smarttech_wvs

February 23, 2025

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

# Get the notebook's directory
notebook_dir = os.path.abspath('')

# Construct the path to the .csv file
csv_path = os.path.join(notebook_dir, "data",␣
↪"WVS_Cross-National_Wave_7_csv_v6_0.csv")

# Load the .csv file
df = pd.read_csv(csv_path, low_memory=False)

# Display the first few rows
df.head()
```

[2]:
```
# Check the shape of the dataset
print(f"Dataset shape: {df.shape}")

# Check column names
print(df.columns.tolist())

# Check basic info about the dataset
df.info()

# Check for missing values
missing_values = df.isnull().sum()
print("Missing values per column:")
print(missing_values[missing_values > 0])
```

```
Dataset shape: (97220, 613)
['version', 'doi', 'A_WAVE', 'A_YEAR', 'A_STUDY', 'B_COUNTRY',
'B_COUNTRY_ALPHA', 'C_COW_NUM', 'C_COW_ALPHA', 'D_INTERVIEW', 'S007',
'J_INTDATE', 'FW_START', 'FW_END', 'K_TIME_START', 'K_TIME_END', 'K_DURATION',
'Q_MODE', 'N_REGION_ISO', 'N_REGION_WVS', 'N_REGION_NUTS2', 'N_REG_NUTS1',
```

```
'N_TOWN', 'G_TOWNSIZE', 'G_TOWNSIZE2', 'H_SETTLEMENT', 'H_URBRURAL', 'I_PSU',
'O1_LONGITUDE', 'O2_LATITUDE', 'L_INTERVIEWER_NUMBER', 'S_INTLANGUAGE',
'LNGE_ISO', 'E_RESPINT', 'F_INTPRIVACY', 'E1_LITERACY', 'W_WEIGHT', 'S018',
'PWGHT', 'S025', 'Q1', 'Q2', 'Q3', 'Q4', 'Q5', 'Q6', 'Q7', 'Q8', 'Q9', 'Q10',
'Q11', 'Q12', 'Q13', 'Q14', 'Q15', 'Q16', 'Q17', 'Q18', 'Q19', 'Q20', 'Q21',
'Q22', 'Q23', 'Q24', 'Q25', 'Q26', 'Q27', 'Q28', 'Q29', 'Q30', 'Q31', 'Q32',
'Q33', 'Q33_3', 'Q34', 'Q34_3', 'Q35', 'Q35_3', 'Q36', 'Q37', 'Q38', 'Q39',
'Q40', 'Q41', 'Q42', 'Q43', 'Q44', 'Q45', 'Q46', 'Q47', 'Q48', 'Q49', 'Q50',
'Q51', 'Q52', 'Q53', 'Q54', 'Q55', 'Q56', 'Q57', 'Q58', 'Q59', 'Q60', 'Q61',
'Q62', 'Q63', 'Q64', 'Q65', 'Q66', 'Q67', 'Q68', 'Q69', 'Q70', 'Q71', 'Q72',
'Q73', 'Q74', 'Q75', 'Q76', 'Q77', 'Q78', 'Q79', 'Q80', 'Q81', 'Q82',
'Q82_AFRICANUNION', 'Q82_APEC', 'Q82_ARABLEAGUE', 'Q82_ASEAN', 'Q82_CIS',
'Q82_CUSMA', 'Q82_ECO', 'Q82_EU', 'Q82_GULFCOOP', 'Q82_ISLCOOP', 'Q82_MERCOSUR',
'Q82_NAFTA', 'Q82_OAS', 'Q82_SAARC', 'Q82_SCO', 'Q82_TLC', 'Q82_UNDP', 'Q83',
'Q84', 'Q85', 'Q86', 'Q87', 'Q88', 'Q89', 'Q90', 'Q91', 'Q92', 'Q93', 'Q94',
'Q94R', 'Q95', 'Q95R', 'Q96', 'Q96R', 'Q97', 'Q97R', 'Q98', 'Q98R', 'Q99',
'Q99R', 'Q100', 'Q100R', 'Q101', 'Q101R', 'Q102', 'Q102R', 'Q103', 'Q103R',
'Q104', 'Q104R', 'Q105', 'Q105R', 'Q106', 'Q107', 'Q108', 'Q109', 'Q110',
'Q111', 'Q112', 'Q113', 'Q114', 'Q115', 'Q116', 'Q117', 'Q118', 'Q119', 'Q120',
'Q121', 'Q122', 'Q123', 'Q124', 'Q125', 'Q126', 'Q127', 'Q128', 'Q129', 'Q130',
'Q131', 'Q132', 'Q133', 'Q134', 'Q135', 'Q136', 'Q137', 'Q138', 'Q139', 'Q140',
'Q141', 'Q142', 'Q143', 'Q144', 'Q145', 'Q146', 'Q147', 'Q148', 'Q149', 'Q150',
'Q151', 'Q152', 'Q153', 'Q154', 'Q155', 'Q156', 'Q157', 'Q158', 'Q159', 'Q160',
'Q161', 'Q162', 'Q163', 'Q164', 'Q165', 'Q166', 'Q167', 'Q168', 'Q169', 'Q170',
'Q171', 'Q172', 'Q172R', 'Q173', 'Q174', 'Q175', 'Q176', 'Q177', 'Q178', 'Q179',
'Q180', 'Q181', 'Q182', 'Q183', 'Q184', 'Q185', 'Q186', 'Q187', 'Q188', 'Q189',
'Q190', 'Q191', 'Q192', 'Q193', 'Q194', 'Q195', 'Q196', 'Q197', 'Q198', 'Q199',
'Q200', 'Q201', 'Q202', 'Q203', 'Q204', 'Q205', 'Q206', 'Q207', 'Q208', 'Q209',
'Q210', 'Q211', 'Q212', 'Q213', 'Q214', 'Q215', 'Q216', 'Q217', 'Q218', 'Q219',
'Q220', 'Q221', 'Q222', 'Q223', 'Q223_ABREV', 'Q223_LOCAL', 'Q224', 'Q225',
'Q226', 'Q227', 'Q228', 'Q229', 'Q230', 'Q231', 'Q232', 'Q233', 'Q234', 'Q234A',
'Q235', 'Q236', 'Q237', 'Q238', 'Q239', 'Q240', 'Q241', 'Q242', 'Q243', 'Q244',
'Q245', 'Q246', 'Q247', 'Q248', 'Q249', 'Q250', 'Q251', 'Q252', 'Q253', 'Q254',
'Q255', 'Q256', 'Q257', 'Q258', 'Q259', 'Q260', 'Q261', 'Q262', 'X003R',
'X003R2', 'Q263', 'Q264', 'V002', 'Q265', 'V001', 'Q266', 'X002_02B', 'Q267',
'V002A_01', 'Q268', 'V001A_01', 'Q269', 'Q270', 'Q271', 'Q272', 'Q273', 'Q274',
'Q275', 'Q275A', 'Q275R', 'Q276', 'Q276A', 'Q276R', 'Q277', 'Q277A', 'Q277R',
'Q278', 'Q278A', 'Q278R', 'Q279', 'Q280', 'Q281', 'Q282', 'Q283', 'Q284',
'Q285', 'Q286', 'Q287', 'Q288', 'Q288R', 'Q289', 'Q289CS9', 'Q290', 'Q291G1',
'Q291G2', 'Q291G3', 'Q291G4', 'Q291G5', 'Q291G6', 'Q291P1', 'Q291P2', 'Q291P3',
'Q291P4', 'Q291P5', 'Q291P6', 'Q291UN1', 'Q291UN2', 'Q291UN3', 'Q291UN4',
'Q291UN5', 'Q291UN6', 'Q292A', 'Q292B', 'Q292C', 'Q292D', 'Q292E', 'Q292F',
'Q292G', 'Q292H', 'Q292I', 'Q292J', 'Q292K', 'Q292L', 'Q292M', 'Q292N', 'Q292O',
'Q293', 'Q294A', 'Q294B', 'Y001', 'Y002', 'Y003', 'SACSECVAL', 'RESEMAVAL',
'I_AUTHORITY', 'I_NATIONALISM', 'I_DEVOUT', 'DEFIANCE', 'I_RELIGIMP',
'I_RELIGBEL', 'I_RELIGPRAC', 'DISBELIEF', 'I_NORM1', 'I_NORM2', 'I_NORM3',
'RELATIVISM', 'I_TRUSTARMY', 'I_TRUSTPOLICE', 'I_TRUSTCOURTS', 'SCEPTICISM',
'I_INDEP', 'I_IMAGIN', 'I_NONOBED', 'AUTONOMY', 'I_WOMJOB', 'I_WOMPOL',
```

```
'I_WOMEDU', 'EQUALITY', 'I_HOMOLIB', 'I_ABORTLIB', 'I_DIVORLIB', 'CHOICE',
'I_VOICE1', 'I_VOICE2', 'I_VOI2_00', 'VOICE', 'SECVALWGT', 'RESEMAVALWGT',
'fhregion', 'polregfh', 'freestfh', 'prfhrat', 'prfhscore', 'clfhrat',
'clfhscore', 'democ', 'autoc', 'polity', 'durable', 'regtype', 'ruleoflaw',
'corrupttransp', 'electintegr', 'btiregion', 'btistatus', 'btidemstatus',
'btistate', 'btipolpart', 'btiruleoflaw', 'btistability', 'btiintegration',
'btimarket', 'btigovindex', 'btigoveperform', 'btiregime', 'regionWB',
'incomeWB', 'landWB', 'GDPpercap1', 'GDPpercap2', 'giniWB', 'incrichest10p',
'popWB1990', 'popWB2000', 'popWB2019', 'lifeexpect', 'popgrowth', 'urbanpop',
'laborforce', 'deathrate', 'unemployfem', 'unemploymale', 'unemploytotal',
'accessclfuel', 'accesselectr', 'renewelectr', 'co2emis', 'co2percap',
'easeofbusiness', 'militaryexp', 'Trade', 'healthexp', 'educationexp',
'medageun', 'meanschooling', 'educationHDI', 'compulseduc', 'GII', 'DGI',
'womenparl', 'hdi', 'incomeindexHDI', 'humanineqiality', 'lifeexpectHDI',
'homiciderate', 'Refugeesorigin', 'internetusers', 'mobphone', 'migrationrate',
'schoolgpi', 'femchoutsch', 'choutsch', 'v2x_polyarchy', 'v2x_libdem',
'v2x_partipdem', 'v2x_delibdem', 'v2x_egaldem', 'v2x_freexp_altinf',
'v2x_frassoc_thick', 'v2xel_frefair', 'v2xcl_rol', 'v2x_cspart', 'v2xeg_eqdr',
'v2excrptps', 'v2exthftps', 'v2juaccnt', 'v2cltrnslw', 'v2clacjust',
'v2clsocgrp', 'v2clacfree', 'v2clrelig', 'v2csrlgrep', 'v2mecenefm',
'v2mecenefi', 'v2mebias', 'v2pepwrses', 'v2pepwrgen', 'v2peedueq', 'v2pehealth',
'v2peapsecon', 'v2peasjsoecon', 'v2clgencl', 'v2peasjgen', 'v2peasbgen',
'v2cafres', 'v2cafexch', 'v2x_corr', 'v2x_gender', 'v2x_gencl', 'v2x_genpp',
'v2x_rule', 'v2xcl_acjst', 'td_voiacc', 'td_polstab', 'td_goveff', 'td_regqual',
'td_rulelaw', 'td_ctrlcorr', 'ID_GPS', 'ID_PartyFacts', 'Partyname', 'Partyabb',
'CPARTY', 'CPARTYABB', 'Type_Values', 'Type_Populism', 'Type_Populist_Values',
'Type_Partysize_vote', 'Type_Partysize_seat', 'GPS_V4_Scale', 'GPS_V6_Scale',
'GPS_V8_Scale', 'GPS_V9', 'GPS_V10', 'GPS_V11', 'GPS_V12', 'GPS_V13', 'GPS_V14',
'GPS_V15', 'GPS_V16', 'GPS_V17', 'WVS_LR_PartyVoter', 'WVS_LibCon_PartyVoter',
'WVS_Polmistrust_PartyVoter', 'WVS_LR_MedianVoter', 'WVS_LibCon_MedianVoter',
'v2psbars', 'v2psorgs', 'v2psprbrch', 'v2psprlnks', 'v2psplats', 'v2xnp_client',
'v2xps_party']
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 97220 entries, 0 to 97219
Columns: 613 entries, version to v2xps_party
dtypes: float64(195), int64(406), object(12)
memory usage: 454.7+ MB
Missing values per column:
N_TOWN              1
O1_LONGITUDE        4
O2_LATITUDE         4
SACSECVAL         480
RESEMAVAL         748
                ...
v2psprbrch      93302
v2psprlnks      93302
v2psplats       93302
v2xnp_client    93302
```

```
v2xps_party     93302
Length: 192, dtype: int64
```

[3]:

```
# Summary statistics for numerical columns
print(df.describe())

# Summary statistics for categorical columns
print(df.describe(include='object'))
```

```
        A_WAVE       A_YEAR  A_STUDY     B_COUNTRY     C_COW_NUM  \
count  97220.0  97220.000000  97220.0  97220.000000  97220.000000
mean       7.0   2019.132082      2.0    447.872146    476.555153
std        0.0      1.601004      0.0    256.491312    288.386918
min        7.0   2017.000000      2.0     20.000000      2.000000
25%        7.0   2018.000000      2.0    218.000000    201.000000
50%        7.0   2018.000000      2.0    422.000000    552.000000
75%        7.0   2020.000000      2.0    688.000000    714.000000
max        7.0   2023.000000      2.0    909.000000    920.000000

        D_INTERVIEW          S007     J_INTDATE       FW_START        FW_END  \
count  9.722000e+04  9.722000e+04  9.722000e+04   97220.000000   97220.000000
mean   4.479431e+08  4.485726e+08  1.905207e+07  201901.606881  201919.989683
std    2.564912e+08  2.564602e+08  4.658281e+06     160.980181     160.412353
min    2.007000e+07  2.072000e+07 -5.000000e+00  201701.000000  201703.000000
25%    2.180700e+08  2.187200e+08  2.018022e+07  201804.000000  201806.000000
50%    4.220707e+08  4.227207e+08  2.018111e+07  201811.000000  201812.000000
75%    6.880703e+08  6.887203e+08  2.020041e+07  202003.000000  202010.000000
max    9.090704e+08  9.090704e+08  2.023070e+07  202306.000000  202307.000000

       ...  WVS_Polmistrust_PartyVoter  WVS_LR_MedianVoter  \
count  ...                 3918.000000         3918.000000
mean   ...                   67.689823         -331.856360
std    ...                    9.814691          474.786005
min    ...                   43.750000         -999.000000
25%    ...                   66.964286         -999.000000
50%    ...                   68.210839            5.420000
75%    ...                   74.000000            5.650000
max    ...                   83.705786            7.260000

       WVS_LibCon_MedianVoter     v2psbars     v2psorgs   v2psprbrch  \
count             3918.000000  3918.000000  3918.000000  3918.000000
mean              -331.510837  -334.689260  -334.827539  -335.095391
std                475.033906   472.769807   472.671155   472.481026
min               -999.000000  -999.000000  -999.000000  -999.000000
25%               -999.000000  -999.000000  -999.000000  -999.000000
50%                  5.083400     0.552000     0.869000    -0.403000
75%                  6.512500     2.043000     1.737000     1.676000
max                  9.402100     2.407000     1.737000     1.676000
```

```
        v2psprlnks    v2psplats  v2xnp_client  v2xps_party
count  3918.000000  3918.000000   3918.000000  3918.000000
mean   -334.788026  -334.811147   -335.648640  -335.268652
std     472.700209   472.683543    472.086732   472.357142
min    -999.000000  -999.000000   -999.000000  -999.000000
25%    -999.000000  -999.000000   -999.000000  -999.000000
50%      -0.107000    -0.099000      0.059000     0.591000
75%       2.525000     2.354000      0.459000     0.927000
max       2.525000     2.354000      0.624000     0.927000

[8 rows x 601 columns]
                   version                          doi B_COUNTRY_ALPHA  \
count                97220                        97220           97220
unique                   1                            1              66
top     6-0-0 (2024-04-30)  doi.org/10.14281/18241.24             CAN
freq                 97220                        97220            4018

       C_COW_ALPHA LNGE_ISO X002_02B V002A_01 V001A_01   Partyname Partyabb  \
count        97220    97220    97220    97220    97220       34808     2601
unique          66       52      158      163      158          21       10
top            CAN       es       CA       -4       -4  Don´t know       LP
freq          4018    16190     3329     6092     6092       10193      676

