

4. **Cross-tabulation:** To examine the relationship between categorical variables such as home ownership status and energy consumption profiles.
5. **ANOVA (Analysis of Variance):** To assess significant differences in perceptions and behaviors between Generation Z and Millennials.
6. **Box-Cox Transformation:** Applied to normalize the data where necessary.

## Ethical Considerations

The study was conducted in accordance with ethical guidelines for research involving human participants. Informed consent was obtained from all respondents, and data confidentiality was maintained throughout the study. Participants were assured that their responses would be anonymized and used solely for research purposes.

## Limitations

The study acknowledges potential limitations, including self-report bias and the representativeness of the sample. Future research could expand the sample size and include additional demographic variables to enhance the generalizability of the findings.

In summary, this methodology outlines a rigorous approach to investigating generational differences in energy consumption and technology adoption, providing valuable insights to inform targeted strategies for promoting energy efficiency and sustainability.

## Results and Discussions

Initial data preprocessing is done in the coded excel sheet and tabulation is completed. Further SPSS 2026 is used for baseline analysis and cross tabulation of data. All the tables shown in this report are generated with SPSS software.

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the data
df = pd.read_csv("DatasetSM.csv") # Replace 'DatasetSM.csv' with your actual file path

# Print the column names to check for any discrepancies
print(df.columns)

# Replace column names to match them to your request:
df.columns = ["Age Group", "Class", "Gender", "Mother tongue", "State", "Education", "Occupation",
              "Household income", "Average monthly Electricity Bill", "Payment mode", "Ownership",
              "Home size", "House type", "Consumption Profile", "Perception on Individual Usage",
              "Perception on Sharing Consumption information", "Perception on load control incentivised",
              "Perception on load control Self", "Perception on smart grid", "Perception on smart home appliances",
              "Perception on Solar PV and EV", "Perception on Vehicle to Grid", "Adoption of Roof top PV",
              "Percpective on RPV EV combination"]

# Data Cleaning
# Replace any spaces in column names with _ and make them all lowercase
df.columns = df.columns.str.replace(' ', '_').str.lower()

# Some specific changes based on unique values in your dataset:
df['household_income'] = df['household_income'].str.replace('0- 16000 (BPL- Urban)', '< 1 Lakhs', regex=True)
df['household_income'] = df['household_income'].str.replace('< 1 Lakhs', '<1 Lakhs', regex=True)
df['household_income'] = df['household_income'].str.replace('2.5 lakhs - 5 lakhs', '2.5-5 Lakhs', regex=True)
df['household_income'] = df['household_income'].str.replace('7.5 - 10 Lakhs', '7.5-10 Lakhs', regex=True)
df['household_income'] = df['household_income'].str.replace('Above 10 lakhs', '>10 Lakhs', regex=True)
df['occupation'] = df['occupation'].str.replace('Student;Higher Education', 'Student and Higher Education', regex=True)
df['occupation'] = df['occupation'].str.replace('Student;Self Employed and Business', 'Student, Self Employed and Business', regex=True)
df['occupation'] = df['occupation'].str.replace('Employed (Govt. Sector and private)', 'Employed (Govt. Sector)', regex=True)
df['payment_mode'] = df['payment_mode'].str.replace('By Visiting Utility office - Seeks others help', 'By Visiting Utility office', regex=True)
df['house_type'] = df['house_type'].str.replace('Some what Liberal', 'Somewhat Liberal', regex=True)

# Handle non-numeric values in numeric columns (eg. 'NR')
numeric_cols = ['average_monthly_electricity_bill', 'perception_on_individual_usage',
                 'perception_on_sharing_consumption_information',
                 'perception_on_load_control_incentivised', 'perception_on_load_control_self',
                 'perception_on_smart_grid', 'perception_on_smart_home_appliances',
                 'perception_on_solar_pv_and_ev', 'perception_on_vehicle_to_grid',
                 'adoption_of_roof_top_pv', 'percpective_on_rpvev_combination']

for col in numeric_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce') # Replace 'errors='coerce'' with errors='raise' to identify if there are any errors while numeric conversion.
df.dropna(subset=numeric_cols, inplace=True) #Dropping all rows with null values for the numeric variables

Index(['Age Group', 'Class', 'Gender', 'Mother tongue ', 'State', 'Education',
       'Occupation', 'Household income', 'Average monthly Electricity Bill',
       'Payment mode', 'Ownership', 'Home size', 'House type',
       'Consumption Profile', 'Perception on Individual Usage',
       'Perception on Sharing Consumption information',
       'Perception on load control incentivised',
```

```
'Perception on load control Self', 'Perception on smart grid',
'Perception on smart home appliances', 'Perception on Solar PV and EV',
'Perception on Vehicle to Grid', 'Adoption of Roof top PV',
'Percpective on RPV EV combination'],
dtype='object')
```

In [2]: # --- Exploratory Data Analysis (EDA) ---

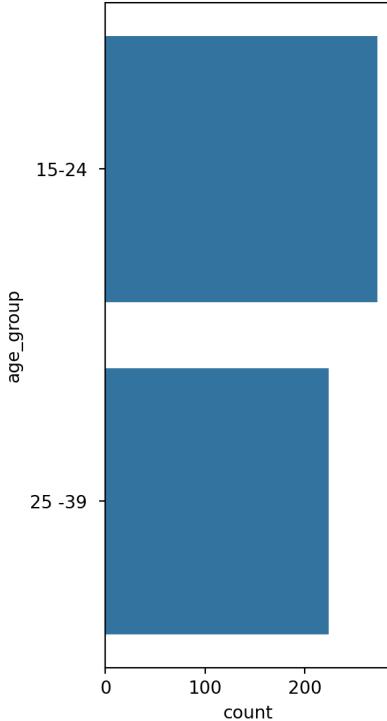
```
# 1. Distribution of Categorical Variables
def plot_categorical_distributions(df, cols, rows=3, cols_per_row=3):
    fig, axes = plt.subplots(rows, cols_per_row, figsize=(18, 6*rows))
    axes = axes.flatten() # Convert axes into a flat list
    for i, col in enumerate(cols):
        sns.countplot(y=df[col], ax=axes[i], order=df[col].value_counts().index)
        axes[i].set_title(f"Distribution of {col}")
        axes[i].set_ylabel(col) # Set y-axis label for better readability

    for j in range(i + 1, len(axes)): #Turn off unused axes
        axes[j].axis('off')

    plt.tight_layout()
    plt.show()

categorical_cols = ['age_group', 'class', 'gender', 'mother_tongue', 'state', 'education', 'occupation', 'household_income', 'payment_mo
plot_categorical_distributions(df, categorical_cols, rows=5, cols_per_row=3)
```

Distribution of age\_group



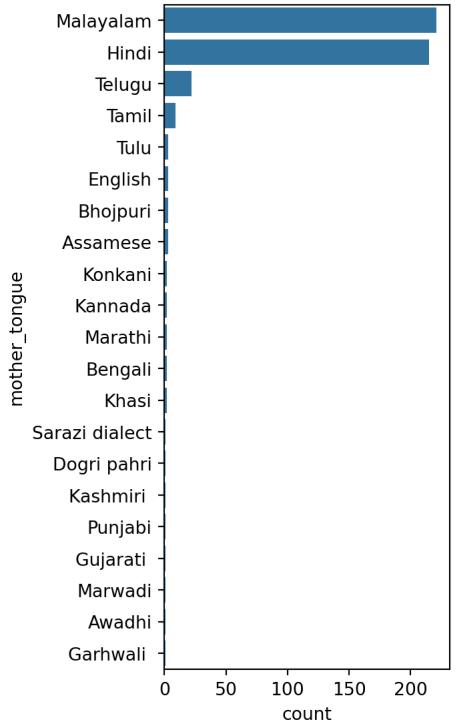
Generation Z

Millennials

class

0

Distribution of mother\_tongue



Kerala

Uttarakhand

Uttar Pradesh

Bihar

Rajasthan

Tamil Nadu

Andhra Pradesh

Delhi

Karnataka

Telangana

Jammu and Kashmir

Madhya Pradesh

Haryana

Assam

Jharkhand

West Bengal

Maharashtra

Meghalaya

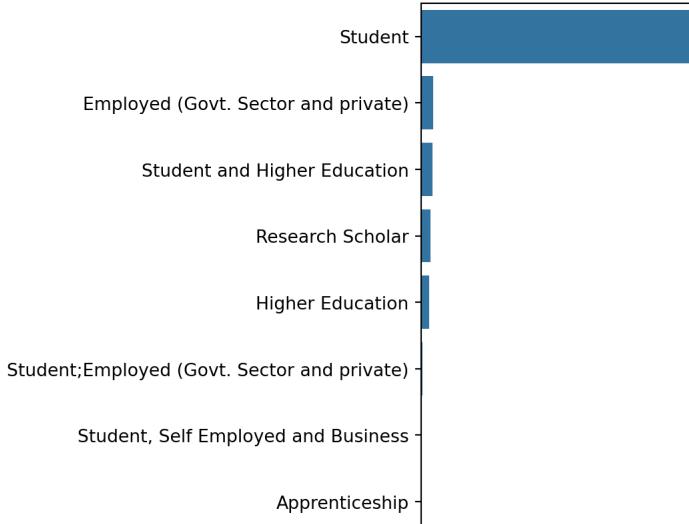
Punjab

Gujarat

0

Distribution of occupation

occupation



Distr

&lt;1 Lakhs

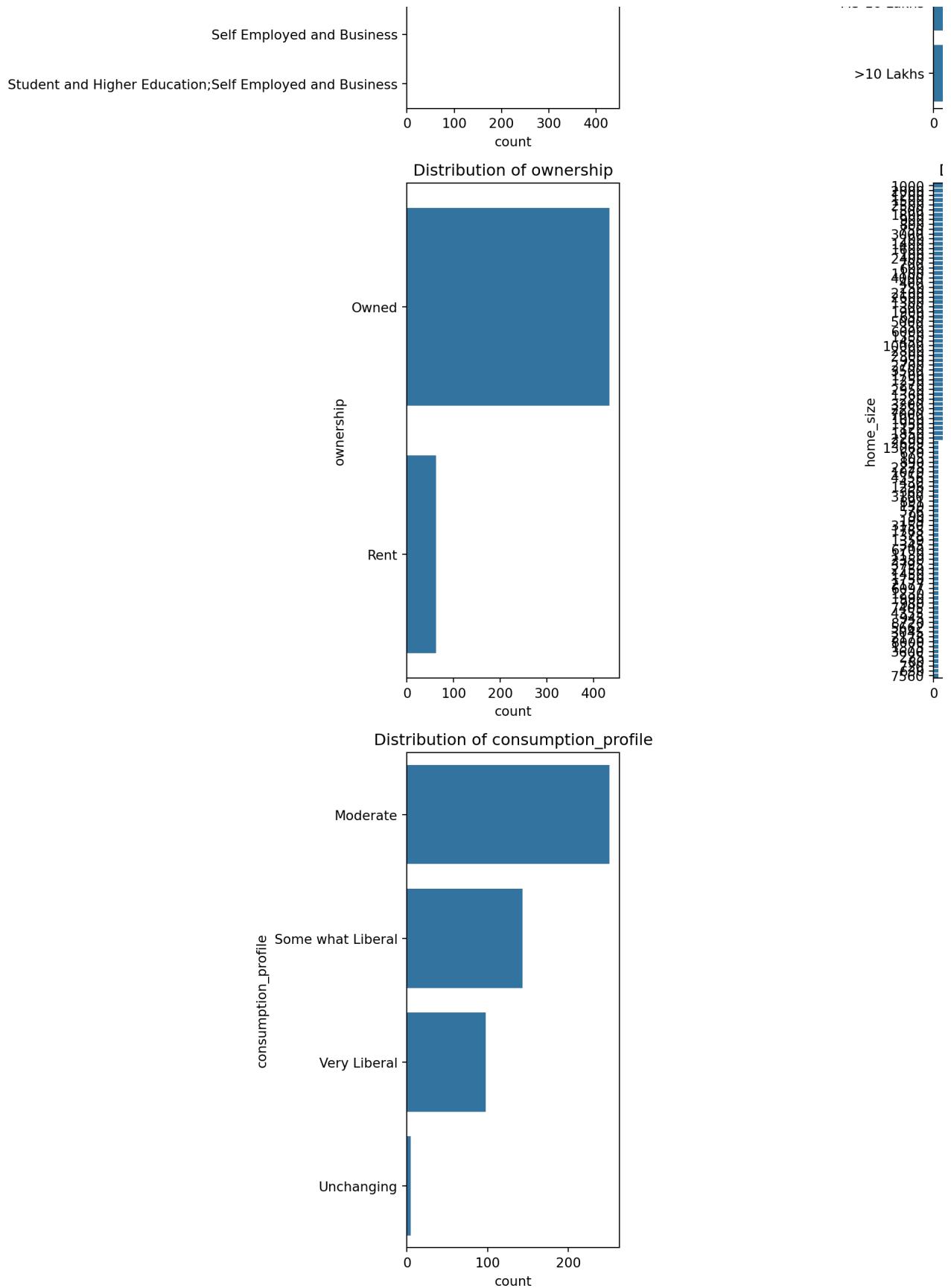
2.5-5 Lakhs

&lt;2.5 Lakhs

5-7.5 lakhs

0- 16000 (BPL- Urban)

7.5-10 Lakhs



