# Calculate the mean consumption for each meter location across all months
df_meter_mean = df.set_index("Meter_location").mean(axis=1)
df_meter_mean = pd.DataFrame(df_meter_mean, columns=["Mean_Consumption"])

# 1. **Z-Score Method for Anomaly Detection**
df_meter_mean["Z_Score"] = (df_meter_mean["Mean_Consumption"] - df_meter_mean["M
df_meter_mean["Z_Anomaly"] = df_meter_mean["Z_Score"].apply(lambda x: "Anomaly"

# 2. **IQR (Interquartile Range) Method**
Q1 = df_meter_mean["Mean_Consumption"].quantile(0.25)
Q3 = df_meter_mean["Mean_Consumption"].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

df_meter_mean["IQR_Anomaly"] = df_meter_mean["Mean_Consumption"].apply(lambda x:

# 3. **Isolation Forest for Anomaly Detection**
iso_forest = IsolationForest(contamination=0.05, random_state=42)  # 5% contamin
df_meter_mean["IsoForest_Anomaly"] = iso_forest.fit_predict(df_meter_mean[["Mean
df_meter_mean["IsoForest_Anomaly"] = df_meter_mean["IsoForest_Anomaly"].apply(la

# 4. **Visualizing Anomalies Using Boxplot**
plt.figure(figsize=(10, 6))
sns.boxplot(y=df_meter_mean["Mean_Consumption"])
plt.title("Boxplot of Mean Energy Consumption with Anomalies")
plt.ylabel("Mean Consumption (kWh)")
plt.grid(True)
plt.show()
```

In [20]:

```
# Load the dataset
file_path = "Janitza_UO_F8_X_Cleaned.csv"
df = pd.read_csv(file_path)

# Reshape data for trend analysis
df_melted = df.melt(id_vars=["Meter_location"], var_name="Month", value_name="Co
df_melted["Month"] = pd.to_datetime(df_melted["Month"], format="%b_%Y")

# 1. **Energy Consumption Trend Analysis**
```

```
plt.figure(figsize=(14, 6))
sns.lineplot(data=df_melted, x="Month", y="Consumption", hue="Meter_location", l
plt.title("Energy Consumption Trend Over Time")
plt.xlabel("Month")
plt.ylabel("Consumption (kWh)")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()

# Calculate mean consumption per meter location
df_meter_mean = df.set_index("Meter_location").mean(axis=1)
df_meter_mean = pd.DataFrame(df_meter_mean, columns=["Mean_Consumption"])

# 2. **Anomaly Detection**
# a. Z-Score Method
df_meter_mean["Z_Score"] = (df_meter_mean["Mean_Consumption"] - df_meter_mean["M
df_meter_mean["Z_Anomaly"] = df_meter_mean["Z_Score"].apply(lambda x: "Anomaly"

# b. IQR Method
Q1 = df_meter_mean["Mean_Consumption"].quantile(0.25)
Q3 = df_meter_mean["Mean_Consumption"].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_meter_mean["IQR_Anomaly"] = df_meter_mean["Mean_Consumption"].apply(lambda x:

# c. Isolation Forest Method
iso_forest = IsolationForest(contamination=0.05, random_state=42)
df_meter_mean["IsoForest_Anomaly"] = iso_forest.fit_predict(df_meter_mean[["Mean
df_meter_mean["IsoForest_Anomaly"] = df_meter_mean["IsoForest_Anomaly"].apply(la

# Visualize anomalies using a boxplot
plt.figure(figsize=(10, 6))
sns.boxplot(y=df_meter_mean["Mean_Consumption"])
plt.title("Boxplot of Mean Energy Consumption with Anomalies")
plt.ylabel("Mean Consumption (kWh)")
plt.grid(True)
plt.show()

# Extract detected anomalies
anomalies = df_meter_mean[(df_meter_mean["Z_Anomaly"] == "Anomaly") |
                          (df_meter_mean["IQR_Anomaly"] == "Anomaly") |
                          (df_meter_mean["IsoForest_Anomaly"] == "Anomaly")]

# Save anomalies to a CSV file
anomalies.to_csv("anomalies_detected.csv")
print("Anomalies saved to 'anomalies_detected.csv'")
# 3. **Clustering Analysis (K-Means)**
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df_meter_mean[["Mean_Consumption"]])

# Apply K-Means Clustering
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
df_meter_mean["Cluster"] = kmeans.fit_predict(df_scaled)
```






