

02_feature_analysis

November 24, 2024

```
[1]: import warnings
from pathlib import Path

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
import seaborn as sns
from scipy import stats
from sklearn.decomposition import PCA
from sklearn.feature_selection import mutual_info_regression
from sklearn.preprocessing import StandardScaler

warnings.filterwarnings('ignore')

# Set plotting styles
plt.style.use('bmh')
sns.set_palette("husl")
plt.rcParams['figure.figsize'] = [12, 6]

[2]: # Load Processed Data from the Pipeline

# Get the current notebook directory and construct the correct path
notebook_dir = Path().absolute()
project_root = notebook_dir.parent if notebook_dir.name == 'notebooks' else_
↳ notebook_dir
processed_data_path = project_root / 'processed_data' / 'final_processed_data.
↳ csv'

print(f"Looking for data file at: {processed_data_path}")
df = pd.read_csv(processed_data_path)

# Display basic information about the processed dataset
print("Dataset Overview:")
print("=" * 80)
print(f"\nShape: {df.shape}")
```

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print("\nFeatures:")
for col in df.columns:
    dtype = df[col].dtype
    missing = df[col].isnull().sum()
    print(f"- {col}: {dtype} (Missing: {missing})")

```

Looking for data file at:

/Users/katejohnson/Documents/Other/Northeastern/CS6140/Course
Project/cs6140-course-project/processed_data/final_processed_data.csv

Dataset Overview:

=====

Shape: (643, 31)

Features:

- year: float64 (Missing: 0)
- hydro_generation: float64 (Missing: 0)
- biofuel_generation: float64 (Missing: 0)
- solar_generation: float64 (Missing: 0)
- geothermal_generation: float64 (Missing: 0)
- country: object (Missing: 0)
- total_energy_consumption: float64 (Missing: 0)
- renewable_share_pct: float64 (Missing: 0)
- other_renewable_generation: float64 (Missing: 0)
- solar_generation_alt: float64 (Missing: 0)
- wind_generation: float64 (Missing: 0)
- hydro_generation_alt: float64 (Missing: 0)
- renewable_generation: float64 (Missing: 0)
- decade: float64 (Missing: 0)
- period: object (Missing: 0)
- renewable_generation_lag_1: float64 (Missing: 38)
- renewable_generation_lag_3: float64 (Missing: 114)
- renewable_generation_lag_6: float64 (Missing: 223)
- renewable_generation_lag_12: float64 (Missing: 408)
- renewable_generation_rolling_mean_3: float64 (Missing: 0)
- renewable_generation_rolling_std_3: float64 (Missing: 38)
- renewable_generation_rolling_mean_6: float64 (Missing: 0)
- renewable_generation_rolling_std_6: float64 (Missing: 38)
- renewable_generation_rolling_mean_12: float64 (Missing: 0)
- renewable_generation_rolling_std_12: float64 (Missing: 38)
- total_renewable: float64 (Missing: 0)
- renewable_share: float64 (Missing: 0)
- hydro_generation_share: float64 (Missing: 0)
- solar_generation_share: float64 (Missing: 0)
- wind_generation_share: float64 (Missing: 0)
- renewable_yoy_growth: float64 (Missing: 38)

```
[3]: # Feature Distribution Analysis
def analyze_feature_distributions():
    """Analyze the distribution of engineered features"""

    # Select numerical columns
    numeric_cols = df.select_dtypes(include=[np.number]).columns

    # Create distribution plots
    for i in range(0, len(numeric_cols), 3):
        cols = numeric_cols[i:i + 3]
        fig, axes = plt.subplots(1, len(cols), figsize=(18, 6))
        if len(cols) == 1:
            axes = [axes]

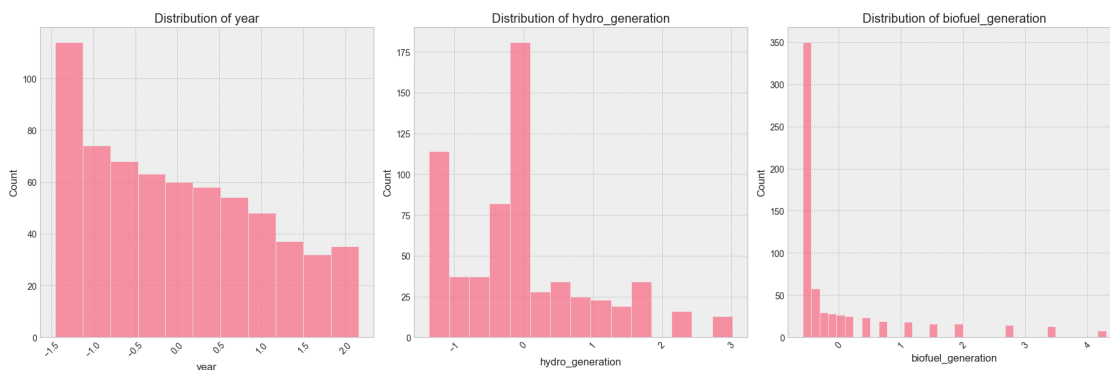
        for ax, col in zip(axes, cols):
            sns.histplot(data=df, x=col, ax=ax)
            ax.set_title(f'Distribution of {col}')
            ax.tick_params(axis='x', rotation=45)

        plt.tight_layout()
        plt.show()

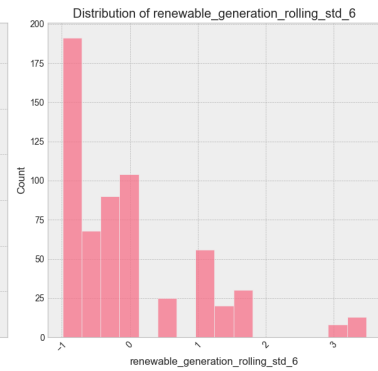
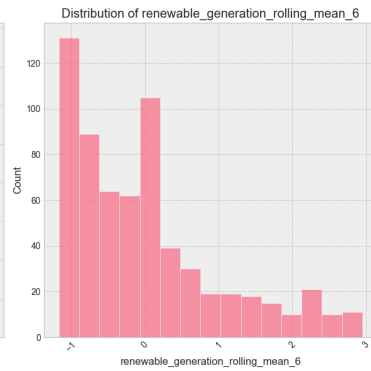
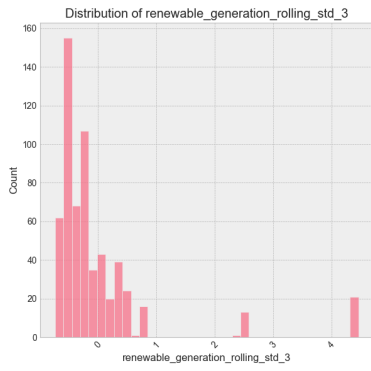
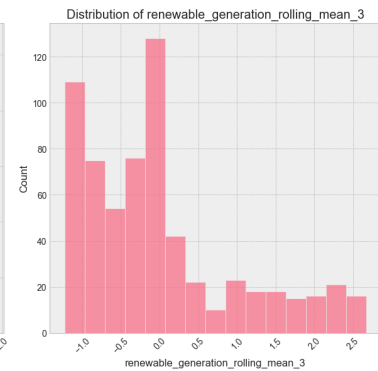
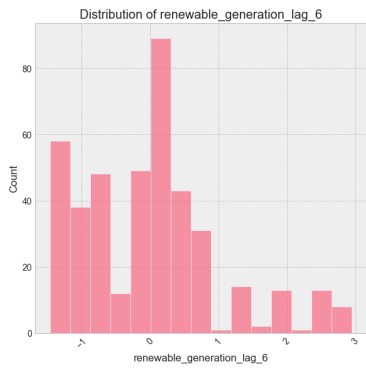
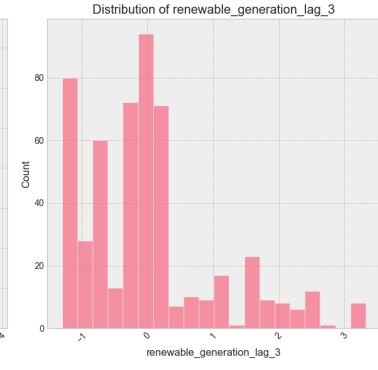
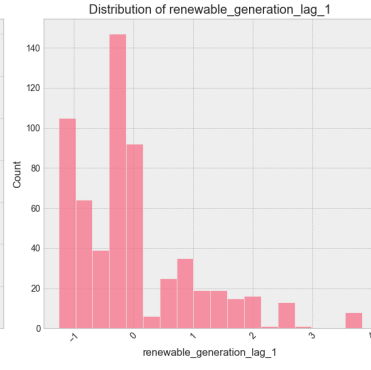
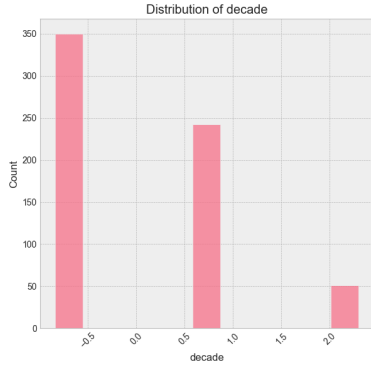
    # Test for normality
    normality_tests = {}
    for col in numeric_cols:
        stat, p_value = stats.normaltest(df[col].dropna())
        normality_tests[col] = {'statistic': stat, 'p_value': p_value}

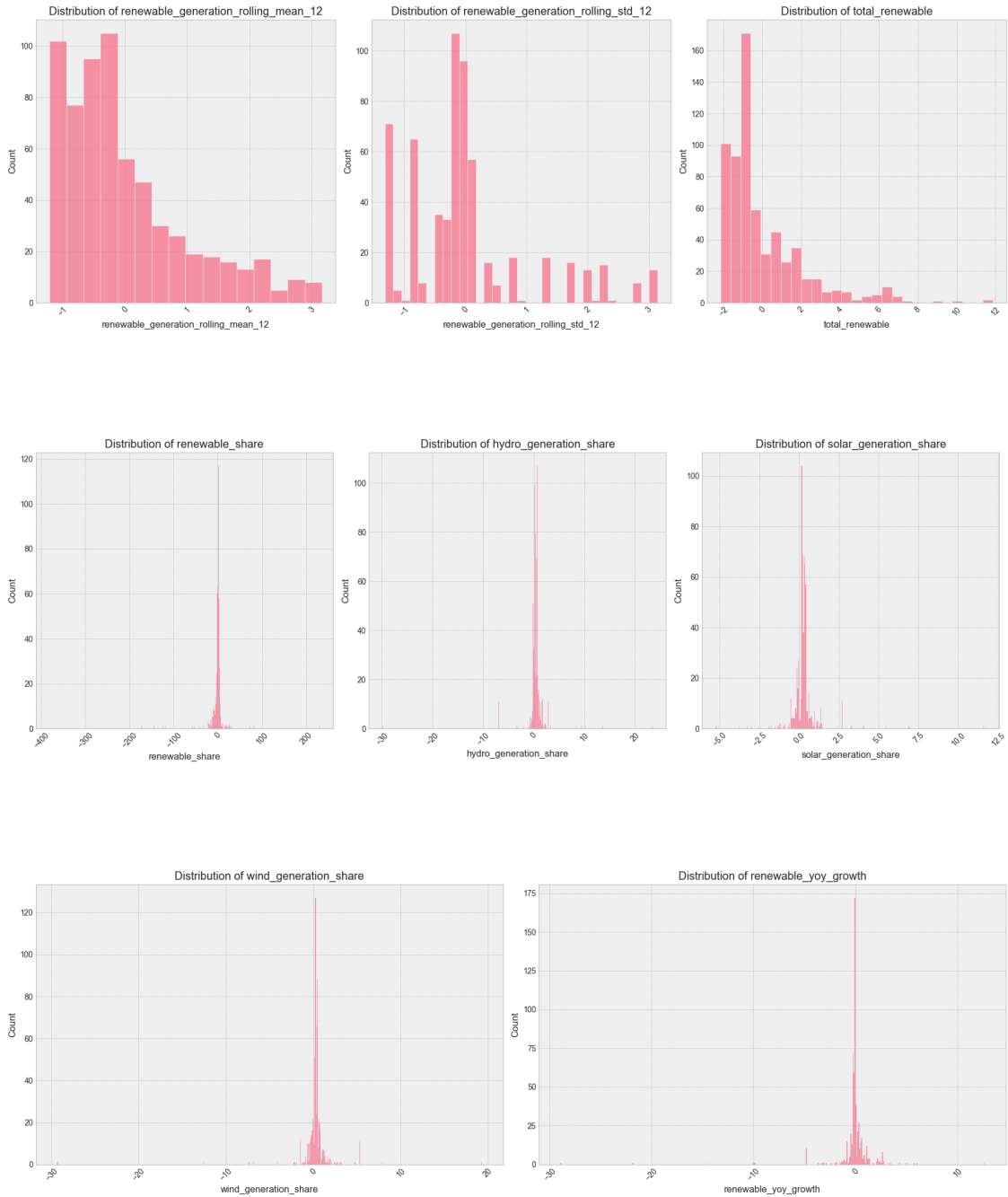
    return pd.DataFrame(normality_tests).T

# Run distribution analysis
distribution_results = analyze_feature_distributions()
print("\nNormality Test Results:")
display(distribution_results)
```









Normality Test Results:

	statistic	p_value
year	113.226438	2.589354e-25
hydro_generation	80.844695	2.784822e-18
biofuel_generation	329.399574	2.963407e-72
solar_generation	566.506611	9.652782e-124

geothermal_generation	100.253547	1.699099e-22
total_energy_consumption	298.909736	1.237586e-65
renewable_share_pct	203.481938	6.523168e-45
other_renewable_generation	429.997125	4.239462e-94
solar_generation_alt	486.426367	2.365138e-106
wind_generation	404.734225	1.297418e-88
hydro_generation_alt	210.014280	2.488735e-46
renewable_generation	133.607568	9.715949e-30
decade	60.749123	6.434215e-14
renewable_generation_lag_1	136.670932	2.100314e-30
renewable_generation_lag_3	90.284680	2.482737e-20
renewable_generation_lag_6	35.440488	2.014633e-08
renewable_generation_lag_12	1946.852238	0.000000e+00
renewable_generation_rolling_mean_3	75.971813	3.183687e-17
renewable_generation_rolling_std_3	439.361665	3.924883e-96
renewable_generation_rolling_mean_6	93.607219	4.714662e-21
renewable_generation_rolling_std_6	172.914956	2.831355e-38
renewable_generation_rolling_mean_12	102.215180	6.371706e-23
renewable_generation_rolling_std_12	132.123582	2.040463e-29
total_renewable	269.829879	2.553797e-59
renewable_share	826.228714	3.861129e-180
hydro_generation_share	587.223872	3.061656e-128
solar_generation_share	793.212219	5.703680e-173
wind_generation_share	788.697547	5.451347e-172
renewable_yoy_growth	799.879011	2.034602e-174

```
[4]: # Correlation Analysis
def analyze_correlations():
    """Analyze correlations between features"""

    # Filter out non-numerical columns
    numerical_cols = df.select_dtypes(include=[np.number]).columns
    df_numerical = df[numerical_cols]

    # Calculate correlation matrix
    corr_matrix = df_numerical.corr()

    # Plot correlation heatmap
    plt.figure(figsize=(15, 12))
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0, fmt='.2f')
    plt.title('Feature Correlation Matrix')
    plt.show()

    # Identify highly correlated features
    high_corr = np.where(np.abs(corr_matrix) > 0.8)
    high_corr = [(corr_matrix.index[x], corr_matrix.columns[y], corr_matrix.
↵iloc[x, y])
```

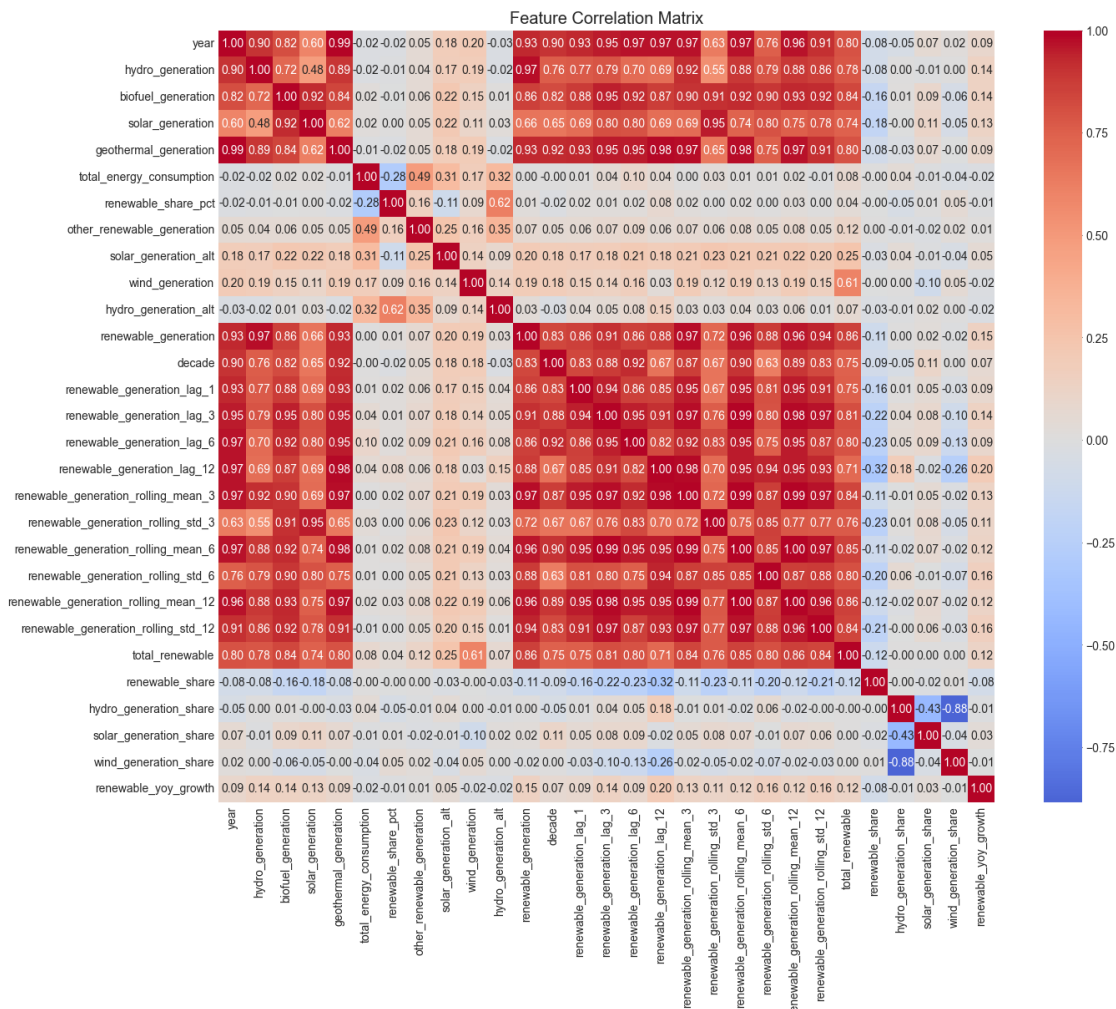
```

for x, y in zip(*high_corr) if x != y]

print("\nHighly Correlated Feature Pairs (|correlation| > 0.8):")
for feat1, feat2, corr in high_corr:
    print(f"{feat1} - {feat2}: {corr:.3f}")

analyze_correlations()

```



Highly Correlated Feature Pairs (|correlation| > 0.8):

```

year - hydro_generation: 0.901
year - biofuel_generation: 0.815
year - geothermal_generation: 0.989
year - renewable_generation: 0.932
year - decade: 0.902

```


year - renewable_generation_lag_1: 0.932
 year - renewable_generation_lag_3: 0.955
 year - renewable_generation_lag_6: 0.966
 year - renewable_generation_lag_12: 0.970
 year - renewable_generation_rolling_mean_3: 0.968
 year - renewable_generation_rolling_mean_6: 0.967
 year - renewable_generation_rolling_mean_12: 0.964
 year - renewable_generation_rolling_std_12: 0.911
 hydro_generation - year: 0.901
 hydro_generation - geothermal_generation: 0.890
 hydro_generation - renewable_generation: 0.971
 hydro_generation - renewable_generation_rolling_mean_3: 0.916
 hydro_generation - renewable_generation_rolling_mean_6: 0.885
 hydro_generation - renewable_generation_rolling_mean_12: 0.882
 hydro_generation - renewable_generation_rolling_std_12: 0.856
 biofuel_generation - year: 0.815
 biofuel_generation - solar_generation: 0.920
 biofuel_generation - geothermal_generation: 0.845
 biofuel_generation - renewable_generation: 0.860
 biofuel_generation - decade: 0.822
 biofuel_generation - renewable_generation_lag_1: 0.882
 biofuel_generation - renewable_generation_lag_3: 0.945
 biofuel_generation - renewable_generation_lag_6: 0.922
 biofuel_generation - renewable_generation_lag_12: 0.872
 biofuel_generation - renewable_generation_rolling_mean_3: 0.899
 biofuel_generation - renewable_generation_rolling_std_3: 0.909
 biofuel_generation - renewable_generation_rolling_mean_6: 0.922
 biofuel_generation - renewable_generation_rolling_std_6: 0.896
 biofuel_generation - renewable_generation_rolling_mean_12: 0.930
 biofuel_generation - renewable_generation_rolling_std_12: 0.924
 biofuel_generation - total_renewable: 0.836
 solar_generation - biofuel_generation: 0.920
 solar_generation - renewable_generation_lag_3: 0.803
 solar_generation - renewable_generation_rolling_std_3: 0.954
 geothermal_generation - year: 0.989
 geothermal_generation - hydro_generation: 0.890
 geothermal_generation - biofuel_generation: 0.845
 geothermal_generation - renewable_generation: 0.934
 geothermal_generation - decade: 0.922
 geothermal_generation - renewable_generation_lag_1: 0.933
 geothermal_generation - renewable_generation_lag_3: 0.954
 geothermal_generation - renewable_generation_lag_6: 0.952
 geothermal_generation - renewable_generation_lag_12: 0.980
 geothermal_generation - renewable_generation_rolling_mean_3: 0.971
 geothermal_generation - renewable_generation_rolling_mean_6: 0.976
 geothermal_generation - renewable_generation_rolling_mean_12: 0.970
 geothermal_generation - renewable_generation_rolling_std_12: 0.907
 renewable_generation - year: 0.932

renewable_generation - hydro_generation: 0.971
renewable_generation - biofuel_generation: 0.860
renewable_generation - geothermal_generation: 0.934
renewable_generation - decade: 0.832
renewable_generation - renewable_generation_lag_1: 0.859
renewable_generation - renewable_generation_lag_3: 0.908
renewable_generation - renewable_generation_lag_6: 0.855
renewable_generation - renewable_generation_lag_12: 0.876
renewable_generation - renewable_generation_rolling_mean_3: 0.972
renewable_generation - renewable_generation_rolling_mean_6: 0.958
renewable_generation - renewable_generation_rolling_std_6: 0.879
renewable_generation - renewable_generation_rolling_mean_12: 0.960
renewable_generation - renewable_generation_rolling_std_12: 0.939
renewable_generation - total_renewable: 0.857
decade - year: 0.902
decade - biofuel_generation: 0.822
decade - geothermal_generation: 0.922
decade - renewable_generation: 0.832
decade - renewable_generation_lag_1: 0.833
decade - renewable_generation_lag_3: 0.875
decade - renewable_generation_lag_6: 0.919
decade - renewable_generation_rolling_mean_3: 0.874
decade - renewable_generation_rolling_mean_6: 0.902
decade - renewable_generation_rolling_mean_12: 0.893
decade - renewable_generation_rolling_std_12: 0.826
renewable_generation_lag_1 - year: 0.932
renewable_generation_lag_1 - biofuel_generation: 0.882
renewable_generation_lag_1 - geothermal_generation: 0.933
renewable_generation_lag_1 - renewable_generation: 0.859
renewable_generation_lag_1 - decade: 0.833
renewable_generation_lag_1 - renewable_generation_lag_3: 0.943
renewable_generation_lag_1 - renewable_generation_lag_6: 0.858
renewable_generation_lag_1 - renewable_generation_lag_12: 0.851
renewable_generation_lag_1 - renewable_generation_rolling_mean_3: 0.950
renewable_generation_lag_1 - renewable_generation_rolling_mean_6: 0.952
renewable_generation_lag_1 - renewable_generation_rolling_std_6: 0.807
renewable_generation_lag_1 - renewable_generation_rolling_mean_12: 0.954
renewable_generation_lag_1 - renewable_generation_rolling_std_12: 0.914
renewable_generation_lag_3 - year: 0.955
renewable_generation_lag_3 - biofuel_generation: 0.945
renewable_generation_lag_3 - solar_generation: 0.803
renewable_generation_lag_3 - geothermal_generation: 0.954
renewable_generation_lag_3 - renewable_generation: 0.908
renewable_generation_lag_3 - decade: 0.875
renewable_generation_lag_3 - renewable_generation_lag_1: 0.943
renewable_generation_lag_3 - renewable_generation_lag_6: 0.947
renewable_generation_lag_3 - renewable_generation_lag_12: 0.911
renewable_generation_lag_3 - renewable_generation_rolling_mean_3: 0.973

renewable_generation_lag_3 - renewable_generation_rolling_mean_6: 0.991
renewable_generation_lag_3 - renewable_generation_rolling_mean_12: 0.984
renewable_generation_lag_3 - renewable_generation_rolling_std_12: 0.965
renewable_generation_lag_3 - total_renewable: 0.812
renewable_generation_lag_6 - year: 0.966
renewable_generation_lag_6 - biofuel_generation: 0.922
renewable_generation_lag_6 - geothermal_generation: 0.952
renewable_generation_lag_6 - renewable_generation: 0.855
renewable_generation_lag_6 - decade: 0.919
renewable_generation_lag_6 - renewable_generation_lag_1: 0.858
renewable_generation_lag_6 - renewable_generation_lag_3: 0.947
renewable_generation_lag_6 - renewable_generation_lag_12: 0.820
renewable_generation_lag_6 - renewable_generation_rolling_mean_3: 0.920
renewable_generation_lag_6 - renewable_generation_rolling_std_3: 0.829
renewable_generation_lag_6 - renewable_generation_rolling_mean_6: 0.954
renewable_generation_lag_6 - renewable_generation_rolling_mean_12: 0.955
renewable_generation_lag_6 - renewable_generation_rolling_std_12: 0.866
renewable_generation_lag_12 - year: 0.970
renewable_generation_lag_12 - biofuel_generation: 0.872
renewable_generation_lag_12 - geothermal_generation: 0.980
renewable_generation_lag_12 - renewable_generation: 0.876
renewable_generation_lag_12 - renewable_generation_lag_1: 0.851
renewable_generation_lag_12 - renewable_generation_lag_3: 0.911
renewable_generation_lag_12 - renewable_generation_lag_6: 0.820
renewable_generation_lag_12 - renewable_generation_rolling_mean_3: 0.978
renewable_generation_lag_12 - renewable_generation_rolling_mean_6: 0.953
renewable_generation_lag_12 - renewable_generation_rolling_std_6: 0.937
renewable_generation_lag_12 - renewable_generation_rolling_mean_12: 0.953
renewable_generation_lag_12 - renewable_generation_rolling_std_12: 0.930
renewable_generation_rolling_mean_3 - year: 0.968
renewable_generation_rolling_mean_3 - hydro_generation: 0.916
renewable_generation_rolling_mean_3 - biofuel_generation: 0.899
renewable_generation_rolling_mean_3 - geothermal_generation: 0.971
renewable_generation_rolling_mean_3 - renewable_generation: 0.972
renewable_generation_rolling_mean_3 - decade: 0.874
renewable_generation_rolling_mean_3 - renewable_generation_lag_1: 0.950
renewable_generation_rolling_mean_3 - renewable_generation_lag_3: 0.973
renewable_generation_rolling_mean_3 - renewable_generation_lag_6: 0.920
renewable_generation_rolling_mean_3 - renewable_generation_lag_12: 0.978
renewable_generation_rolling_mean_3 - renewable_generation_rolling_mean_6: 0.994
renewable_generation_rolling_mean_3 - renewable_generation_rolling_std_6: 0.869
renewable_generation_rolling_mean_3 - renewable_generation_rolling_mean_12:
0.993
renewable_generation_rolling_mean_3 - renewable_generation_rolling_std_12: 0.970
renewable_generation_rolling_mean_3 - total_renewable: 0.844
renewable_generation_rolling_std_3 - biofuel_generation: 0.909
renewable_generation_rolling_std_3 - solar_generation: 0.954
renewable_generation_rolling_std_3 - renewable_generation_lag_6: 0.829

renewable_generation_rolling_std_3 - renewable_generation_rolling_std_6: 0.854
renewable_generation_rolling_mean_6 - year: 0.967
renewable_generation_rolling_mean_6 - hydro_generation: 0.885
renewable_generation_rolling_mean_6 - biofuel_generation: 0.922
renewable_generation_rolling_mean_6 - geothermal_generation: 0.976
renewable_generation_rolling_mean_6 - renewable_generation: 0.958
renewable_generation_rolling_mean_6 - decade: 0.902
renewable_generation_rolling_mean_6 - renewable_generation_lag_1: 0.952
renewable_generation_rolling_mean_6 - renewable_generation_lag_3: 0.991
renewable_generation_rolling_mean_6 - renewable_generation_lag_6: 0.954
renewable_generation_rolling_mean_6 - renewable_generation_lag_12: 0.953
renewable_generation_rolling_mean_6 - renewable_generation_rolling_mean_3: 0.994
renewable_generation_rolling_mean_6 - renewable_generation_rolling_std_6: 0.847
renewable_generation_rolling_mean_6 - renewable_generation_rolling_mean_12:
0.997
renewable_generation_rolling_mean_6 - renewable_generation_rolling_std_12: 0.970
renewable_generation_rolling_mean_6 - total_renewable: 0.850
renewable_generation_rolling_std_6 - biofuel_generation: 0.896
renewable_generation_rolling_std_6 - renewable_generation: 0.879
renewable_generation_rolling_std_6 - renewable_generation_lag_1: 0.807
renewable_generation_rolling_std_6 - renewable_generation_lag_12: 0.937
renewable_generation_rolling_std_6 - renewable_generation_rolling_mean_3: 0.869
renewable_generation_rolling_std_6 - renewable_generation_rolling_std_3: 0.854
renewable_generation_rolling_std_6 - renewable_generation_rolling_mean_6: 0.847
renewable_generation_rolling_std_6 - renewable_generation_rolling_mean_12: 0.873
renewable_generation_rolling_std_6 - renewable_generation_rolling_std_12: 0.882
renewable_generation_rolling_std_6 - total_renewable: 0.804
renewable_generation_rolling_mean_12 - year: 0.964
renewable_generation_rolling_mean_12 - hydro_generation: 0.882
renewable_generation_rolling_mean_12 - biofuel_generation: 0.930
renewable_generation_rolling_mean_12 - geothermal_generation: 0.970
renewable_generation_rolling_mean_12 - renewable_generation: 0.960
renewable_generation_rolling_mean_12 - decade: 0.893
renewable_generation_rolling_mean_12 - renewable_generation_lag_1: 0.954
renewable_generation_rolling_mean_12 - renewable_generation_lag_3: 0.984
renewable_generation_rolling_mean_12 - renewable_generation_lag_6: 0.955
renewable_generation_rolling_mean_12 - renewable_generation_lag_12: 0.953
renewable_generation_rolling_mean_12 - renewable_generation_rolling_mean_3:
0.993
renewable_generation_rolling_mean_12 - renewable_generation_rolling_mean_6:
0.997
renewable_generation_rolling_mean_12 - renewable_generation_rolling_std_6: 0.873
renewable_generation_rolling_mean_12 - renewable_generation_rolling_std_12:
0.962
renewable_generation_rolling_mean_12 - total_renewable: 0.857
renewable_generation_rolling_std_12 - year: 0.911
renewable_generation_rolling_std_12 - hydro_generation: 0.856
renewable_generation_rolling_std_12 - biofuel_generation: 0.924

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renewable_generation_rolling_std_12 - geothermal_generation: 0.907
renewable_generation_rolling_std_12 - renewable_generation: 0.939
renewable_generation_rolling_std_12 - decade: 0.826
renewable_generation_rolling_std_12 - renewable_generation_lag_1: 0.914
renewable_generation_rolling_std_12 - renewable_generation_lag_3: 0.965
renewable_generation_rolling_std_12 - renewable_generation_lag_6: 0.866
renewable_generation_rolling_std_12 - renewable_generation_lag_12: 0.930
renewable_generation_rolling_std_12 - renewable_generation_rolling_mean_3: 0.970
renewable_generation_rolling_std_12 - renewable_generation_rolling_mean_6: 0.970
renewable_generation_rolling_std_12 - renewable_generation_rolling_std_6: 0.882
renewable_generation_rolling_std_12 - renewable_generation_rolling_mean_12:
0.962
renewable_generation_rolling_std_12 - total_renewable: 0.838
total_renewable - biofuel_generation: 0.836
total_renewable - renewable_generation: 0.857
total_renewable - renewable_generation_lag_3: 0.812
total_renewable - renewable_generation_rolling_mean_3: 0.844
total_renewable - renewable_generation_rolling_mean_6: 0.850
total_renewable - renewable_generation_rolling_std_6: 0.804
total_renewable - renewable_generation_rolling_mean_12: 0.857
total_renewable - renewable_generation_rolling_std_12: 0.838
hydro_generation_share - wind_generation_share: -0.884
wind_generation_share - hydro_generation_share: -0.884

```

```

[5]: # Feature Importance Analysis
def analyze_feature_importance(target_col='renewable_share'):
    """Analyze feature importance using mutual information"""

    # Prepare data
    X = df.select_dtypes(include=[np.number]).drop(columns=[target_col])
    y = df[target_col]

    # Handle NaN values
    data = pd.concat([X, y], axis=1)
    data = data.dropna()

    X = data.drop(columns=[target_col])
    y = data[target_col]

    # Calculate mutual information scores
    mi_scores = mutual_info_regression(X, y)

    # Create importance DataFrame
    importance_df = pd.DataFrame({
        'feature': X.columns,
        'importance': mi_scores
    }).sort_values('importance', ascending=False)

```

```

# Plot feature importance
plt.figure(figsize=(12, 6))
sns.barplot(data=importance_df, x='importance', y='feature')
plt.title('Feature Importance (Mutual Information)')
plt.xlabel('Mutual Information Score')
plt.show()

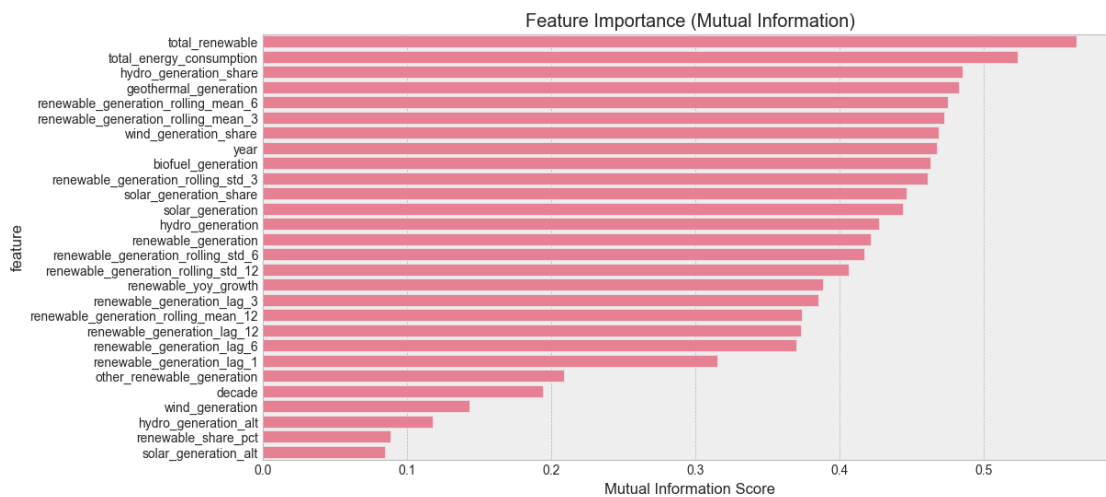
return importance_df

```

```

# Run feature importance analysis
importance_results = analyze_feature_importance()
print("\nFeature Importance Rankings:")
display(importance_results)

```



Feature Importance Rankings:

	feature	importance
23	total_renewable	0.564535
5	total_energy_consumption	0.523810
24	hydro_generation_share	0.485603
4	geothermal_generation	0.483365
19	renewable_generation_rolling_mean_6	0.475199
17	renewable_generation_rolling_mean_3	0.472664
26	wind_generation_share	0.469328
0	year	0.467498
2	biofuel_generation	0.463234
18	renewable_generation_rolling_std_3	0.461647
25	solar_generation_share	0.447060

3	solar_generation	0.444076
1	hydro_generation	0.427795
11	renewable_generation	0.421878
20	renewable_generation_rolling_std_6	0.417347
22	renewable_generation_rolling_std_12	0.406414
27	renewable_yoy_growth	0.388578
14	renewable_generation_lag_3	0.385669
21	renewable_generation_rolling_mean_12	0.373811
16	renewable_generation_lag_12	0.373591
15	renewable_generation_lag_6	0.370171
13	renewable_generation_lag_1	0.315162
7	other_renewable_generation	0.208758
12	decade	0.194460
9	wind_generation	0.143512
10	hydro_generation_alt	0.117908
6	renewable_share_pct	0.088586
8	solar_generation_alt	0.084458

```
[6]: # Time Series Feature Analysis
def analyze_temporal_features():
    """Analyze temporal features and their relationships"""

    # Plot time series features
    temporal_features = [col for col in df.columns if 'lag' in col or 'rolling' in col]

    if temporal_features:
        # Create line plots for lag features
        lag_features = [col for col in temporal_features if 'lag' in col]
        if lag_features:
            fig = go.Figure()
            for col in lag_features:
                fig.add_trace(go.Scatter(x=df.index, y=df[col], name=col))
            fig.update_layout(title='Lag Features Over Time',
                              xaxis_title='Time',
                              yaxis_title='Value')
            fig.show()

        # Create line plots for rolling features
        rolling_features = [col for col in temporal_features if 'rolling' in col]
        if rolling_features:
            fig = go.Figure()
            for col in rolling_features:
                fig.add_trace(go.Scatter(x=df.index, y=df[col], name=col))
            fig.update_layout(title='Rolling Features Over Time',
                              xaxis_title='Time',
```

```

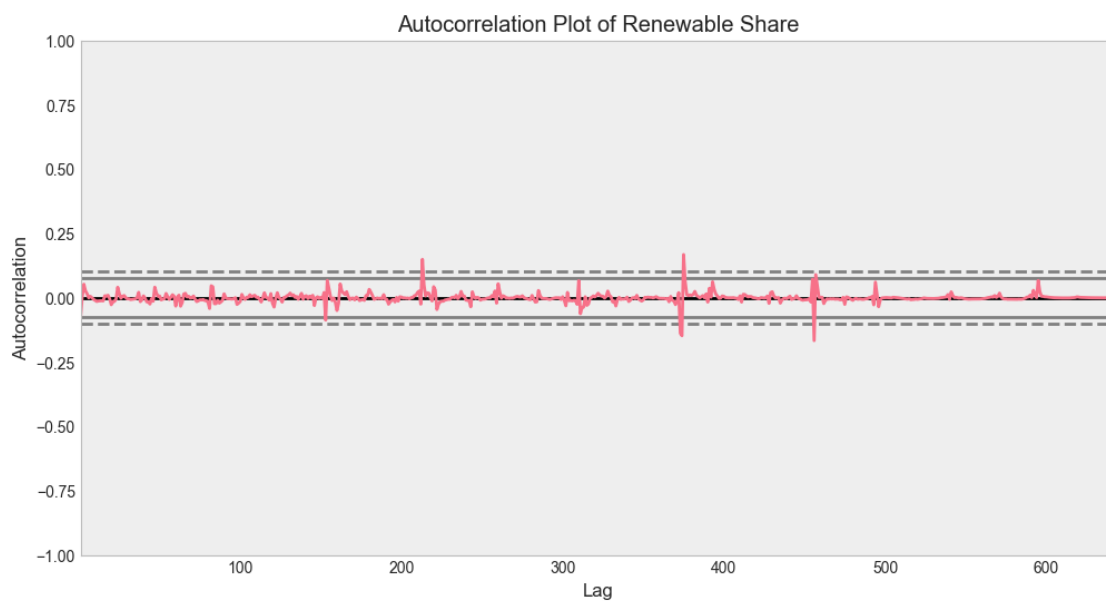
        yaxis_title='Value')

    fig.show()

    # Analyze autocorrelation
    if 'renewable_share' in df.columns:
        plt.figure(figsize=(12, 6))
        pd.plotting.autocorrelation_plot(df['renewable_share'])
        plt.title('Autocorrelation Plot of Renewable Share')
        plt.show()

analyze_temporal_features()

```



```

[7]: # Geographic Feature Analysis
def analyze_geographic_features():
    """Analyze geographic features and regional patterns"""

    if 'country' in df.columns and 'renewable_share' in df.columns:
        # Calculate regional statistics
        regional_stats = df.groupby('country').agg({
            'renewable_share': ['mean', 'std', 'min', 'max'],
            'total_renewable': ['mean', 'std']
        }).round(3)

        # Plot regional patterns
        fig = px.choropleth(
            df,

```



```

        locations='country',
        color='renewable_share',
        title='Geographic Distribution of Renewable Share',
        color_continuous_scale='Viridis'
    )
    fig.show()

    # Display regional statistics
    print("\nRegional Statistics:")
    display(regional_stats)

```

```
analyze_geographic_features()
```

Regional Statistics:

	renewable_share \			
country	mean	std	min	max
Algeria	-0.819	3.885	-12.148	2.406
Argentina	-9.071	30.369	-144.199	3.679
Australia	-38.585	167.832	-381.439	230.129
Belgium	0.113	4.715	-13.408	3.900
Chile	-1.148	4.662	-17.338	2.138
Colombia	-0.788	3.445	-10.469	2.485
Czechia	0.670	2.929	-7.990	4.299
Egypt	0.476	2.792	-6.193	2.910
France	-0.213	0.799	-1.096	1.720
Germany	-0.020	0.415	-0.332	0.450
India	-0.159	0.295	-0.569	0.254
Indonesia	-1.137	3.439	-11.421	3.996
Iran	-1.146	18.500	-80.001	30.012
Italy	-0.573	1.997	-2.464	3.661
Japan	-0.351	0.066	-0.432	-0.269
Kazakhstan	-5.722	26.673	-119.149	20.916
Kuwait	-0.483	2.745	-8.285	1.998
Malaysia	-3.861	12.401	-54.530	2.439
Mexico	-0.742	1.869	-3.962	3.393
Netherlands	-2.902	8.018	-16.465	5.474
New Zealand	0.244	1.851	-4.806	2.138
Nigeria	8.551	20.472	-21.289	73.092
Poland	-0.708	13.105	-13.492	24.803
Portugal	0.084	2.117	-4.793	2.218
Romania	0.677	3.208	-9.738	6.446
Saudi Arabia	2.233	49.617	-171.498	138.009
South Africa	-7.015	14.701	-57.478	5.038
South Korea	-2.366	4.808	-18.218	2.018

Spain	-2.774	17.200	-31.864	19.245
Sweden	-0.613	3.976	-7.420	3.823
Taiwan	1.720	37.790	-123.731	82.169
Thailand	3.052	4.840	-12.123	12.669
Turkey	1.670	14.845	-48.010	26.672
Ukraine	0.508	2.400	-1.339	6.193
United Arab Emirates	-1.219	5.353	-21.709	2.333
United Kingdom	0.215	1.435	-1.203	2.101
Uzbekistan	-0.384	4.067	-11.272	3.965
Venezuela	-3.801	12.924	-52.653	3.485

	total_renewable	
country	mean	std
Algeria	0.233	2.298
Argentina	0.601	2.816
Australia	-1.494	0.491
Belgium	-0.167	1.969
Chile	0.678	3.422
Colombia	0.511	2.566
Czechia	-0.413	1.665
Egypt	-0.501	1.630
France	-0.363	1.885
Germany	-0.097	1.499
India	-0.493	0.976
Indonesia	0.242	2.311
Iran	1.227	3.419
Italy	-0.370	2.093
Japan	-1.822	0.277
Kazakhstan	0.237	2.308
Kuwait	0.233	2.298
Malaysia	-0.017	1.988
Mexico	-0.227	1.840
Netherlands	0.474	1.596
New Zealand	-0.267	1.799
Nigeria	0.345	1.722
Poland	-0.375	1.667
Portugal	-0.161	1.868
Romania	-0.219	1.987
Saudi Arabia	-0.017	1.988
South Africa	-0.334	1.477
South Korea	-0.566	1.495
Spain	0.323	2.070
Sweden	0.254	2.022
Taiwan	-0.604	1.528
Thailand	-1.044	0.669
Turkey	-0.247	1.831
Ukraine	-0.049	1.679

United Arab Emirates	-0.017	1.988
United Kingdom	0.440	2.598
Uzbekistan	0.233	2.298
Venezuela	0.280	2.429

```
[8]: # Principal Component Analysis
def perform_pca_analysis():
    """Perform PCA on numerical features"""

    # Prepare data
    numeric_cols = df.select_dtypes(include=[np.number]).columns
    X = df[numeric_cols]

    # Handle NaN values
    X = X.dropna(axis=0)

    # Scale the data
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    # Perform PCA
    pca = PCA()
    X_pca = pca.fit_transform(X_scaled)

    # Calculate explained variance ratio
    explained_variance = pca.explained_variance_ratio_
    cumulative_variance = np.cumsum(explained_variance)

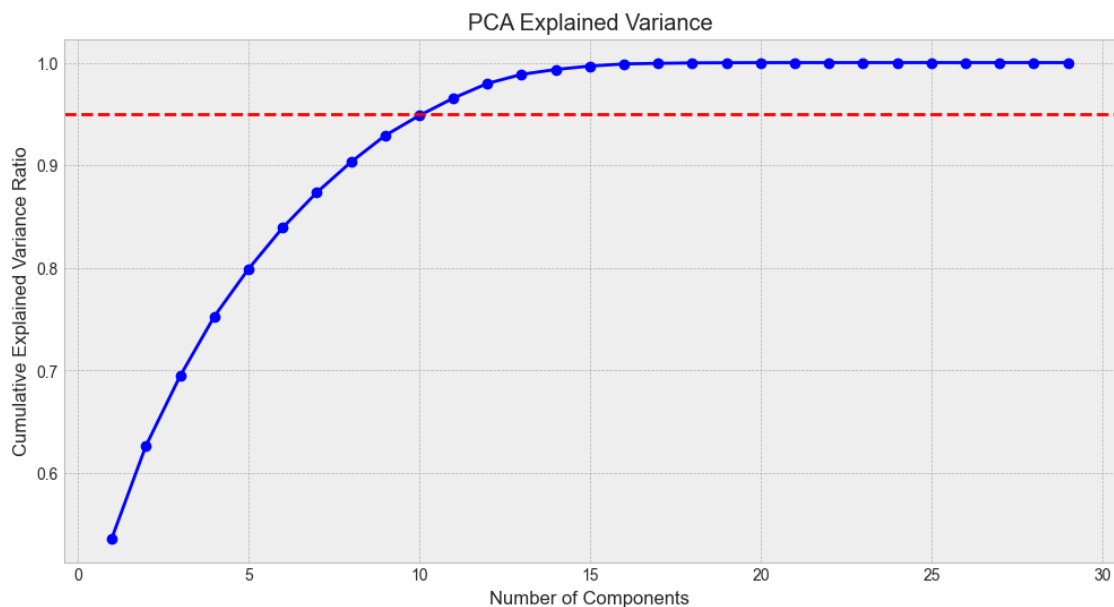
    # Plot explained variance
    plt.figure(figsize=(12, 6))
    plt.plot(range(1, len(explained_variance) + 1), cumulative_variance, 'bo-')
    plt.axhline(y=0.95, color='r', linestyle='--')
    plt.xlabel('Number of Components')
    plt.ylabel('Cumulative Explained Variance Ratio')
    plt.title('PCA Explained Variance')
    plt.show()

    # Print component loadings
    components_df = pd.DataFrame(
        pca.components_.T,
        columns=[f'PC{i + 1}' for i in range(len(pca.components_))],
        index=numeric_cols
    )

    print("\nPrincipal Component Loadings:")
    display(components_df)
```

```
return pca, components_df
```

```
pca_results = perform_pca_analysis()
```



Principal Component Loadings:

	PC1	PC2	PC3	PC4 \
year	0.249206	0.010644	-0.017462	-0.045600
hydro_generation	0.158566	0.130260	0.036737	0.038867
biofuel_generation	0.247670	-0.051631	-0.039457	-0.039598
solar_generation	0.222070	-0.101547	-0.056909	-0.020681
geothermal_generation	0.244789	0.022758	-0.010745	-0.051190
total_energy_consumption	0.012622	0.116119	-0.376554	0.437588
renewable_share_pct	0.015072	-0.149638	0.617425	0.173398
other_renewable_generation	0.015265	0.012467	-0.088411	0.497102
solar_generation_alt	0.059644	0.067512	-0.286489	0.138172
wind_generation	0.018491	0.012529	0.025635	0.562720
hydro_generation_alt	0.031611	-0.108727	0.549486	0.260894
renewable_generation	0.223971	0.061330	0.031254	0.024952
decade	0.211355	-0.095847	-0.063268	-0.028056
renewable_generation_lag_1	0.212435	0.003873	0.015356	-0.078224
renewable_generation_lag_3	0.247569	-0.035463	-0.001914	-0.034155
renewable_generation_lag_6	0.242023	-0.077920	-0.011045	-0.000731
renewable_generation_lag_12	0.238480	0.059992	0.045277	-0.020926
renewable_generation_rolling_mean_3	0.246790	0.030080	0.021375	-0.022339
renewable_generation_rolling_std_3	0.220226	-0.080444	-0.056383	-0.003712

renewable_generation_rolling_mean_6	0.251447	-0.008333	0.009030	-0.025022
renewable_generation_rolling_std_6	0.242249	0.039678	-0.004472	-0.010690
renewable_generation_rolling_mean_12	0.252356	-0.012869	0.014035	-0.017587
renewable_generation_rolling_std_12	0.249466	-0.000894	-0.010899	-0.031206
total_renewable	0.209570	-0.009580	-0.009138	0.294543
renewable_share	-0.108720	0.079137	-0.139794	0.080506
hydro_generation_share	0.032825	0.588835	0.132230	-0.032094
solar_generation_share	0.008003	-0.517774	-0.119204	-0.064430
wind_generation_share	-0.054588	-0.512103	-0.112927	0.093353
renewable_yoy_growth	0.053522	-0.018945	-0.049262	0.022802

	PC5	PC6	PC7	PC8	\
year	0.035842	-0.086339	-0.062410	0.003621	
hydro_generation	0.583327	0.046480	-0.058885	0.062294	
biofuel_generation	-0.135681	0.006796	0.004456	-0.034027	
solar_generation	-0.289746	0.122721	0.072629	-0.074253	
geothermal_generation	0.083996	-0.122710	-0.086184	0.014328	
total_energy_consumption	-0.057448	-0.286737	0.148981	-0.006660	
renewable_share_pct	-0.053511	-0.092081	0.051048	0.184620	
other_renewable_generation	-0.048891	-0.395107	0.176441	-0.385650	
solar_generation_alt	-0.126798	0.078731	0.210672	0.831492	
wind_generation	0.005909	0.461076	-0.321506	-0.031193	
hydro_generation_alt	-0.078548	-0.199356	0.168240	0.205977	
renewable_generation	0.339416	0.032252	-0.027094	0.033492	
decade	-0.244912	0.065062	0.029348	-0.017068	
renewable_generation_lag_1	-0.131355	-0.239551	-0.096628	-0.009067	
renewable_generation_lag_3	-0.095191	-0.054021	0.001052	-0.019030	
renewable_generation_lag_6	-0.190037	0.040933	0.045874	-0.021414	
renewable_generation_lag_12	0.148521	-0.145204	-0.060205	0.033685	
renewable_generation_rolling_mean_3	0.131149	-0.099090	-0.053843	0.026445	
renewable_generation_rolling_std_3	-0.226110	0.152648	0.062558	-0.053216	
renewable_generation_rolling_mean_6	0.018286	-0.068961	-0.027751	0.006626	
renewable_generation_rolling_std_6	0.118510	-0.005947	-0.030934	0.002379	
renewable_generation_rolling_mean_12	-0.002047	-0.064276	-0.025298	0.004195	
renewable_generation_rolling_std_12	0.041695	-0.025527	-0.008435	-0.000391	
total_renewable	0.035732	0.335478	-0.143286	-0.040275	
renewable_share	0.085741	-0.406170	-0.370605	0.232160	
hydro_generation_share	-0.152218	0.034735	0.057711	-0.033438	
solar_generation_share	0.048472	-0.144572	0.015991	0.038431	
wind_generation_share	0.192686	0.050332	-0.097329	0.022703	
renewable_yoy_growth	0.320615	0.147277	0.742346	-0.076917	

	PC9	PC10	...	PC20	\
year	0.056627	0.036656	...	-0.184049	
hydro_generation	-0.300377	-0.067861	...	0.136823	
biofuel_generation	0.033214	-0.037054	...	-0.195686	
solar_generation	-0.032334	-0.120746	...	-0.240980	
geothermal_generation	0.066753	0.067385	...	-0.378240	

total_energy_consumption	-0.078416	0.529175	...	-0.000533
renewable_share_pct	0.016305	-0.210284	...	-0.000926
other_renewable_generation	-0.241354	-0.467082	...	-0.006287
solar_generation_alt	-0.160569	-0.164576	...	-0.000297
wind_generation	0.308819	0.115921	...	0.040742
hydro_generation_alt	-0.033151	0.292087	...	-0.057851
renewable_generation	-0.204707	-0.059057	...	-0.000160
decade	0.042463	-0.133293	...	-0.178219
renewable_generation_lag_1	0.285392	0.208287	...	0.307001
renewable_generation_lag_3	0.069181	0.024390	...	-0.057865
renewable_generation_lag_6	0.006232	-0.073357	...	0.446058
renewable_generation_lag_12	0.054106	0.098233	...	0.240204
renewable_generation_rolling_mean_3	0.034110	0.048248	...	0.004215
renewable_generation_rolling_std_3	-0.124286	-0.174612	...	0.362188
renewable_generation_rolling_mean_6	0.039559	0.024420	...	0.008606
renewable_generation_rolling_std_6	-0.059388	-0.024448	...	-0.281939
renewable_generation_rolling_mean_12	0.032097	0.025265	...	-0.110929
renewable_generation_rolling_std_12	0.013429	-0.019087	...	0.294777
total_renewable	0.028823	-0.041484	...	-0.080994
renewable_share	0.503674	-0.393899	...	0.001978
hydro_generation_share	0.020948	-0.026450	...	-0.008326
solar_generation_share	-0.020182	0.145599	...	-0.004726
wind_generation_share	-0.016975	-0.063409	...	0.015750
renewable_yoy_growth	0.549155	-0.085058	...	-0.006183

	PC21	PC22	PC23	PC24	\
year	-0.311750	0.717212	0.332093	0.019331	
hydro_generation	0.081088	0.021322	0.069816	-0.054197	
biofuel_generation	-0.021456	0.039227	-0.394660	0.733439	
solar_generation	-0.236117	0.051031	-0.155385	-0.337147	
geothermal_generation	0.432302	-0.046739	-0.372836	-0.328401	
total_energy_consumption	0.000027	0.000046	0.000220	0.000076	
renewable_share_pct	-0.000417	-0.001643	0.001093	-0.000040	
other_renewable_generation	0.001985	0.007745	-0.001609	-0.000740	
solar_generation_alt	-0.000429	0.000695	0.000417	-0.000154	
wind_generation	0.051101	-0.014253	0.029822	0.095970	
hydro_generation_alt	0.023332	0.062871	-0.013956	-0.003963	
renewable_generation	0.037262	0.016618	-0.094373	0.247807	
decade	0.052722	0.017197	0.022233	-0.003099	
renewable_generation_lag_1	0.099287	0.035038	-0.002240	0.015489	
renewable_generation_lag_3	0.478067	-0.094363	0.559471	0.133929	
renewable_generation_lag_6	0.121137	-0.057935	-0.147887	-0.050498	
renewable_generation_lag_12	-0.207279	-0.042141	-0.313975	-0.011001	
renewable_generation_rolling_mean_3	-0.315314	-0.219116	0.136926	0.097597	
renewable_generation_rolling_std_3	0.079815	-0.027792	0.157950	0.063725	
renewable_generation_rolling_mean_6	-0.190404	-0.309165	0.076120	-0.246667	
renewable_generation_rolling_std_6	0.253857	-0.071473	0.103573	0.017831	
renewable_generation_rolling_mean_12	-0.346883	-0.415400	0.201920	0.020815	

renewable_generation_rolling_std_12	0.119385	0.368301	-0.133103	-0.191369
total_renewable	-0.093209	0.032902	-0.057212	-0.184242
renewable_share	0.000119	-0.002603	-0.000522	0.000135
hydro_generation_share	0.000007	-0.000057	0.000069	0.000017
solar_generation_share	0.000583	0.000969	-0.000082	0.000157
wind_generation_share	-0.000422	-0.000600	-0.000046	-0.000136
renewable_yoy_growth	0.002784	0.000660	0.000072	-0.000079

	PC25	PC26	PC27 \
year	0.008781	0.004761	0.105932
hydro_generation	-0.161687	-0.484051	0.014857
biofuel_generation	-0.078702	-0.299415	0.150302
solar_generation	-0.111053	0.083212	-0.103970
geothermal_generation	-0.041229	0.018309	-0.167956
total_energy_consumption	0.000027	-0.000084	0.000078
renewable_share_pct	0.000229	-0.000253	0.000057
other_renewable_generation	-0.001588	-0.003413	-0.000052
solar_generation_alt	-0.000029	0.000068	-0.000026
wind_generation	0.053410	0.052124	0.024851
hydro_generation_alt	-0.015665	-0.030397	0.000124
renewable_generation	0.280284	0.735325	0.024929
decade	0.008663	-0.002981	-0.000718
renewable_generation_lag_1	0.010294	-0.003703	0.002547
renewable_generation_lag_3	-0.099215	0.020677	-0.041132
renewable_generation_lag_6	-0.063521	0.026295	-0.005724
renewable_generation_lag_12	-0.016033	0.010214	0.013049
renewable_generation_rolling_mean_3	-0.603135	0.200775	-0.408454
renewable_generation_rolling_std_3	-0.030853	0.005285	-0.030895
renewable_generation_rolling_mean_6	-0.059732	0.046217	0.788987
renewable_generation_rolling_std_6	0.072081	-0.026216	0.131562
renewable_generation_rolling_mean_12	0.627061	-0.248468	-0.307132
renewable_generation_rolling_std_12	0.283419	-0.091143	-0.140061
total_renewable	-0.102754	-0.099785	-0.047563
renewable_share	-0.000062	0.000074	0.000006
hydro_generation_share	-0.000049	0.000014	0.000002
solar_generation_share	-0.000332	0.000168	0.000063
wind_generation_share	0.000308	-0.000140	-0.000048
renewable_yoy_growth	-0.000096	-0.000274	0.000042

	PC28	PC29
year	0.000000e+00	-0.000000e+00
hydro_generation	9.732747e-02	-2.581305e-01
biofuel_generation	2.518893e-14	1.007086e-15
solar_generation	1.664141e-01	-4.413610e-01
geothermal_generation	-1.043222e-14	-3.537318e-15
total_energy_consumption	6.253481e-17	1.366446e-16
renewable_share_pct	3.373520e-16	2.377916e-16
other_renewable_generation	2.171567e-16	-4.542928e-17

solar_generation_alt	2.928376e-16	-9.599714e-18
wind_generation	1.365461e-01	-3.621455e-01
hydro_generation_alt	1.038624e-15	-2.129667e-17
renewable_generation	-4.060432e-14	-1.235894e-14
decade	-5.391757e-16	1.939449e-16
renewable_generation_lag_1	3.203581e-15	1.026703e-15
renewable_generation_lag_3	-1.136063e-14	-5.164456e-15
renewable_generation_lag_6	1.207100e-15	-1.298821e-15
renewable_generation_lag_12	3.657583e-15	3.711487e-16
renewable_generation_rolling_mean_3	-6.508888e-14	-3.076592e-14
renewable_generation_rolling_std_3	-3.105347e-15	-1.042463e-15
renewable_generation_rolling_mean_6	7.070028e-14	2.067023e-14
renewable_generation_rolling_std_6	1.336242e-14	6.101790e-15
renewable_generation_rolling_mean_12	-7.080674e-16	1.453337e-14
renewable_generation_rolling_std_12	2.148140e-15	7.646609e-15
total_renewable	-2.620277e-01	6.949461e-01
renewable_share	1.255861e-16	-1.210514e-16
hydro_generation_share	7.231025e-01	2.726440e-01
solar_generation_share	3.426043e-01	1.291781e-01
wind_generation_share	4.850519e-01	1.828876e-01
renewable_yoy_growth	-3.502050e-17	-4.564755e-17

[29 rows x 29 columns]

```
[9]: # Feature Interaction Analysis
def analyze_feature_interactions():
    """Analyze interactions between important features"""

    # Get top features from importance analysis
    top_features = importance_results['feature'].head(5).tolist()

    if 'renewable_share' in df.columns:
        top_features.append('renewable_share')

    # Create scatter matrix
    fig = px.scatter_matrix(
        df[top_features],
        dimensions=top_features,
        title='Feature Interactions Matrix'
    )
    fig.show()

    # Calculate interaction terms
    for i in range(len(top_features) - 1):
        for j in range(i + 1, len(top_features) - 1):
            feat1, feat2 = top_features[i], top_features[j]
            interaction_name = f'{feat1}_{feat2}_interaction'
```


feature	Mutual Information Score
total_energy_consumption_hydro_generation_share_interaction	1.05
total_renewable_total_energy_consumption_interaction	0.88
total_energy_consumption_renewable_generation_rolling_mean_6_interaction	0.85
total_renewable_geothermal_generation_interaction	0.82
total_energy_consumption_geothermal_generation_interaction	0.60
total_renewable	0.58
total_energy_consumption	0.55
total_renewable_renewable_generation_rolling_mean_6_interaction	0.52
hydro_generation_share	0.50
renewable_generation_rolling_mean_6	0.48
geothermal_generation	0.45
wind_generation_share	0.42
renewable_generation_rolling_mean_3	0.40
year	0.38
renewable_generation_rolling_std_3	0.35
solar_generation	0.32
solar_generation_share	0.30
geothermal_generation_renewable_generation_rolling_mean_6_interaction	0.28
total_renewable_hydro_generation_share_interaction	0.25
hydro_generation	0.22
renewable_generation	0.20
renewable_generation_rolling_std_6	0.18
renewable_generation_rolling_std_12	0.15
hydro_generation_share_geothermal_generation_interaction	0.12
renewable_yoy_growth	0.10
renewable_generation_lag_3	0.08
renewable_generation_rolling_mean_12	0.05
renewable_generation_lag_6	0.02
renewable_generation_lag_12	0.01
hydro_generation_share_renewable_generation_rolling_mean_6_interaction	0.00
renewable_generation_lag_1	0.00
other_renewable_generation	0.00
decade	0.00
wind_generation	0.00
hydro_generation_alt	0.00
renewable_share_pct	0.00
solar_generation_alt	0.00

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4. Temporal Features:
 - Lag features capture historical patterns
 - Rolling features smooth out noise
 - Strong autocorrelation present
5. Geographic Analysis:
 - Clear regional patterns in renewable adoption
 - Significant variation between countries
 - Consider regional clustering
6. PCA Analysis:
 - First few components explain majority of variance
 - Consider dimensionality reduction
 - Important feature combinations identified

Recommendations:

1. Feature Selection:
 - Remove highly correlated features
 - Focus on top important features
 - Consider PCA for dimensionality reduction
2. Feature Engineering:
 - Create interaction terms for top features
 - Log transform skewed features
 - Standardize numerical features
3. Modeling Considerations:
 - Handle temporal autocorrelation
 - Account for geographic patterns
 - Consider hierarchical modeling
4. Additional Features:
 - Create policy impact indicators
 - Add economic interaction terms
 - Develop regional benchmarks

"""

```
from IPython.display import display, HTML
display(HTML(f"<pre>{summary}</pre>"))
```

```
generate_feature_summary()
```

```
<IPython.core.display.HTML object>
```