```
# 2. Distribution of Numerical Variables
def plot_numerical_distributions(df, cols, rows=2, cols_per_row=3):
    fig, axes = plt.subplots(rows, cols_per_row, figsize=(18, 4*rows))
    axes = axes.flatten() # Convert axes into a flat list
    for i, col in enumerate(cols):
        sns.histplot(df[col], ax=axes[i], kde=True)
        axes[i].set_title(f"Distribution of {col}")
        axes[i].set_ylabel("Frequency")

    for j in range(i + 1, len(axes)): #Turn off unused axes
        axes[j].axis('off')
```

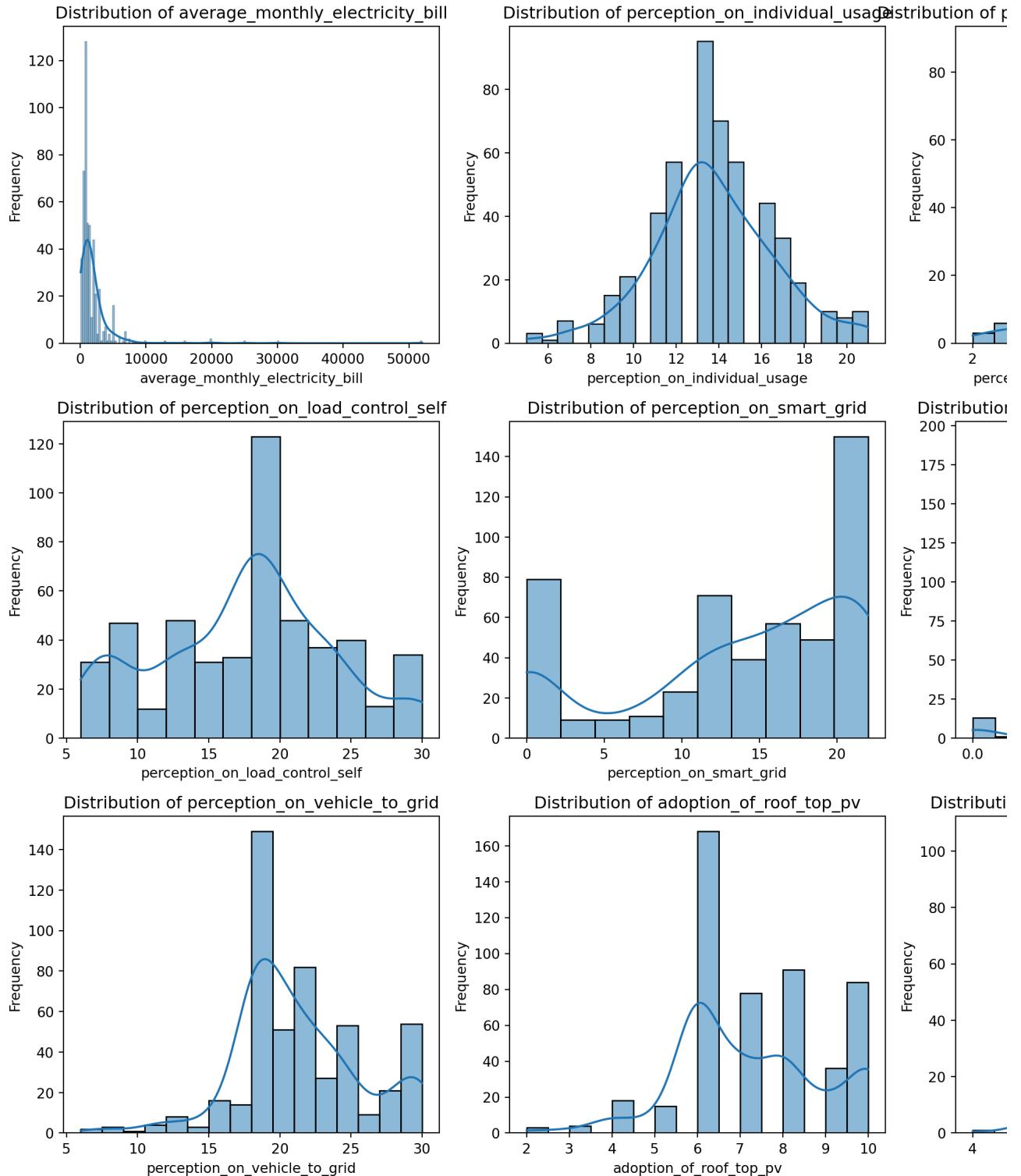
```

plt.tight_layout()
plt.show()

numerical_perception_cols = ['average_monthly_electricity_bill', 'perception_on_individual_usage',
                             'perception_on_sharing_consumption_information',
                             'perception_on_load_control_incentivised', 'perception_on_load_control_self',
                             'perception_on_smart_grid', 'perception_on_smart_home_appliances',
                             'perception_on_solar_pv_and_ev', 'perception_on_vehicle_to_grid',
                             'adoption_of_roof_top_pv', 'percpective_on_rpv_ev_combination']

plot_numerical_distributions(df, numerical_perception_cols, rows=3, cols_per_row=4)

```



```

In [4]: # 3. Relationship between Numerical and Categorical Variables (using Boxplot)
def plot_boxplots(df, cat_cols, num_cols, rows=3, cols_per_row=3):
    for num_col in num_cols:
        fig, axes = plt.subplots(rows, cols_per_row, figsize=(18, 4*rows))
        axes = axes.flatten()
        for i, cat_col in enumerate(cat_cols):
            sns.boxplot(y=df[cat_col], x=df[num_col], ax=axes[i])

```

```

        axes[i].set_title(f"{num_col} vs {cat_col}")
        axes[i].set_xlabel(num_col)
        axes[i].set_ylabel(cat_col)

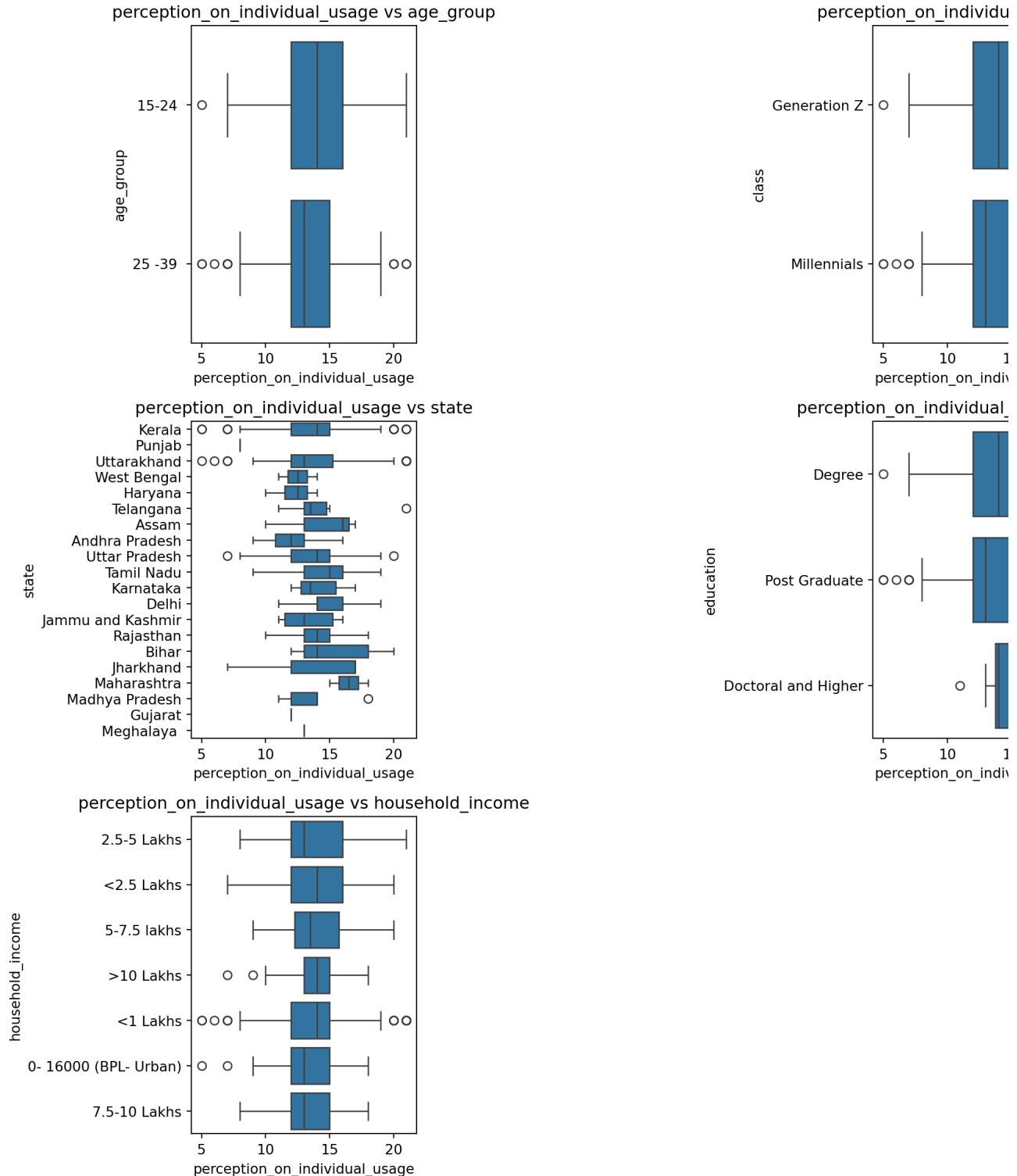
    for j in range(i + 1, len(axes)): #Turn off unused axes
        axes[j].axis('off')

    plt.tight_layout()
    plt.show()

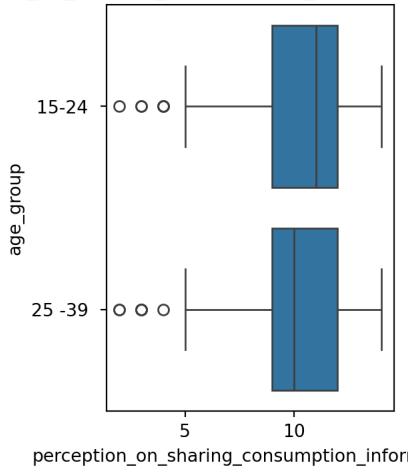
cat_cols = ['age_group', 'class','gender', 'state', 'education', 'occupation', 'household_income'] #Can be extended
num_cols_box = ['perception_on_individual_usage',
                 'perception_on_sharing_consumption_information',
                 'perception_on_load_control_incentivised', 'perception_on_load_control_self',
                 'perception_on_smart_grid', 'perception_on_smart_home_appliances',
                 'perception_on_solar_pv_and_ev', 'perception_on_vehicle_to_grid',
                 'adoption_of_roof_top_pv', 'percpective_on_rpv_ev_combination'] #Can be extended.

plot_boxplots(df, cat_cols, num_cols_box, rows=3, cols_per_row=3)

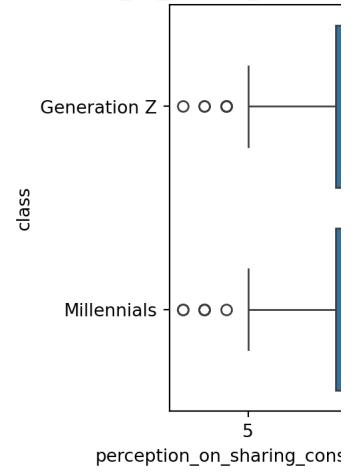
```



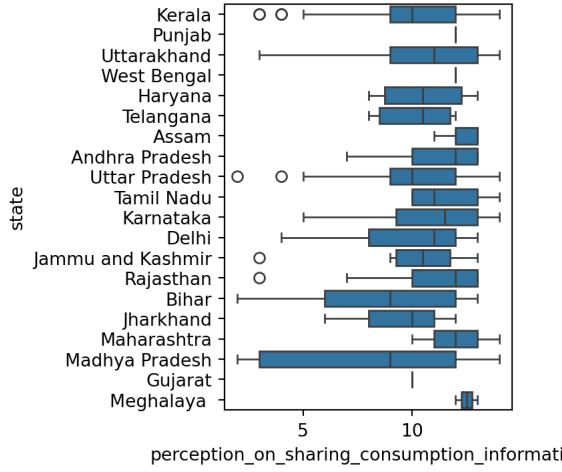
perception\_on\_sharing\_consumption\_information vs age\_group



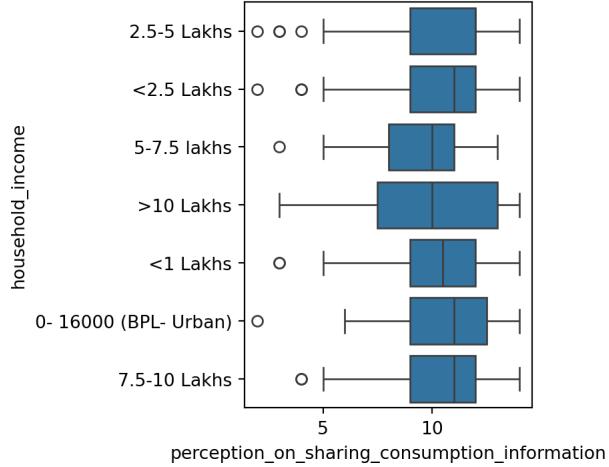
perception\_on\_sharing\_consumption\_vs\_class



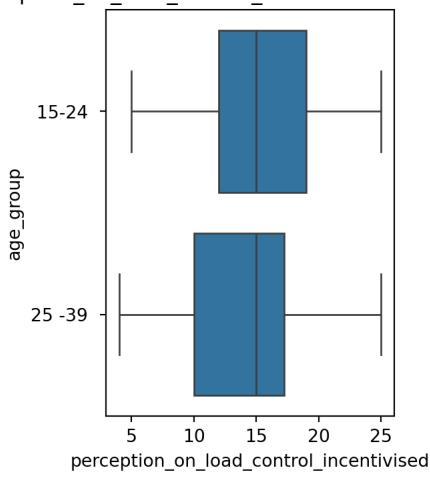
perception\_on\_sharing\_consumption\_vs\_state



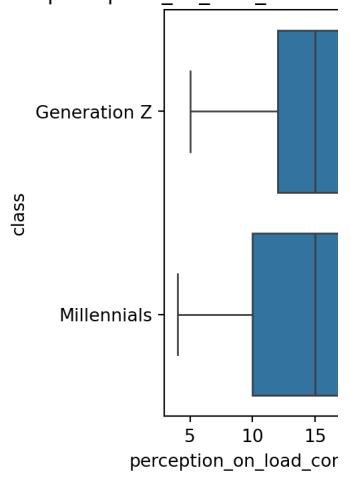
perception\_on\_sharing\_consumption\_vs\_household\_income



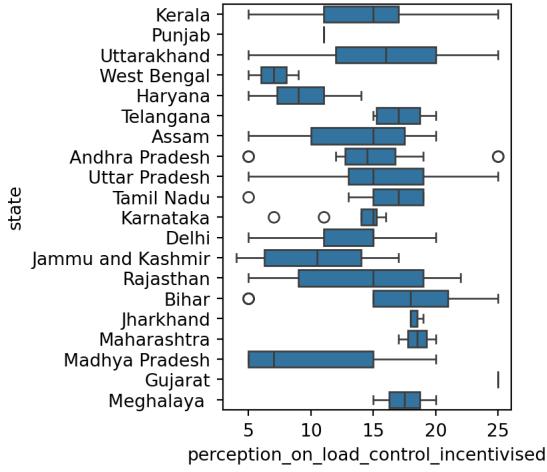
perception\_on\_load\_control\_incentivised vs age\_group



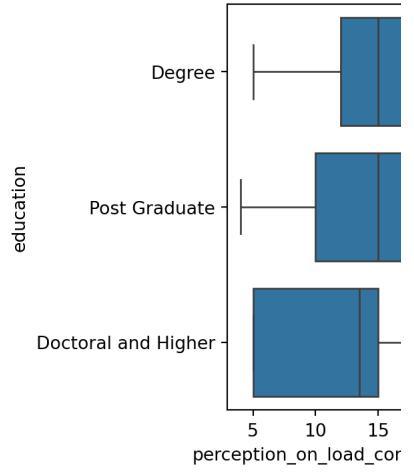
perception\_on\_load\_control



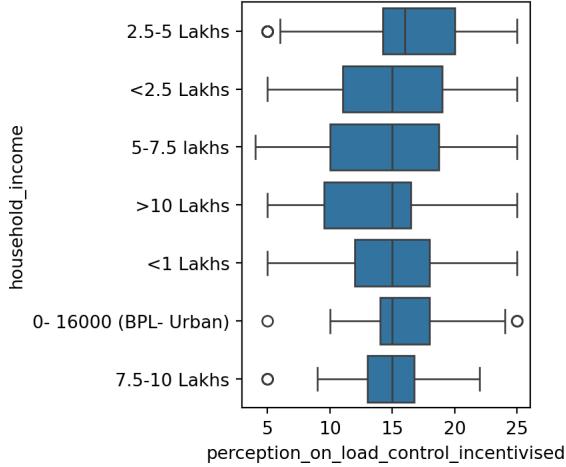
perception\_on\_load\_control\_incentivised vs state



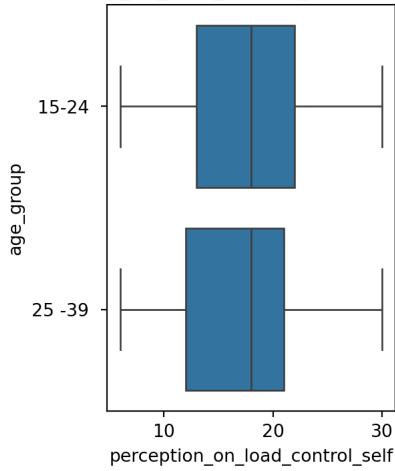
perception\_on\_load\_control\_ir



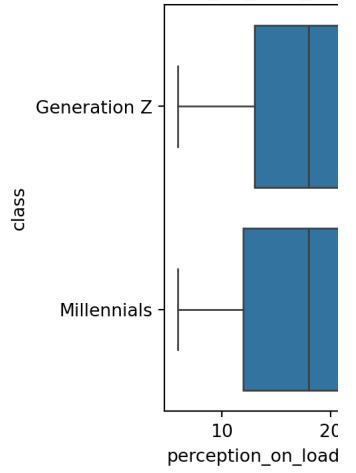
perception\_on\_load\_control\_incentivised vs household\_income



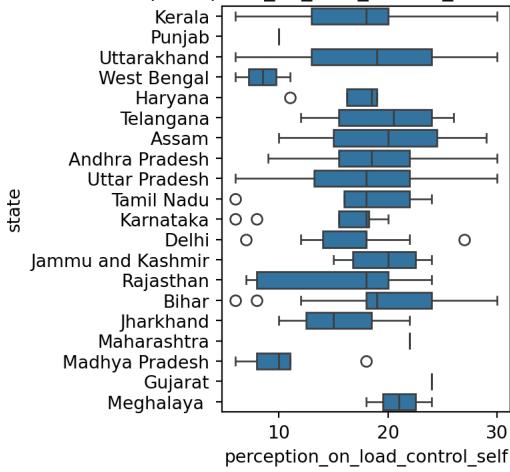
perception\_on\_load\_control\_self vs age\_group



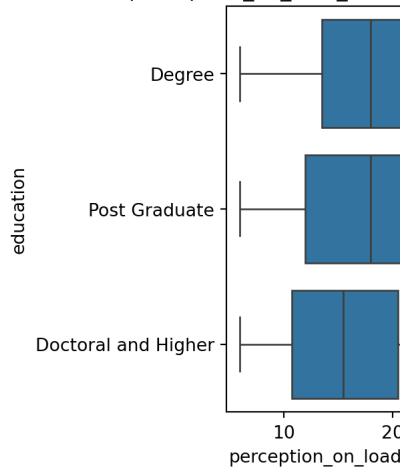
perception\_on\_load\_co



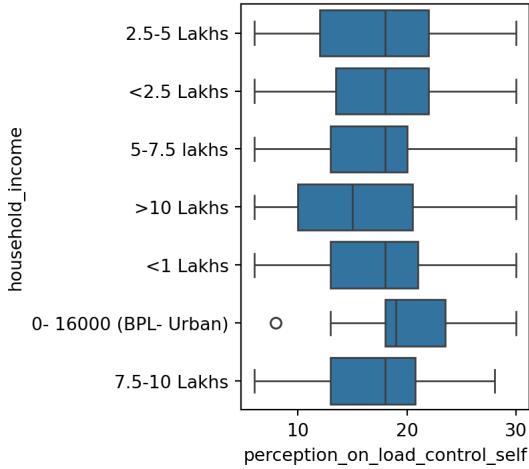
perception\_on\_load\_control\_self vs state



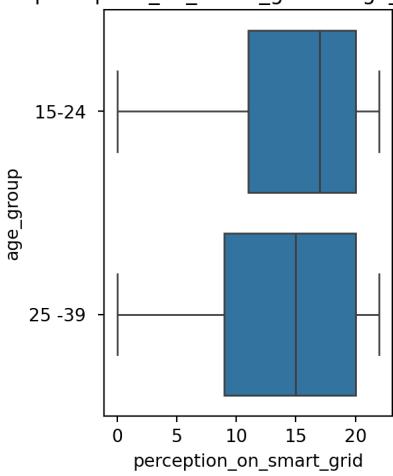
perception\_on\_load\_contr



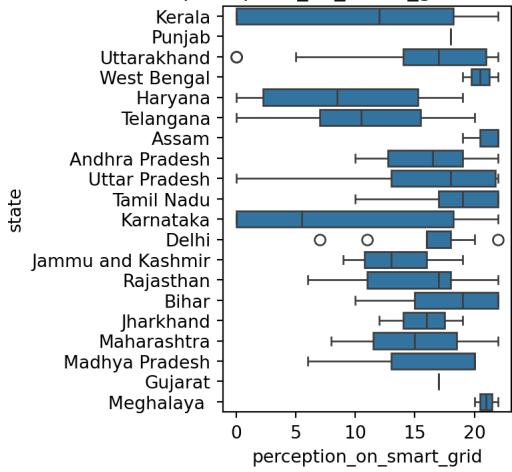
perception\_on\_load\_control\_self vs household\_income



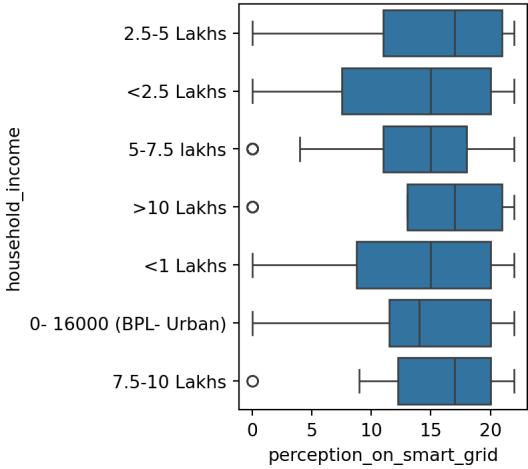
perception\_on\_smart\_grid vs age\_group



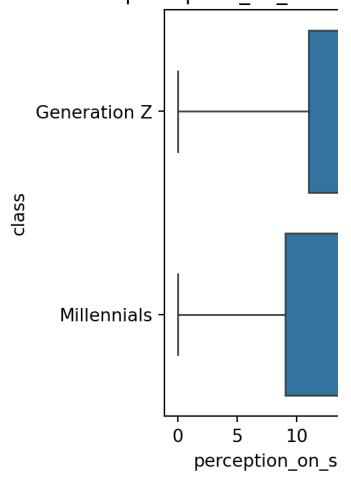
perception\_on\_smart\_grid vs state



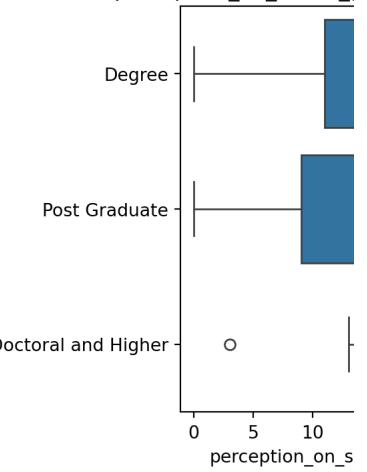
perception\_on\_smart\_grid vs household\_income



perception\_on\_smar

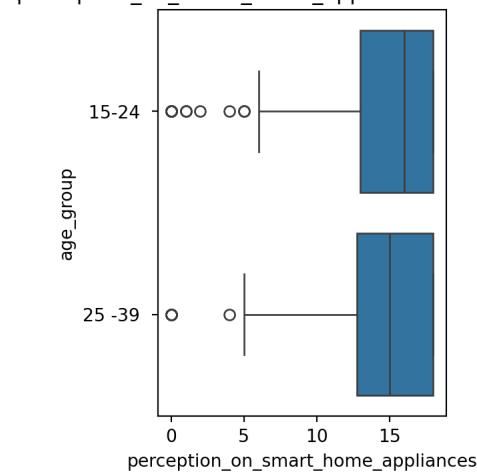


perception\_on\_smar

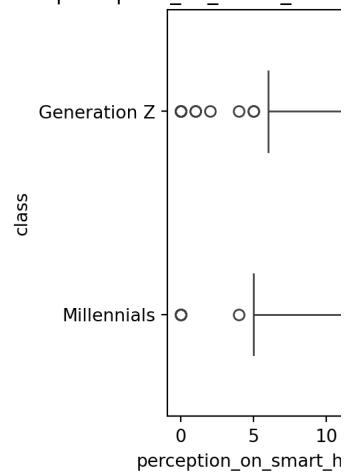


perception\_on\_smar

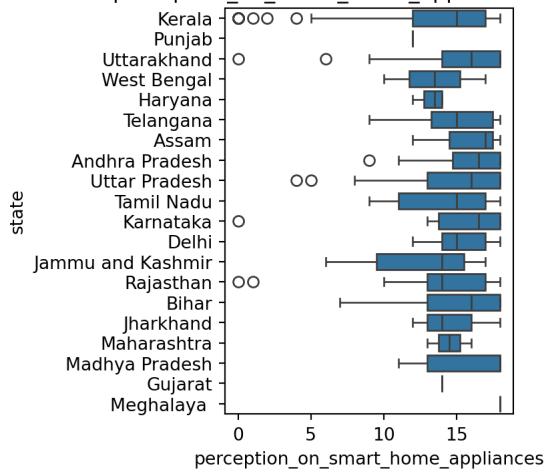
perception\_on\_smart\_home\_appliances vs age\_group



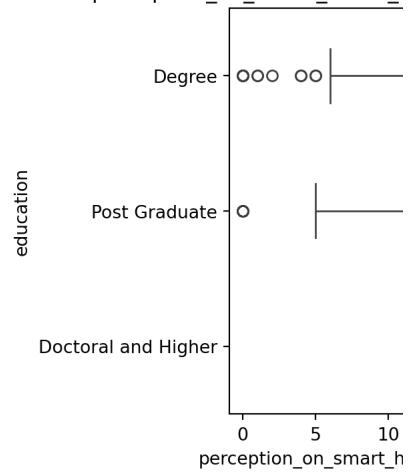
perception\_on\_smart\_home\_appliances vs class



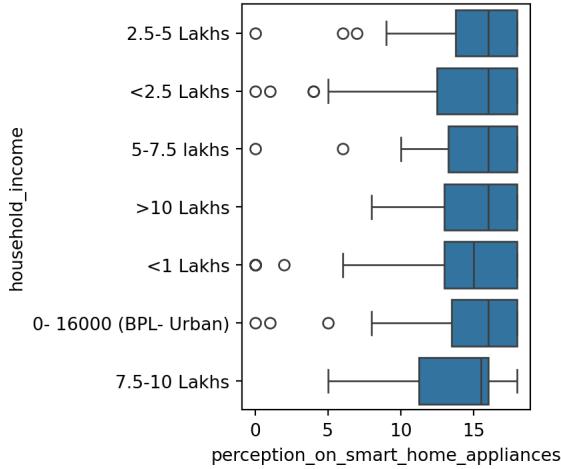
perception\_on\_smart\_home\_appliances vs state



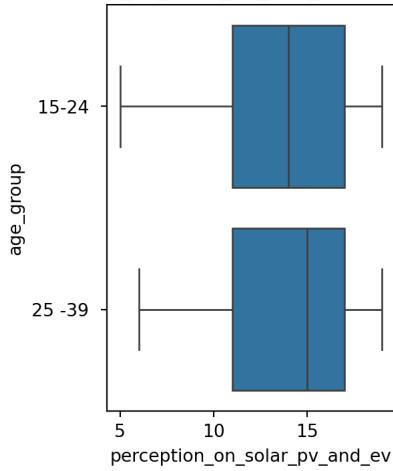
perception\_on\_smart\_home\_appliances vs education



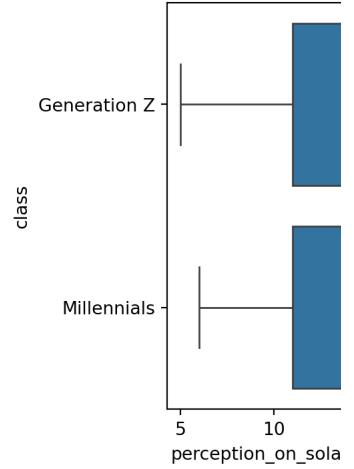
perception\_on\_smart\_home\_appliances vs household\_income



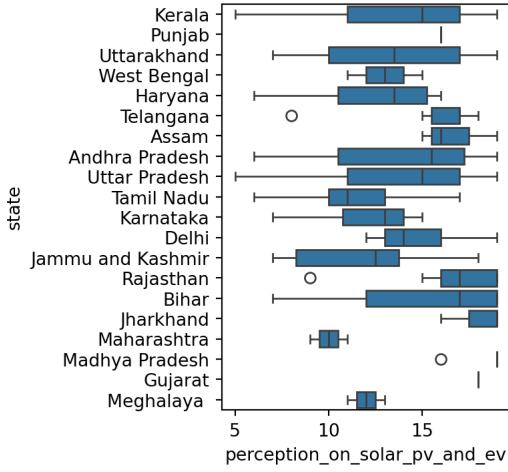
perception\_on\_solar\_pv\_and\_ev vs age\_group



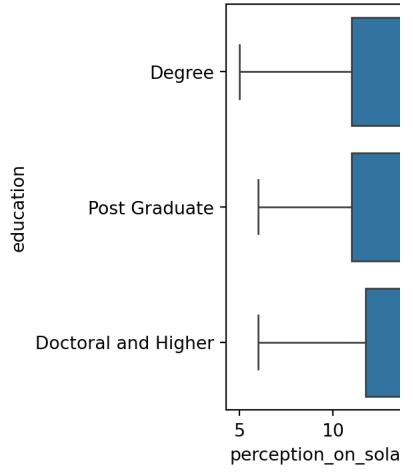
perception\_on\_solar\_pv\_and\_ev vs class



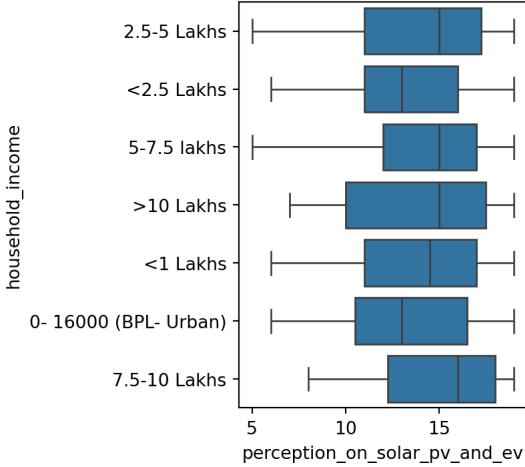
perception\_on\_solar\_pv\_and\_ev vs state



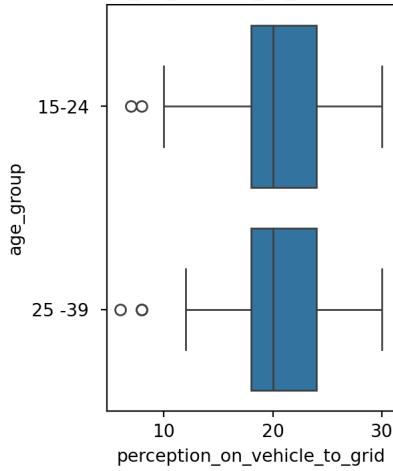
perception\_on\_solar\_pv\_and\_ev vs education



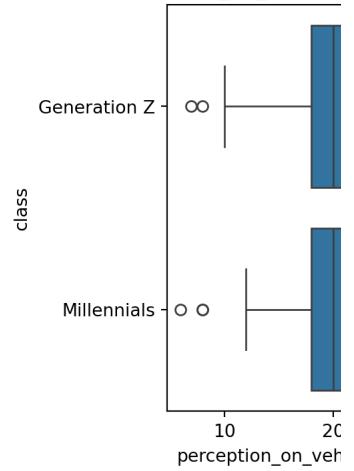
perception\_on\_solar\_pv\_and\_ev vs household\_income



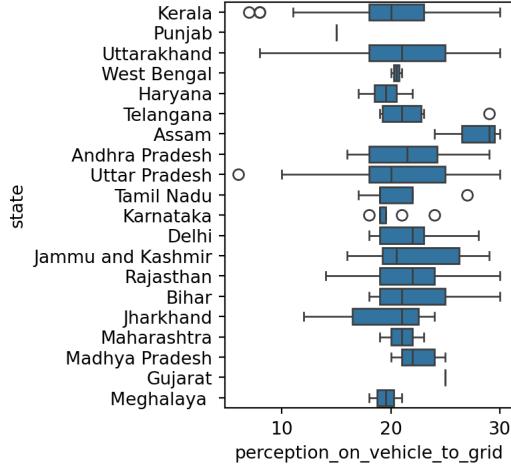
perception\_on\_vehicle\_to\_grid vs age\_group



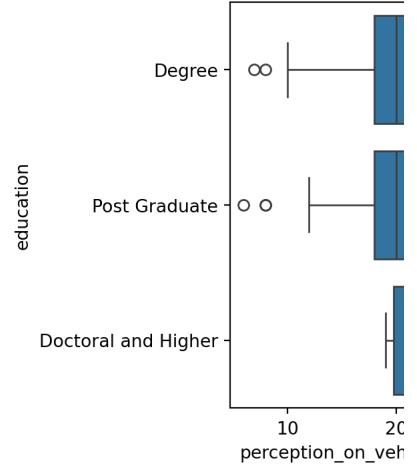
perception\_on\_vehicle



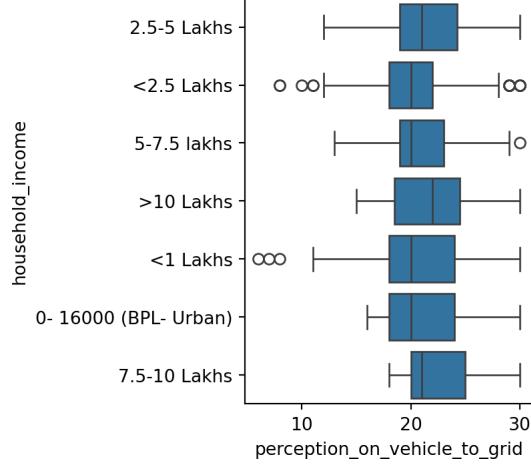
perception\_on\_vehicle\_to\_grid vs state



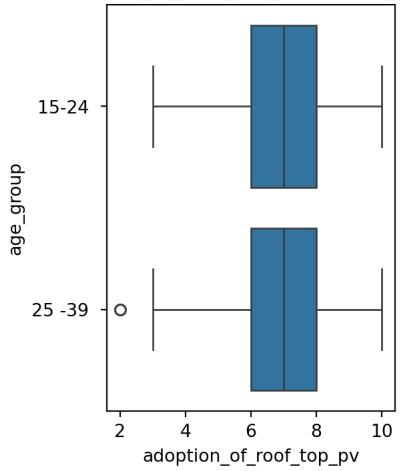
perception\_on\_vehicle\_to\_grid vs education



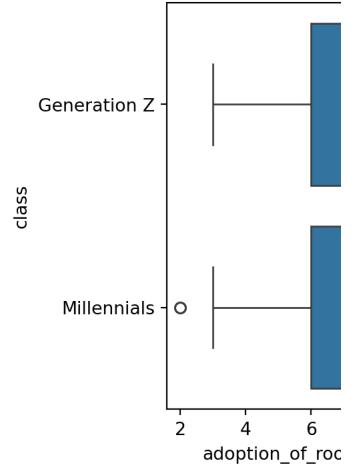
perception\_on\_vehicle\_to\_grid vs household\_income



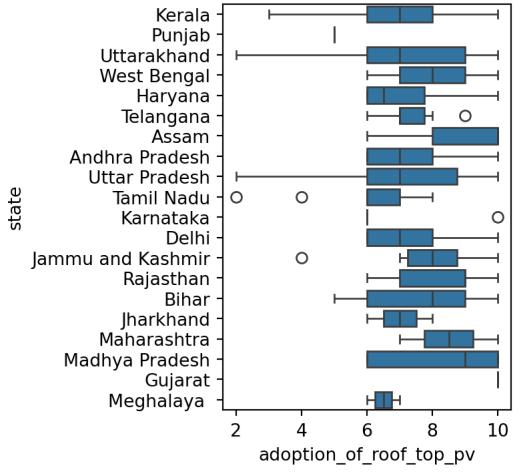
adoption\_of\_roof\_top\_pv vs age\_group



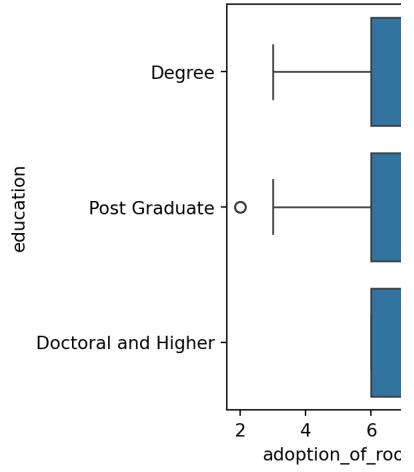
adoption\_of\_roof\_tc



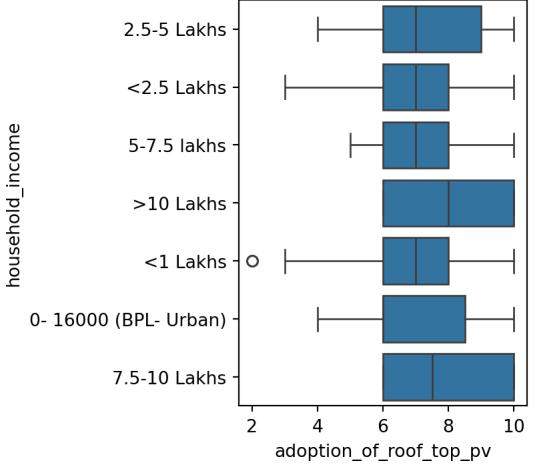
adoption\_of\_roof\_top\_pv vs state

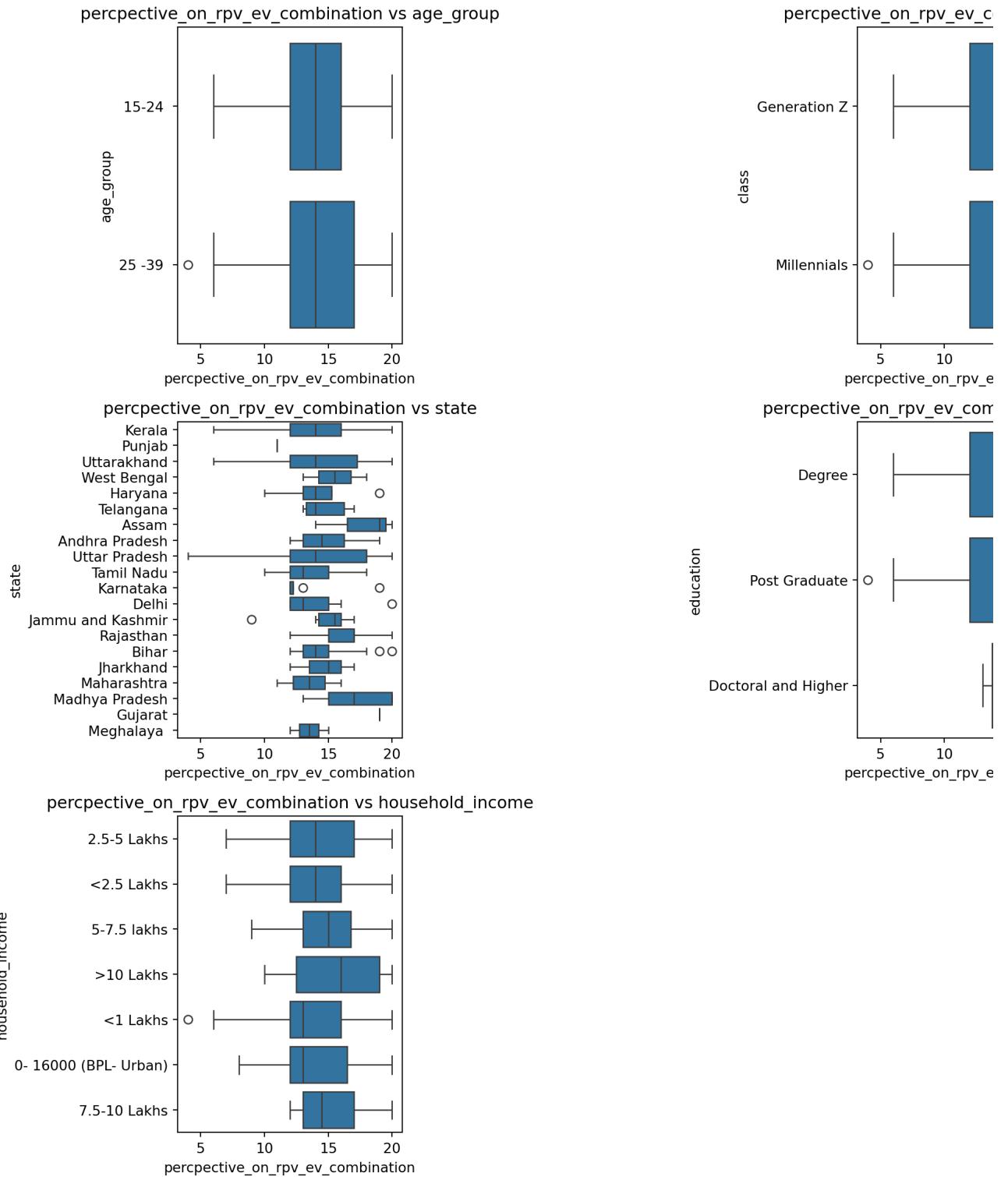


adoption\_of\_roof\_top\_tc



adoption\_of\_roof\_top\_pv vs household\_income

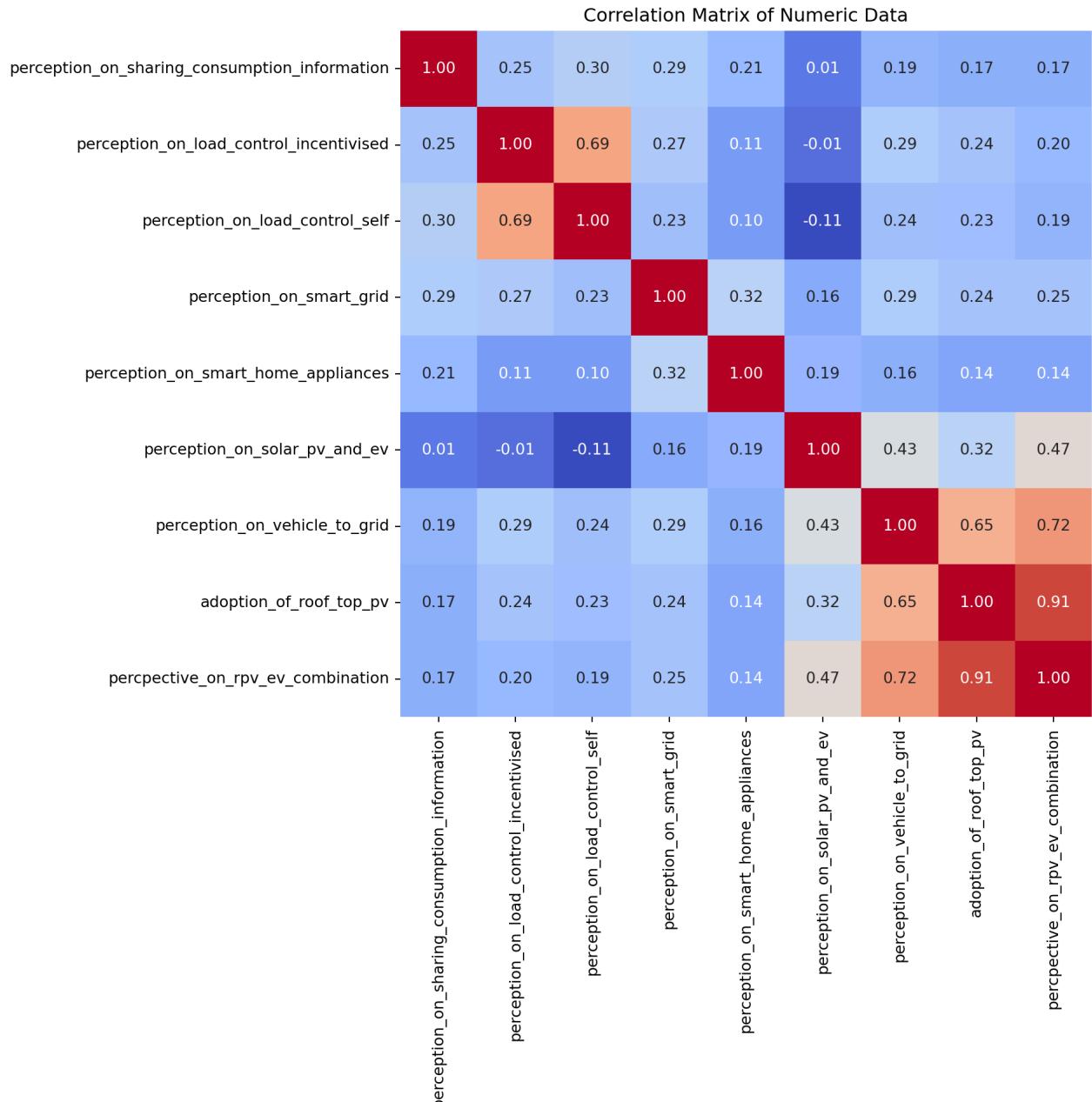




```
In [5]: numeric_perception_cols = [
    'perception_on_sharing_consumption_information',
    'perception_on_load_control_incentivised', 'perception_on_load_control_self',
    'perception_on_smart_grid', 'perception_on_smart_home_appliances',
    'perception_on_solar_pv_and_ev', 'perception_on_vehicle_to_grid',
    'adoption_of_roof_top_pv', 'percpective_on_rpv_ev_combination']

#4. Pairwise correlation between numeric data
def plot_corr_matrix(df, cols):
    corr_matrix = df[cols].corr()
    plt.figure(figsize=(10, 8))
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
    plt.title('Correlation Matrix of Numeric Data')
    plt.show()

plot_corr_matrix(df, numeric_perception_cols)
```



In [6]: # --- Demographic Analysis with Perceptions ---

```
# 1. Perceptions by Generation
def analyze_by_generation(df):
    gen_group = df.groupby('class')[numeric_perception_cols].mean().round(2)
    print("\nAverage Perceptions by Generation Group:\n", gen_group)
    gen_group.plot(kind='bar', figsize=(14,8))
    plt.title("Perception Averages by Generation Group")
    plt.ylabel("Average Score")
    plt.show()

analyze_by_generation(df)
```

```
Average Perceptions by Generation Group:
    perception_on_sharing_consumption_information \
class
Generation Z                      10.34
Millennials                         10.10

    perception_on_load_control_incentivised \
class
Generation Z                      15.33
Millennials                         14.38

    perception_on_load_control_self  perception_on_smart_grid \
class
Generation Z                      17.69           14.40
```

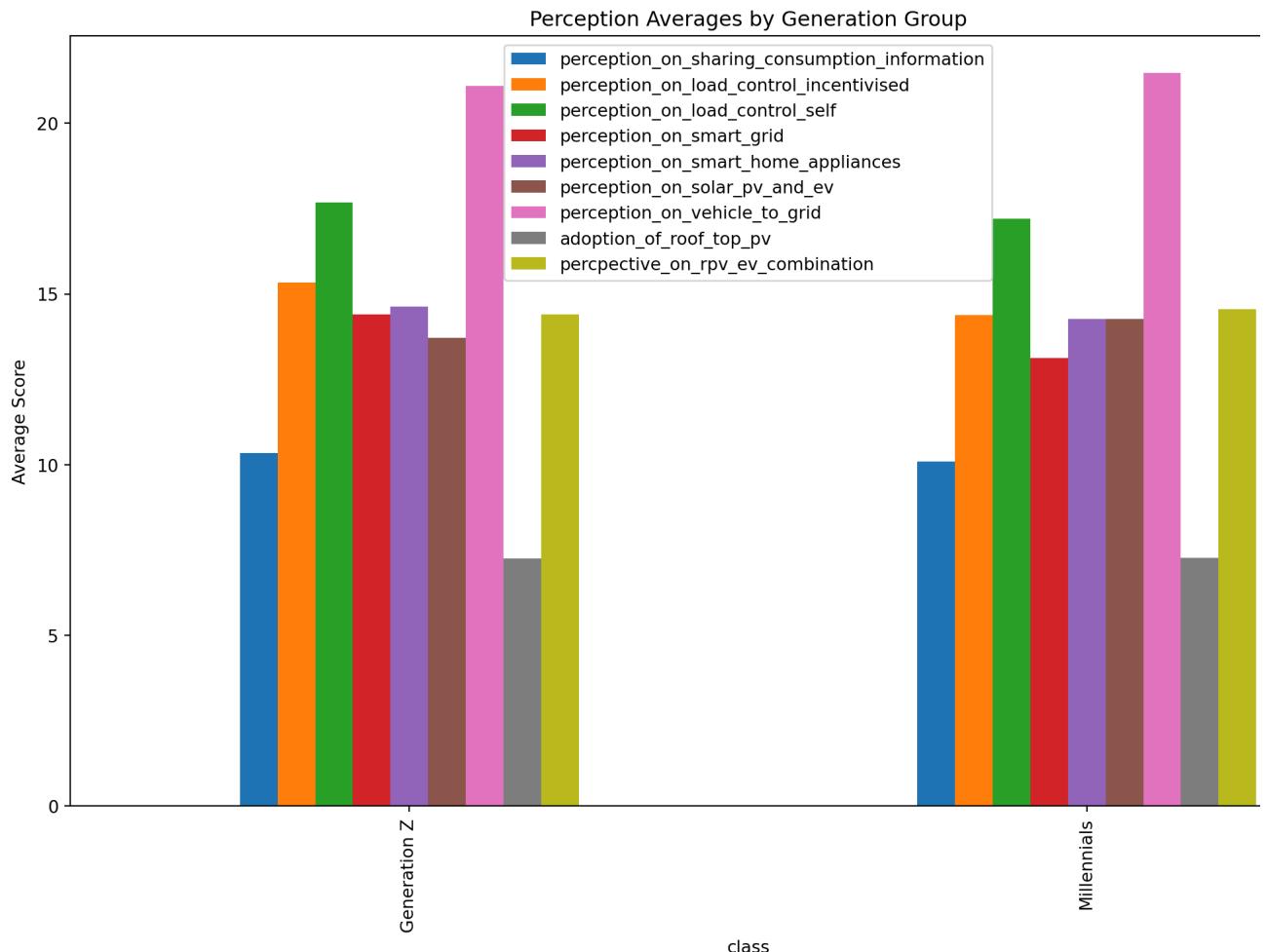
```

Millennials           17.20          13.13
perception_on_smart_home_appliances \
class
Generation Z          14.63
Millennials            14.26

perception_on_solar_pv_and_ev  perception_on_vehicle_to_grid \
class
Generation Z          13.72          21.10
Millennials            14.26          21.48

adoption_of_roof_top_pv  percpective_on_rpv_ev_combination
class
Generation Z          7.26           14.40
Millennials            7.27           14.55

```



```

In [7]: # 2. Perceptions by State
def analyze_by_state(df):
    state_group = df.groupby('state')[numeric_perception_cols].mean().round(2)
    print("\nAverage Perceptions by State:\n", state_group)
    state_group.plot(kind='bar', figsize=(14,8))
    plt.title("Perception Averages by State")
    plt.ylabel("Average Score")
    plt.show()

analyze_by_state(df)

```

```

Average Perceptions by State:
perception_on_sharing_consumption_information \
state
Andhra Pradesh          11.17
Assam                   12.33
Bihar                   9.08
Delhi                  10.00
Gujarat                10.00
Haryana                10.50
Jammu and Kashmir      9.67
Jharkhand               9.33
Karnataka              10.62

```

Kerala	10.03
Madhya Pradesh	8.00
Maharashtra	12.00
Meghalaya	12.50
Punjab	12.00
Rajasthan	10.69
Tamil Nadu	11.69
Telangana	10.17
Uttar Pradesh	10.24
Uttarakhand	10.44
West Bengal	12.00

```
perception_on_load_control_incentivised \
state
Andhra Pradesh          14.75
Assam                   13.33
Bihar                   16.15
Delhi                   13.00
Gujarat                 25.00
Haryana                 9.25
Jammu and Kashmir      10.33
Jharkhand                18.33
Karnataka               13.75
Kerala                  14.57
Madhya Pradesh           10.40
Maharashtra              18.50
Meghalaya                17.50
Punjab                   11.00
Rajasthan                13.69
Tamil Nadu                15.92
Telangana                 17.17
Uttar Pradesh              15.79
Uttarakhand               15.60
West Bengal                7.00
```

```
perception_on_load_control_self  perception_on_smart_grid \
state
Andhra Pradesh           18.50          16.33
Assam                   19.67          21.00
Bihar                   19.00          17.69
Delhi                   17.11          15.89
Gujarat                 24.00          17.00
Haryana                 16.75          9.00
Jammu and Kashmir      19.67          13.50
Jharkhand                15.67          15.67
Karnataka               15.62          9.00
Kerala                  17.10          10.86
Madhya Pradesh            10.60          15.80
Maharashtra              22.00          15.00
Meghalaya                21.00          21.00
Punjab                   10.00          18.00
Rajasthan                15.15          14.77
Tamil Nadu                18.31          18.31
Telangana                 19.67          10.67
Uttar Pradesh              17.90          16.40
Uttarakhand               18.15          16.80
West Bengal                8.50          20.50
```

```
perception_on_smart_home_appliances \
state
Andhra Pradesh           15.67
Assam                   15.67
Bihar                   15.08
Delhi                   15.44
Gujarat                 14.00
Haryana                 13.25
Jammu and Kashmir      12.50
Jharkhand                14.67
Karnataka               14.25
Kerala                  13.88
Madhya Pradesh            15.60
Maharashtra              14.50
Meghalaya                18.00
Punjab                   12.00
Rajasthan                12.85
Tamil Nadu                14.38
Telangana                 14.67
Uttar Pradesh              14.96
Uttarakhand               15.36
West Bengal                13.50
```

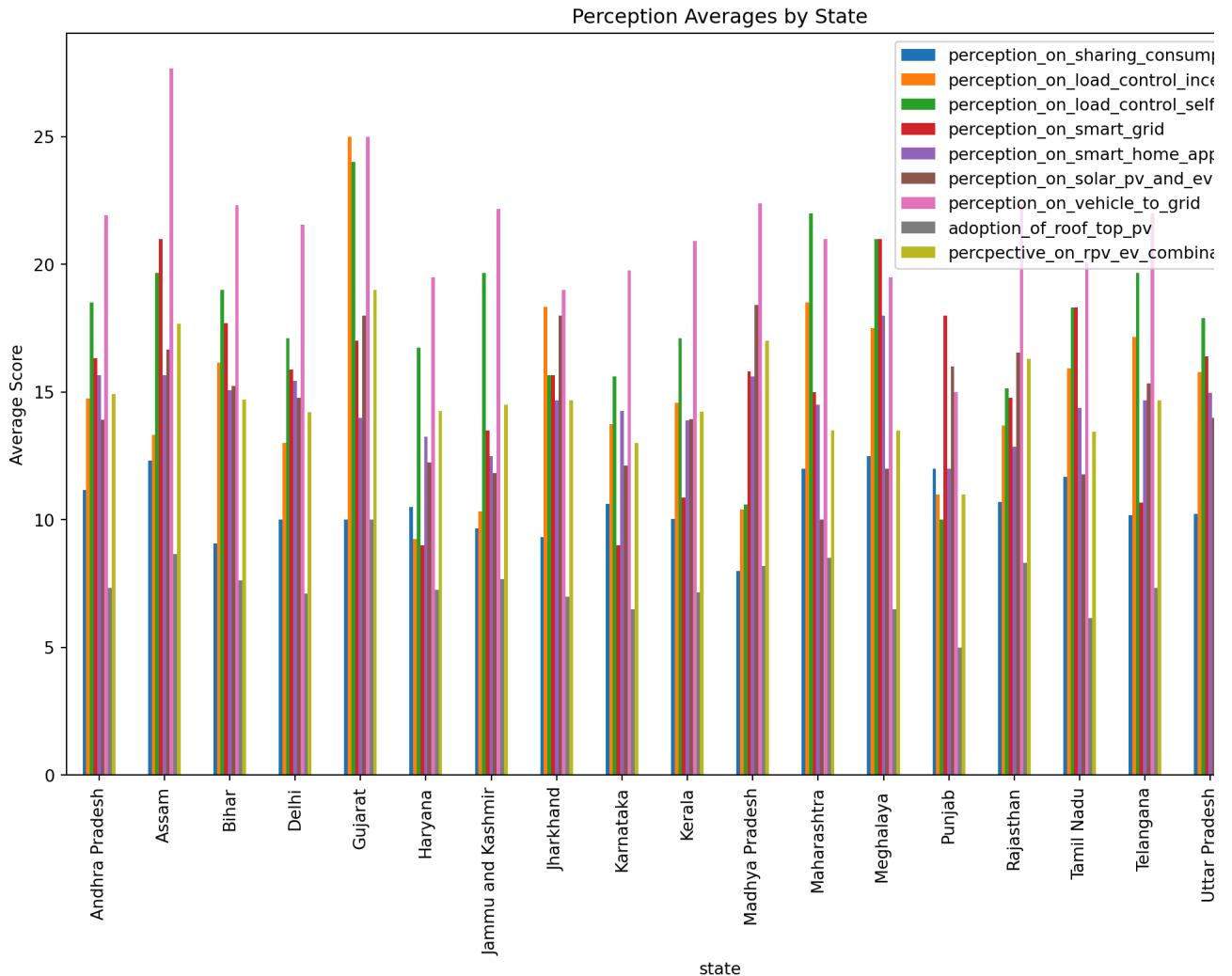
```

perception_on_solar_pv_and_ev \
state
Andhra Pradesh          13.92
Assam                   16.67
Bihar                  15.23
Delhi                  14.78
Gujarat                18.00
Haryana                12.25
Jammu and Kashmir     11.83
Jharkhand               18.00
Karnataka              12.12
Kerala                 13.94
Madhya Pradesh          18.40
Maharashtra             10.00
Meghalaya               12.00
Punjab                 16.00
Rajasthan               16.54
Tamil Nadu              11.77
Telangana               15.33
Uttar Pradesh            13.99
Uttarakhand             13.61
West Bengal              13.00

perception_on_vehicle_to_grid  adoption_of_roof_top_pv \
state
Andhra Pradesh          21.92           7.33
Assam                   27.67           8.67
Bihar                  22.31           7.62
Delhi                  21.56           7.11
Gujarat                25.00           10.00
Haryana                19.50           7.25
Jammu and Kashmir     22.17           7.67
Jharkhand               19.00           7.00
Karnataka              19.75           6.50
Kerala                 20.91           7.17
Madhya Pradesh          22.40           8.20
Maharashtra             21.00           8.50
Meghalaya               19.50           6.50
Punjab                 15.00           5.00
Rajasthan               22.38           8.31
Tamil Nadu              20.08           6.15
Telangana               22.00           7.33
Uttar Pradesh            21.24           7.33
Uttarakhand             21.89           7.31
West Bengal              20.50           8.00

percpective_on_rpv_ev_combination
state
Andhra Pradesh          14.92
Assam                   17.67
Bihar                  14.69
Delhi                  14.22
Gujarat                19.00
Haryana                14.25
Jammu and Kashmir     14.50
Jharkhand               14.67
Karnataka              13.00
Kerala                 14.24
Madhya Pradesh          17.00
Maharashtra             13.50
Meghalaya               13.50
Punjab                 11.00
Rajasthan               16.31
Tamil Nadu              13.46
Telangana               14.67
Uttar Pradesh            14.67
Uttarakhand             14.54
West Bengal              15.50

```



```
In [8]: # 3. Perceptions by Occupation
def analyze_by_occupation(df):
    occupation_group = df.groupby('occupation')[numeric_perception_cols].mean().round(2)
    print("\nAverage Perceptions by Occupation:\n", occupation_group)
    occupation_group.plot(kind='bar', figsize=(14,8))
    plt.title("Perception Averages by Occupation")
    plt.ylabel("Average Score")
    plt.show()
analyze_by_occupation(df)
```

#### Average Perceptions by Occupation:

occupation	perception_on_sharing_consumption_information \
Apprenticeship	12.00
Employed (Govt. Sector and private)	11.05
Higher Education	10.75
Research Scholar	11.71
Self Employed and Business	13.00
Student	10.11
Student and Higher Education	10.56
Student and Higher Education;Self Employed and ...	7.00
Student, Self Employed and Business	10.00
Student;Employed (Govt. Sector and private)	11.00

#### perception\_on\_load\_control\_incentivised \

occupation	perception_on_load_control_incentivised \
Apprenticeship	10.00
Employed (Govt. Sector and private)	14.11
Higher Education	11.50
Research Scholar	11.43
Self Employed and Business	18.00
Student	15.12
Student and Higher Education	15.72
Student and Higher Education;Self Employed and ...	19.00
Student, Self Employed and Business	19.00
Student;Employed (Govt. Sector and private)	10.00

```

perception_on_load_control_self \
occupation
Apprenticeship 13.00
Employed (Govt. Sector and private) 17.89
Higher Education 15.33
Research Scholar 16.14
Self Employed and Business 22.00
Student 17.46
Student and Higher Education 19.00
Student and Higher Education;Self Employed and ... 24.00
Student, Self Employed and Business 23.00
Student;Employed (Govt. Sector and private) 17.50

perception_on_smart_grid \
occupation
Apprenticeship 18.00
Employed (Govt. Sector and private) 16.26
Higher Education 16.00
Research Scholar 16.21
Self Employed and Business 13.00
Student 13.46
Student and Higher Education 16.39
Student and Higher Education;Self Employed and ... 12.00
Student, Self Employed and Business 19.00
Student;Employed (Govt. Sector and private) 13.50

perception_on_smart_home_appliances \
occupation
Apprenticeship 17.00
Employed (Govt. Sector and private) 14.21
Higher Education 15.08
Research Scholar 15.00
Self Employed and Business 15.00
Student 14.40
Student and Higher Education 14.94
Student and Higher Education;Self Employed and ... 17.00
Student, Self Employed and Business 17.00
Student;Employed (Govt. Sector and private) 15.50

perception_on_solar_pv_and_ev \
occupation
Apprenticeship 17.00
Employed (Govt. Sector and private) 14.58
Higher Education 14.42
Research Scholar 15.14
Self Employed and Business 15.00
Student 13.84
Student and Higher Education 15.28
Student and Higher Education;Self Employed and ... 11.00
Student, Self Employed and Business 8.00
Student;Employed (Govt. Sector and private) 14.50

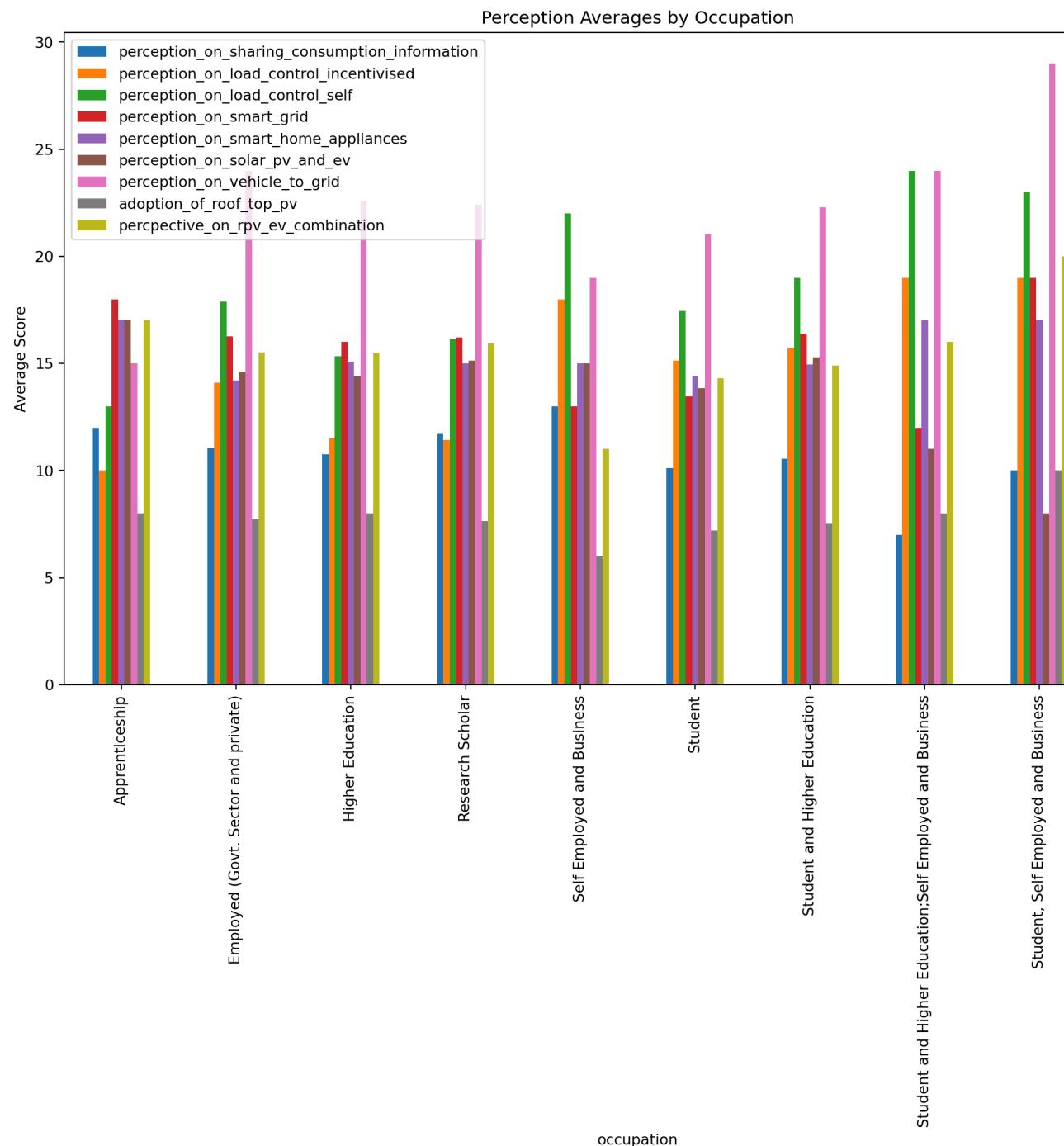
perception_on_vehicle_to_grid \
occupation
Apprenticeship 15.00
Employed (Govt. Sector and private) 24.00
Higher Education 22.58
Research Scholar 22.43
Self Employed and Business 19.00
Student 21.02
Student and Higher Education 22.28
Student and Higher Education;Self Employed and ... 24.00
Student, Self Employed and Business 29.00
Student;Employed (Govt. Sector and private) 24.00

adoption_of_roof_top_pv \
occupation
Apprenticeship 8.00
Employed (Govt. Sector and private) 7.74
Higher Education 8.00
Research Scholar 7.64
Self Employed and Business 6.00
Student 7.19
Student and Higher Education 7.50
Student and Higher Education;Self Employed and ... 8.00
Student, Self Employed and Business 10.00
Student;Employed (Govt. Sector and private) 7.50

percpective_on_rpv_ev_combination
occupation

```

Apprenticeship	17.00
Employed (Govt. Sector and private)	15.53
Higher Education	15.50
Research Scholar	15.93
Self Employed and Business	11.00
Student	14.31
Student and Higher Education	14.89
Student and Higher Education;Self Employed and ...	16.00
Student, Self Employed and Business	20.00
Student;Employed (Govt. Sector and private)	15.50



```
In [9]: #4. Perceptions by House-type
def analyze_by_house_type(df):
    house_type_group = df.groupby('house_type')[numeric_perception_cols].mean().round(2)
    print("\nAverage Perceptions by House Type:\n", house_type_group)
    house_type_group.plot(kind='bar', figsize=(14,8))
    plt.title("Perception Averages by House Type")
    plt.ylabel("Average Score")
    plt.show()

analyze_by_house_type(df)
```

Average Perceptions by House Type:  
perception\_on\_sharing\_consumption\_information \

```

house_type
Large 9.88
Medium 10.26
Small 10.40

perception_on_load_control_incentivised \
house_type
Large 14.77
Medium 14.90
Small 14.98

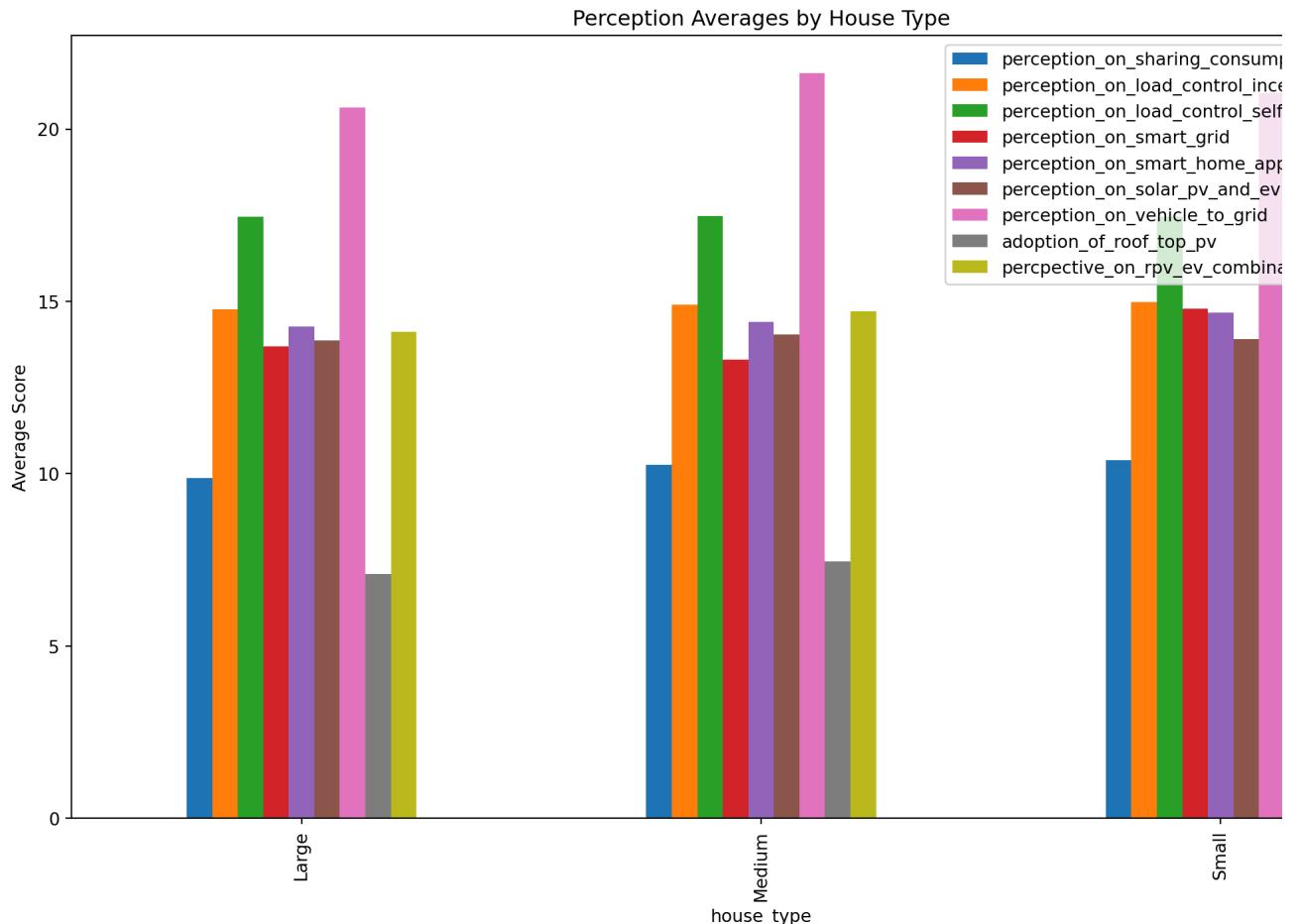
perception_on_load_control_self perception_on_smart_grid \
house_type
Large 17.45 13.70
Medium 17.48 13.30
Small 17.45 14.79

perception_on_smart_home_appliances \
house_type
Large 14.27
Medium 14.41
Small 14.68

perception_on_solar_pv_and_ev perception_on_vehicle_to_grid \
house_type
Large 13.86 20.63
Medium 14.04 21.63
Small 13.91 21.05

adoption_of_roof_top_pv percpective_on_rpv_ev_combination
house_type
Large 7.09 14.12
Medium 7.45 14.72
Small 7.06 14.26

```