```
Anomalies saved to 'anomalies_detected.csv'
```

In [18]:

```
# Visualize clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_meter_mean, x=df_meter_mean.index, y=df_meter_mean["Mean
plt.title("Cluster Formation of Meter Locations Based on Energy Consumption")
plt.xlabel("Meter Location")
plt.ylabel("Mean Consumption (kWh)")
plt.xticks(rotation=90, fontsize=8)
plt.legend(title="Cluster")
plt.grid(True)
plt.show()

# Save clustered data
df_meter_mean.to_csv("clustered_meter_data.csv")
print("Clustered data saved to 'clustered_meter_data.csv'")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[18], line 3
      1 # Visualize clusters
      2 plt.figure(figsize=(10, 6))
----> 3 sns.scatterplot(data=df_meter_mean, x=df_meter_mean.index, y=df_meter_mea
n["Mean_Consumption"], hue=df_meter_mean["Cluster"], palette="viridis")
      4 plt.title("Cluster Formation of Meter Locations Based on Energy Consumpti
on")
      5 plt.xlabel("Meter Location")

NameError: name 'df_meter_mean' is not defined
<Figure size 1000x600 with 0 Axes>
```

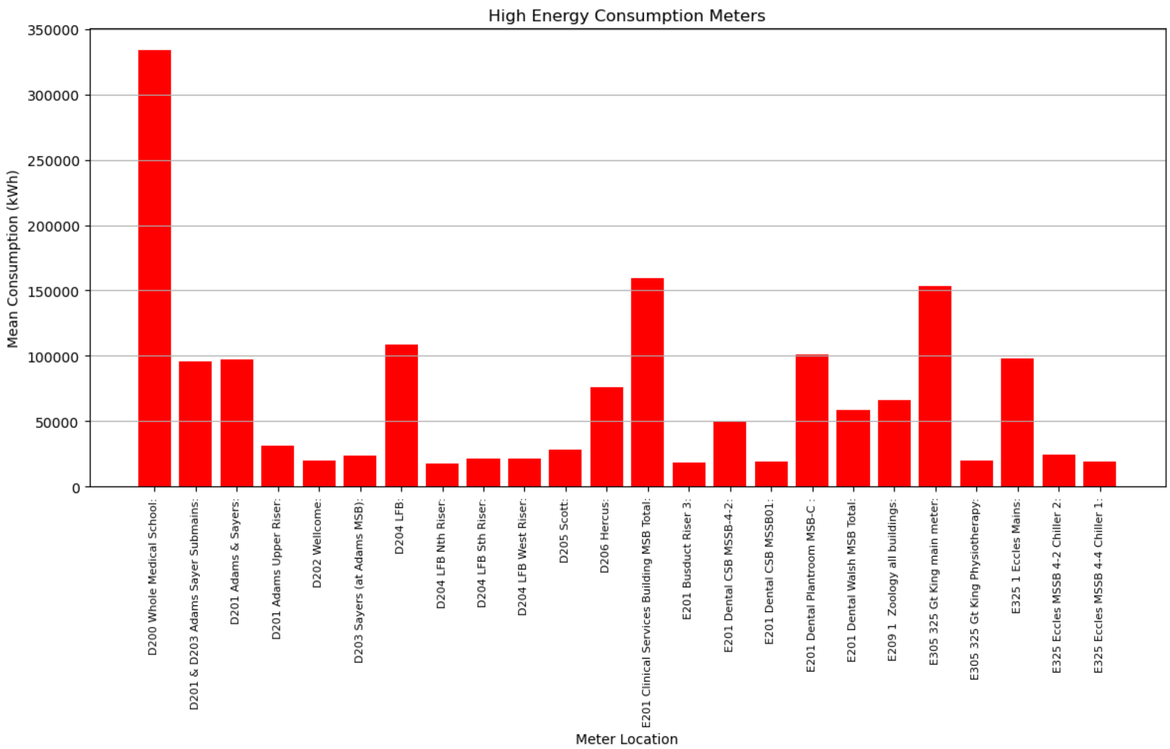
In [ ]:

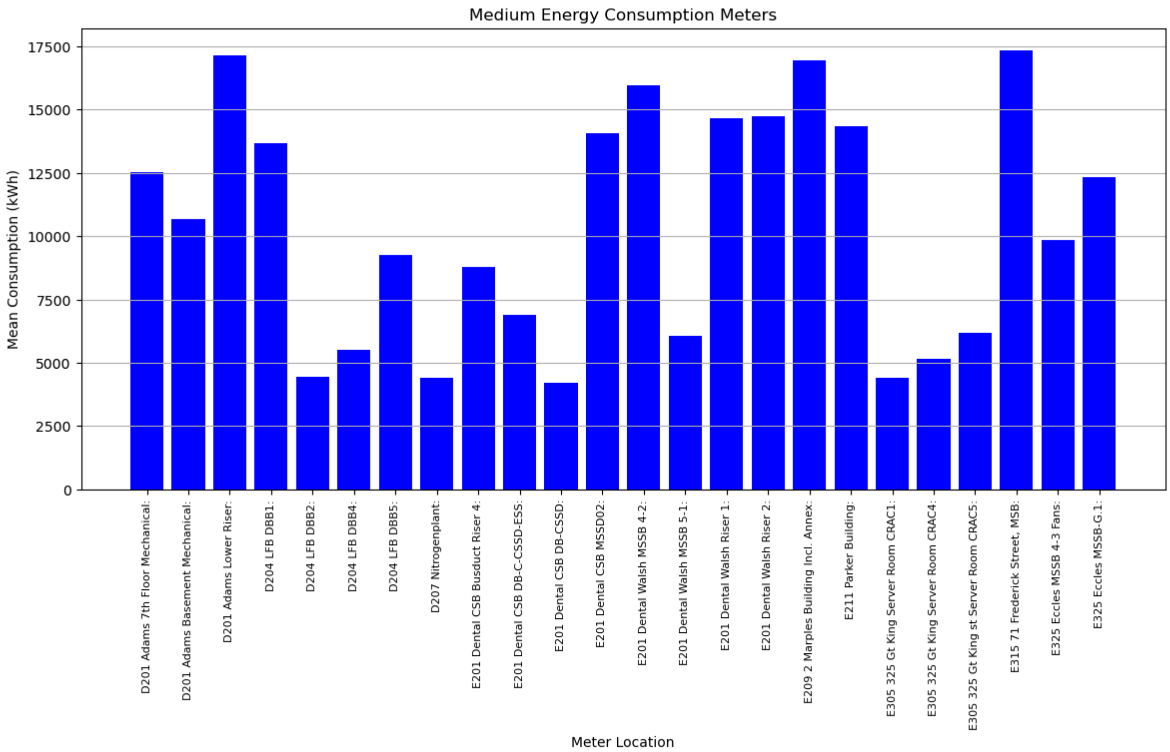
```
# Extract and display the detected anomalies
anomalies = df_meter_mean[(df_meter_mean["Z_Anomaly"] == "Anomaly") |
                          (df_meter_mean["IQR_Anomaly"] == "Anomaly") |
                          (df_meter_mean["IsoForest_Anomaly"] == "Anomaly")]