                                 CPARTY CPARTYABB
count                              2601      2601
unique                               10        10
top     AUS_ Liberal Party of Australia   AUS_ LP
freq                                676       676
```

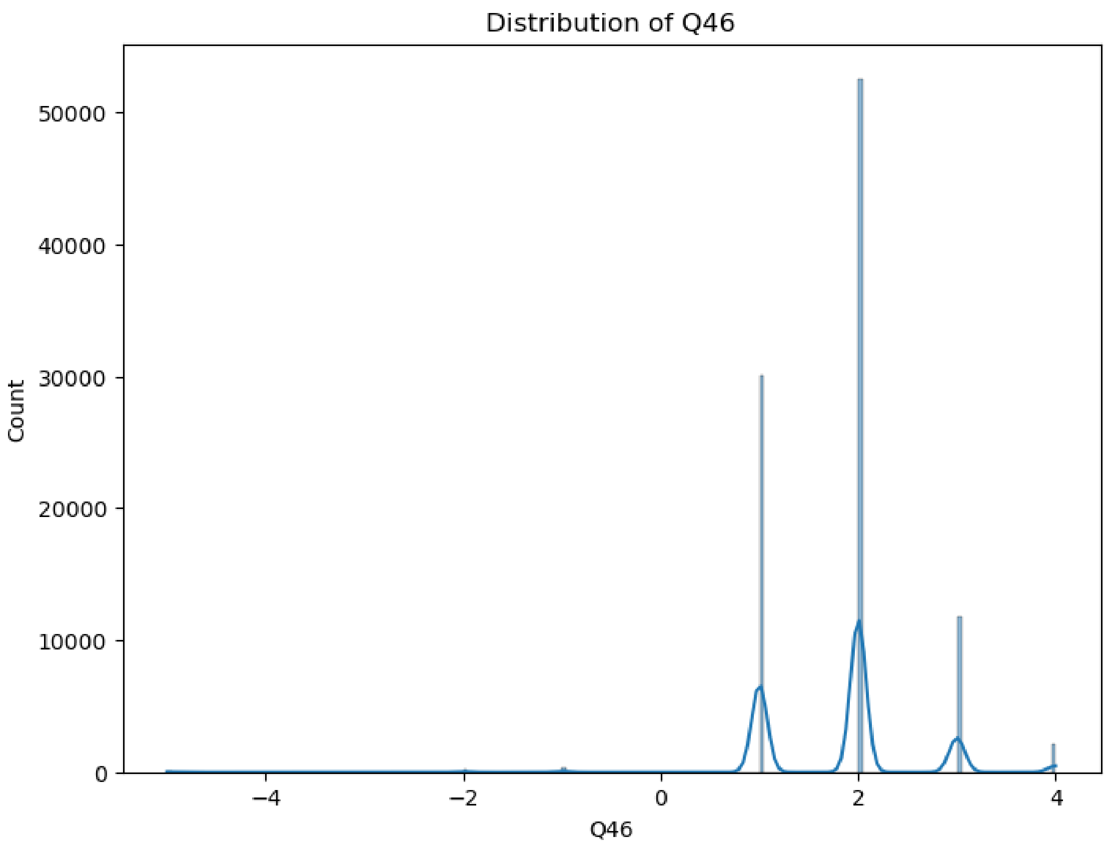
[4]:

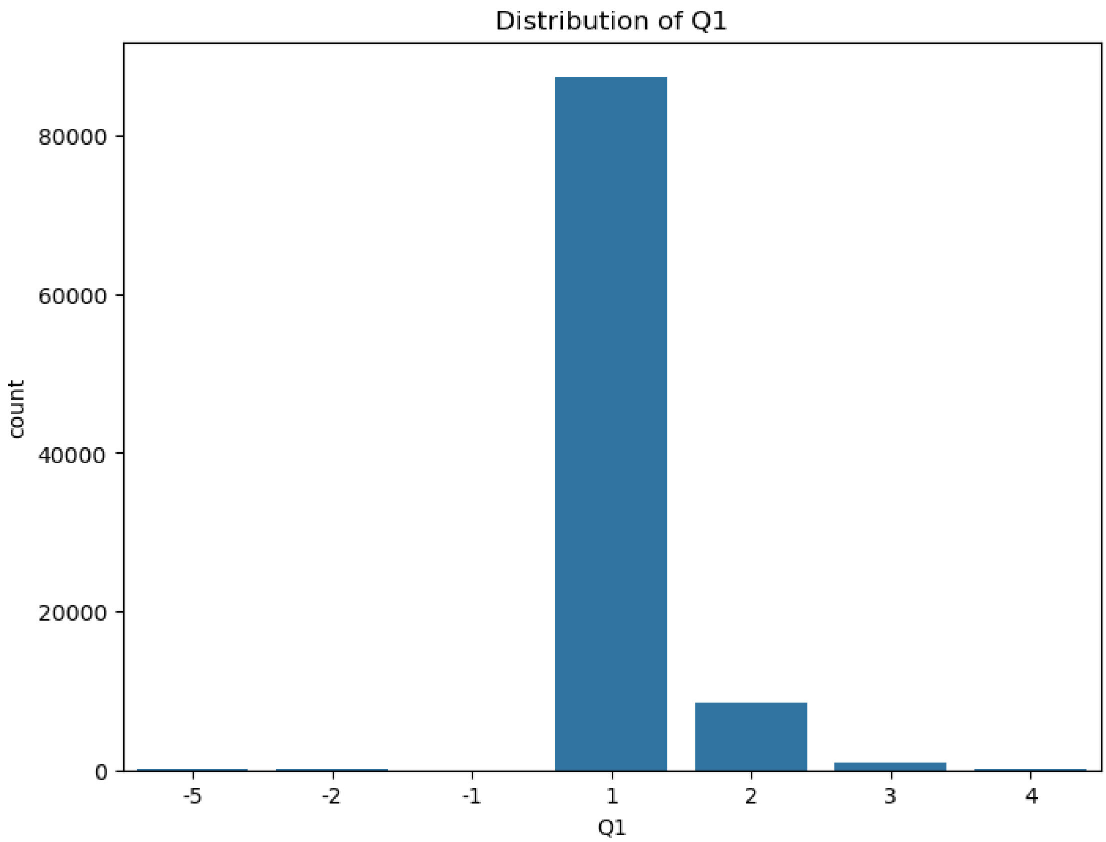
```python
# Example: Explore columns related to economic values
economic_columns = ['Q46', 'Q47', 'Q48', 'Q49', 'Q50']  # Replace with actual␣
 ↪column names
print(df[economic_columns].head())

# Example: Explore columns related to societal values
societal_columns = ['Q1', 'Q2', 'Q3', 'Q4', 'Q5']  # Replace with actual column␣
 ↪names
print(df[societal_columns].head())
```

```
   Q46  Q47  Q48  Q49  Q50
0    1    3   10   10    5
1    1    1    9    9    9
2    2    1    9    9    8
3    2    2    9    8    6
4    2    2    8    7    7
   Q1  Q2  Q3  Q4  Q5
0   1   1   1   3   1
```

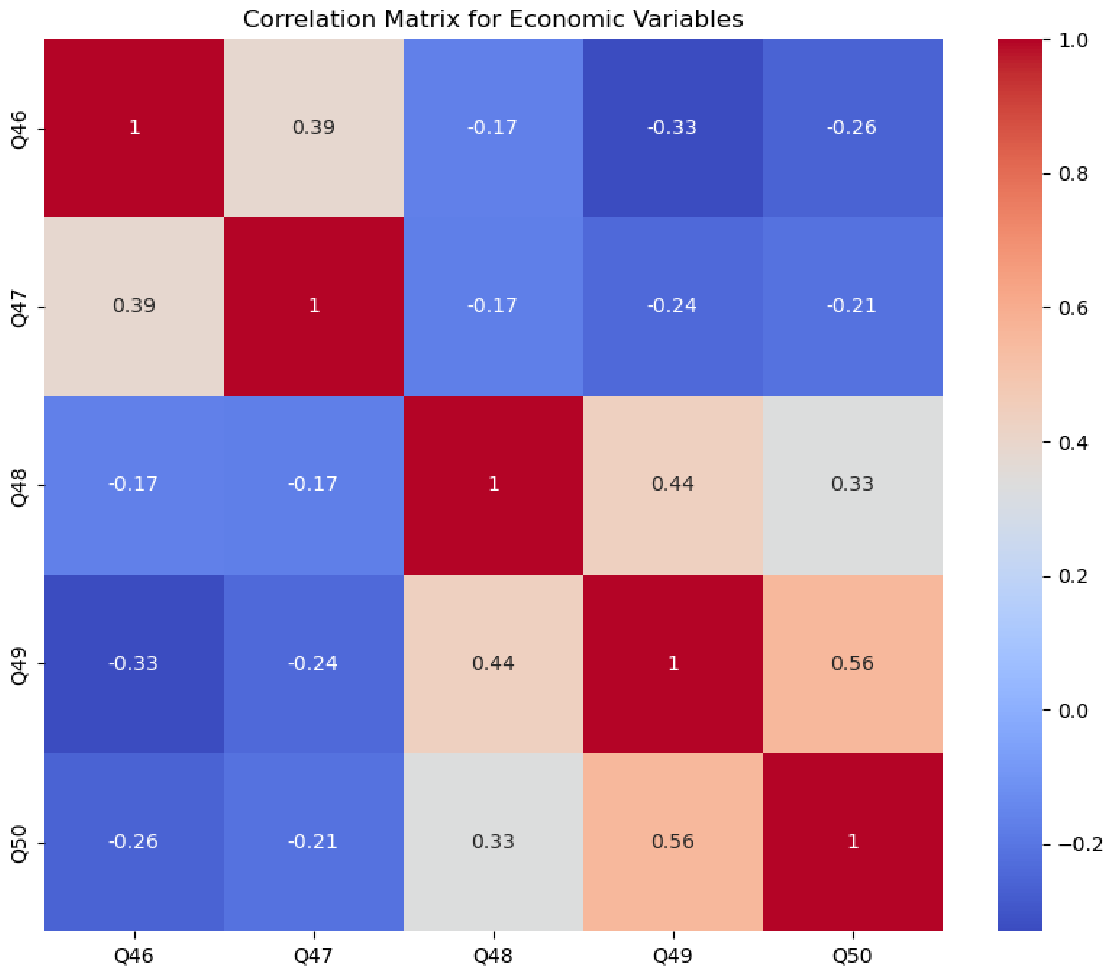
1	1	1	1	4	1
2	1	2	2	2	3
3	1	1	1	4	2
4	1	1	1	3	1

[5]:
```
# Example: Histogram for a numerical column
plt.figure(figsize=(8, 6))
sns.histplot(df['Q46'], kde=True)  # Replace 'Q46' with a relevant column
plt.title('Distribution of Q46')
plt.show()

# Example: Bar plot for a categorical column
plt.figure(figsize=(8, 6))
sns.countplot(x='Q1', data=df)  # Replace 'Q1' with a relevant column
plt.title('Distribution of Q1')
plt.show()
```



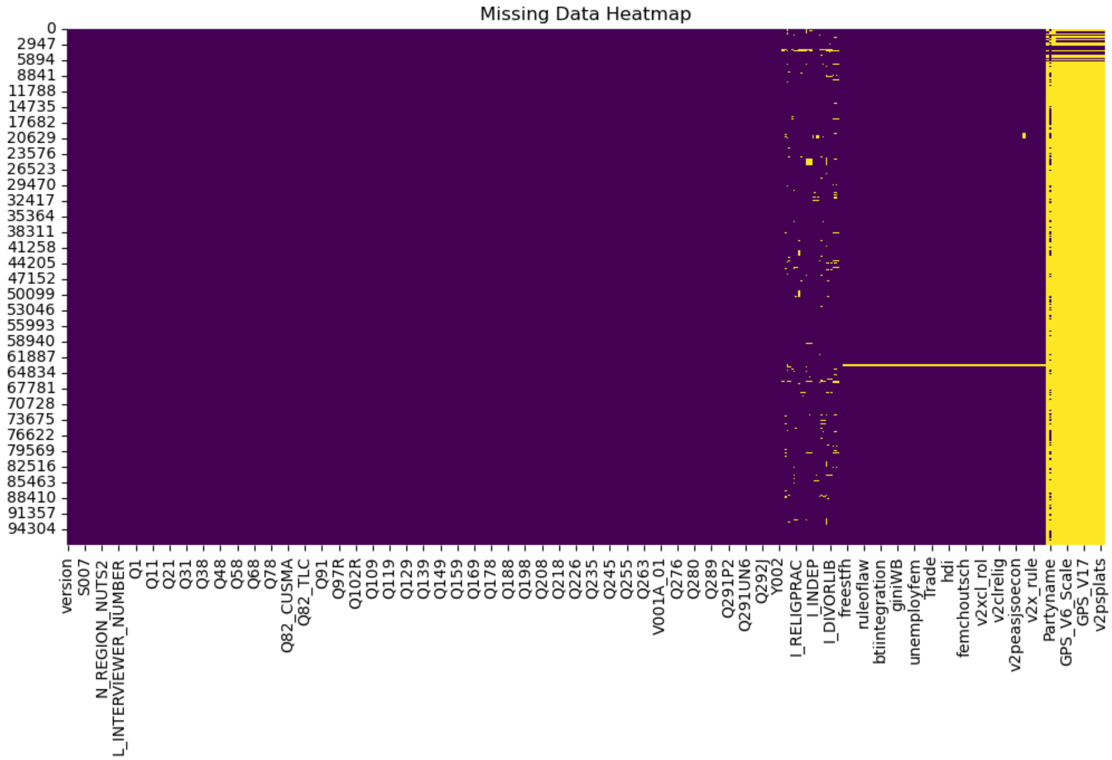


[6]:
```
# Correlation matrix for numerical columns
corr_matrix = df[economic_columns].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix for Economic Variables')
plt.show()
```



[7]:

```
# Visualize missing data
plt.figure(figsize=(12, 6))
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Data Heatmap')
plt.show()
```



[8]:
```python
def generate_summary_statistics(df):
    """
    Generate summary statistics for numerical and categorical columns.
    """
    # Numerical columns
    num_summary = df.describe()

    # Categorical columns
    cat_summary = df.describe(include='object')

    return num_summary, cat_summary

# Example usage
num_summary, cat_summary = generate_summary_statistics(df)
print("Numerical Summary:")
print(num_summary)
print("\nCategorical Summary:")
print(cat_summary)
```

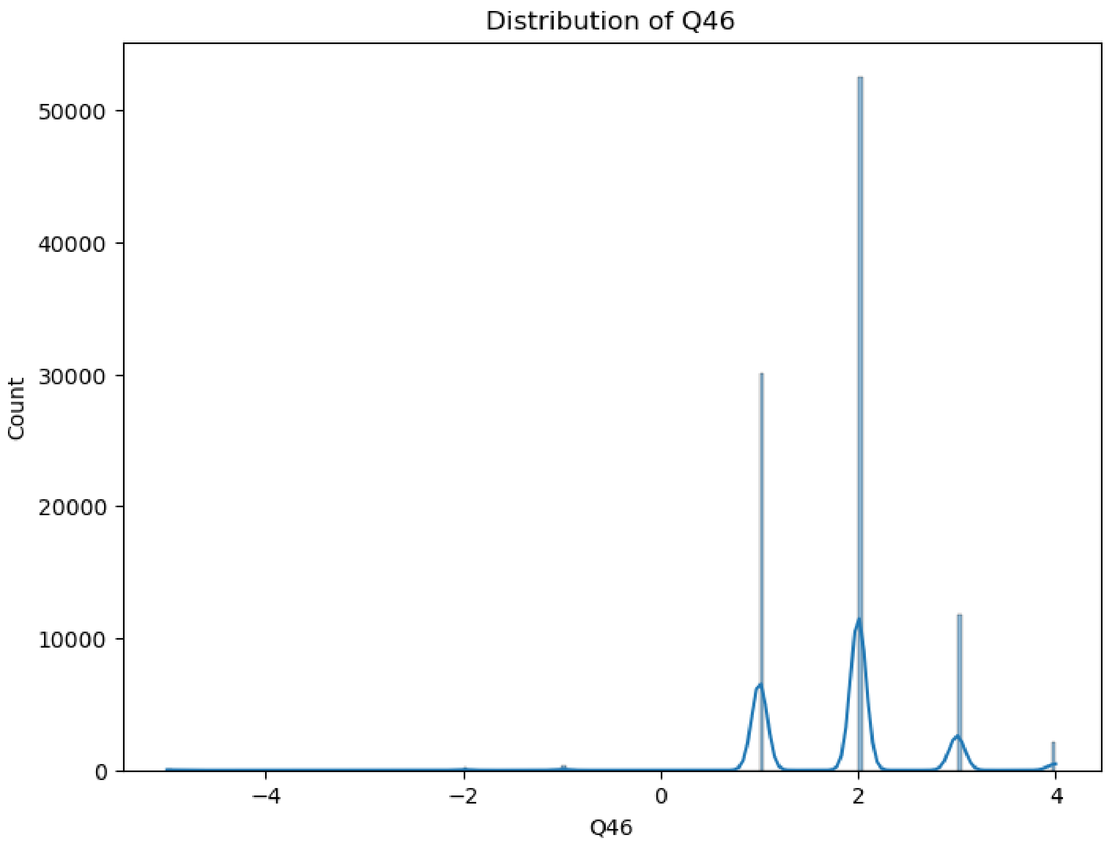
```
Numerical Summary:
        A_WAVE        A_YEAR  A_STUDY     B_COUNTRY     C_COW_NUM  \
count  97220.0  97220.000000  97220.0  97220.000000  97220.000000
mean       7.0   2019.132082      2.0    447.872146    476.555153
```

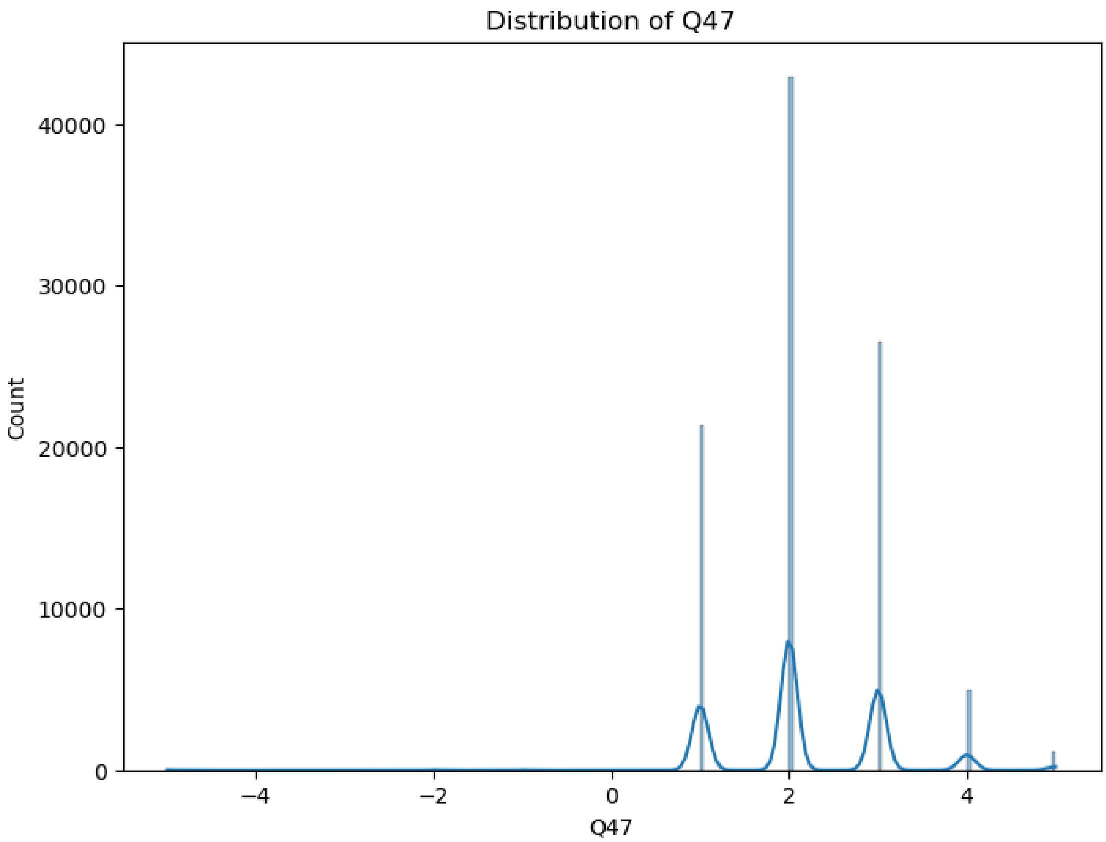
```
std        0.0     1.601004     0.0    256.491312    288.386918
min        7.0  2017.000000     2.0     20.000000      2.000000
25%        7.0  2018.000000     2.0    218.000000    201.000000
50%        7.0  2018.000000     2.0    422.000000    552.000000
75%        7.0  2020.000000     2.0    688.000000    714.000000
max        7.0  2023.000000     2.0    909.000000    920.000000

        D_INTERVIEW          S007     J_INTDATE       FW_START         FW_END  \
count  9.722000e+04  9.722000e+04  9.722000e+04   97220.000000   97220.000000
mean   4.479431e+08  4.485726e+08  1.905207e+07  201901.606881  201919.989683
std    2.564912e+08  2.564602e+08  4.658281e+06     160.980181     160.412353
min    2.007000e+07  2.072000e+07 -5.000000e+00  201701.000000  201703.000000
25%    2.180700e+08  2.187200e+08  2.018022e+07  201804.000000  201806.000000
50%    4.220707e+08  4.227207e+08  2.018111e+07  201811.000000  201812.000000
75%    6.880703e+08  6.887203e+08  2.020041e+07  202003.000000  202010.000000
max    9.090704e+08  9.090704e+08  2.023070e+07  202306.000000  202307.000000

       ...  WVS_Polmistrust_PartyVoter  WVS_LR_MedianVoter  \
count  ...                 3918.000000         3918.000000
mean   ...                   67.689823         -331.856360
std    ...                    9.814691          474.786005
min    ...                   43.750000         -999.000000
25%    ...                   66.964286         -999.000000
50%    ...                   68.210839            5.420000
75%    ...                   74.000000            5.650000
max    ...                   83.705786            7.260000

       WVS_LibCon_MedianVoter     v2psbars     v2psorgs   v2psprbrch  \
count             3918.000000  3918.000000  3918.000000  3918.000000
mean              -331.510837  -334.689260  -334.827539  -335.095391
std                475.033906   472.769807   472.671155   472.481026
min               -999.000000  -999.000000  -999.000000  -999.000000
25%               -999.000000  -999.000000  -999.000000  -999.000000
50%                  5.083400     0.552000     0.869000    -0.403000
75%                  6.512500     2.043000     1.737000     1.676000
max                  9.402100     2.407000     1.737000     1.676000

        v2psprlnks    v2psplats  v2xnp_client  v2xps_party
count  3918.000000  3918.000000   3918.000000  3918.000000
mean   -334.788026  -334.811147   -335.648640  -335.268652
std     472.700209   472.683543    472.086732   472.357142
min    -999.000000  -999.000000   -999.000000  -999.000000
25%    -999.000000  -999.000000   -999.000000  -999.000000
50%      -0.107000    -0.099000      0.059000     0.591000
75%       2.525000     2.354000      0.459000     0.927000
max       2.525000     2.354000      0.624000     0.927000

[8 rows x 601 columns]
```

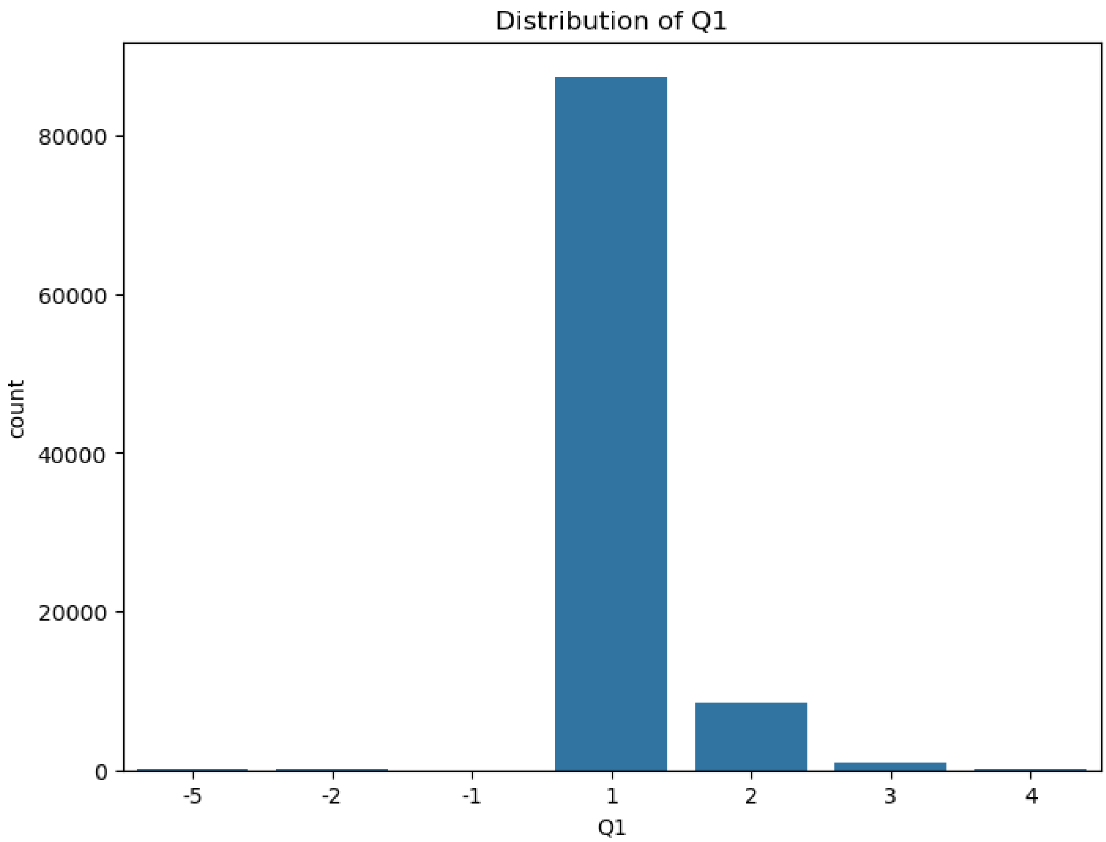
```
Categorical Summary:
                    version                           doi B_COUNTRY_ALPHA  \
count                 97220                         97220           97220
unique                    1                             1              66
top     6-0-0 (2024-04-30)  doi.org/10.14281/18241.24             CAN
freq                  97220                         97220            4018

       C_COW_ALPHA LNGE_ISO X002_02B V002A_01 V001A_01   Partyname Partyabb  \
count        97220    97220    97220    97220    97220       34808     2601
unique          66       52      158      163      158          21       10
top            CAN       es       CA       -4       -4  Don´t know       LP
freq          4018    16190     3329     6092     6092       10193      676

                             CPARTY CPARTYABB
count                          2601      2601
unique                           10        10
top     AUS_ Liberal Party of Australia   AUS_ LP
freq                            676       676
```

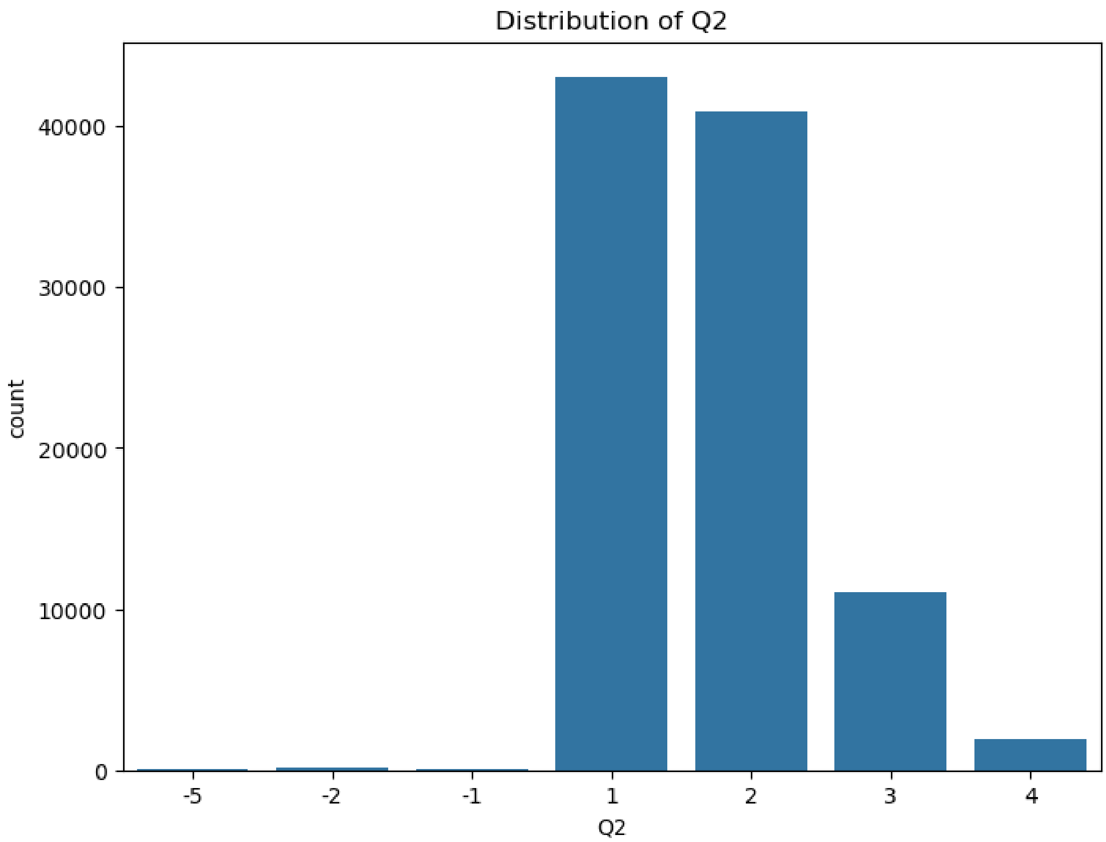
[9]:

```python
def plot_distributions(df, numerical_cols, categorical_cols):
    """
    Plot distributions for numerical and categorical columns.
    """
    # Plot numerical columns
    for col in numerical_cols:
        plt.figure(figsize=(8, 6))
        sns.histplot(df[col], kde=True)
        plt.title(f'Distribution of {col}')
        plt.show()

    # Plot categorical columns
    for col in categorical_cols:
        plt.figure(figsize=(8, 6))
        sns.countplot(x=col, data=df)
        plt.title(f'Distribution of {col}')
        plt.show()

# Example usage
numerical_cols = ['Q46', 'Q47']  # Replace with relevant numerical columns
categorical_cols = ['Q1', 'Q2']  # Replace with relevant categorical columns
plot_distributions(df, numerical_cols, categorical_cols)
```

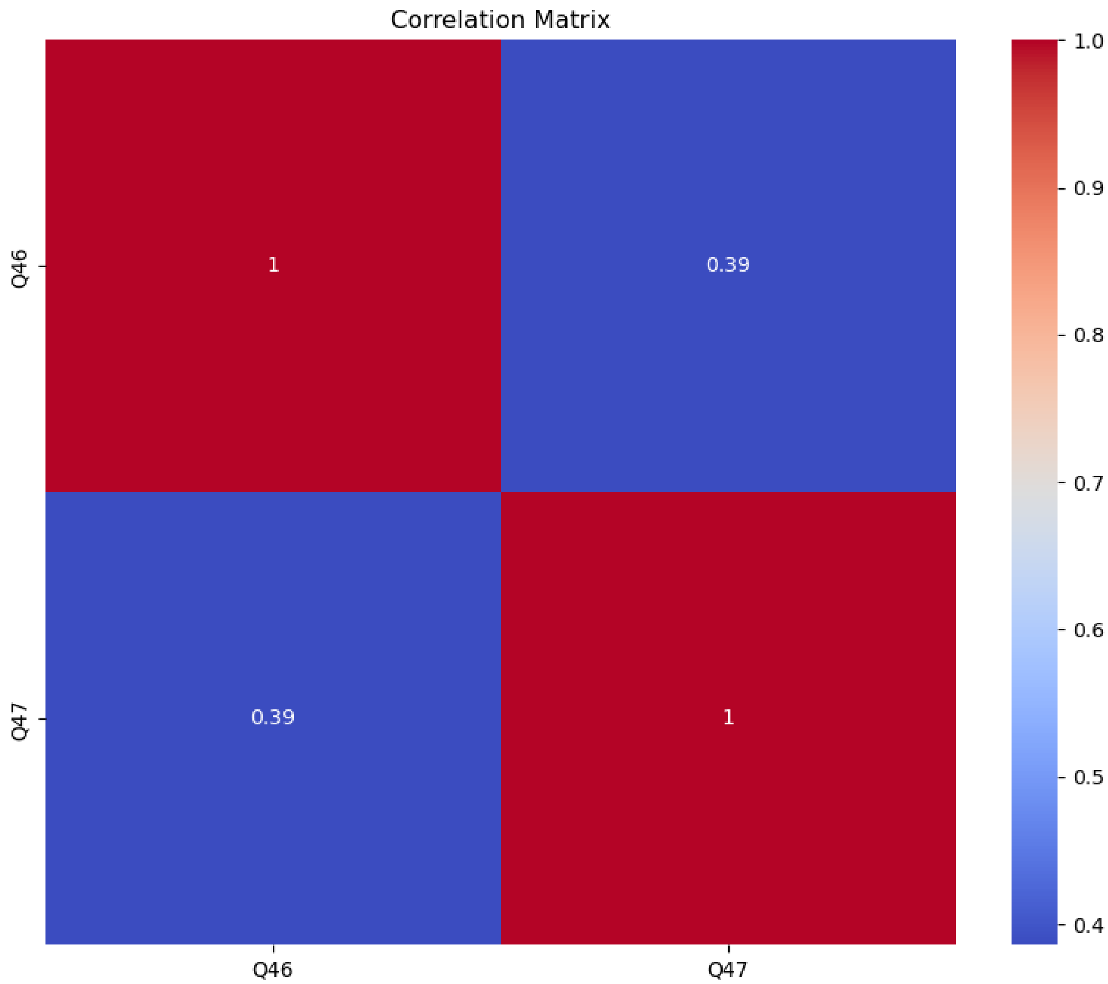

Distribution of Q46
Count
Q46
0
10000
20000
30000
40000
50000
−4
−2
0
2
4


Distribution of Q47
40000
30000
20000
10000
0
Count
−4
−2
0
2
4
Q47


Distribution of Q1
count
80000
60000
40000
20000
0
-5
-2
-1
1
2
3
4
Q1

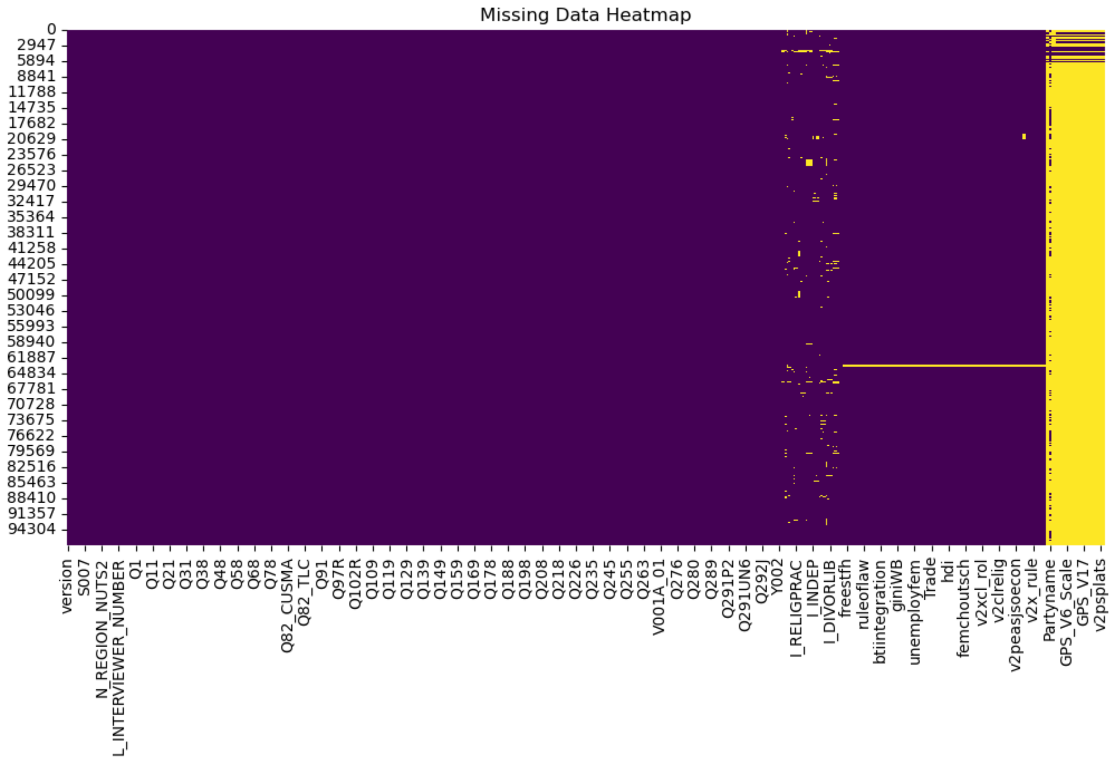


[10]:
```
def plot_correlation_matrix(df, numerical_cols):
    """
    Plot a correlation matrix for numerical columns.
    """
    corr_matrix = df[numerical_cols].corr()
    plt.figure(figsize=(10, 8))
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
    plt.title('Correlation Matrix')
    plt.show()

# Example usage
plot_correlation_matrix(df, numerical_cols)
```



[11]:
```python
def analyze_missing_data(df):
    """
    Analyze and visualize missing data.
    """
    # Count missing values per column
    missing_values = df.isnull().sum()
    missing_values = missing_values[missing_values > 0]

    # Plot missing data heatmap
    plt.figure(figsize=(12, 6))
    sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
    plt.title('Missing Data Heatmap')
    plt.show()

    return missing_values
```

```python
# Example usage
missing_values = analyze_missing_data(df)
print("Missing values per column:")
print(missing_values)
```




```
Missing values per column:
N_TOWN               1
O1_LONGITUDE         4
O2_LATITUDE          4
SACSECVAL          480
RESEMAVAL          748
                  ...
v2psprbrch       93302
v2psprlnks       93302
v2psplats        93302
v2xnp_client     93302
v2xps_party      93302
Length: 192, dtype: int64
```

[12]:
```python
def generate_descriptive_report(df, numerical_cols, categorical_cols):
    """
    Generate a descriptive report for the dataset.
    """
```

```python
    # Generate summary statistics
    num_summary, cat_summary = generate_summary_statistics(df)
    print("Numerical Summary:")
    print(num_summary)
    print("\nCategorical Summary:")
    print(cat_summary)

    # Plot distributions
    plot_distributions(df, numerical_cols, categorical_cols)

    # Plot correlation matrix
    plot_correlation_matrix(df, numerical_cols)

    # Analyze missing data
    missing_values = analyze_missing_data(df)
    print("Missing values per column:")
    print(missing_values)

# Example usage
generate_descriptive_report(df, numerical_cols, categorical_cols)
```

```
Numerical Summary:
        A_WAVE        A_YEAR  A_STUDY     B_COUNTRY     C_COW_NUM  \
count  97220.0  97220.000000  97220.0  97220.000000  97220.000000
mean       7.0   2019.132082      2.0    447.872146    476.555153
std        0.0      1.601004      0.0    256.491312    288.386918
min        7.0   2017.000000      2.0     20.000000      2.000000
25%        7.0   2018.000000      2.0    218.000000    201.000000
50%        7.0   2018.000000      2.0    422.000000    552.000000
75%        7.0   2020.000000      2.0    688.000000    714.000000
max        7.0   2023.000000      2.0    909.000000    920.000000

        D_INTERVIEW          S007     J_INTDATE       FW_START        FW_END  \
count  9.722000e+04  9.722000e+04  9.722000e+04   97220.000000   97220.000000
mean   4.479431e+08  4.485726e+08  1.905207e+07  201901.606881  201919.989683
std    2.564912e+08  2.564602e+08  4.658281e+06     160.980181     160.412353
min    2.007000e+07  2.072000e+07 -5.000000e+00  201701.000000  201703.000000
25%    2.180700e+08  2.187200e+08  2.018022e+07  201804.000000  201806.000000
50%    4.220707e+08  4.227207e+08  2.018111e+07  201811.000000  201812.000000
75%    6.880703e+08  6.887203e+08  2.020041e+07  202003.000000  202010.000000
max    9.090704e+08  9.090704e+08  2.023070e+07  202306.000000  202307.000000

        ...  WVS_Polmistrust_PartyVoter  WVS_LR_MedianVoter  \
count   ...                 3918.000000         3918.000000
mean    ...                   67.689823         -331.856360
std     ...                    9.814691          474.786005
min     ...                   43.750000         -999.000000
25%     ...                   66.964286         -999.000000
```

50%	...	68.210839	5.420000
75%	...	74.000000	5.650000
max	...	83.705786	7.260000

	WVS_LibCon_MedianVoter	v2psbars	v2psorgs	v2psprbrch	\
count	3918.000000	3918.000000	3918.000000	3918.000000	
mean	-331.510837	-334.689260	-334.827539	-335.095391	
std	475.033906	472.769807	472.671155	472.481026	
min	-999.000000	-999.000000	-999.000000	-999.000000	
25%	-999.000000	-999.000000	-999.000000	-999.000000	
50%	5.083400	0.552000	0.869000	-0.403000	
75%	6.512500	2.043000	1.737000	1.676000	
max	9.402100	2.407000	1.737000	1.676000	

	v2psprlnks	v2psplats	v2xnp_client	v2xps_party
count	3918.000000	3918.000000	3918.000000	3918.000000
mean	-334.788026	-334.811147	-335.648640	-335.268652
std	472.700209	472.683543	472.086732	472.357142
min	-999.000000	-999.000000	-999.000000	-999.000000
25%	-999.000000	-999.000000	-999.000000	-999.000000
50%	-0.107000	-0.099000	0.059000	0.591000
75%	2.525000	2.354000	0.459000	0.927000
max	2.525000	2.354000	0.624000	0.927000

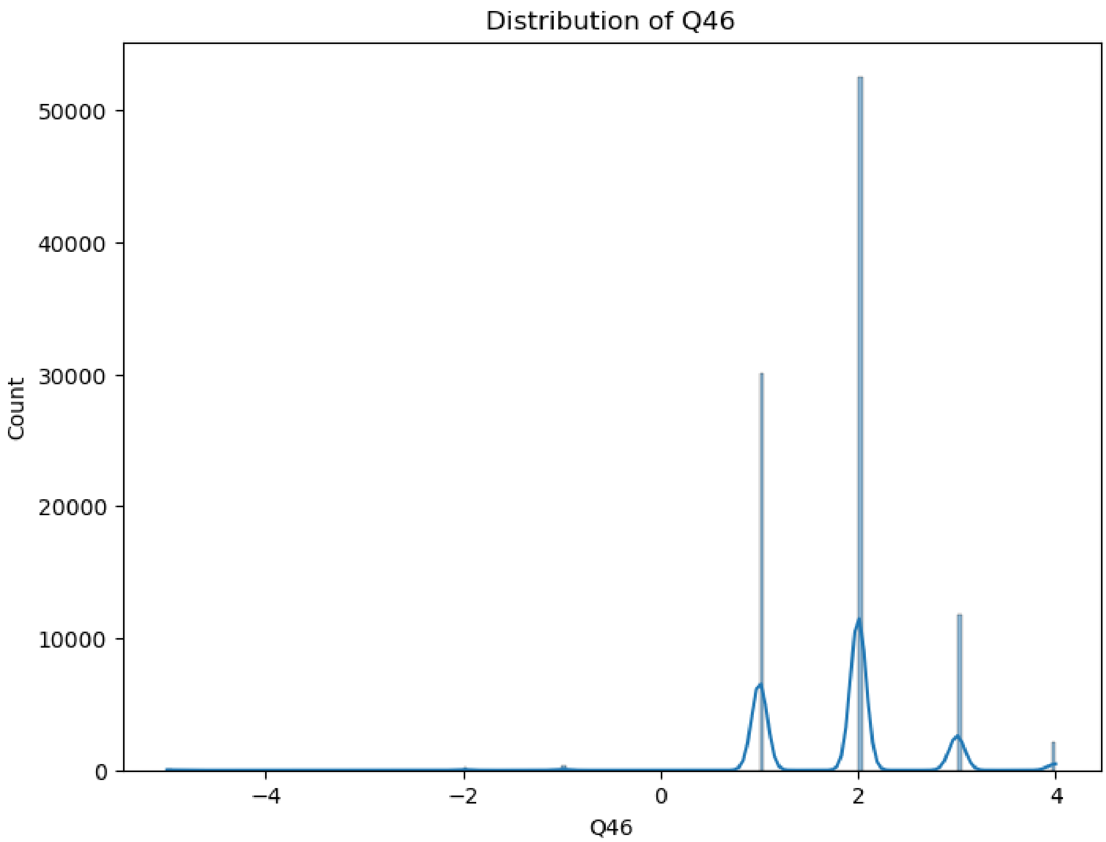
[8 rows x 601 columns]

Categorical Summary:

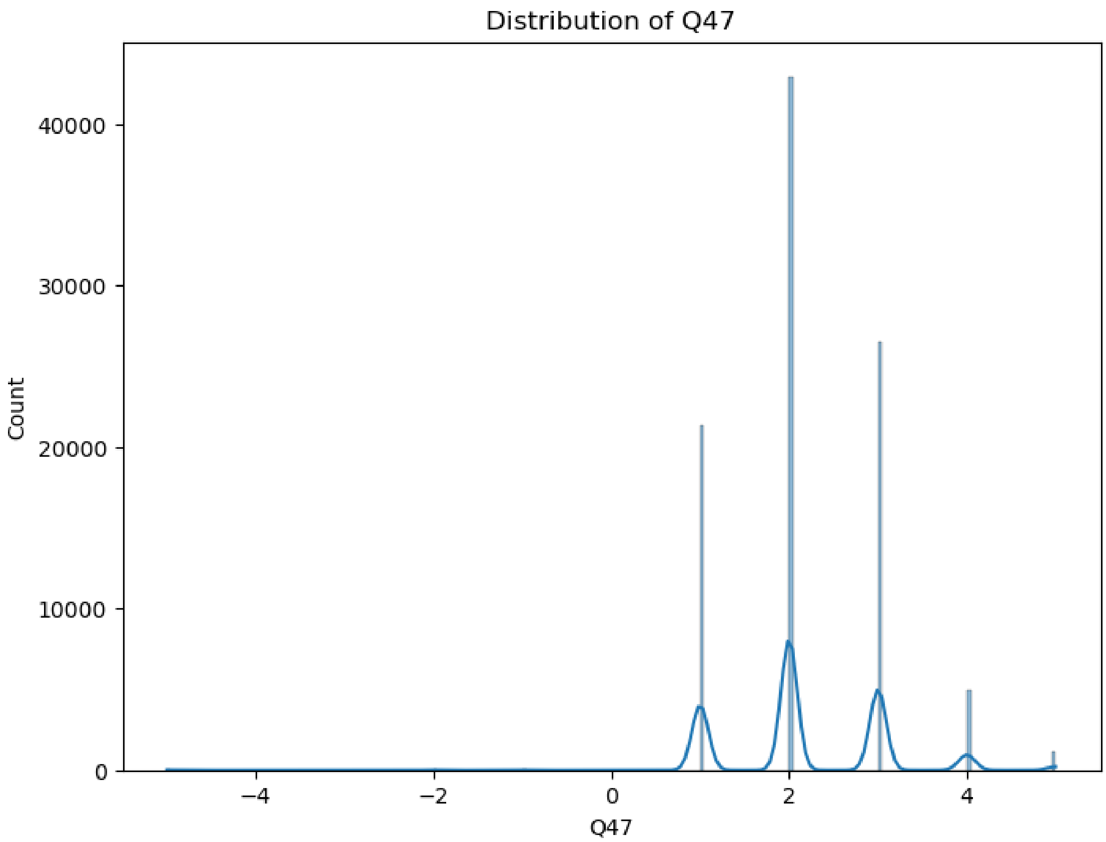
	version	doi	B_COUNTRY_ALPHA	\
count	97220	97220	97220	
unique	1	1	66	
top	6-0-0 (2024-04-30)	doi.org/10.14281/18241.24	CAN	
freq	97220	97220	4018	

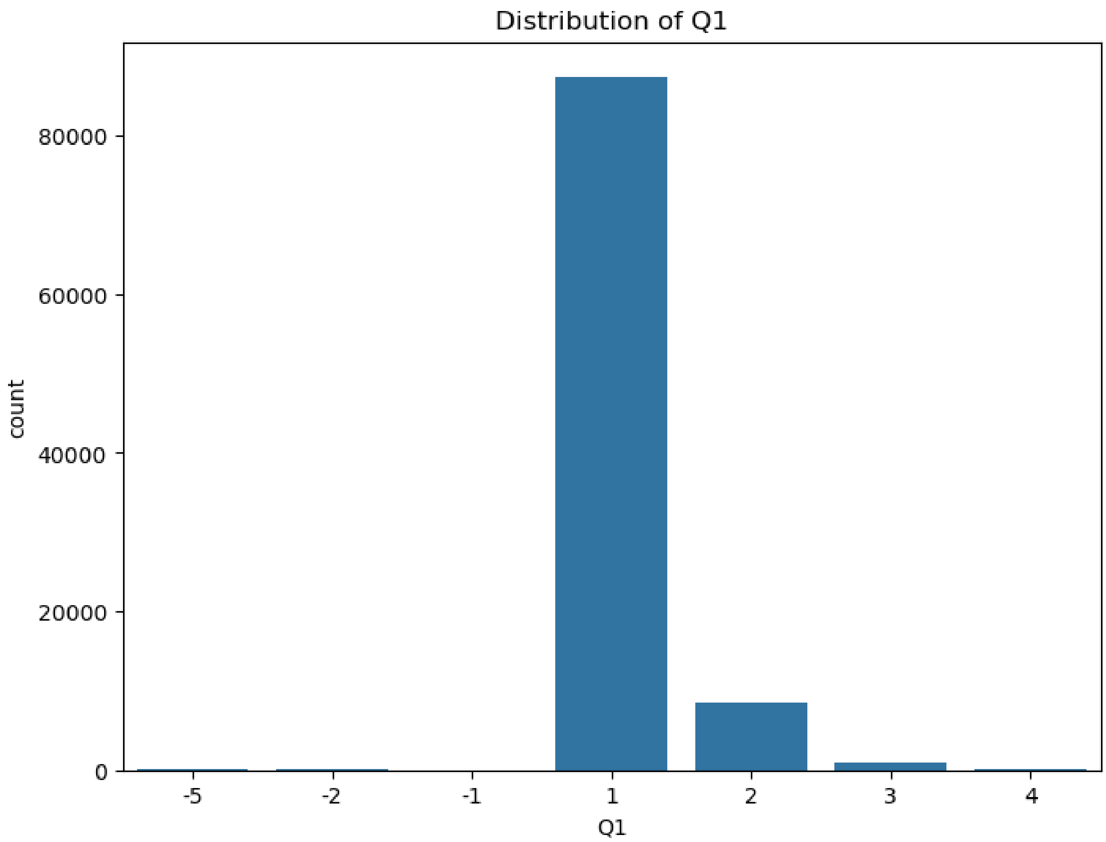
	C_COW_ALPHA	LNGE_ISO	X002_02B	V002A_01	V001A_01	Partyname	Partyabb	\
count	97220	97220	97220	97220	97220	34808	2601	
unique	66	52	158	163	158	21	10	
top	CAN	es	CA	-4	-4	Don´t know	LP	
freq	4018	16190	3329	6092	6092	10193	676	

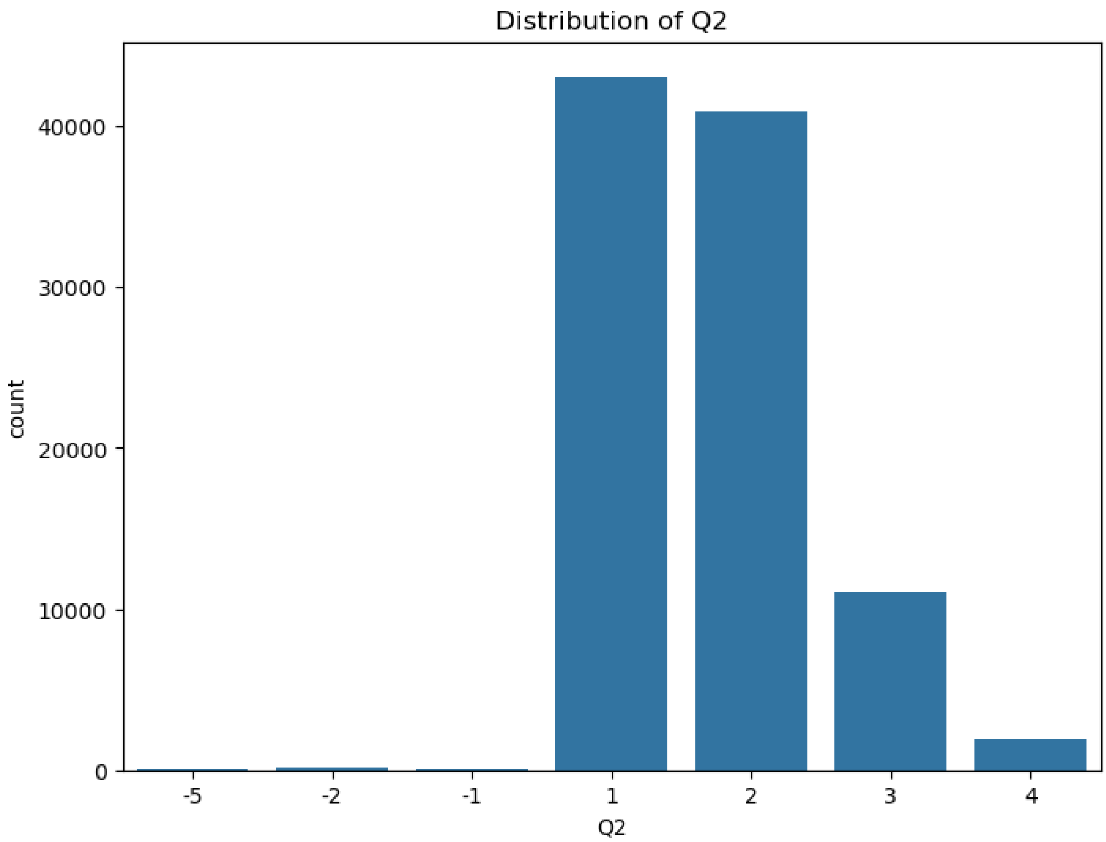
	CPARTY	CPARTYABB
count	2601	2601
unique	10	10
top	AUS_ Liberal Party of Australia	AUS_ LP
freq	676	676

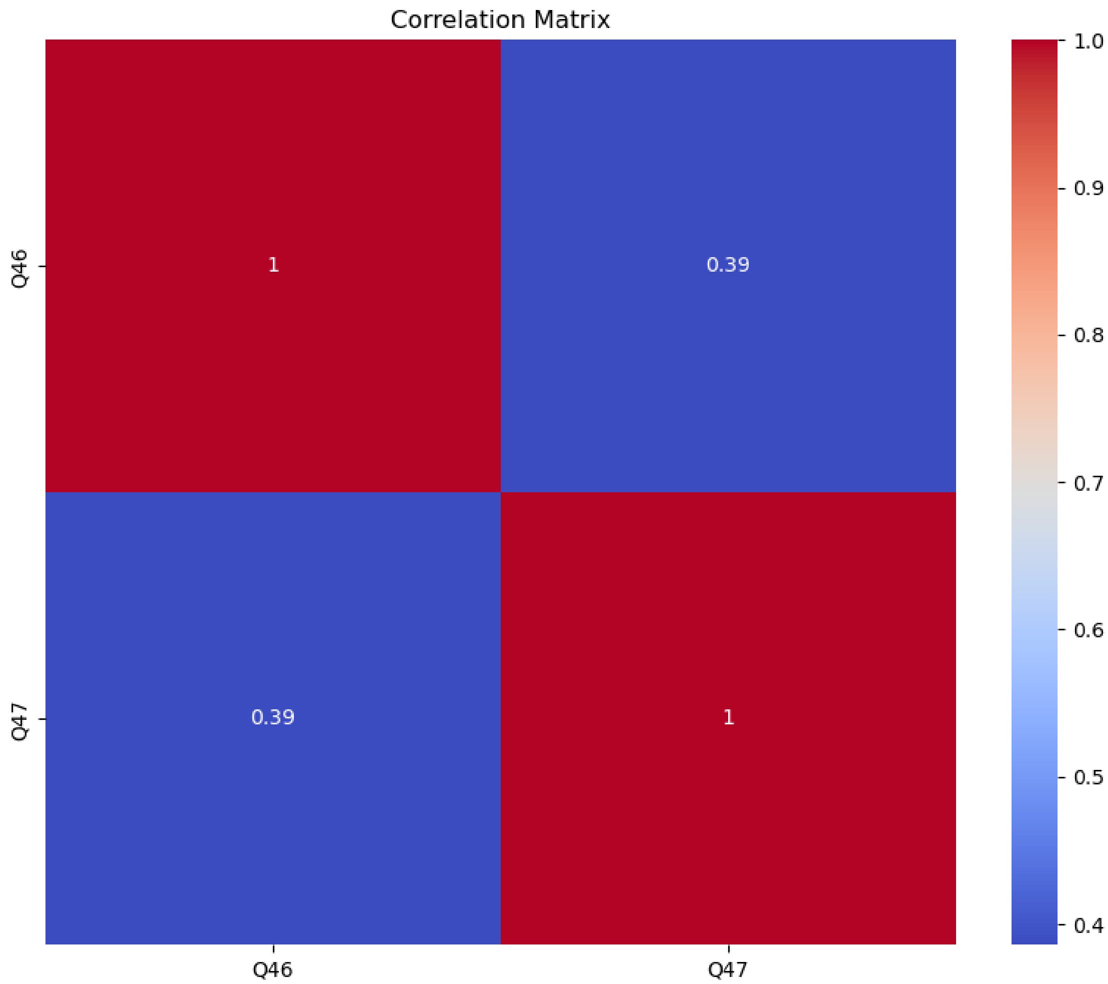


Distribution of Q46
Count
Q46
0
10000
20000
30000
40000
50000
−4
−2
0
2
4

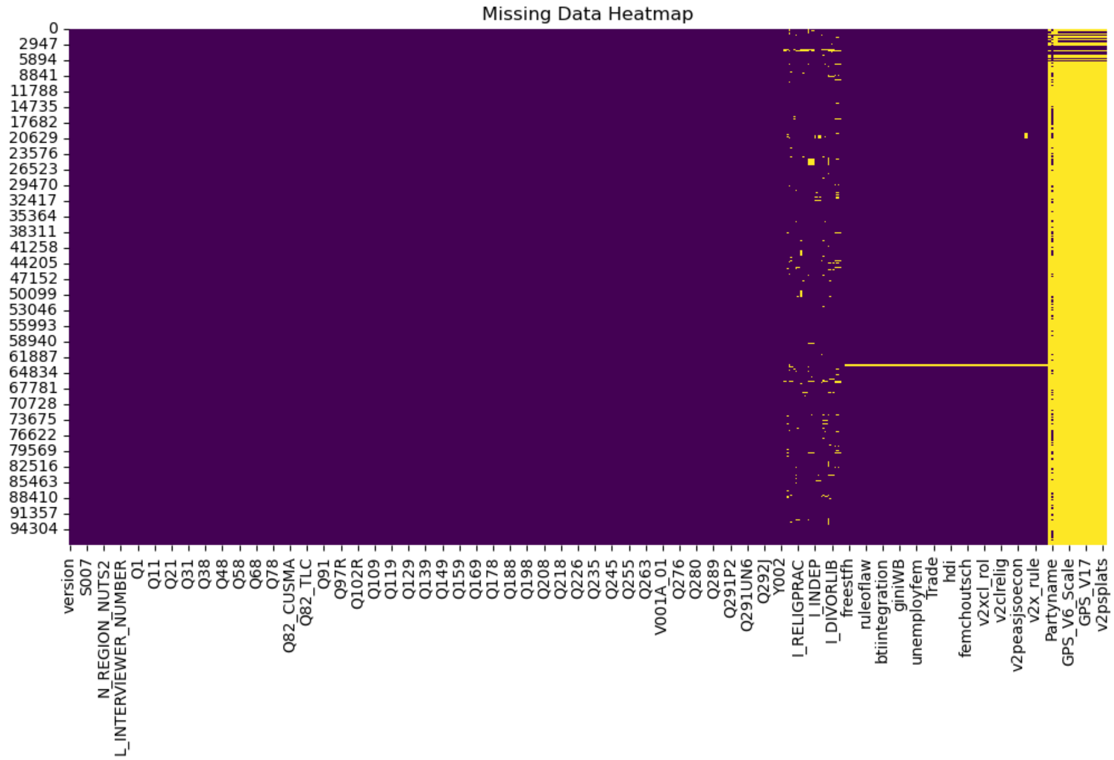

Distribution of Q47
40000
30000
20000
10000
0
Count
−4
−2
0
2
4
Q47


Distribution of Q1
80000
60000
40000
20000
0
count
-5
-2
-1
1
2
3
4
Q1


Distribution of Q2
count
40000
30000
20000
10000
0
-5
-2
-1
1
2
3
4
Q2



Correlation Matrix
Q46
Q47
1
0.39
0.39
1
Q46
Q47
1.0
0.9
0.8
0.7
0.6
0.5
0.4




```
Missing values per column:
N_TOWN              1
O1_LONGITUDE        4
O2_LATITUDE         4
SACSECVAL         480
RESEMAVAL         748
                 ...
v2psprbrch      93302
v2psprlnks      93302
v2psplats       93302
v2xnp_client    93302
v2xps_party     93302
Length: 192, dtype: int64
```

[13]:

```
# Check the percentage of missing values in each column
missing_percentage = df.isnull().sum() / len(df) * 100
print("Percentage of missing values per column:")
print(missing_percentage[missing_percentage > 0].sort_values(ascending=False))

# Drop columns with more than 50% missing values (adjust threshold as needed)
columns_to_drop = missing_percentage[missing_percentage > 50].index
df = df.drop(columns=columns_to_drop)
print(f"Dropped columns: {columns_to_drop.tolist()}")
```

```python
# Impute missing values for numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns
df[numerical_cols] = df[numerical_cols].fillna(df[numerical_cols].median())

# Impute missing values for categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
df[categorical_cols] = df[categorical_cols].fillna(df[categorical_cols].mode().
 ↪iloc[0])

# Verify no missing values remain
print("Remaining missing values after imputation:")
print(df.isnull().sum().sum())
```

```
Percentage of missing values per column:
Partyabb                      97.324625
CPARTY                        97.324625
CPARTYABB                     97.324625
v2xps_party                   95.969965
WVS_Polmistrust_PartyVoter    95.969965
                                ...
Trade                          0.459782
healthexp                      0.459782
O1_LONGITUDE                   0.004114
O2_LATITUDE                    0.004114
N_TOWN                         0.001029
Length: 192, dtype: float64
Dropped columns: ['ID_GPS', 'ID_PartyFacts', 'Partyname', 'Partyabb', 'CPARTY',
'CPARTYABB', 'Type_Values', 'Type_Populism', 'Type_Populist_Values',
'Type_Partysize_vote', 'Type_Partysize_seat', 'GPS_V4_Scale', 'GPS_V6_Scale',
'GPS_V8_Scale', 'GPS_V9', 'GPS_V10', 'GPS_V11', 'GPS_V12', 'GPS_V13', 'GPS_V14',
'GPS_V15', 'GPS_V16', 'GPS_V17', 'WVS_LR_PartyVoter', 'WVS_LibCon_PartyVoter',
'WVS_Polmistrust_PartyVoter', 'WVS_LR_MedianVoter', 'WVS_LibCon_MedianVoter',
'v2psbars', 'v2psorgs', 'v2psprbrch', 'v2psprlnks', 'v2psplats', 'v2xnp_client',
'v2xps_party']
Remaining missing values after imputation:
0
```

[14]:
```python
# One-hot encode categorical variables
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)

# Check the updated dataframe
print(df.head())
```

```
   A_WAVE  A_YEAR  A_STUDY  B_COUNTRY  C_COW_NUM  D_INTERVIEW      S007  \
0       7    2018        2         20        232     20070001  20720001
1       7    2018        2         20        232     20070002  20720002
2       7    2018        2         20        232     20070003  20720003
```

```
3       7   2018        2         20         232     20070004  20720004
4       7   2018        2         20         232     20070005  20720005

   J_INTDATE  FW_START  FW_END  ...  V001A_01_UG  V001A_01_US  V001A_01_UY  \
0   20180704    201807  201809  ...        False        False        False
1   20180714    201807  201809  ...        False        False        False
2   20180704    201807  201809  ...        False        False        False
3   20180702    201807  201809  ...        False        False        False
4   20180708    201807  201809  ...        False        False        False

   V001A_01_UZ  V001A_01_VE  V001A_01_VN  V001A_01_XK  V001A_01_ZA  \
0        False        False        False        False        False
1        False        False        False        False        False
2        False        False        False        False        False
3        False        False        False        False        False
4        False        False        False        False        False

   V001A_01_ZM  V001A_01_ZW
0        False        False
1        False        False
2        False        False
3        False        False
4        False        False

[5 rows x 1227 columns]
```

[15]:

```
from sklearn.preprocessing import StandardScaler

# Initialize the scaler
scaler = StandardScaler()

# Scale numerical columns
df[numerical_cols] = scaler.fit_transform(df[numerical_cols])

# Check the updated dataframe
print(df.head())
```

```
   A_WAVE    A_YEAR  A_STUDY  B_COUNTRY  C_COW_NUM  D_INTERVIEW      S007  \
0     0.0 -0.707111      0.0  -1.668183  -0.848015    -1.668187 -1.668309
1     0.0 -0.707111      0.0  -1.668183  -0.848015    -1.668187 -1.668309
2     0.0 -0.707111      0.0  -1.668183  -0.848015    -1.668187 -1.668309
3     0.0 -0.707111      0.0  -1.668183  -0.848015    -1.668187 -1.668309
4     0.0 -0.707111      0.0  -1.668183  -0.848015    -1.668187 -1.668309

   J_INTDATE  FW_START    FW_END  ...  V001A_01_UG  V001A_01_US  V001A_01_UY  \
0   0.242288 -0.587696 -0.691906  ...        False        False        False
1   0.242290 -0.587696 -0.691906  ...        False        False        False
2   0.242288 -0.587696 -0.691906  ...        False        False        False
```

```
3   0.242287 -0.587696 -0.691906  ...        False        False        False
4   0.242288 -0.587696 -0.691906  ...        False        False        False

   V001A_01_UZ  V001A_01_VE  V001A_01_VN  V001A_01_XK  V001A_01_ZA  \
0        False        False        False        False        False
1        False        False        False        False        False
2        False        False        False        False        False
3        False        False        False        False        False
4        False        False        False        False        False

   V001A_01_ZM  V001A_01_ZW
0        False        False
1        False        False
2        False        False
3        False        False
4        False        False

[5 rows x 1227 columns]
```

[16]:

```
# Example: Select relevant columns for segmentation
relevant_columns = ['Q46', 'Q47', 'Q48', 'Q49', 'Q50', 'Q1', 'Q2', 'Q3', 'Q4',␣
 ↪'Q5']  # Replace with actual relevant columns
df_segmentation = df[relevant_columns]

# Check the selected dataframe
print(df_segmentation.head())
```

```
        Q46       Q47       Q48       Q49       Q50        Q1        Q2  \
0 -1.056911  0.898981  1.189985  1.278604 -0.460394 -0.261085 -0.884662
1 -1.056911 -1.284001  0.775382  0.850646  1.132897 -0.261085 -0.884662
2  0.219982 -1.284001  0.775382  0.850646  0.734574 -0.261085  0.387854
3  0.219982 -0.192510  0.775382  0.422689 -0.062071 -0.261085 -0.884662
4  0.219982 -0.192510  0.360779 -0.005269  0.336251 -0.261085 -0.884662

         Q3        Q4        Q5
0 -0.894481  0.411360 -0.536249
1 -0.894481  1.326287 -0.536249
2  0.279658 -0.503568  1.568522
3 -0.894481  1.326287  0.516136
4 -0.894481  0.411360 -0.536249
```

[17]:

```
# Save the cleaned dataset
df_segmentation.to_csv('cleaned_wvs_data.csv', index=False)
print("Cleaned dataset saved as 'cleaned_wvs_data.csv'.")
```

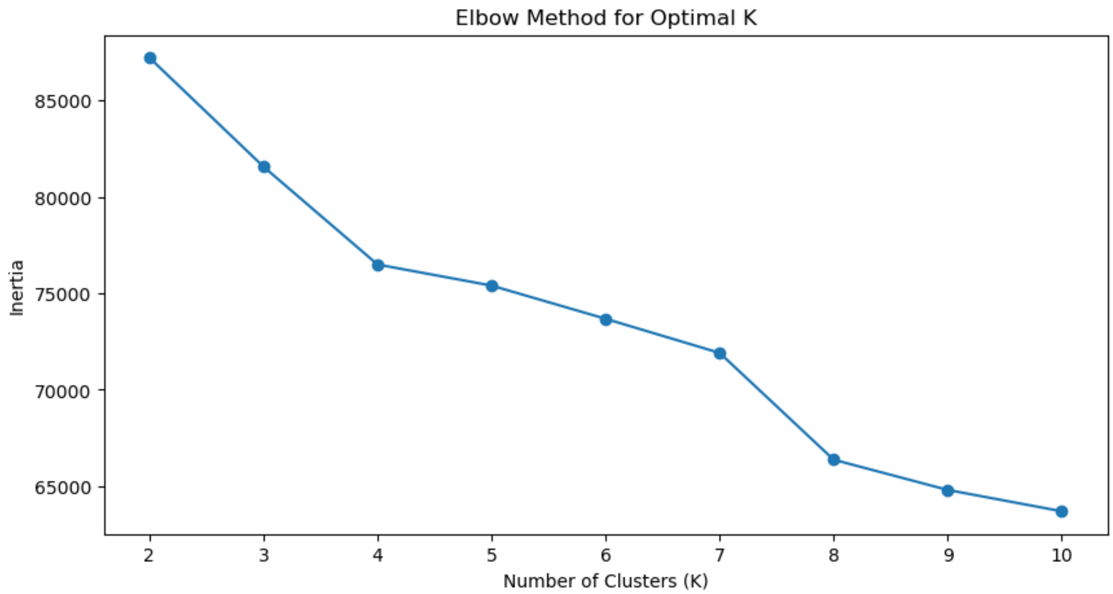
```
Cleaned dataset saved as 'cleaned_wvs_data.csv'.
```

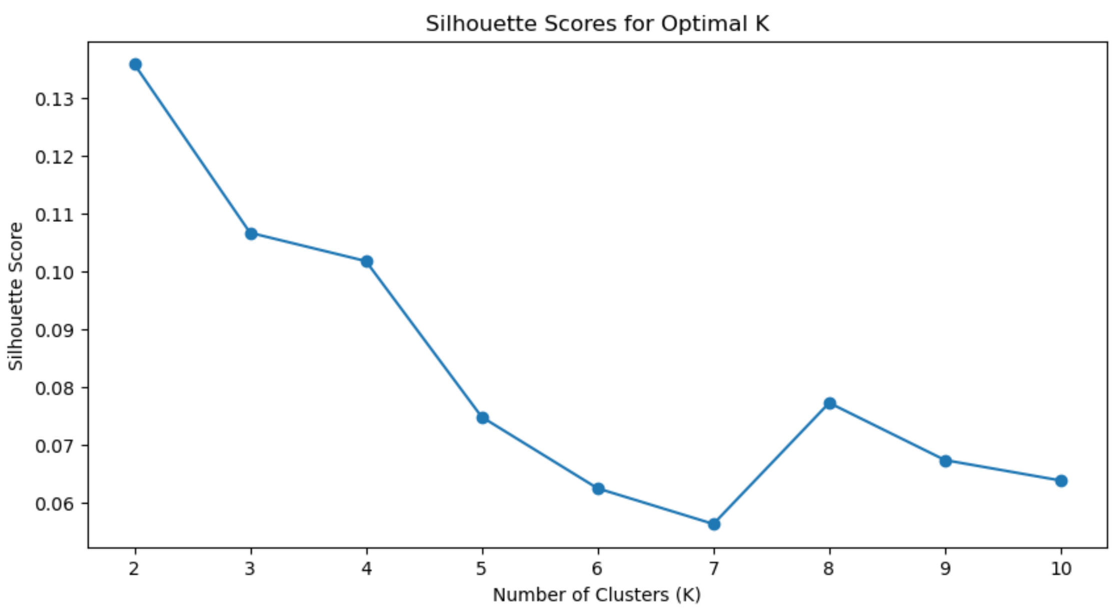
[18]:
```python
# Load the cleaned dataset
df_segmentation = pd.read_csv('cleaned_wvs_data.csv')

# Check the dataset
print(df_segmentation.head())
```

```
        Q46       Q47       Q48       Q49       Q50        Q1        Q2  \
0 -1.056911  0.898981  1.189985  1.278604 -0.460394 -0.261085 -0.884662
1 -1.056911 -1.284001  0.775382  0.850646  1.132897 -0.261085 -0.884662
2  0.219982 -1.284001  0.775382  0.850646  0.734574 -0.261085  0.387854
3  0.219982 -0.192510  0.775382  0.422689 -0.062071 -0.261085 -0.884662
4  0.219982 -0.192510  0.360779 -0.005269  0.336251 -0.261085 -0.884662

         Q3        Q4        Q5
0 -0.894481  0.411360 -0.536249
1 -0.894481  1.326287 -0.536249
2  0.279658 -0.503568  1.568522
3 -0.894481  1.326287  0.516136
4 -0.894481  0.411360 -0.536249
```

[19]:
```python
from sklearn.cluster import MiniBatchKMeans
from sklearn.metrics import silhouette_score
from sklearn.utils import resample
import matplotlib.pyplot as plt

# Sample a subset of the data for faster processing
df_sample = resample(df_segmentation, n_samples=10000, random_state=42)

# Define the range of K values to test
k_values = range(2, 11)
inertia = []
silhouette_scores = []

# Calculate inertia and silhouette score for each K
for k in k_values:
    kmeans = MiniBatchKMeans(n_clusters=k, random_state=42, n_init=1)
    kmeans.fit(df_sample)
    inertia.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(df_sample, kmeans.labels_))

# Plot the Elbow Method
plt.figure(figsize=(10, 5))
plt.plot(k_values, inertia, marker='o')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()
```

```
# Plot the Silhouette Scores
plt.figure(figsize=(10, 5))
plt.plot(k_values, silhouette_scores, marker='o')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Scores for Optimal K')
plt.show()
```





[21]:
```
# Choose the optimal K (e.g., K=4 based on the plots)
optimal_k = 4

# Train the K-Means model
kmeans = MiniBatchKMeans (n_clusters=optimal_k, random_state=42)
kmeans.fit(df_segmentation)

# Add cluster labels to the dataframe
df_segmentation['Cluster'] = kmeans.labels_

# Check the cluster distribution
print(df_segmentation['Cluster'].value_counts())
```

```
Cluster
1    41970
3    26916
0    19522
2     8812
Name: count, dtype: int64
```

[22]:
```
from sklearn.cluster import DBSCAN

# Train DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)  # Adjust parameters as needed
dbscan_labels = dbscan.fit_predict(df_segmentation)

# Add DBSCAN labels to the dataframe
df_segmentation['DBSCAN_Cluster'] = dbscan_labels

# Check the cluster distribution
print(df_segmentation['DBSCAN_Cluster'].value_counts())
```

```
DBSCAN_Cluster
-1       46396
 44        825
 27        784
 148       778
 43        635
          ...
 1255        1
 1268        1
 1176        1
 1294        1
 1331        1
Name: count, Length: 1365, dtype: int64
```

[23]:
```
# Compare cluster distributions
print("K-Means Cluster Distribution:")
```

```
print(df_segmentation['Cluster'].value_counts())

print("\nDBSCAN Cluster Distribution:")
print(df_segmentation['DBSCAN_Cluster'].value_counts())
```

```
K-Means Cluster Distribution:
Cluster
1    41970
3    26916
0    19522
2     8812
Name: count, dtype: int64

DBSCAN Cluster Distribution:
DBSCAN_Cluster
-1       46396
 44        825
 27        784
 148       778
 43        635
         ...
 1255        1
 1268        1
 1176        1
 1294        1
 1331        1
Name: count, Length: 1365, dtype: int64
```

[24]:
```
# Save the clustered dataset
df_segmentation.to_csv('clustered_wvs_data.csv', index=False)
print("Clustered dataset saved as 'clustered_wvs_data.csv'.")
```

```
Clustered dataset saved as 'clustered_wvs_data.csv'.
```

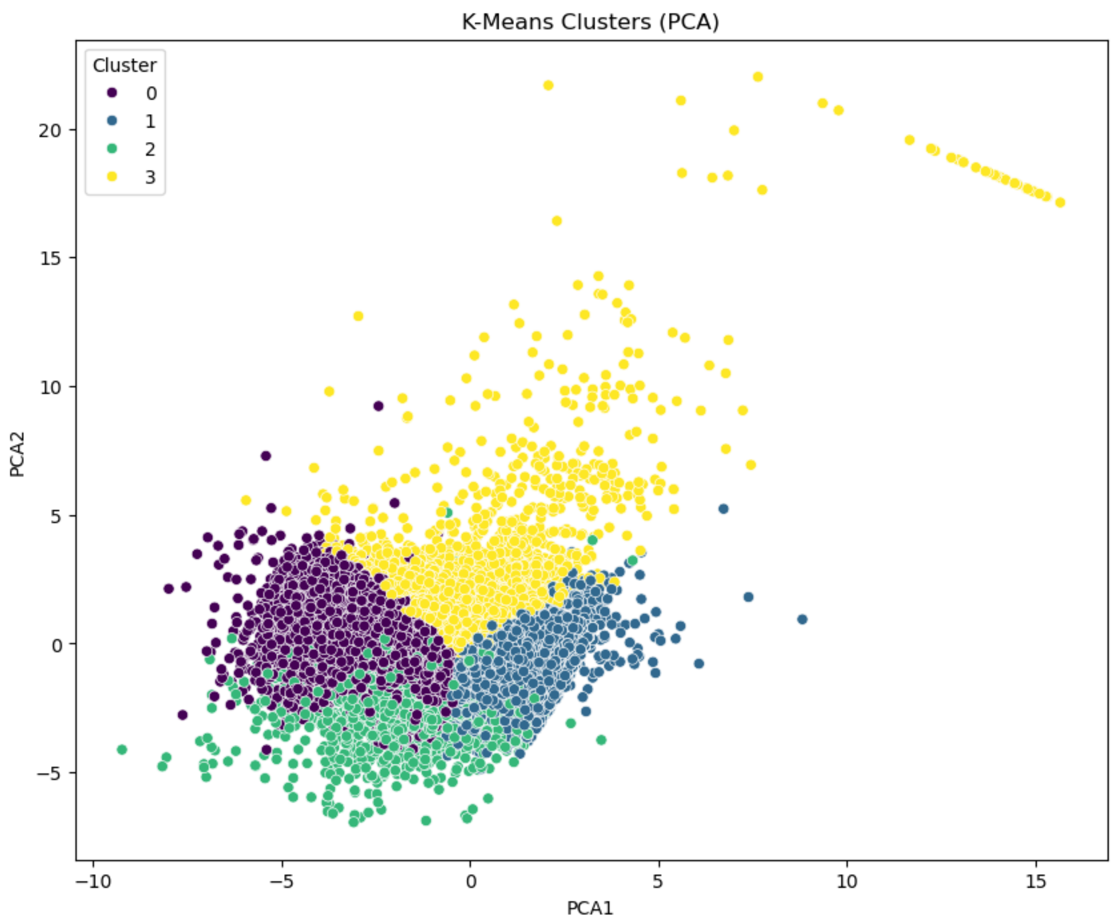
[29]:
```
from sklearn.metrics import silhouette_score

# Calculate Silhouette Score for K-Means
kmeans_silhouette = silhouette_score(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster']), df_segmentation['Cluster'])
print(f"Silhouette Score for K-Means: {kmeans_silhouette:.3f}")

# Calculate Silhouette Score for DBSCAN (if applicable)
if 'DBSCAN_Cluster' in df_segmentation.columns:
    dbscan_silhouette = silhouette_score(df_segmentation.
↪drop(columns=['Cluster', 'DBSCAN_Cluster']), df_segmentation['DBSCAN_Cluster'])
    print(f"Silhouette Score for DBSCAN: {dbscan_silhouette:.3f}")
```

```
Silhouette Score for K-Means: 0.120
Silhouette Score for DBSCAN: -0.220
```

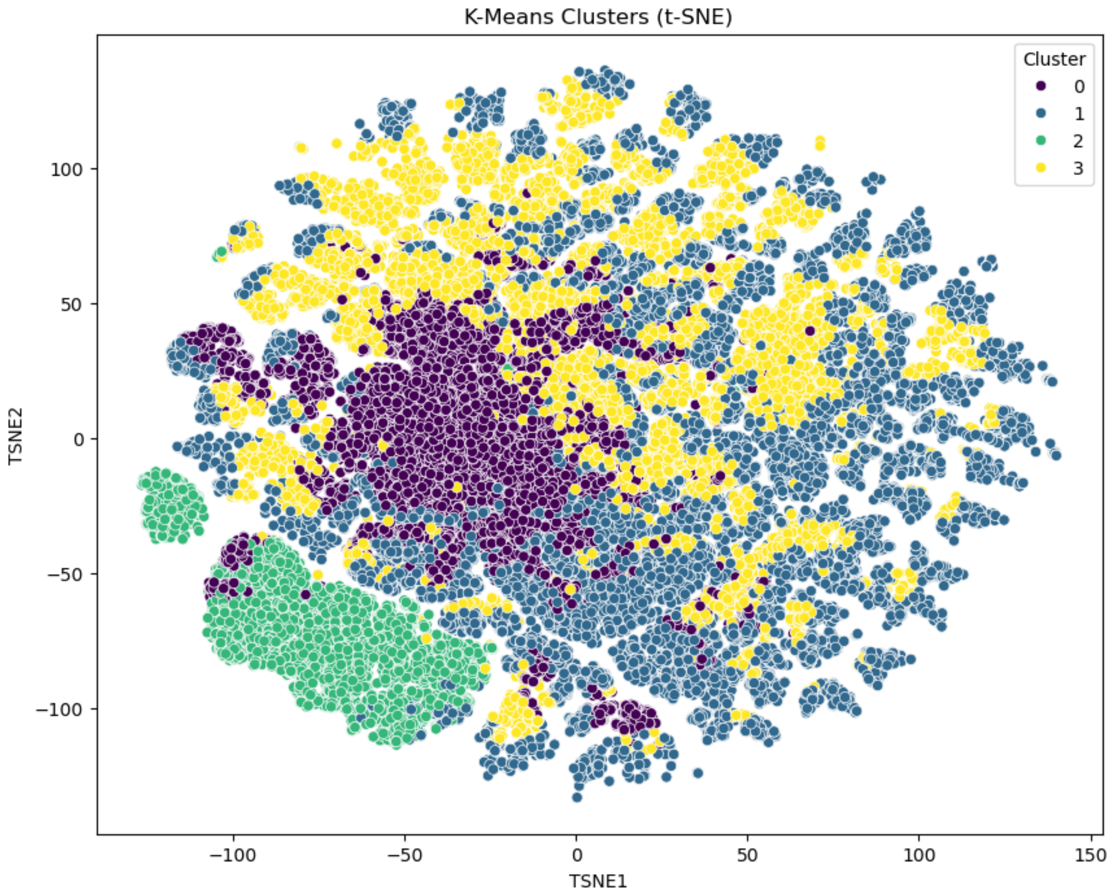
[30]:
```
from sklearn.metrics import davies_bouldin_score

# Calculate Davies-Bouldin Index for K-Means
kmeans_db = davies_bouldin_score(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster']), df_segmentation['Cluster'])
print(f"Davies-Bouldin Index for K-Means: {kmeans_db:.3f}")

# Calculate Davies-Bouldin Index for DBSCAN (if applicable)
if 'DBSCAN_Cluster' in df_segmentation.columns:
    dbscan_db = davies_bouldin_score(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster']), df_segmentation['DBSCAN_Cluster'])
    print(f"Davies-Bouldin Index for DBSCAN: {dbscan_db:.3f}")
```

```
Davies-Bouldin Index for K-Means: 2.195
Davies-Bouldin Index for DBSCAN: 1.539
```

[31]:
```
from sklearn.decomposition import PCA

# Apply PCA to reduce data to 2 dimensions
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster']))

# Add PCA results to the dataframe
df_segmentation['PCA1'] = pca_result[:, 0]
df_segmentation['PCA2'] = pca_result[:, 1]

# Plot clusters using PCA
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=df_segmentation,␣
↪palette='viridis')
plt.title('K-Means Clusters (PCA)')
plt.show()
```



[32]:
```
from sklearn.manifold import TSNE

# Apply t-SNE to reduce data to 2 dimensions
tsne = TSNE(n_components=2, random_state=42)
tsne_result = tsne.fit_transform(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster']))

# Add t-SNE results to the dataframe
df_segmentation['TSNE1'] = tsne_result[:, 0]
df_segmentation['TSNE2'] = tsne_result[:, 1]

# Plot clusters using t-SNE
plt.figure(figsize=(10, 8))
sns.scatterplot(x='TSNE1', y='TSNE2', hue='Cluster', data=df_segmentation,␣
↪palette='viridis')
plt.title('K-Means Clusters (t-SNE)')
plt.show()
```



[33]:

```
# Group by cluster and compute mean values
cluster_summary = df_segmentation.groupby('Cluster').mean()

# Display cluster summary
print(cluster_summary)
```

```
              Q46       Q47       Q48       Q49       Q50        Q1        Q2  \
Cluster
0        0.785892  0.816736 -0.645379 -0.917370 -0.833559 -0.211681  0.531976
1       -0.414205 -0.364855  0.536627  0.685357  0.650060 -0.248513 -0.022219
2        0.230126  0.153567 -0.113624 -0.106188 -0.018225  2.574265  0.515799
3        0.000525 -0.073734 -0.331473 -0.368547 -0.403093 -0.301749 -0.520059

               Q3        Q4        Q5  DBSCAN_Cluster      PCA1      PCA2  \
Cluster
0        0.499185  0.398940  0.194092       96.737783 -1.904193  0.002734
1        0.004685  0.106035  0.024447      153.033595  1.149005 -0.426728
2        0.195582  0.068002  0.453796       64.184748 -0.904533 -1.400334
3       -0.433393 -0.476952 -0.327461      128.284849 -0.114406  1.121866
```

```
              TSNE1      TSNE2
Cluster
0        -32.294903  -1.435901
1         30.949547  -8.330511
2        -74.770172 -69.872490
3          0.862062  38.110565
```

[34]:
```python
# Compare Silhouette Scores
print(f"K-Means Silhouette Score: {kmeans_silhouette:.3f}")
if 'DBSCAN_Cluster' in df_segmentation.columns:
    print(f"DBSCAN Silhouette Score: {dbscan_silhouette:.3f}")

# Compare Davies-Bouldin Indices
print(f"K-Means Davies-Bouldin Index: {kmeans_db:.3f}")
if 'DBSCAN_Cluster' in df_segmentation.columns:
    print(f"DBSCAN Davies-Bouldin Index: {dbscan_db:.3f}")
```

```
K-Means Silhouette Score: 0.120
DBSCAN Silhouette Score: -0.220
K-Means Davies-Bouldin Index: 2.195
DBSCAN Davies-Bouldin Index: 1.539
```

[35]:
```python
# Save cluster summary to a CSV file
cluster_summary.to_csv('cluster_summary.csv')
print("Cluster summary saved as 'cluster_summary.csv'.")
```

```
Cluster summary saved as 'cluster_summary.csv'.
```

[36]:
```python
# Group by cluster and compute mean values of features
cluster_summary = df_segmentation.groupby('Cluster').mean()

# Display the cluster summary
print(cluster_summary)
```

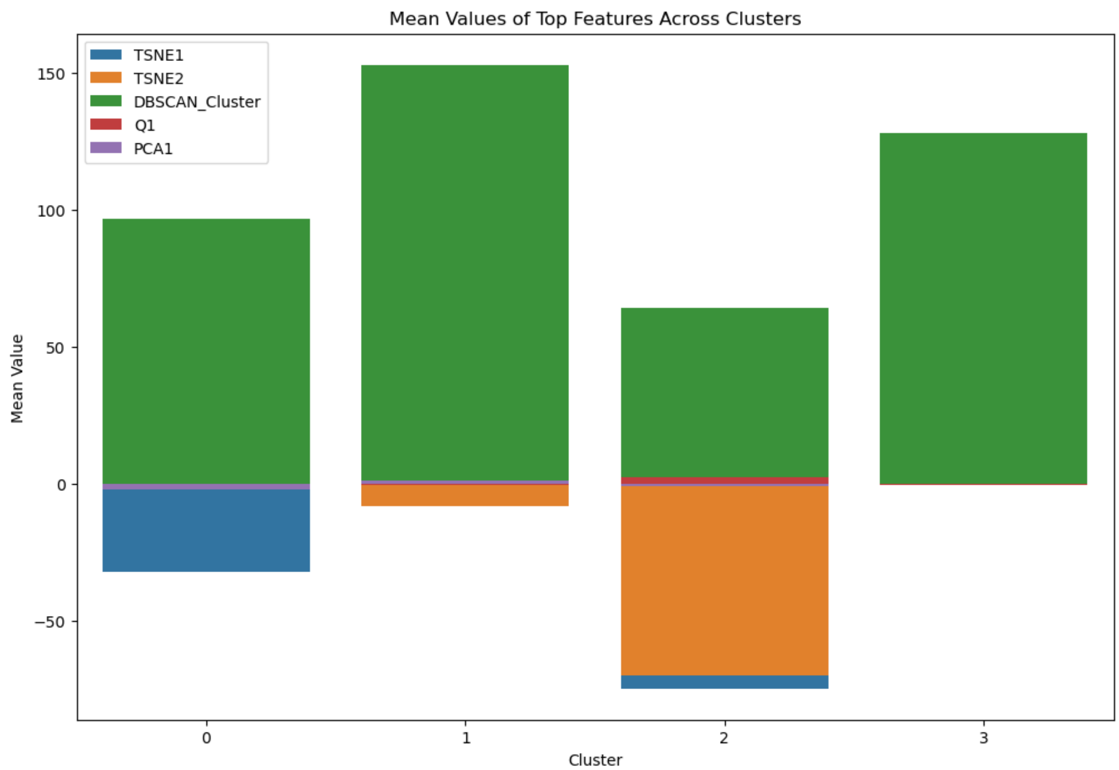
```
               Q46       Q47       Q48       Q49       Q50        Q1        Q2  \
Cluster
0         0.785892  0.816736 -0.645379 -0.917370 -0.833559 -0.211681  0.531976
1        -0.414205 -0.364855  0.536627  0.685357  0.650060 -0.248513 -0.022219
2         0.230126  0.153567 -0.113624 -0.106188 -0.018225  2.574265  0.515799
3         0.000525 -0.073734 -0.331473 -0.368547 -0.403093 -0.301749 -0.520059

                Q3        Q4        Q5  DBSCAN_Cluster      PCA1      PCA2  \
Cluster
0         0.499185  0.398940  0.194092       96.737783 -1.904193  0.002734
1         0.004685  0.106035  0.024447      153.033595  1.149005 -0.426728
2         0.195582  0.068002  0.453796       64.184748 -0.904533 -1.400334
3        -0.433393 -0.476952 -0.327461      128.284849 -0.114406  1.121866
```

```
              TSNE1      TSNE2
Cluster
0       -32.294903  -1.435901
1        30.949547  -8.330511
2       -74.770172 -69.872490
3         0.862062  38.110565
```

[37]:
```
# Calculate the standard deviation of each feature across clusters
cluster_std = cluster_summary.std()

# Sort features by their standard deviation (most important first)
important_features = cluster_std.sort_values(ascending=False)
print("Features with the highest variation across clusters:")
print(important_features)
```

```
Features with the highest variation across clusters:
TSNE1             45.373951
TSNE2             44.627678
DBSCAN_Cluster    38.556860
Q1                 1.414606
PCA1               1.289774
PCA2               1.045348
Q49                0.666711
Q50                0.629487
Q47                0.502831
Q2                 0.502036
Q46                0.500482
Q48                0.500193
Q3                 0.390552
Q4                 0.365239
Q5                 0.327463
dtype: float64
```

[38]:
```
# Select the top N most important features (e.g., top 5)
top_n = 5
top_features = important_features.index[:top_n]

# Plot the mean values of the top features across clusters
plt.figure(figsize=(12, 8))
for feature in top_features:
    sns.barplot(x=cluster_summary.index, y=cluster_summary[feature],␣
 ↪label=feature)
plt.title('Mean Values of Top Features Across Clusters')
plt.xlabel('Cluster')
plt.ylabel('Mean Value')
plt.legend()
plt.show()
```



[39]:
```
# Example interpretation
print("Key variables for segmentation:")
for feature in top_features:
    print(f"- {feature}: This feature shows significant variation across␣
 ↪clusters, suggesting it plays a key role in defining the segments.")
```

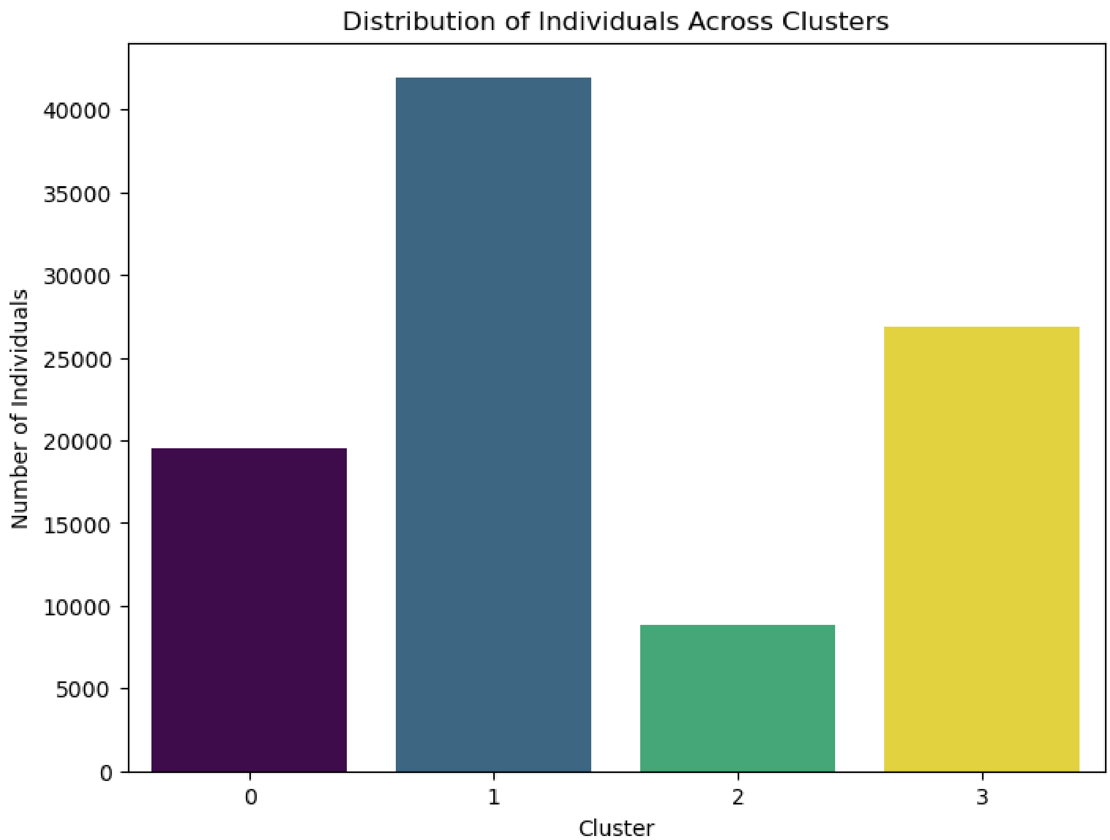
```
Key variables for segmentation:
- TSNE1: This feature shows significant variation across clusters, suggesting it
plays a key role in defining the segments.
- TSNE2: This feature shows significant variation across clusters, suggesting it
plays a key role in defining the segments.
- DBSCAN_Cluster: This feature shows significant variation across clusters,
suggesting it plays a key role in defining the segments.
- Q1: This feature shows significant variation across clusters, suggesting it
plays a key role in defining the segments.
- PCA1: This feature shows significant variation across clusters, suggesting it
plays a key role in defining the segments.
```

[40]:
```
# Save cluster summary to a CSV file
cluster_summary.to_csv('cluster_summary.csv')
print("Cluster summary saved as 'cluster_summary.csv'.")

# Save important features to a CSV file
```

```
important_features.to_csv('important_features.csv')
print("Important features saved as 'important_features.csv'.")
```

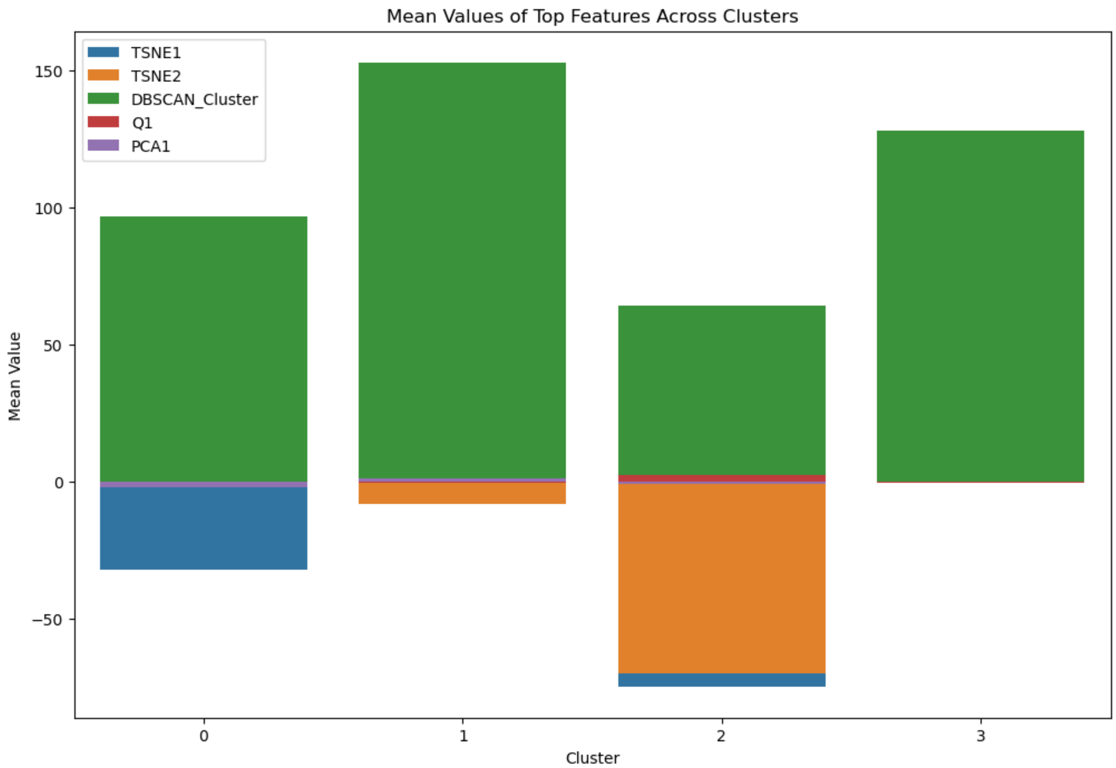
```
Cluster summary saved as 'cluster_summary.csv'.
Important features saved as 'important_features.csv'.
```

[42]:
```
# Plot cluster sizes
plt.figure(figsize=(8, 6))
sns.countplot(x='Cluster', hue='Cluster', data=df_segmentation,␣
 ↪palette='viridis', legend=False)
plt.title('Distribution of Individuals Across Clusters')
plt.xlabel('Cluster')
plt.ylabel('Number of Individuals')
plt.show()
```



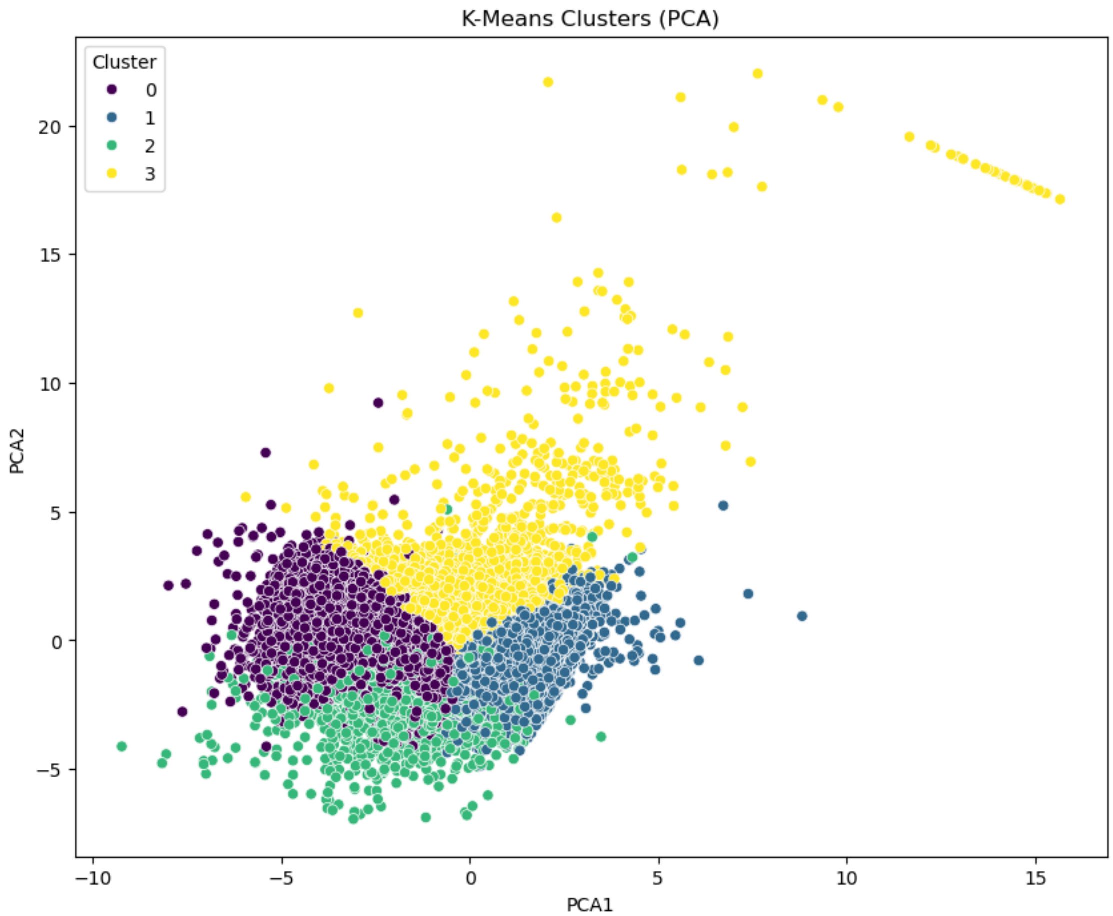
[43]:
```
# Select the top N most important features (e.g., top 5)
top_n = 5
top_features = important_features.index[:top_n]

# Plot the mean values of the top features across clusters
```

```python
plt.figure(figsize=(12, 8))
for feature in top_features:
    sns.barplot(x=cluster_summary.index, y=cluster_summary[feature],␣
 ↪label=feature)
plt.title('Mean Values of Top Features Across Clusters')
plt.xlabel('Cluster')
plt.ylabel('Mean Value')
plt.legend()
plt.show()
```



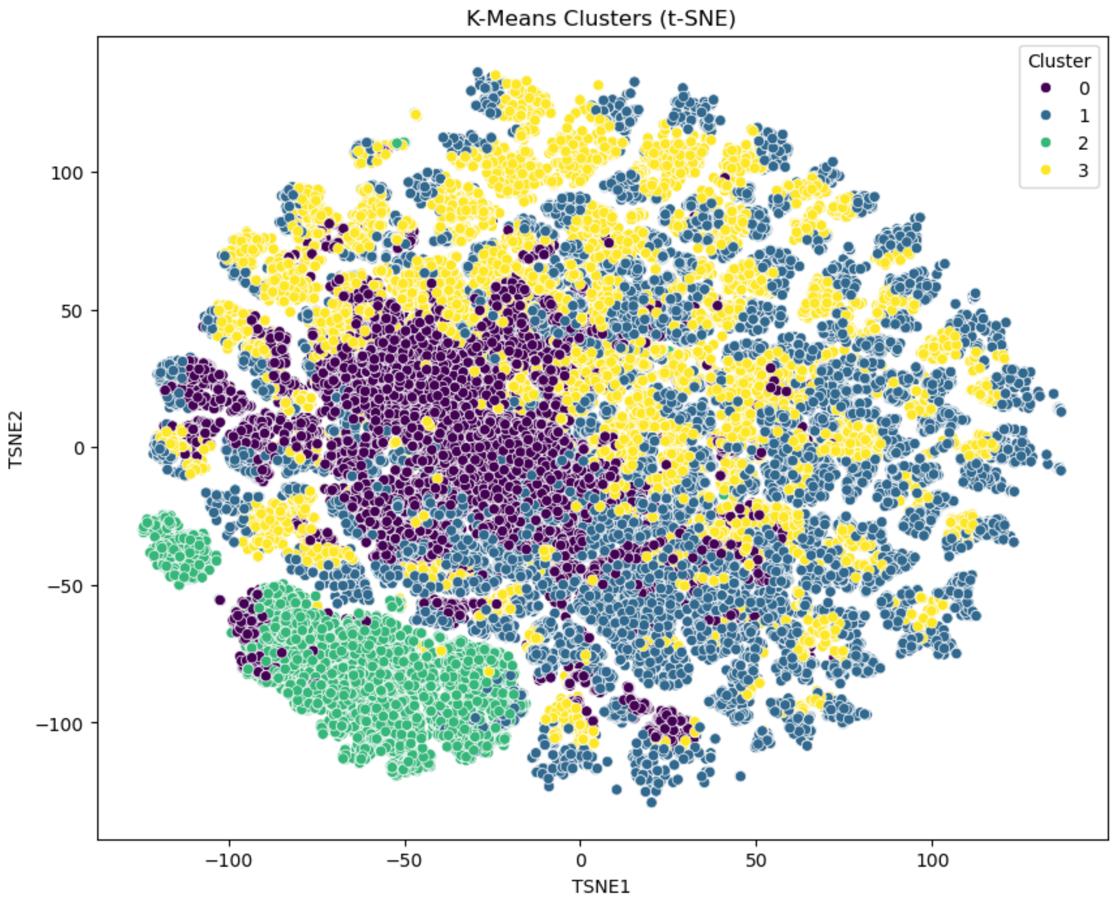
[44]:
```python
from sklearn.decomposition import PCA

# Apply PCA to reduce data to 2 dimensions
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df_segmentation.drop(columns=['Cluster',␣
 ↪'DBSCAN_Cluster', 'PCA1', 'PCA2', 'TSNE1', 'TSNE2']))

# Add PCA results to the dataframe
df_segmentation['PCA1'] = pca_result[:, 0]
df_segmentation['PCA2'] = pca_result[:, 1]

# Plot clusters using PCA
```

```
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=df_segmentation,␣
 ↪palette='viridis')
plt.title('K-Means Clusters (PCA)')
plt.show()
```



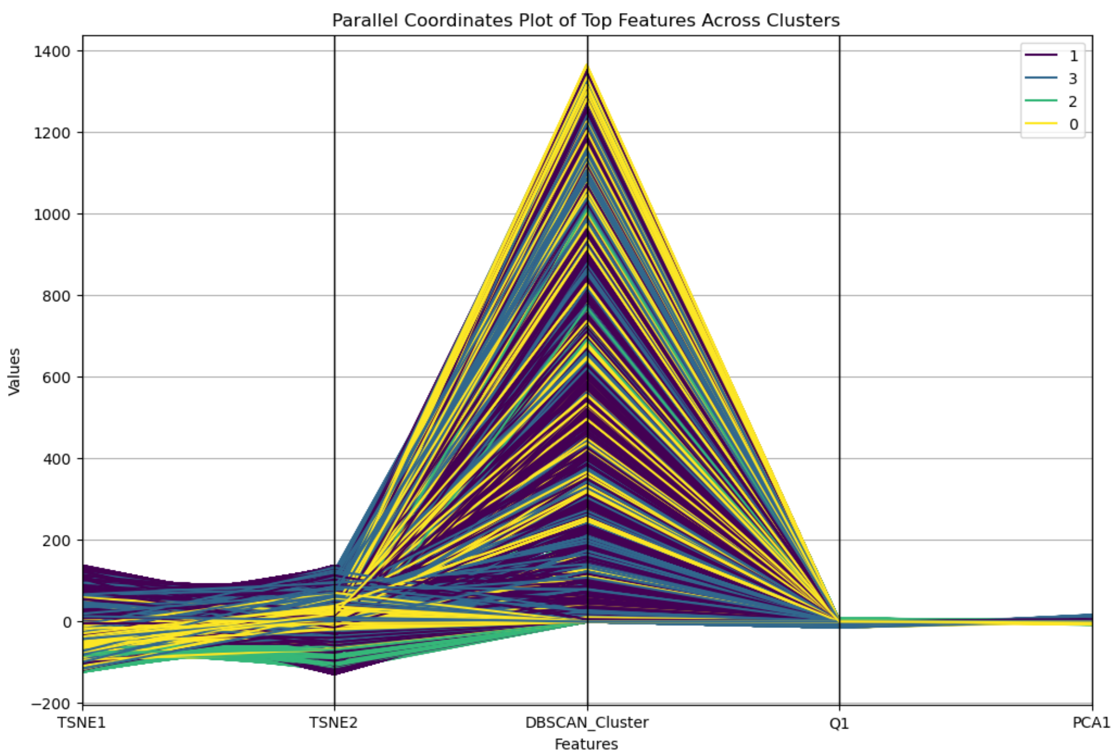
[45]:
```
from sklearn.manifold import TSNE

# Apply t-SNE to reduce data to 2 dimensions
tsne = TSNE(n_components=2, random_state=42)
tsne_result = tsne.fit_transform(df_segmentation.drop(columns=['Cluster',␣
 ↪'DBSCAN_Cluster', 'PCA1', 'PCA2', 'TSNE1', 'TSNE2']))

# Add t-SNE results to the dataframe
df_segmentation['TSNE1'] = tsne_result[:, 0]
df_segmentation['TSNE2'] = tsne_result[:, 1]

# Plot clusters using t-SNE
```

```
plt.figure(figsize=(10, 8))
sns.scatterplot(x='TSNE1', y='TSNE2', hue='Cluster', data=df_segmentation,␣
 ↪palette='viridis')
plt.title('K-Means Clusters (t-SNE)')
plt.show()
```



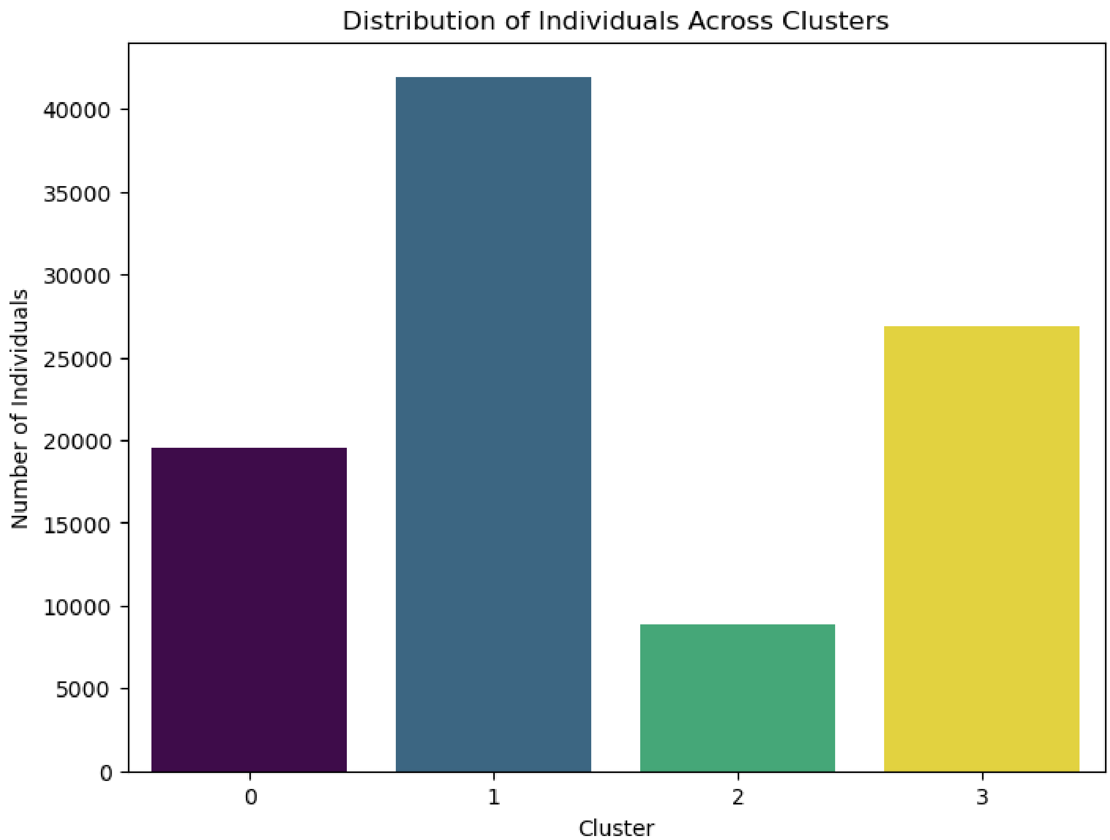
[52]:
```
from pandas.plotting import parallel_coordinates
import matplotlib.pyplot as plt

# Step 1: Check and clean column names in df_segmentation
df_segmentation.columns = df_segmentation.columns.str.strip()  # Remove any␣
 ↪trailing/leading spaces

# Step 2: Verify that all columns in top_features exist in df_segmentation
# Replace 'top_features' with your list of feature names if not already defined
top_features = ['TSNE1', 'TSNE2', 'DBSCAN_Cluster', 'Q1', 'PCA1']  # Example␣
 ↪features
```

```python
# Filter valid features that exist in the DataFrame
valid_features = [feature for feature in top_features if feature in␣
 ↪df_segmentation.columns]

# Check if 'Cluster' column exists
if 'Cluster' not in df_segmentation.columns:
    raise KeyError("'Cluster' column is missing from the DataFrame.")

# Combine valid features with the 'Cluster' column
selected_columns = valid_features + ['Cluster']

# Step 3: Create a subset of the DataFrame for plotting
parallel_data = df_segmentation[selected_columns]

# Step 4: Plot parallel coordinates
plt.figure(figsize=(12, 8))
parallel_coordinates(parallel_data, 'Cluster', colormap='viridis')
plt.title('Parallel Coordinates Plot of Top Features Across Clusters')
plt.xlabel('Features')
plt.ylabel('Values')
plt.grid(True)
plt.show()
```

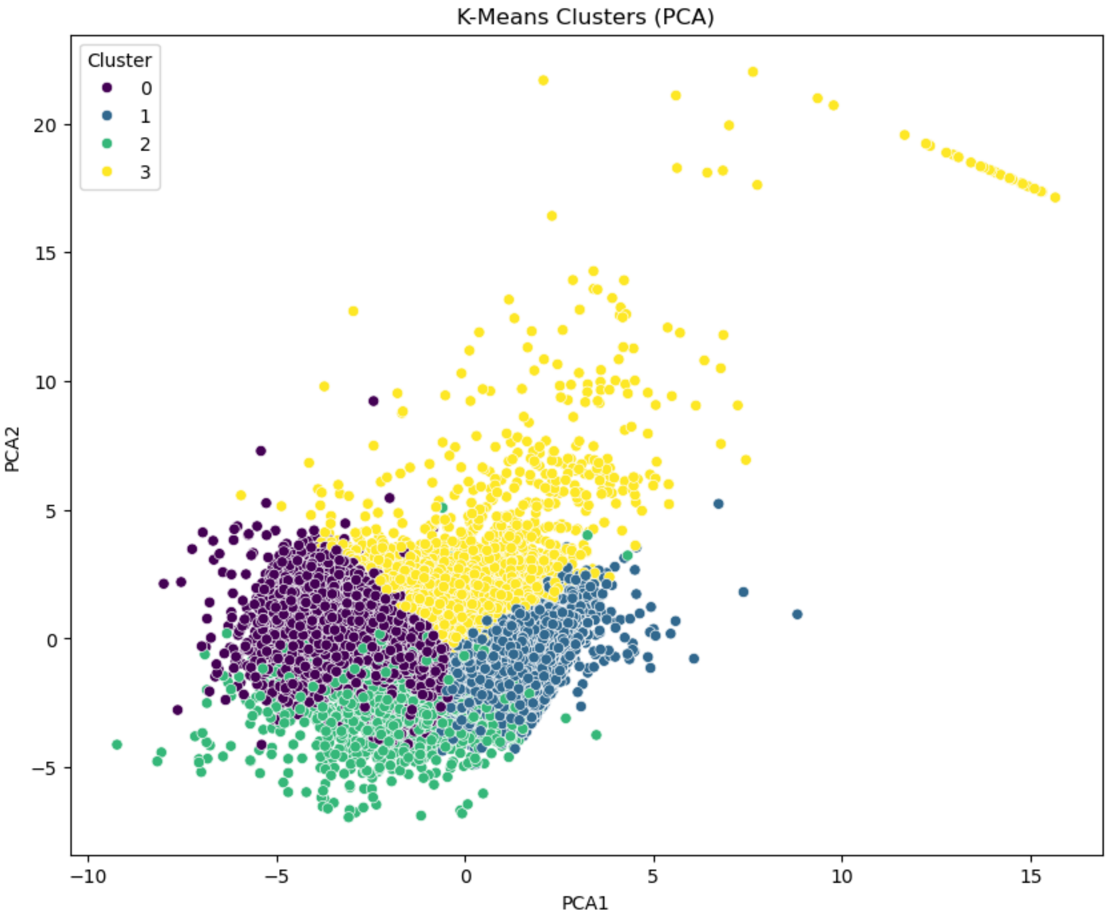


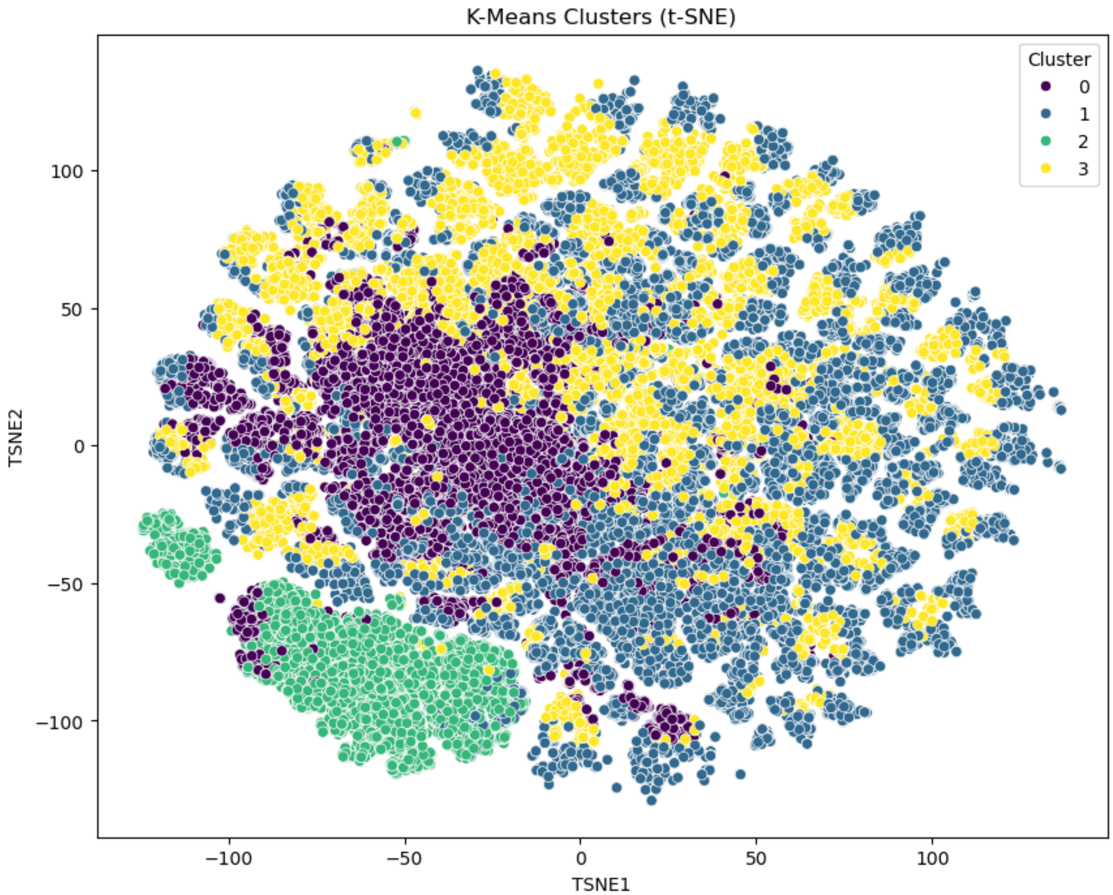
[70]:

```
# Save and display cluster size plot
plt.figure(figsize=(8, 6))
sns.countplot(x='Cluster', hue='Cluster', data=df_segmentation,␣
↪palette='viridis', legend=False)
plt.title('Distribution of Individuals Across Clusters')
plt.xlabel('Cluster')
plt.ylabel('Number of Individuals')
plt.savefig('cluster_sizes.png')  # Save the plot as an image
plt.show()  # Display the plot in the notebook
plt.close()

# Save and display PCA plot
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=df_segmentation,␣
↪palette='viridis')
plt.title('K-Means Clusters (PCA)')
plt.savefig('pca_clusters.png')  # Save the plot as an image
plt.show()  # Display the plot in the notebook
plt.close()

# Save and display t-SNE plot
plt.figure(figsize=(10, 8))
sns.scatterplot(x='TSNE1', y='TSNE2', hue='Cluster', data=df_segmentation,␣
↪palette='viridis')
plt.title('K-Means Clusters (t-SNE)')
plt.savefig('tsne_clusters.png')  # Save the plot as an image
plt.show()  # Display the plot in the notebook
plt.close()
```



Distribution of Individuals Across Clusters
Number of Individuals
40000
35000
30000
25000
20000
15000
10000
5000
0
0
1
2
3
Cluster


K-Means Clusters (PCA)
Cluster
0
1
2
3
PCA2
PCA1
20
15
10
5
0
−5
−10
−5
0
5
10
15

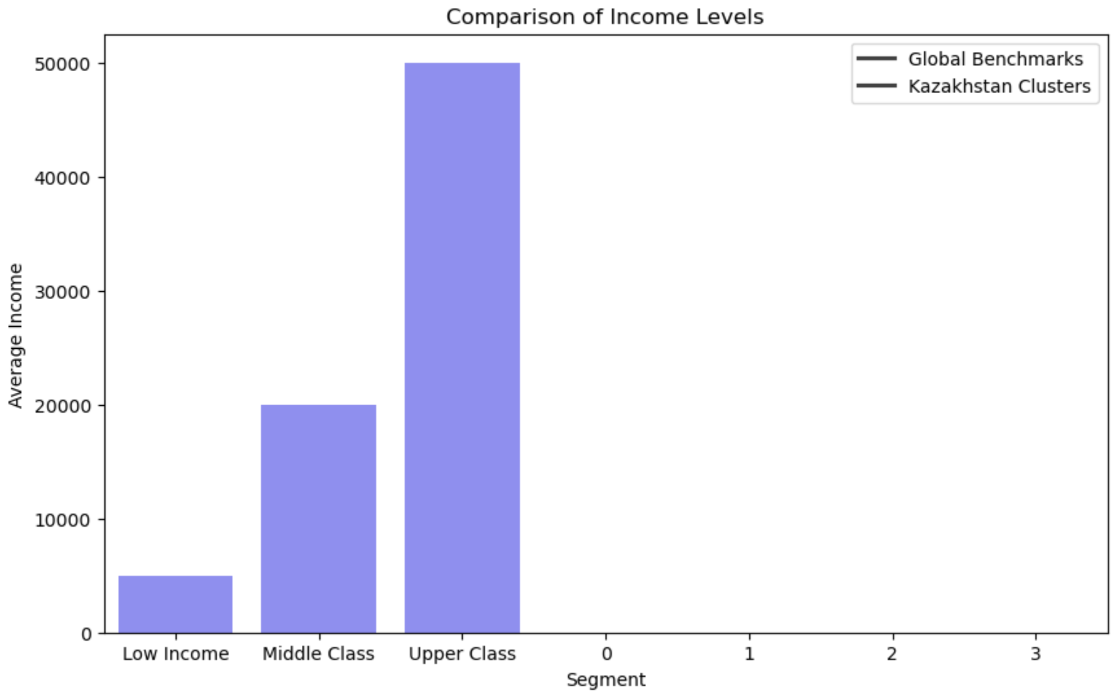


[71]:
```python
# Step 1: Analyze Cluster Characteristics
cluster_summary = df_segmentation.groupby('Cluster').mean()
print("Cluster Summary:")
print(cluster_summary)

# Step 2: Define Sociological Insights for Each Cluster
sociological_insights = {
    0: {
        'description': 'Rural Poor',
        'characteristics': {
            'Income': cluster_summary.loc[0, 'Q46'],  # Replace with actual␣
↪income column
            'Education Level': cluster_summary.loc[0, 'Q47'],  # Replace with␣
↪actual education column
            'Urban/Rural': 'Rural',
            'Religiosity': 'High'
        }
    },
```

```python
    1: {
        'description': 'Urban Middle Class',
        'characteristics': {
            'Income': cluster_summary.loc[1, 'Q46'],
            'Education Level': cluster_summary.loc[1, 'Q47'],
            'Urban/Rural': 'Urban',
            'Religiosity': 'Moderate'
        }
    },
    2: {
        'description': 'Elite',
        'characteristics': {
            'Income': cluster_summary.loc[2, 'Q46'],
            'Education Level': cluster_summary.loc[2, 'Q47'],
            'Urban/Rural': 'Urban',
            'Religiosity': 'Low'
        }
    },
    # Add more clusters as needed
}

# Step 3: Print Out Portraits of Each Segment
for cluster_id, insights in sociological_insights.items():
    print(f"Cluster {cluster_id}: {insights['description']}")
    for key, value in insights['characteristics'].items():
        print(f" - {key}: {value}")
    print()  # Blank line for better readability

# Step 4: Compare with Global Segmentation (Example)
global_benchmarks = pd.DataFrame({
    'Segment': ['Low Income', 'Middle Class', 'Upper Class'],
    'Avg_Income': [5000, 20000, 50000],  # Example global data
    'Avg_Education_Level': [2, 4, 6]      # Example education levels on a scale
})

print("Global Benchmarks:")
print(global_benchmarks)

# Step 5: Visualize Comparison of Income Levels
plt.figure(figsize=(10, 6))
sns.barplot(x='Segment', y='Avg_Income', data=global_benchmarks, color='blue',␣
 ↪alpha=0.5)
sns.barplot(x=cluster_summary.index, y=cluster_summary['Q46'], color='orange',␣
 ↪alpha=0.7)  # Replace with actual income column
plt.title('Comparison of Income Levels')
plt.xlabel('Segment')
plt.ylabel('Average Income')
```

```python
plt.legend(['Global Benchmarks', 'Kazakhstan Clusters'])
plt.show()
```

```
Cluster Summary:
              Q46       Q47       Q48       Q49       Q50        Q1        Q2  \
Cluster
0        0.785892  0.816736 -0.645379 -0.917370 -0.833559 -0.211681  0.531976
1       -0.414205 -0.364855  0.536627  0.685357  0.650060 -0.248513 -0.022219
2        0.230126  0.153567 -0.113624 -0.106188 -0.018225  2.574265  0.515799
3        0.000525 -0.073734 -0.331473 -0.368547 -0.403093 -0.301749 -0.520059

               Q3        Q4        Q5  DBSCAN_Cluster      PCA1      PCA2  \
Cluster
0        0.499185  0.398940  0.194092       96.737783 -1.904193  0.002734
1        0.004685  0.106035  0.024447      153.033595  1.149005 -0.426728
2        0.195582  0.068002  0.453796       64.184748 -0.904533 -1.400334
3       -0.433393 -0.476952 -0.327461      128.284849 -0.114406  1.121866

             TSNE1      TSNE2
Cluster
0       -36.112911  -0.160917
1        29.858084  -7.229505
2       -63.022194 -78.679855
3         1.298202  38.592617
Cluster 0: Rural Poor
 - Income: 0.7858915071198167
 - Education Level: 0.8167364261192175
 - Urban/Rural: Rural
 - Religiosity: High

Cluster 1: Urban Middle Class
 - Income: -0.41420485691563036
 - Education Level: -0.3648545105617027
 - Urban/Rural: Urban
 - Religiosity: Moderate

Cluster 2: Elite
 - Income: 0.23012560326467316
 - Education Level: 0.15356673255179498
 - Urban/Rural: Urban
 - Religiosity: Low

Global Benchmarks:
        Segment  Avg_Income  Avg_Education_Level
0    Low Income        5000                    2
1  Middle Class       20000                    4
2   Upper Class       50000                    6
```



[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

# Step 1: Analyze Cluster Characteristics
cluster_summary = df_segmentation.groupby('Cluster').mean()
print("Cluster Summary:")
print(cluster_summary)

# Step 2: Visualize Cluster Profiles with Heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(cluster_summary.T, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Cluster Profiles (Mean Values of Features)")
plt.xlabel("Cluster")
plt.ylabel("Features")
plt.show()

# Step 3: Dimensionality Reduction for Visualization (PCA)
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster'], errors='ignore'))
```

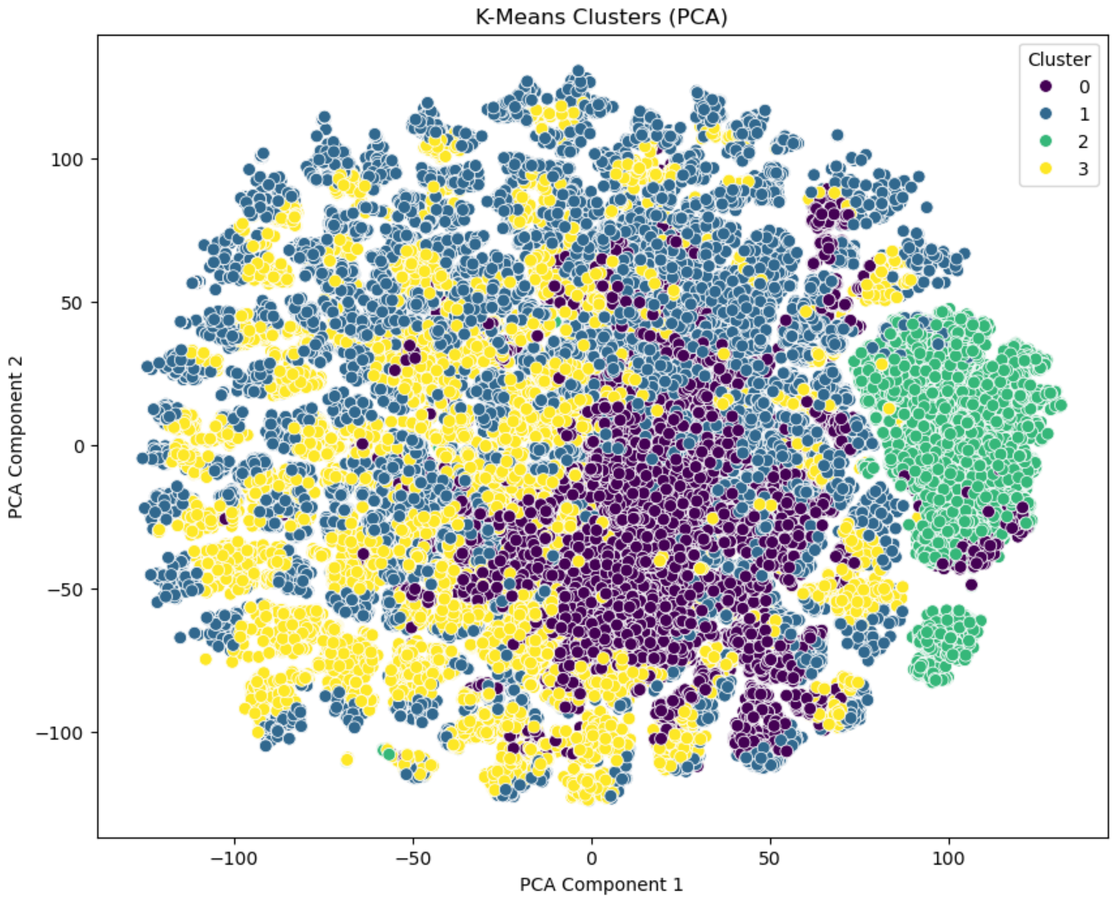
```
df_segmentation['PCA1'] = pca_result[:, 0]
df_segmentation['PCA2'] = pca_result[:, 1]

# Scatter plot of clusters using PCA
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=df_segmentation,␣
↪palette='viridis', s=50)
plt.title('K-Means Clusters (PCA)')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title="Cluster")
plt.show()

# Step 4: Dimensionality Reduction for Visualization (t-SNE)
tsne = TSNE(n_components=2, random_state=42, perplexity=30)
tsne_result = tsne.fit_transform(df_segmentation.drop(columns=['Cluster',␣
↪'DBSCAN_Cluster', 'PCA1', 'PCA2'], errors='ignore'))

df_segmentation['TSNE1'] = tsne_result[:, 0]
df_segmentation['TSNE2'] = tsne_result[:, 1]

# Scatter plot of clusters using t-SNE
plt.figure(figsize=(10, 8))
sns.scatterplot(x='TSNE1', y='TSNE2', hue='Cluster', data=df_segmentation,␣
↪palette='viridis', s=50)
plt.title('K-Means Clusters (t-SNE)')
plt.xlabel('t-SNE Dimension 1')
plt.ylabel('t-SNE Dimension 2')
plt.legend(title="Cluster")
plt.show()

# Step 5: Prepare Sociological Portraits for Each Cluster
sociological_insights = {
    0: {
        'description': 'Rural Poor',
        'characteristics': {
            'Income': cluster_summary.loc[0, 'Q46'],  # Replace with actual␣
↪income column
            'Education Level': cluster_summary.loc[0, 'Q47'],  # Replace with␣
↪actual education column
            'Urban/Rural': 'Rural',
            'Religiosity': 'High',
        }
    },
    1: {
        'description': 'Urban Middle Class',
        'characteristics': {
```

```
            'Income': cluster_summary.loc[1, 'Q46'],
            'Education Level': cluster_summary.loc[1, 'Q47'],
            'Urban/Rural': 'Urban',
            'Religiosity': 'Moderate',
        }
    },
    2: {
        'description': 'Elite',
        'characteristics': {
            'Income': cluster_summary.loc[2, 'Q46'],
            'Education Level': cluster_summary.loc[2, 'Q47'],
            'Urban/Rural': 'Urban',
            'Religiosity': 'Low',
        }
    },
    # Add more clusters as needed
}

print("\nSociological Portraits:")
for cluster_id, insights in sociological_insights.items():
    print(f"Cluster {cluster_id}: {insights['description']}")
    for key, value in insights['characteristics'].items():
        print(f" - {key}: {value}")
    print()

# Step 6: Compare with Global Segmentation Benchmarks
global_benchmarks = pd.DataFrame({
    'Segment': ['Low Income', 'Middle Class', 'Upper Class'],
    'Avg_Income': [5000, 20000, 50000],  # Example global data
    'Avg_Education_Level': [2, 4, 6]     # Example education levels on a scale
})

print("Global Benchmarks:")
print(global_benchmarks)

# Visualize comparison between Kazakhstanis and global benchmarks
plt.figure(figsize=(10, 6))
sns.barplot(x='Segment', y='Avg_Income', data=global_benchmarks, color='blue',␣
 ↪alpha=0.5)
sns.barplot(x=cluster_summary.index.astype(str), y=cluster_summary['Q46'],␣
 ↪color='orange', alpha=0.7)  # Replace with actual income column
plt.title('Comparison of Income Levels: Kazakhstan Clusters vs Global␣
 ↪Benchmarks')
plt.xlabel('Segment/Cluster')
plt.ylabel('Average Income')
plt.legend(['Global Benchmarks', 'Kazakhstan Clusters'])
plt.show()
```

```python
# Step 7: Visualize Cluster Sizes
plt.figure(figsize=(8, 6))
sns.countplot(x='Cluster', data=df_segmentation, palette='viridis')
plt.title('Distribution of Individuals Across Clusters')
plt.xlabel('Cluster')
plt.ylabel('Number of Individuals')
plt.show()
```

```
Cluster Summary:
              Q46       Q47       Q48       Q49       Q50        Q1        Q2  \
Cluster
0        0.785892  0.816736 -0.645379 -0.917370 -0.833559 -0.211681  0.531976
1       -0.414205 -0.364855  0.536627  0.685357  0.650060 -0.248513 -0.022219
2        0.230126  0.153567 -0.113624 -0.106188 -0.018225  2.574265  0.515799
3        0.000525 -0.073734 -0.331473 -0.368547 -0.403093 -0.301749 -0.520059

               Q3        Q4        Q5  DBSCAN_Cluster      PCA1      PCA2  \
Cluster
0        0.499185  0.398940  0.194092       96.737783 -1.904193  0.002734
1        0.004685  0.106035  0.024447      153.033595  1.149005 -0.426728
2        0.195582  0.068002  0.453796       64.184748 -0.904533 -1.400334
3       -0.433393 -0.476952 -0.327461      128.284849 -0.114406  1.121866

             TSNE1      TSNE2
Cluster
0       -36.112911  -0.160917
1        29.858084  -7.229505
2       -63.022194 -78.679855
3         1.298202  38.592617
```

Cluster Profiles (Mean Values of Features)
Features
Q46
Q47
Q48
Q49
Q50
Q1
Q2
Q3
Q4
Q5
DBSCAN_Cluster
PCA1
PCA2
TSNE1
TSNE2
0.79 -0.41 0.23 0.00
0.82 -0.36 0.15 -0.07
-0.65 0.54 -0.11 -0.33
-0.92 0.69 -0.11 -0.37
-0.83 0.65 -0.02 -0.40
-0.21 -0.25 2.57 -0.30
0.53 -0.02 0.52 -0.52
0.50 0.00 0.20 -0.43
0.40 0.11 0.07 -0.48
0.19 0.02 0.45 -0.33
96.74 153.03 64.18 128.28
-1.90 1.15 -0.90 -0.11
0.00 -0.43 -1.40 1.12
-36.11 29.86 -63.02 1.30
-0.16 -7.23 -78.68 38.59
0
1
2
3
Cluster
150
100
50
0
−50


K-Means Clusters (PCA)
Cluster
0
1
2
3
100
50
0
−50
−100
PCA Component 2
−100
−50
0
50
100
PCA Component 1