```
In [10]: #5. Perceptions by Household Income
def analyze_by_household_income(df):
    income_group = df.groupby('household_income')[numeric_perception_cols].mean().round(2)
    print("\nAverage Perceptions by Household Income:\n", income_group)
    income_group.plot(kind='bar', figsize=(14, 8))
    plt.title("Perception Averages by Household Income")
    plt.ylabel("Average Score")
```

```

plt.show()

analyze_by_household_income(df)

Average Perceptions by Household Income:
perception_on_sharing_consumption_information \
household_income
0- 16000 (BPL- Urban) 10.51
2.5-5 Lakhs 10.51
5-7.5 lakhs 9.57
7.5-10 Lakhs 10.18
<1 Lakhs 10.32
<2.5 Lakhs 10.23
>10 Lakhs 9.74

perception_on_load_control_incentivised \
household_income
0- 16000 (BPL- Urban) 16.09
2.5-5 Lakhs 15.59
5-7.5 lakhs 14.28
7.5-10 Lakhs 14.53
<1 Lakhs 14.81
<2.5 Lakhs 14.78
>10 Lakhs 13.61

perception_on_load_control_self \
household_income
0- 16000 (BPL- Urban) 19.89
2.5-5 Lakhs 17.93
5-7.5 lakhs 16.81
7.5-10 Lakhs 17.00
<1 Lakhs 17.06
<2.5 Lakhs 17.84
>10 Lakhs 15.91

perception_on_smart_grid \
household_income
0- 16000 (BPL- Urban) 14.74
2.5-5 Lakhs 14.53
5-7.5 lakhs 13.61
7.5-10 Lakhs 15.71
<1 Lakhs 13.22
<2.5 Lakhs 13.20
>10 Lakhs 14.48

perception_on_smart_home_appliances \
household_income
0- 16000 (BPL- Urban) 14.20
2.5-5 Lakhs 15.02
5-7.5 lakhs 14.91
7.5-10 Lakhs 13.94
<1 Lakhs 14.28
<2.5 Lakhs 14.10
>10 Lakhs 15.22

perception_on_solar_pv_and_ev \
household_income
0- 16000 (BPL- Urban) 13.31
2.5-5 Lakhs 14.34
5-7.5 lakhs 14.56
7.5-10 Lakhs 15.15
<1 Lakhs 13.82
<2.5 Lakhs 13.31
>10 Lakhs 13.96

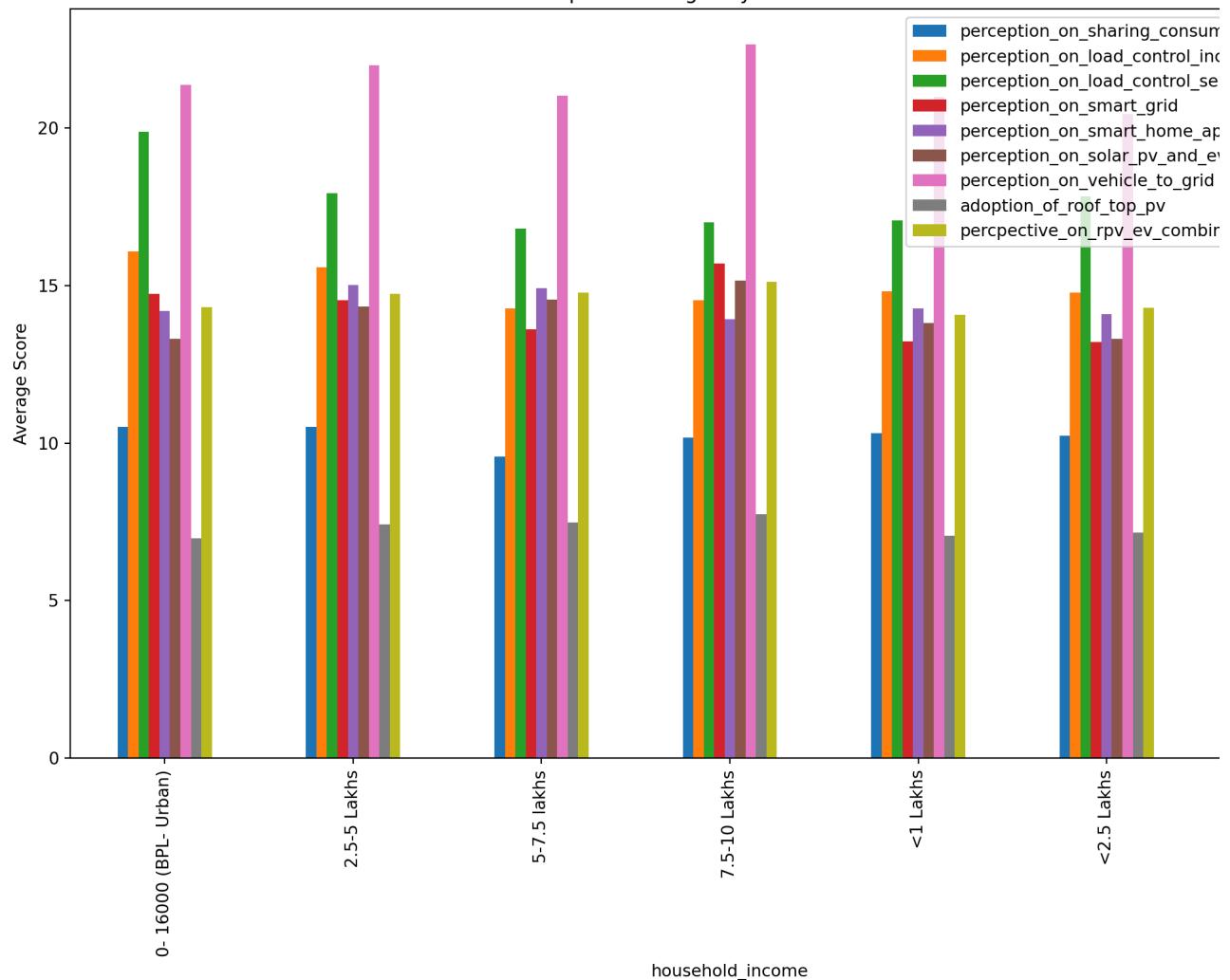
perception_on_vehicle_to_grid_adoption_of_roof_top_pv \
household_income
0- 16000 (BPL- Urban) 21.37 6.97
2.5-5 Lakhs 21.99 7.41
5-7.5 lakhs 21.04 7.48
7.5-10 Lakhs 22.65 7.74
<1 Lakhs 20.99 7.05
<2.5 Lakhs 20.44 7.16
>10 Lakhs 22.17 8.04

percpective_on_rpv_ev_combination
household_income
0- 16000 (BPL- Urban) 14.31
2.5-5 Lakhs 14.73
5-7.5 lakhs 14.78

```

7.5-10 Lakhs	15.12
<1 Lakhs	14.07
<2.5 Lakhs	14.29
>10 Lakhs	15.78

Perception Averages by Household Income



```
In [11]: #Example: Hypothesis testing to check if significant difference exists between perceptions of two different age groups
from scipy import stats

def hypothesis_testing(df, var, age1, age2):
    age_group1 = df[df['class'] == age1][var]
    age_group2 = df[df['class'] == age2][var]
    t_stat, p_val = stats.ttest_ind(age_group1, age_group2, equal_var=False, nan_policy='omit')
    print(f"\nT-test result between {age1} and {age2} for perception on {var}:")
    print("T-statistic:", t_stat)
    print("P-value:", p_val)
    alpha = 0.05
    if p_val < alpha:
        print(f"Reject null hypothesis. Significant difference in {var} between {age1} and {age2}")
    else:
        print(f"Failed to reject null hypothesis. No significant difference in {var} between {age1} and {age2}")

hypothesis_testing(df, 'perception_on_smart_grid', 'Generation Z', 'Millennials')
```

```
T-test result between Generation Z and Millennials for perception on perception_on_smart_grid:
T-statistic: 1.8748124234100918
P-value: 0.061441521579950545
Failed to reject null hypothesis. No significant difference in perception_on_smart_grid between Generation Z and Millennials
```

```
In [12]: #6. Further analysis
```

```
#You can further conduct ANOVA test to compare differences among three or more group's data
# Example: ANOVA test for the above:
import statsmodels.api as sm
from statsmodels.formula.api import ols
def anova_test_by_state(df, var):
    model = ols(f'{var} ~ C(state)', data=df).fit()
    anova_table = sm.stats.anova_lm(model, typ=2)
    print(f"\nANOVA test result by class for {var}:")
```

```

print(anova_table)

anova_test_by_state(df, 'perception_on_smart_grid')

```

```

ANOVA test result by class for perception_on_smart_grid:
      sum_sq    df      F   PR(>F)
C(state)  4623.740753  19.0  5.022068  6.099431e-11
Residual   23114.029871 477.0       NaN       NaN

```

```

In [13]: for col in numeric_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce') # Replace 'errors='coerce'' with errors='raise' to identify if there are any
    errors while numeric conversion.
df.dropna(subset=numeric_cols, inplace=True) #Dropping all rows with null values for the numeric variables

# --- ANOVA Test ---

def anova_test_by_class(df, var):
    model = ols(f'{var} ~ C(age_group)', data=df).fit()
    anova_table = sm.stats.anova_lm(model, typ=2)
    print(f"\nANOVA test result for {var} across Class:")
    print(anova_table)

# Perform ANOVA for each perception variable
for col in numeric_cols[1:]: # Exclude 'average_monthly_electricity_bill' from ANOVA test as it is not a perception variable
    anova_test_by_class(df, col)

```

```

ANOVA test result for perception_on_individual_usage across Class:
      sum_sq    df      F   PR(>F)
C(age_group)  69.634448  1.0  8.551152  0.003611
Residual     4030.924908 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_sharing_consumption_information across Class:
      sum_sq    df      F   PR(>F)
C(age_group)  6.968479  1.0  1.052943  0.305331
Residual     3275.957074 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_load_control_incentivised across Class:
      sum_sq    df      F   PR(>F)
C(age_group) 111.093808  1.0  3.883281  0.049326
Residual     14161.075206 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_load_control_self across Class:
      sum_sq    df      F   PR(>F)
C(age_group) 29.810272  1.0  0.76791  0.381289
Residual     19215.891941 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_smart_grid across Class:
      sum_sq    df      F   PR(>F)
C(age_group) 197.250363  1.0  3.545283  0.060301
Residual     27540.520261 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_smart_home_appliances across Class:
      sum_sq    df      F   PR(>F)
C(age_group) 17.281697  1.0  1.072206  0.300953
Residual     7978.352106 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_solar_pv_and_ev across Class:
      sum_sq    df      F   PR(>F)
C(age_group) 35.523455  1.0  2.701995  0.100858
Residual     6507.824634 495.0       NaN       NaN

```

```

ANOVA test result for perception_on_vehicle_to_grid across Class:
      sum_sq    df      F   PR(>F)
C(age_group) 18.071738  1.0  0.912597  0.339893
Residual     9802.258242 495.0       NaN       NaN

```

```

ANOVA test result for adoption_of_roof_top_pv across Class:
      sum_sq    df      F   PR(>F)
C(age_group)  0.018459  1.0  0.006153  0.937508
Residual     1484.923191 495.0       NaN       NaN

```

```

ANOVA test result for percpective_on_rpv_ev_combination across Class:
      sum_sq    df      F   PR(>F)
C(age_group)  2.629122  1.0  0.272997  0.601562
Residual     4767.137477 495.0       NaN       NaN

```