# Display the first few anomalies
print("Detected Anomalies:")
print(anomalies.head())

# Save anomalies to a CSV file for further review
anomalies.to_csv("anomalies_detected.csv", index=True)
print("Anomalies saved to 'anomalies_detected.csv'")
```

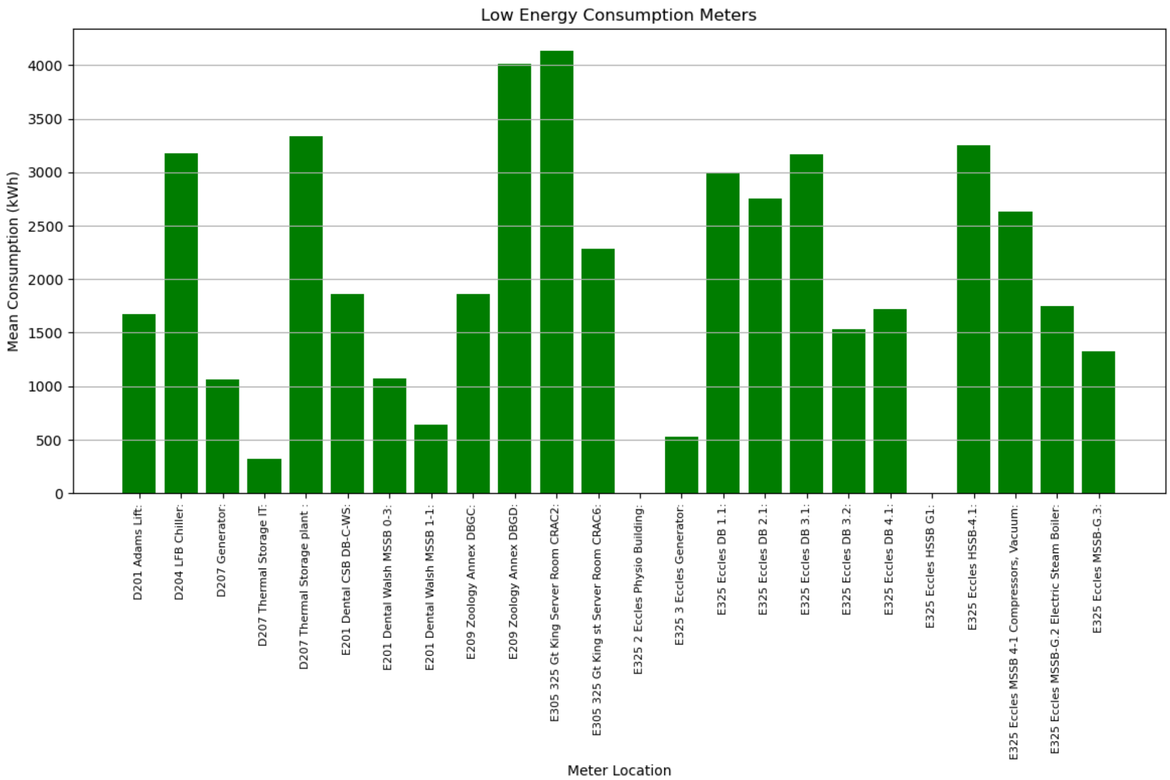
In [28]:

```
# Calculate the mean consumption for each meter location across all months
df_meter_mean = df.set_index("Meter_location").mean(axis=1)
df_meter_mean = pd.DataFrame(df_meter_mean, columns=["Mean_Consumption"])

# Define consumption ranges based on quantiles
high_threshold = df_meter_mean["Mean_Consumption"].quantile(0.67)  # Top 33% as
low_threshold = df_meter_mean["Mean_Consumption"].quantile(0.33)   # Bottom 33%

# Split data into three categories
high_consumption = df_meter_mean[df_meter_mean["Mean_Consumption"] >= high_thres
medium_consumption = df_meter_mean[(df_meter_mean["Mean_Consumption"] < high_thr
                                   (df_meter_mean["Mean_Consumption"] >= low_thr
low_consumption = df_meter_mean[df_meter_mean["Mean_Consumption"] < low_threshol

# Function to plot consumption categories with solid colors
def plot_consumption_solid(data, title, color):
    plt.figure(figsize=(14, 6))
    plt.bar(data.index, data["Mean_Consumption"], color=color)

    plt.xticks(rotation=90, fontsize=8)  # Rotate meter locations for better rea
    plt.ylabel("Mean Consumption (kWh)")
    plt.xlabel("Meter Location")
    plt.title(title)
    plt.grid(axis="y")

    plt.show()

# Plot each category separately with solid colors
plot_consumption_solid(high_consumption, "High Energy Consumption Meters", "red"
plot_consumption_solid(medium_consumption, "Medium Energy Consumption Meters", "
plot_consumption_solid(low_consumption, "Low Energy Consumption Meters", "green"
```

```python
# Save categorized data for further analysis
high_consumption.to_csv("high_consumption_meters.csv")
medium_consumption.to_csv("medium_consumption_meters.csv")
low_consumption.to_csv("low_consumption_meters.csv")

print("High, Medium, and Low consumption data saved as CSV files.")

# Display the categorized data
import ace_tools as tools
tools.display_dataframe_to_user(name="High Consumption Meters", dataframe=high_c
tools.display_dataframe_to_user(name="Medium Consumption Meters", dataframe=medi
tools.display_dataframe_to_user(name="Low Consumption Meters", dataframe=low_con
```








```
High, Medium, and Low consumption data saved as CSV files.
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[28], line 41
     38 print("High, Medium, and Low consumption data saved as CSV files.")
     40 # Display the categorized data
---> 41 import ace_tools as tools
     42 tools.display_dataframe_to_user(name="High Consumption Meters", dataframe
=high_consumption)
     43 tools.display_dataframe_to_user(name="Medium Consumption Meters", datafra
me=medium_consumption)

ModuleNotFoundError: No module named 'ace_tools'
```

In [ ]: