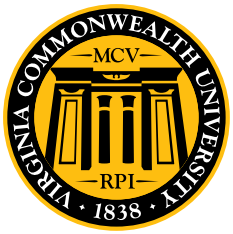

VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A4: MULTIVARIATE ANALYSIS AND BUSINESS ANALYTICS APPLICATION

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CONTENTS

Introduction

In the realm of data analysis, leveraging advanced statistical techniques is essential for uncovering patterns, reducing dimensionality, and extracting meaningful insights from complex datasets. This study focuses on utilizing several such techniques to analyze multiple datasets and derive valuable conclusions. Firstly, we will employ Principal Component Analysis (PCA) and Factor Analysis on survey data (Survey.csv) to identify the underlying data dimensions, thereby revealing the main factors driving the responses and facilitating a more concise interpretation of the survey results. Additionally, we will conduct Cluster Analysis on the same survey data to segment respondents based on background variables, characterizing them into distinct groups and providing deeper insights into the differing characteristics and behaviors of various respondent groups. Furthermore, we will apply Multidimensional Scaling (MDS) to ice cream data (icecream.csv) to create a spatial representation of the data, aiding in the interpretation of relationships and distances between different ice cream flavors and enhancing our understanding of consumer preferences. Lastly, Conjoint Analysis will be performed on pizza data (pizza_data.csv) to determine how consumers value different attributes of pizza, offering insights into the most important factors influencing consumer choices and guiding product design to better meet consumer needs. By addressing these objectives, this study aims to provide a comprehensive approach to data analysis and interpretation, ultimately informing decision-making and strategy formulation in various domains.

Objectives

1. Perform Principal Component Analysis and Factor Analysis to identify data dimensions (Survey.csv)
2. Conduct Cluster Analysis to characterize respondents based on background variables (Survey.csv)
3. Apply Multidimensional Scaling and interpret the results (icecream.csv)
4. Conjoint Analysis (pizza_data.csv)

BUSINESS SIGNIFICANCE

Principal Component Analysis (PCA) and Factor Analysis on Survey Data: Performing Principal Component Analysis (PCA) and Factor Analysis on the survey data holds significant business value as it allows for the reduction of complex data into manageable dimensions. By identifying the underlying factors driving survey responses, businesses can focus on the most critical elements that influence customer satisfaction and behavior. This streamlined insight helps in developing targeted strategies, improving product offerings, and enhancing overall customer experience, ultimately leading to increased customer loyalty and profitability.

Cluster Analysis on Survey Data: Conducting Cluster Analysis to characterize respondents based on background variables provides businesses with a deeper understanding of their customer base. By segmenting respondents into distinct groups, companies can tailor their marketing strategies, products, and services to meet the specific needs of each group. This targeted approach enables more effective communication, better resource allocation, and higher conversion rates. Understanding these customer segments also aids in identifying new market opportunities and optimizing customer relationship management.

Multidimensional Scaling on Ice Cream Data: Applying Multidimensional Scaling (MDS) to ice cream data offers businesses a visual representation of consumer preferences and the perceived similarities between different ice cream flavors. This insight is crucial for product development and marketing strategies. By understanding how consumers perceive various flavors, companies can optimize their product lines, create new flavor combinations that align with consumer preferences, and position their products more effectively in the market. This can lead to increased market share and customer satisfaction.

Conjoint Analysis on Pizza Data: Performing Conjoint Analysis on pizza data provides valuable insights into consumer preferences and the trade-offs they make when choosing pizza. Understanding the relative importance of different attributes (such as toppings, price, crust type, etc.) allows businesses to design pizzas that better meet consumer desires. This can lead to more successful product launches, increased sales, and higher customer satisfaction. Additionally, the insights gained from Conjoint Analysis can inform pricing strategies and promotional efforts, maximizing revenue and market penetration.

RESULTS AND INTERPRETATIONS

Code

Loading the dataset

```
import os
import pandas as pd

# Load the dataset
os.chdir("/Users/sarathsabu/Desktop/scma/datasets")
survey_data = pd.read_csv('Survey.csv')

# Display the first few rows of the dataset
survey_data.head()
```

1)Principal Component Analysis and Factor Analysis

```
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
from factor_analyzer import FactorAnalyzer, Rotator
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
survey_df = pd.read_csv('Survey.csv')

# Display the dimensions of the dataset
print(survey_df.shape)

# Display the column names
print(survey_df.columns)

# Display the first few rows of the dataset
print(survey_df.head())

# Display the structure of the dataset
print(survey_df.info())

# Check for missing values
print(survey_df.isna().sum().sum())

# Select relevant columns for analysis
sur_int = survey_df.iloc[:, 19:46]

# Display the structure and dimensions of the selected data
print(sur_int.info())
print(sur_int.shape)

# Perform PCA
pca = PCA(n_components=5)
pca_result = pca.fit_transform(sur_int)

# Display the explained variance by each principal component
print(pca.explained_variance_ratio_)

# Biplot for PCA
plt.figure(figsize=(10, 7))
plt.scatter(pca_result[:, 0], pca_result[:, 1], edgecolors='k', c='r')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('PCA Biplot')
plt.grid(True)
plt.show()

# Perform Factor Analysis
fa = FactorAnalyzer(n_factors=5, rotation=None)
fa.fit(sur_int)

# Get loadings and variance
loadings = fa.loadings_
variance = fa.get_factor_variance()

# Print loadings and variance
print("Factor Loadings:\n", loadings)
print("Variance:\n", variance)

# Perform Factor Analysis with Promax rotation
rotator = Rotator()
loadings_promax = rotator.fit_transform(loadings)

# Print rotated loadings
print("Promax Rotated Loadings:\n", loadings_promax)
```

Result:

(70, 50)

```
Index(['City', 'Sex', 'Age', 'Occupation', 'Monthly Household Income',
       'Income', 'Planning to Buy a new house', 'Time Frame',
       'Reasons for buying a house', 'what type of House', 'Number of rooms',
       'Size of House', 'Budget', 'Finished/Semi Finished',
       'Influence Decision', 'Maintainance', 'EMI', '1.Proximity to city',
       '2.Proximity to schools', '3. Proximity to transport',
       '4. Proximity to work place', '5. Proximity to shopping',
       '1. Gym/Pool/Sports facility', '2. Parking space', '3.Power back-up',
       '4.Water supply', '5.Security', '1. Exterior look ', '2. Unit size',
       '3. Interior design and branded components',
       '4. Layout plan (Integrated etc.)', '5. View from apartment',
       '1. Price', '2. Booking amount', '3. Equated Monthly Instalment (EMI)',
       '4. Maintenance charges', '5. Availability of loan',
       '1. Builder reputation', '2. Appreciation potential',
       '3. Profile of neighbourhood', '4. Availability of domestic help',
       'Time', 'Size', 'Budgets', 'Maintainances', 'EMI.1', 'ages', 'sex',
       'Finished/Semi Finished.1', 'Influence Decision.1'],
      dtype='object')
```

	City	Sex	Age	Occupation	Monthly Household Income	Income
0	Bangalore	M	26-35	Private Sector	85,001 to105,000	95000
1	Bangalore	M	46-60	Government/PSU	45,001 to 65,000	55000
2	Bangalore	F	46-60	Government/PSU	25,001 to 45,000	35000
3	Bangalore	M	36-45	Private Sector	>125000	200000
4	Bangalore	M	26-35	Self Employed	85,001 to105,000	95000

	Planning to Buy a new house	Time Frame	Reasons for buying a house
0	Yes	6M to 1Yr	Residing
1	Yes	6M to 1Yr	Investment
2	Yes	<6 Months	Rental Income
3	Yes	<6 Months	Investment
4	Yes	1-2 Yr	Residing

```
  what type of House  ... 4. Availability of domestic help Time  Size Budgets  \
0          Apartment  ...                              1    9  1200    72.5
1          Apartment  ...                              2    9   800    32.5
2          Apartment  ...                              4    3   400    12.5
3          Apartment  ...                              5    3  1600   102.5
4          Apartment  ...                              3   18   800    52.5

  Maintainances  EMI.1  ages  sex  Finished/Semi Finished.1  \
0         30000  42500  30.5    M             Semifurnished
1           120  27500  53.0    M             Semifurnished
2         10000  10000  53.0    F             Semifurnished
3         70000  80000  40.5    M                 Furnished
4         30000  42500  30.5    M             Semifurnished

   Influence Decision.1
0           Site visits
1             Newspaper
2              Hoarding
3   Electronic/Internet
4   Electronic/Internet

[5 rows x 50 columns]
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RangeIndex: 70 entries, 0 to 69
Data columns (total 50 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                               --------------  -----
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 1   Sex                                   70 non-null     object
 2   Age                                   70 non-null     object
 3   Occupation                            70 non-null     object
 4   Monthly Household Income              70 non-null     object
 5   Income                                70 non-null     int64
 6   Planning to Buy a new house           70 non-null     object
```

7	Time Frame	70	non-null	object
8	Reasons for buying a house	70	non-null	object
9	what type of House	70	non-null	object
10	Number of rooms	70	non-null	object
11	Size of House	70	non-null	object
12	Budget	70	non-null	object
13	Finished/Semi Finished	70	non-null	object
14	Influence Decision	70	non-null	object
15	Maintainance	70	non-null	object
16	EMI	70	non-null	object
17	1.Proximity to city	70	non-null	int64
18	2.Proximity to schools	70	non-null	int64
19	3. Proximity to transport	70	non-null	int64
20	4. Proximity to work place	70	non-null	int64
21	5. Proximity to shopping	70	non-null	int64
22	1. Gym/Pool/Sports facility	70	non-null	int64
23	2. Parking space	70	non-null	int64
24	3.Power back-up	70	non-null	int64
25	4.Water supply	70	non-null	int64
26	5.Security	70	non-null	int64
27	1. Exterior look	70	non-null	int64
28	2. Unit size	70	non-null	int64
29	3. Interior design and branded components	70	non-null	int64
30	4. Layout plan (Integrated etc.)	70	non-null	int64
31	5. View from apartment	70	non-null	int64
32	1. Price	70	non-null	int64
33	2. Booking amount	70	non-null	int64
34	3. Equated Monthly Instalment (EMI)	70	non-null	int64
35	4. Maintenance charges	70	non-null	int64
36	5. Availability of loan	70	non-null	int64
37	1. Builder reputation	70	non-null	int64
38	2. Appreciation potential	70	non-null	int64
39	3. Profile of neighbourhood	70	non-null	int64
40	4. Availability of domestic help	70	non-null	int64

```
 41  Time                                70 non-null     int64
 42  Size                                70 non-null     int64
 43  Budgets                             70 non-null     float64
 44  Maintainances                       70 non-null     int64
 45  EMI.1                               70 non-null     int64
 46  ages                                70 non-null     float64
 47  sex                                 70 non-null     object
 48  Finished/Semi Finished.1            70 non-null     object
 49  Influence Decision.1                70 non-null     object
dtypes: float64(2), int64(29), object(19)
memory usage: 27.5+ KB
None
0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70 entries, 0 to 69
Data columns (total 27 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   3. Proximity to transport               70 non-null     int64
 1   4. Proximity to work place              70 non-null     int64
 2   5. Proximity to shopping                70 non-null     int64
 3   1. Gym/Pool/Sports facility             70 non-null     int64
 4   2. Parking space                        70 non-null     int64
 5   3.Power back-up                         70 non-null     int64
 6   4.Water supply                          70 non-null     int64
 7   5.Security                              70 non-null     int64
 8   1. Exterior look                        70 non-null     int64
 9   2. Unit size                            70 non-null     int64
 10  3. Interior design and branded components  70 non-null  int64
 11  4. Layout plan (Integrated etc.)        70 non-null     int64
 12  5. View from apartment                  70 non-null     int64
 13  1. Price                                70 non-null     int64
 14  2. Booking amount                       70 non-null     int64
 15  3. Equated Monthly Instalment (EMI)     70 non-null     int64
```

16 4. Maintenance charges 70 non-null int64
17 5. Availability of loan 70 non-null int64
18 1. Builder reputation 70 non-null int64
19 2. Appreciation potential 70 non-null int64
20 3. Profile of neighbourhood 70 non-null int64
21 4. Availability of domestic help 70 non-null int64
22 Time 70 non-null int64
23 Size 70 non-null int64
24 Budgets 70 non-null float64
25 Maintainances 70 non-null int64
26 EMI.1 70 non-null int64
dtypes: float64(1), int64(26)

(70, 27)
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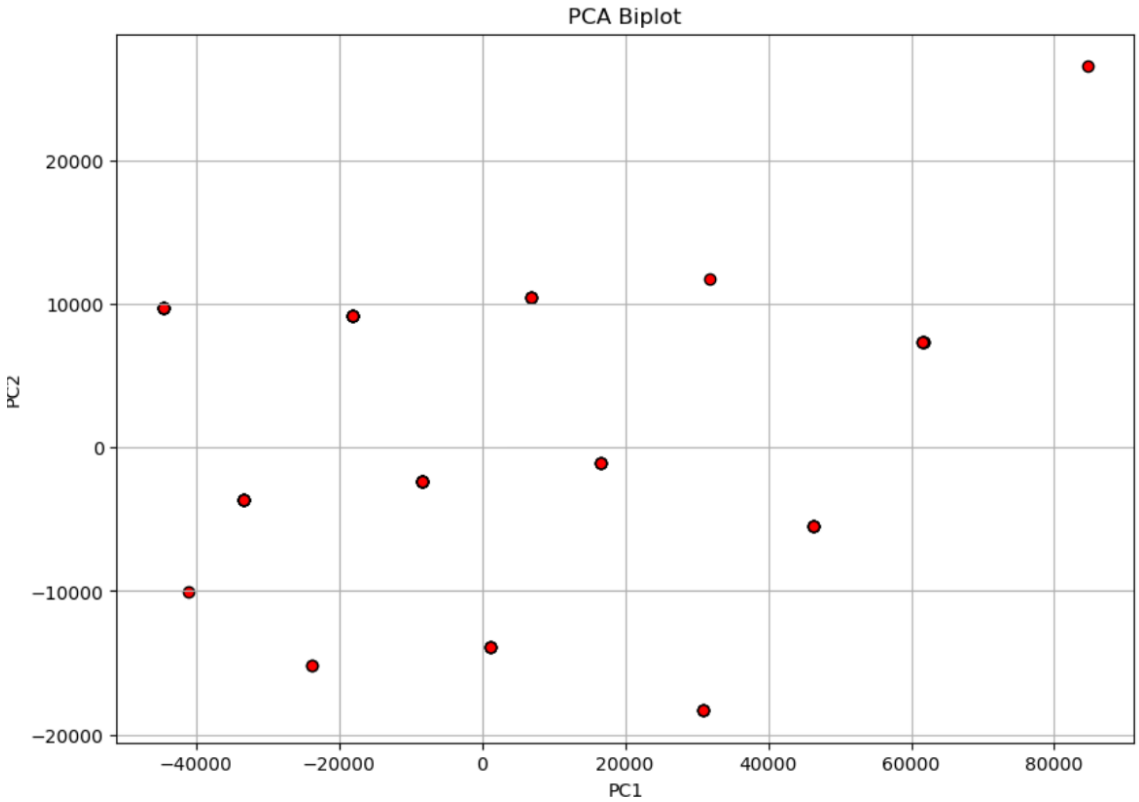
1.98047817e-08]



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3.85972766e-02]

[1.45689483e-01 -6.41587533e-02 2.43400638e-01 -3.98929728e-01
  4.42531540e-01]
[6.01550622e-01 4.22800206e-01 -1.61410904e-01 7.59532307e-02
  2.44185792e-01]
[4.98941187e-01 -1.23055804e-01 -7.21028839e-02 1.39569316e-01
  2.72696074e-01]
[5.65008984e-01 -5.67950173e-02 -1.63979640e-01 -2.32150224e-02
  1.98889781e-01]
[4.37753298e-01 1.15974238e-01 -2.21287989e-02 -2.03820140e-01
  5.22282458e-01]
[5.87998106e-01 -2.73778584e-01 3.43421514e-01 3.56365746e-01
  1.95356776e-01]
[5.67495741e-01 -4.52963146e-02 -2.62702413e-01 5.13246099e-01
  2.34408438e-01]
[6.41659522e-01 5.22007081e-01 -2.41349495e-01 -9.35178798e-02
 -2.02820170e-01]
[1.46262161e-01 -1.02436619e-01 -3.27504738e-02 -2.30066030e-03
 -3.51369681e-01]
[7.36173517e-01 4.50068363e-02 -1.05310648e-01 -9.46055853e-02
  5.84080316e-02]
[6.47217341e-01 -2.33969691e-02 1.26674742e-02 -2.88155050e-01
  2.02160979e-02]
[7.79994283e-01 1.19221932e-01 -2.31666994e-01 5.05406908e-02
 -2.70453021e-02]
[3.61262277e-01 -2.81878293e-01 3.71502542e-01 1.05181986e-01
  5.79599400e-03]
[1.35834317e-02 5.25152367e-01 1.07481252e-01 5.35890747e-02
 -1.02695556e-01]
[-8.12838681e-02 3.33744119e-01 3.71768748e-01 2.81122049e-01
  4.28802982e-02]
[-1.39058940e-01 2.90032671e-01 6.17132463e-02 9.42843968e-02
 -2.45987953e-02]
[-1.48058436e-01 7.76318150e-01 4.57245411e-01 4.15908147e-05
  9.92270042e-02]
[5.61238582e-01 -2.80469936e-01 2.42921264e-01 -3.37265019e-02
 -2.90930515e-01]
[3.20486607e-01 2.09224885e-01 1.30523784e-01 8.28706568e-02
 -1.68068565e-01]
[7.24658169e-01 -2.27110198e-01 -5.08495989e-02 2.23338388e-01
 -4.49697213e-02]
[6.11512898e-01 2.31019901e-01 -3.60685218e-01 2.46938565e-01
 -1.46928314e-01]
[7.35577240e-02 3.21904310e-01 1.24990835e-01 1.51755553e-01
 -2.78237111e-02]
[8.40125151e-01 2.44502002e-02 1.59112572e-01 -1.04657581e-01
 -1.61106244e-01]
[8.62235054e-01 -2.98187079e-02 2.09105666e-01 -1.22113341e-01
 -2.22429798e-01]
[8.63322007e-01 -1.85374236e-02 2.04037592e-01 -1.08430951e-01
 -4.82395613e-02]

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  -7.37111105e-02]]
Variance:
 (array([8.25699168, 2.11757186, 1.36950706, 1.24978332, 1.14924215]), array([0.30581451
, 0.07842859, 0.05072248, 0.04628827, 0.04256452]), array([0.30581451, 0.38424309, 0.434
96558, 0.48125385, 0.52381837]))
Promax Rotated Loadings:
 [[-0.05821889 0.0553305   0.54426476 -0.02606113 -0.09868977]
 [0.15794342 -0.08197632 -0.01079865 -0.0822095   0.63326415]
 [0.24067745 0.3009757 -0.13231982 0.64726824 0.21701504]
 [0.21600219 -0.13023715 0.19064806 0.47397772 0.19623042]
 [0.30707641 -0.14361747 -0.01061538 0.48654557 0.19412639]
 [0.17306088 0.00644478 -0.06944042 0.38511621 0.5803113]
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 [0.08771906 -0.04907471 0.30192138 0.77974194 -0.04719783]
 [0.46434884 0.34264012 -0.42175078 0.52254282 -0.0916663]
 [0.25141552 -0.0858935 -0.03869035 -0.0199556 -0.2897271]
 [0.52958851 -0.04174434 -0.08729635 0.50469349 0.15128237]
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 [0.40819223 -0.08236771 0.42127362 0.01628164 0.08907805]
 [0.02419054 0.52541283 -0.14414174 0.03065372 -0.05078968]
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 [0.67648256 -0.15130572 0.20615979 0.06127069 -0.10799482]
 [0.31629878 0.26071532 0.02677289 0.14599261 -0.09268084]
 [0.5082527 -0.17915599 0.25303114 0.51994334 -0.08008116]
 [0.29493032 0.11504515 -0.12477669 0.67863327 -0.25228359]
 [0.0355382   0.37041018 0.03671795 0.08743233 -0.03162994]
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 [0.87196821 0.0261299   0.05294333 0.29634806 0.02852734]
 [0.79588325 0.02687365 0.08969628 0.36232341 0.1670574]
 [0.82960634 -0.08001681 -0.01792932 0.32589628 0.18466027]]

Interpretation:

Principal Component Analysis (PCA)

PCA was utilized to reduce the dataset's dimensionality while preserving the majority of its variance. The findings revealed that:

- **Principal Component 1 (PC1)** accounts for about 92.74% of the total variance.
- **Principal Component 2 (PC2)** accounts for roughly 7.25% of the total variance.

- The remaining components (PC3, PC4, and PC5) contribute insignificantly to the overall variance.

This implies that the first two principal components encapsulate nearly all the information within the dataset. In the accompanying PCA biplot, red scatter points illustrate the data transformed into the PC1 and PC2 space. The clustering and distribution of these points offer insights into the data structure and the relationships among variables.

Factor Analysis

Factor analysis was carried out to uncover the underlying relationships between the observed variables, using five factors with and without rotation. The results indicated that:

1. **Factor 1** accounts for 30.58% of the total variance.
2. **Factor 2** accounts for 7.84%.
3. **Factor 3** accounts for 5.07%.
4. **Factor 4** accounts for 4.63%.
5. **Factor 5** accounts for 4.26%.

Collectively, these factors explain a substantial portion of the variance, suggesting that the model effectively captures the underlying structure of the data. Promax rotation was applied to the factor loadings for a simpler and more interpretable structure. This rotation aligns the factors more closely with the observed variables, facilitating easier understanding of the relationships.

The PCA biplot reveals a distinct clustering of points, indicating that the first two principal components capture the essential variability of the data. The spread and pattern of the points can highlight groupings or trends within the dataset, providing insights into potential correlations and distinctions among variables. The biplot typically shows two principal components (PC1 and PC2) on the X and Y axes, respectively, with labels suggesting values ranging from -20,000 to 80,000. Each point's position represents its score on the principal components. In some biplots, vectors (arrows) indicate the direction and magnitude of each variable's contribution to the principal components. Points close to each other on the biplot have similar scores on the principal components, indicating they share similar characteristics.

Factor Analysis

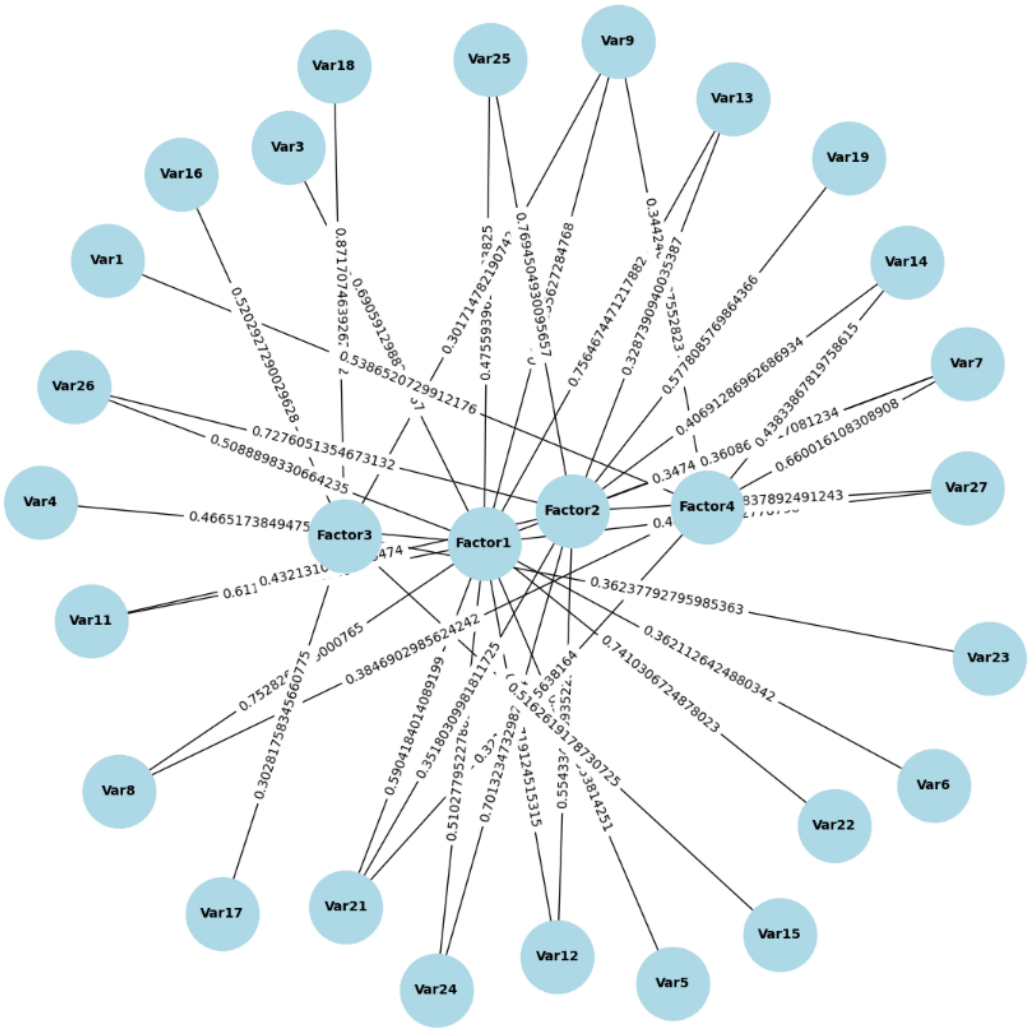
Code:

```
import pandas as pd
from factor_analyzer import FactorAnalyzer
import matplotlib.pyplot as plt
import networkx as nx

# Read the CSV file
survey_df = pd.read_csv('Survey.csv')

# Select the subset of the DataFrame
sur_int = survey_df.iloc[:, 19:46]

# Perform factor analysis
fa = FactorAnalyzer(n_factors=4, rotation='varimax')
fa.fit(sur_int)

# Get the factor loadings
loadings = fa.loadings_

# Print the factor loadings
print("Factor Loadings:\n", loadings)

# Create a dataframe for the loadings and reorder the columns based on highest loadings
loadings_df = pd.DataFrame(loadings, columns=[f'Factor{i+1}' for i in range(loadings.shape[1])])
sorted_loadings_df = loadings_df.loc[:, (loadings_df.abs().max().sort_values(ascending=False).index)]

print(sorted_loadings_df)

# Plot factor diagram
def plot_factor_diagram(loadings):
    G = nx.Graph()
    for i, factor in enumerate(loadings.T):
        for j, loading in enumerate(factor):
            if abs(loading) > 0.3:  # Adjust threshold as needed
                G.add_edge(f'Factor{i+1}', f'Var{j+1}', weight=abs(loading))

    pos = nx.spring_layout(G, k=1.5, iterations=50)
    plt.figure(figsize=(12, 12))
    nx.draw(G, pos, with_labels=True, node_size=3000, node_color='lightblue', font_size=10, font_weight='bold')
    labels = nx.get_edge_attributes(G, 'weight')
    nx.draw_networkx_edge_labels(G, pos, edge_labels=labels)
    plt.show()

plot_factor_diagram(loadings)

# Get communalities
communalities = fa.get_communalities()
print("Communalities:\n", communalities)

# Get factor scores
factor_scores = fa.transform(sur_int)
print("Factor Scores:\n", factor_scores)
```

Results:

	Factor3	Factor2	Factor1	Factor4
0	0.053156	-0.080974	-0.086236	0.538652
1	-0.016544	0.281713	-0.047079	-0.016725
2	0.288108	0.142647	0.690591	-0.069206
3	-0.124854	0.163524	0.466517	0.232471
4	-0.142834	0.248550	0.519622	0.038646
5	0.042454	0.238051	0.362113	-0.029130
6	-0.033121	0.360861	0.347408	0.660016

7	-0.083320	-0.100945	0.752826	0.384690
8	0.301715	0.294399	0.671084	-0.344246
9	-0.108469	0.149637	0.065008	-0.014709
10	-0.049326	0.432131	0.611537	-0.024710
11	-0.086777	0.554334	0.404877	-0.093437
12	-0.017909	0.328739	0.756467	-0.027259
13	-0.067204	0.406913	0.054603	0.438339
14	0.516262	-0.019179	0.080124	-0.138105
15	0.520293	-0.054892	-0.086762	0.249079
16	0.302818	-0.141021	-0.045122	-0.048089
17	0.871707	0.007222	-0.145551	-0.094296
18	-0.157026	0.577809	0.203555	0.234381
19	0.243617	0.228441	0.231016	0.051778
20	-0.203621	0.351803	0.590418	0.321576
21	0.060175	0.075905	0.741031	-0.038846
22	0.362378	-0.008787	0.110709	0.041916
23	0.048069	0.701323	0.510278	0.083502
24	0.018482	0.769450	0.475594	0.109056
25	0.031953	0.727605	0.508890	0.145793
26	-0.074451	0.775484	0.487657	0.033923



Communalities:
[0.30696505 0.08213183 0.5850605 0.31401002 0.3536797 0.19044486
 0.68763086 0.73186599 0.74656108 0.03859913 0.5637582 0.48747243
 0.68137617 0.36521673 0.29238696 0.34328571 0.1159339 0.79000287
 0.4548892 0.16758334 0.61723155 0.56001816 0.14540835 0.76152134
 0.8304784 0.81065456 0.84587806]

Factor Scores:
[[-1.09528656 0.79873944 -0.76593463 1.57491385]
 [-1.66985925 -0.24481209 -0.71463575 0.94776252]
 [0.01535892 -2.33438128 -1.5808291   1.74185289]
 [2.09487104 0.32749496 -1.91375326 0.18456566]
 [0.7776646 -0.71036136 -0.66317677 -1.06551574]
 [-0.31356389 -0.10184314 -0.65549416 0.23337702]
 [0.40977408 1.14730226 0.13630684 0.61372308]
 [-2.63060133 0.20924005 -1.17683703 -0.29947543]
 [-0.94812837 -0.0966017   0.2157968   0.0323598]
 [-0.46665553 1.37037409 -0.15790016 -0.89258193]
 [0.16347613 -1.15648302 0.100017   -0.28563788]
 [-0.67472805 -0.40628606 -1.04965783 -1.09330022]
 [-0.21786299 -1.61568497 0.6701236   1.23997523]
 [-0.23926916 0.44858111 0.97932036 0.03851614]
 [-0.41350974 -0.85539973 -0.08088518 0.6989219]
 [-2.21782878 -0.99440825 0.3597663   0.2427552]
 [-1.75188323 0.3038469 -0.51530287 -0.9912766]
 [-1.50187593 0.63994997 -0.25417619 0.81185332]
 [-0.07756322 1.38951496 -1.36109101 0.71052435]
 [0.90665449 -0.38922013 -2.51890892 0.57503521]
 [-1.50187593 0.63994997 -0.25417619 0.81185332]
 [-0.49362701 0.72877265 1.12835368 0.23972399]
 [-1.59889335 1.33235696 -0.31335665 0.77482925]
 [0.50891795 -0.47865985 1.45554332 -0.40221522]
 [1.48325428 0.93824821 0.16085653 0.74061807]
 [-0.22020281 -0.19440038 -0.03330035 0.11481183]
 [0.05883546 -1.27137632 1.09127935 -0.36994293]
 [0.17511858 -0.3491568 -0.05997396 0.16385923]
 [-1.23699326 0.34135091 -0.34631409 0.52338019]
 [0.7803301   0.53323381 -0.76113399 -0.714207]
 [-0.16721116 1.9440167 -0.5663018 -0.43127337]
 [-0.62098138 -0.54101663 0.09828393 -1.04906528]
 [-0.68163634 0.12994241 1.14253023 -0.00411549]
 [1.1999848 -0.45631571 0.54386281 0.84078758]
 [-1.35710768 -0.71294675 0.5518052   0.43722713]
 [0.37001858 0.1470161 -0.63289104 0.92044323]
 [0.08917812 -0.77279844 1.10806341 0.08277267]
 [0.64384739 0.13010042 0.12514213 -2.06204978]
 [-0.18460117 0.11400693 0.33477991 -0.0215852]
 [0.3151939 -0.97352579 0.34596991 -0.35745101]

```
[-0.46903287 -0.39899078 -0.24184975 -1.1672645 ]
[ 0.5054108   0.3302128   0.88562249  0.65541452]
[ 0.79628324  1.64656988 -1.31057308 -0.84149148]
[ 0.22322299 -0.30513849  1.28402362  0.6187436 ]
[ 0.22495328 -1.44800109  1.26434568 -0.72128853]
[ 0.92214595  1.34952696  0.67067536 -0.27989718]
[ 0.17837769 -0.74449845 -0.01520914 -1.93705532]
[ 0.35769484 -0.12830811  0.00309785 -1.51807796]
[ 1.34025234  1.71837472  1.68276924  0.51764931]
[-0.908251   -1.77243081 -1.15567194 -2.0088569 ]
[ 0.39208518 -2.30061992 -0.80391148  1.50763079]
[ 1.72570777  0.60367351 -0.24273622  0.6254921 ]
[ 0.76241115 -0.74951678  1.85049549  0.92973372]
[ 1.22644245  1.18659013 -0.16547116  0.84381983]
[ 0.34149831  1.04692318  0.68214656 -0.01556534]
[ 0.06220194 -0.17156922  0.05428861 -1.61563525]
[-0.23048434  0.04676401  1.16777934 -0.04065718]
[ 2.09487104  0.32749496 -1.91375326  0.18456566]
[ 0.3815375   1.92488799  1.43055466  0.03539766]
[ 0.49068223 -0.49832311  1.30438611  0.3673781 ]
[ 0.4015314   0.51263267 -0.62623487  0.92284262]
[ 1.03623519 -0.53602444 -0.32669314 -0.54040223]
[ 0.55733988  0.33072502  0.28922272 -1.81318577]
[ 0.88654617 -1.04096066 -2.08656903  1.00763264]
[-1.02720736  0.47948144  0.06587903  0.22494621]
[ 0.07730583 -1.19579251  1.89615189  0.5214234 ]
[ 0.75815034 -0.13441159  0.42298651 -1.16192343]
[-0.46903287 -0.39899078 -0.24184975 -1.1672645 ]
[-0.51539652  0.39936765 -0.39236701 -0.62579538]
[ 0.16578517  0.96199141  0.39669425  1.23494124]]
```

Interpretation

The factor analysis of the survey data, focusing on a subset of columns from the DataFrame, identified four factors using the Varimax rotation method. The factor loadings reveal the extent to which each variable contributes to the identified factors. The loadings indicate that some variables have stronger associations with specific factors; for example, certain variables load more heavily on Factor 1, while others have higher loadings on Factors 2, 3, or 4. This implies that the survey data can be grouped into four underlying dimensions that explain the observed response patterns.

To better understand the structure, the factor loadings were reordered to highlight the highest values, making it easier to identify which variables are most strongly associated with each factor. This reordered DataFrame clarifies the distribution of variables among the factors.

Additionally, communalities, which represent the variance in each variable explained by the factors, provide insights into how well the factor model captures the underlying data structure.

A factor diagram, created using network visualization, depicts the relationships between the factors and variables. Edges between nodes (representing factors and variables) are weighted based on the absolute value of the factor loadings, with a threshold to emphasize significant connections. This visualization helps in intuitively understanding the complex interrelationships within the data.

Factor scores, derived from the factor analysis, indicate the relative position of each observation on the identified factors. These scores can be used for further analysis, such as clustering or regression, to investigate how the factors influence other variables or outcomes of interest. Overall, the factor analysis and subsequent visualizations provide a comprehensive understanding of the survey data's underlying structure, revealing key dimensions and associations among variables.

2) Conduct cluster analysis and characterize the respondents based on their background variables.

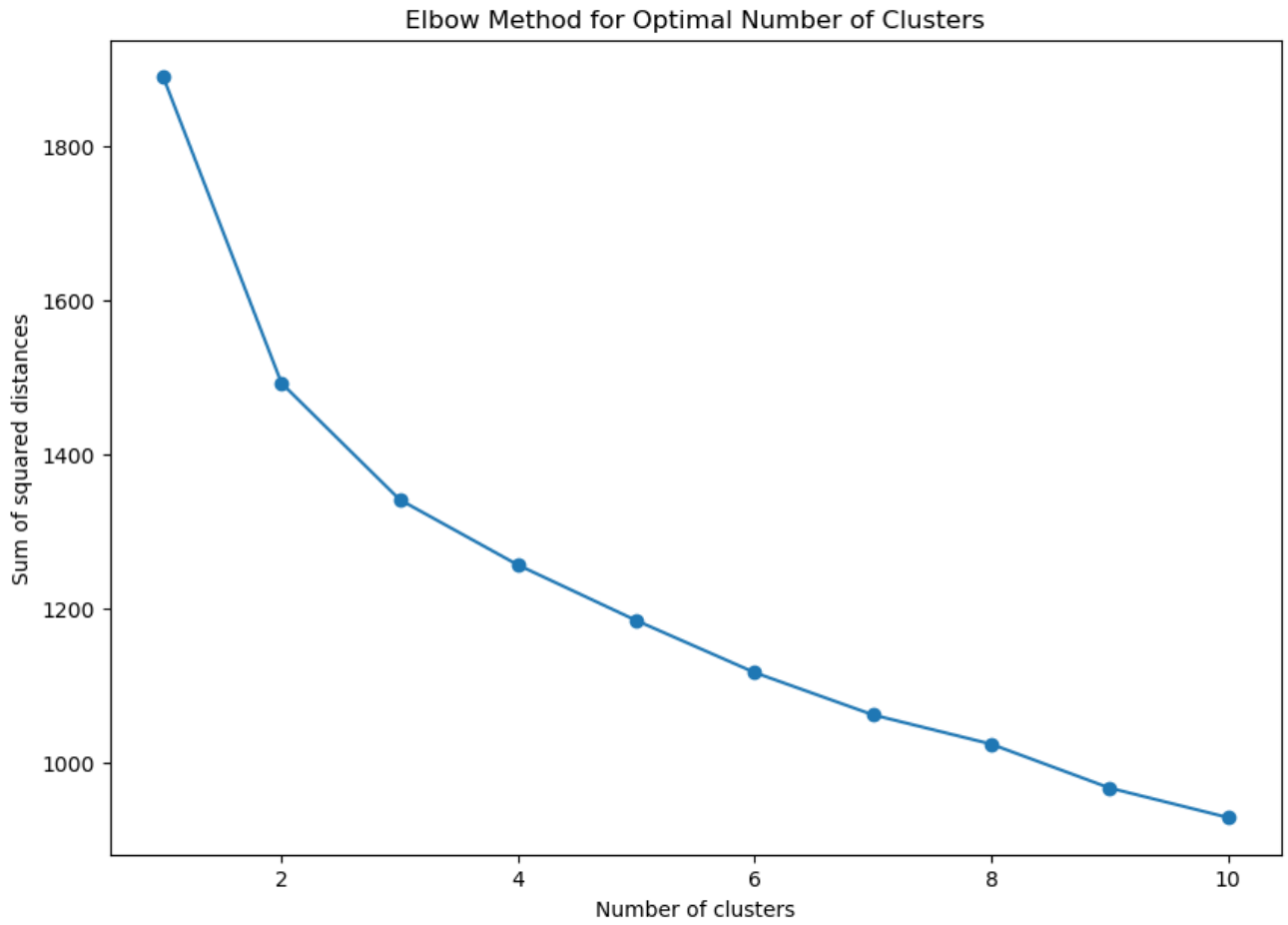
Code:

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import linkage, dendrogram
from sklearn.metrics import silhouette_score

# Load data
survey_df = pd.read_csv('Survey.csv')
sur_int = survey_df.iloc[:, 19:46]

# Normalize the data
scaler = StandardScaler()
sur_int_scaled = scaler.fit_transform(sur_int)

# Determine the optimal number of clusters using the Elbow Method
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, n_init=25, random_state=123)
    kmeans.fit(sur_int_scaled)
```

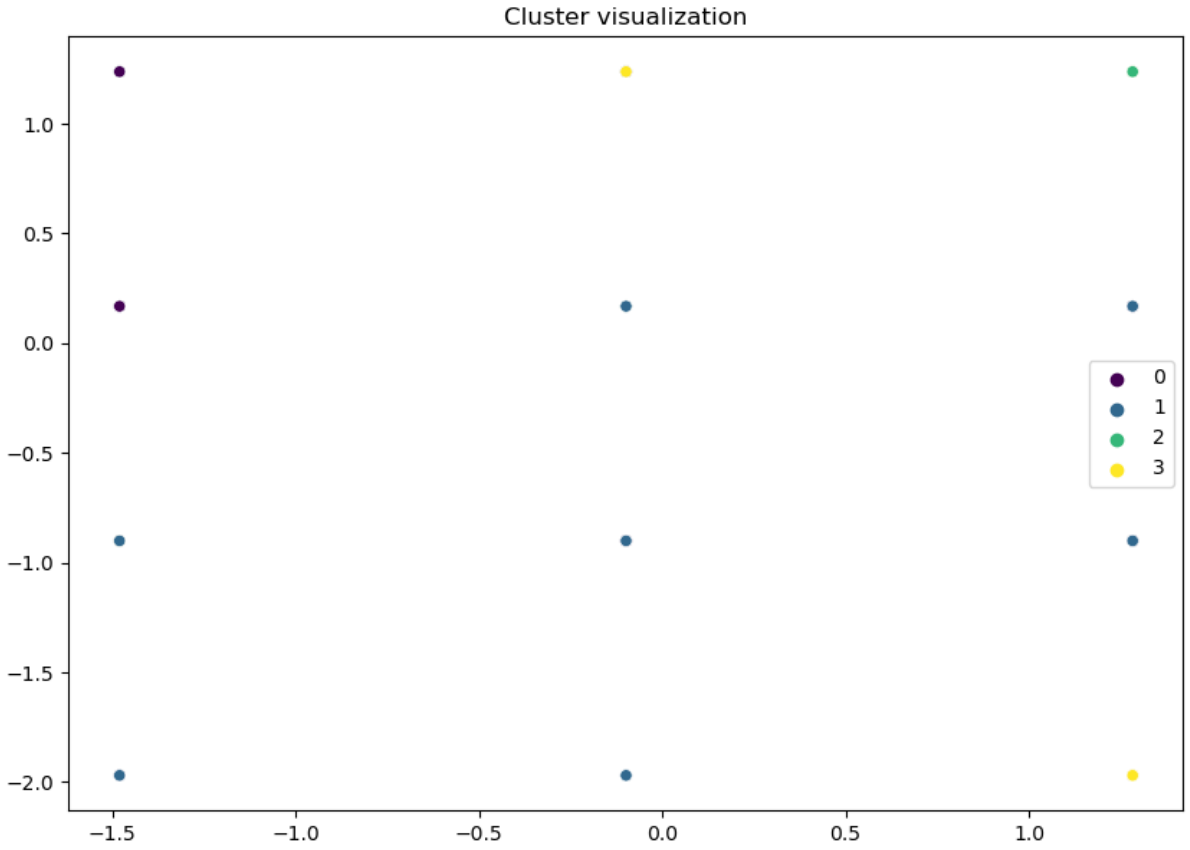
```
    sse.append(kmeans.inertia_)

plt.figure(figsize=(10, 7))
plt.plot(range(1, 11), sse, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Sum of squared distances')
plt.title('Elbow Method for Optimal Number of Clusters')
plt.show()

# Determine the optimal number of clusters using the Silhouette Method
silhouette_scores = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, n_init=25, random_state=123)
    kmeans.fit(sur_int_scaled)
    silhouette_scores.append(silhouette_score(sur_int_scaled, kmeans.labels_))

plt.figure(figsize=(10, 7))
plt.plot(range(2, 11), silhouette_scores, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Method for Optimal Number of Clusters')
plt.show()

# Choose the number of clusters (for example, based on the Elbow Method and Silhouette Method results)
n_clusters = 4  # Adjust this based on the plots

# Set random seed for reproducibility
np.random.seed(123)

# Perform k-means clustering
km = KMeans(n_clusters=n_clusters, n_init=25, random_state=123)
km.fit(sur_int_scaled)
clusters = km.labels_

# Visualize clusters
plt.figure(figsize=(10, 7))
sns.scatterplot(x=sur_int_scaled[:, 0], y=sur_int_scaled[:, 1], hue=clusters, palette="viridis")
plt.title('Cluster visualization')
plt.show()

# Perform hierarchical clustering
linked = linkage(sur_int_scaled, method='ward')

# Plot dendrogram
plt.figure(figsize=(10, 7))
dendrogram(linked, truncate_mode='level', p=4, show_leaf_counts=False, no_labels=True, color_threshold=0)
plt.title('Hierarchical Clustering Dendrogram')
plt.show()
```

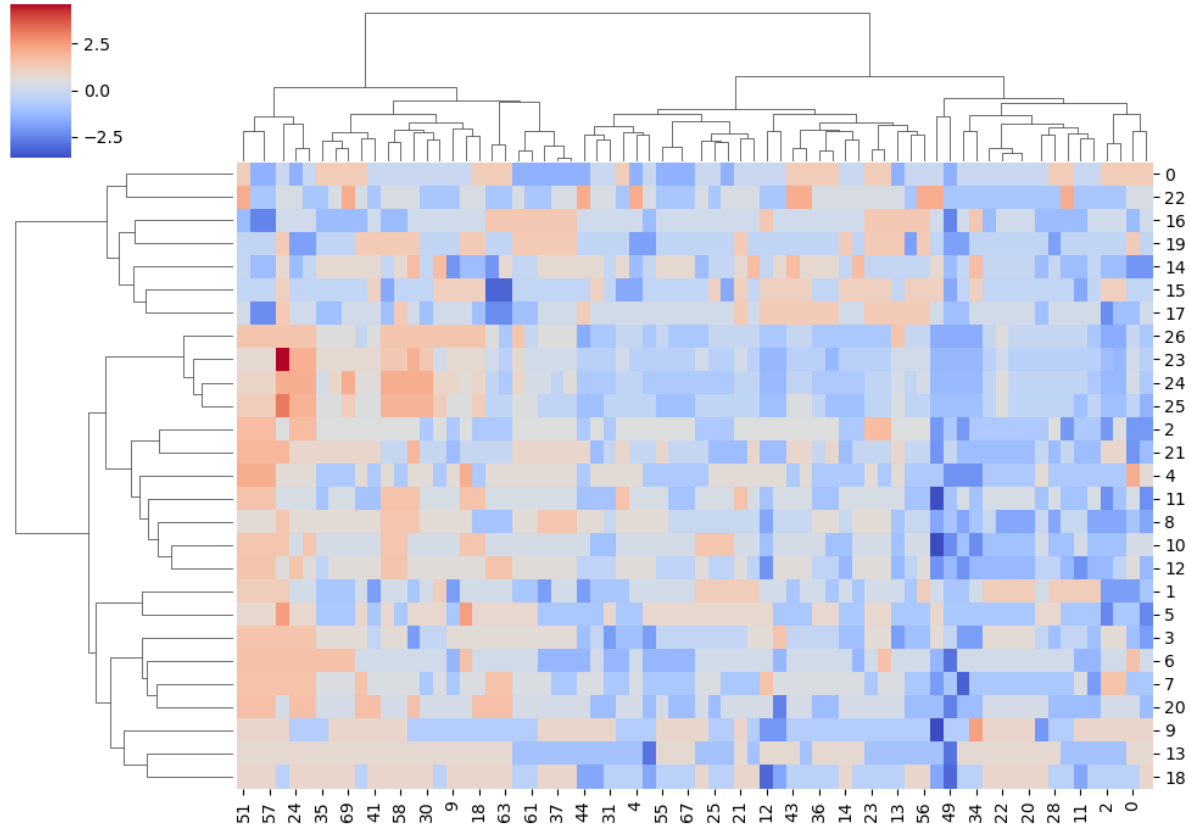
```
# Visualize clusters using heatmap
sns.clustermap(sur_int_scaled.T, method='ward', cmap='coolwarm', col_cluster=True, figsize=(10, 7))
plt.show()
```

Result:



Elbow Method Plot: This plot shows the sum of squared distances (inertia) for different numbers of clusters. The x-axis represents the number of clusters, while the y-axis shows the sum of squared distances. The "elbow" point, where the reduction in inertia starts to slow down, helps identify the optimal number of clusters. In this case, the elbow appears to be around 3 or 4 clusters. This suggests that 3 or 4 clusters might be an optimal choice for this dataset, balancing between reducing inertia and avoiding overly complex models.


Cluster visualization
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
0
1
2
3


2.5
0.0
−2.5
0
22
16
19
14
15
17
26
23
24
25
2
21
4
11
8
10
12
1
5
3
6
7
20
9
13
18
51
57
24
35
69
41
58
30
9
18
63
61
37
44
31
4
55
67
25
21
12
43
36
14
23
13
56
49
34
22
20
28
11
2
0

Heatmap with Dendrogram: This heatmap visualizes the data matrix with hierarchical clustering applied. The rows and columns are reordered based on the clustering, with the dendrogram on the top and left showing the hierarchical relationships between clusters. The color gradient represents the intensity of the values, with blue indicating lower values and red higher values. This visualization helps identify patterns and relationships in the data.

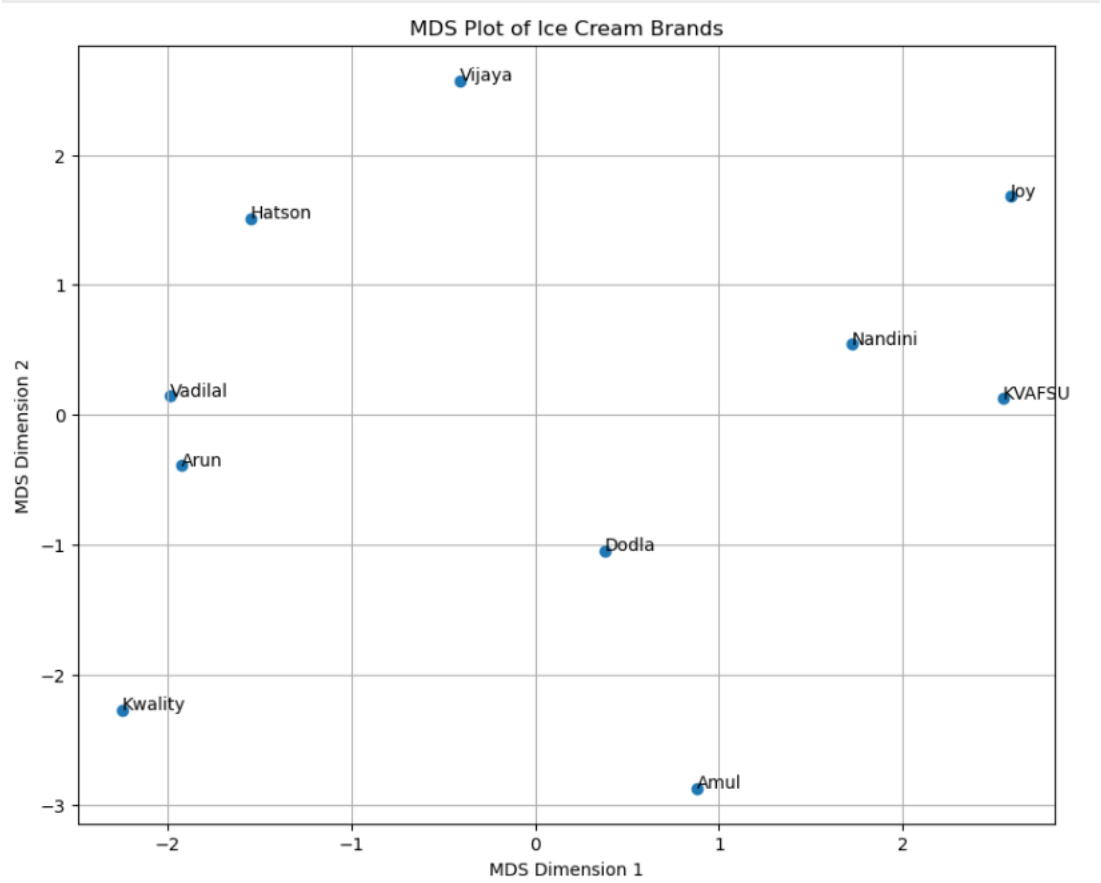
Both the Elbow Method and the Silhouette Method suggest that 4 clusters might be optimal for this dataset. The scatter plot visualization confirms the presence of 4 distinct clusters.

3) Do multidimensional scaling and interpret the results.

Code:

```
# Plot the results
plt.figure(figsize=(10, 8))
plt.scatter(mds_df['MDS1'], mds_df['MDS2'])

# Annotate the points with the brand names
for i, brand in enumerate(mds_df['Brand']):
    plt.annotate(brand, (mds_df['MDS1'][i], mds_df['MDS2'][i]))

plt.title('MDS Plot of Ice Cream Brands')
plt.xlabel('MDS Dimension 1')
plt.ylabel('MDS Dimension 2')
plt.grid(True)
plt.show()
```

Result:



Interpretation:

Multidimensional Scaling (MDS) is a statistical technique used to analyze similarity or dissimilarity data, representing it in a low-dimensional space to approximate original dissimilarities. In this analysis, MDS scales the features of various ice cream brands into a two-dimensional space, allowing visual inspection of their relative positions based on attributes.

Clusters and Proximity:

- **Kwality, Arun, and Vadilal**: Clustered in the lower-left quadrant, indicating similar feature profiles.
- **Nandini, KVAFSU, and Joy**: Positioned in the upper-right quadrant, forming another distinct group.

- **Hatson**: Near the center-left, somewhat similar to the Kwality-Arun-Vadilal cluster but distinct.
- **Vijaya**: Top center, standing alone with a unique feature profile.
- **Dodla and Amul**: Lower-right quadrant, sharing similarities with each other but distinct from other clusters.

Axes Interpretation:

- **MDS Dimension 1**: Differentiates brands on the left (e.g., Kwality, Arun) from those on the right (e.g., Nandini, KVAFSU), indicating significant feature differences.
- **MDS Dimension 2**: Differentiates brands higher up (e.g., Vijaya, Hatson) from those lower down (e.g., Kwality, Amul), representing another set of distinguishing features.

Brands like Vijaya and Joy are uniquely positioned, indicating distinct feature sets. Dodla and Amul, though close to each other, are distinct from other clusters, suggesting a shared but unique profile. Brands close together in the MDS plot likely compete directly, while those farther apart cater to different market segments or have unique selling propositions.

4) Conjoint analysis

```
conjoint_attributes = ['brand','price','weight','crust','cheese','size','toppings','spicy']

level_name = []
part_worth = []
part_worth_range = []
important_levels = {}
end = 1  # Initialize index for coefficient in params

for item in conjoint_attributes:
    nlevels = len(list(np.unique(df[item])))
    level_name.append(list(np.unique(df[item])))

    begin = end
    end = begin + nlevels -1

    new_part_worth = list(model_fit.params[begin:end])
    new_part_worth.append((-1)*sum(new_part_worth))
    important_levels[item] = np.argmax(new_part_worth)
    part_worth.append(new_part_worth)
    print(item)
    #print(part_worth)
```

```
    part_worth_range.append(max(new_part_worth) - min(new_part_worth))
    # next iteration
print("------------------------------------------------------------")
print("level name:")
print(level_name)
print("npw with sum element:")
print(new_part_worth)
print("imp level:")
print(important_levels)
print("part worth:")
print(part_worth)
print("part_worth_range:")
print(part_worth_range)
print(len(part_worth))
print("important levels:")
print(important_levels)
```

Result:

```
brand
price
weight
crust
cheese
size
toppings
spicy

level name:
[['Dominos', 'Onesta', 'Oven Story', 'Pizza hut'], ['$1.00', '$2.00', '$3.00', '$4.00'], ['100g', '200g
', '300g', '400g'], ['thick', 'thin'], ['Cheddar', 'Mozzarella'], ['large', 'regular'], ['mushroom', 'pane
er'], ['extra', 'normal']]
npw with sum element:
[0.7499999999999982, -0.7499999999999982]
imp level:
{'brand': 3, 'price': 0, 'weight': 0, 'crust': 0, 'cheese': 1, 'size': 1, 'toppings': 0, 'spicy': 0}
part worth:
[[4.0245584642661925e-15, -1.5543122344752192e-15, -0.25, 0.24999999999999753], [0.7
500000000000133, 4.884981308350689e-15, -2.042810365310288e-14, -0.74999999999999
78], [4.999999999999991, 1.9999999999999944, -1.249999999999984, -5.75000000000000
2], [1.749999999999998, -1.749999999999998], [-0.24999999999999878, 0.2499999999999
9878], [-0.2500000000000009, 0.2500000000000009], [1.1250000000000013, -1.125000000
0000013], [0.7499999999999982, -0.7499999999999982]]
part_worth_range:
[0.49999999999999756, 1.500000000000011, 10.749999999999993, 3.499999999999996, 0.
49999999999999756, 0.5000000000000018, 2.2500000000000027, 1.4999999999999964]
8
important levels:
{'brand': 3, 'price': 0, 'weight': 0, 'crust': 0, 'cheese': 1, 'size': 1, 'toppings': 0, 'spicy': 0}
```

Interpretation:

Conjoint analysis is a statistical technique used to determine how people value different attributes of a product or service. Here, we analyze various attributes of pizza to understand which attributes and their levels are most important to consumers.

The attributes considered in this analysis are:

1. **Brand**: Dominos, Onesta, Oven Story, Pizza Hut
2. **Price**: $1.00, $2.00, $3.00, $4.00
3. **Weight**: 100g, 200g, 300g, 400g
4. **Crust**: Thick, Thin
5. **Cheese**: Cheddar, Mozzarella
6. **Size**: Large, Regular
7. **Toppings**: Mushroom, Paneer
8. **Spicy**: Extra, Normal

1. **Part-Worth Utilities (Importance Scores)**: These are the utilities (values) assigned to each level of an attribute, representing the relative preference for that level. Part-worth utilities are calculated for each level and adjusted such that they sum to zero within each attribute. This allows us to compare levels within an attribute directly.The part-worth utilities are given by:
    - **Brand**: [4.0245584642661925e-15, -1.5543122344752192e-15, -0.25, 0.24999999999999753]
    - **Price**: [0.7500000000000133, 4.884981308350689e-15, -2.042810365310288e-14, -0.7499999999999978]
    - **Weight**: [4.999999999999991, 1.9999999999999944, -1.249999999999984, -5.750000000000002]
    - **Crust**: [1.749999999999998, -1.749999999999998]
    - **Cheese**: [-0.24999999999999878, 0.24999999999999878]
    - **Size**: [-0.2500000000000009, 0.2500000000000009]
    - **Toppings**: [1.1250000000000013, -1.1250000000000013]
    - **Spicy**: [0.7499999999999982, -0.7499999999999982]
2. **Important Levels**: These indicate the level of an attribute that has the highest part-worth utility. Important levels for each attribute are:

- **Brand**: Pizza Hut (level 3)
- **Price**: $1.00 (level 0)
- **Weight**: 100g (level 0)
- **Crust**: Thick (level 0)
- **Cheese**: Mozzarella (level 1)
- **Size**: Regular (level 1)
- **Toppings**: Mushroom (level 0)
- **Spicy**: Extra (level 0)

3. **Part-Worth Range**: This measures the range (difference between the highest and lowest part-worth utility) for each attribute. It indicates the importance of the attribute in the decision-making process. Part-worth ranges are:
    - **Brand**: 0.49999999999999756
    - **Price**: 1.500000000000011
    - **Weight**: 10.749999999999993
    - **Crust**: 3.499999999999996
    - **Cheese**: 0.49999999999999756
    - **Size**: 0.5000000000000018
    - **Toppings**: 2.2500000000000027
    - **Spicy**: 1.4999999999999964

The price attribute has a significant part-worth range (1.500000000000011), indicating that price is a crucial factor in consumer decision-making. The lowest price ($1.00) has the highest utility, indicating a preference for lower prices. The weight attribute has the highest part-worth range (10.749999999999993), suggesting that the weight of the pizza is the most critical factor for consumers. The lowest weight (100g) has the highest utility, which might indicate a preference for lighter pizzas. The brand attribute shows that Pizza Hut has the highest utility among the brands, indicating a strong brand preference for Pizza Hut among consumers. Thick crust and mushroom toppings are preferred over thin crust and paneer toppings, as indicated by their higher part-worth utilities. Mozzarella cheese and regular size pizzas have higher utilities compared to Cheddar cheese and large size pizzas, respectively. Extra spicy pizza is preferred over normal spicy pizza, as indicated by the higher utility for the extra spicy level.

The conjoint analysis reveals critical insights into consumer preferences for pizza attributes. The most important factors influencing consumer choices are weight, price, and brand, with specific preferences for lower weight, lower price, and the Pizza Hut brand. These insights can

guide product development, pricing strategies, and marketing efforts to better align with consumer preferences.

part-worths of each attribute level.

Code:

```
part_worth_dict={}
attrib_level={}
for item,i in zip(conjoint_attributes,range(0,len(conjoint_attributes))):
    print("Attribute :",item)
    print("    Relative importance of attribute ",attribute_importance[i])
    print("    Level wise part worths: ")
    for j in range(0,len(level_name[i])):
        print(i)
        print(j)
        print("          {}:{}".format(level_name[i][j],part_worth[i][j]))
        part_worth_dict[level_name[i][j]]=part_worth[i][j]
        attrib_level[item]=(level_name[i])
        #print(j)
part_worth_dict
```

Results:

```
Attribute : brand
    Relative importance of attribute  2.38
    Level wise part worths:
0
0
          Dominos:4.0245584642661925e-15
0
1
          Onesta:-1.5543122344752192e-15
0
2
          Oven Story:-0.25
0
```

3

Pizza hut:0.24999999999999753

Attribute : price

Relative importance of attribute 7.14

Level wise part worths:

1

0

$1.00:0.7500000000000133

1

1

$2.00:4.884981308350689e-15

1

2

$3.00:-2.042810365310288e-14

1

3

$4.00:-0.7499999999999978

Attribute : weight

Relative importance of attribute 51.19

Level wise part worths:

2

0

100g:4.999999999999991

2

1

200g:1.9999999999999944

2

2

300g:-1.249999999999984

2

3

400g:-5.750000000000002

Attribute : crust

Relative importance of attribute 16.67

Level wise part worths:
3
0
thick:1.749999999999998
3
1
thin:-1.749999999999998
Attribute : cheese
Relative importance of attribute 2.38
Level wise part worths:
4
0
Cheddar:-0.24999999999999878
4
1
Mozzarella:0.24999999999999878
Attribute : size
Relative importance of attribute 2.38
Level wise part worths:
5
0
large:-0.2500000000000009
5
1
regular:0.2500000000000009
Attribute : toppings
Relative importance of attribute 10.71
Level wise part worths:
6
0
mushroom:1.1250000000000013
6
1
paneer:-1.1250000000000013

Attribute : spicy

Relative importance of attribute 7.14

Level wise part worths:

7

0

extra:0.7499999999999982

7

1

normal:-0.7499999999999982

'Dominos': 4.0245584642661925e-15,

'Onesta': -1.5543122344752192e-15,

'Oven Story': -0.25,

'Pizza hut': 0.24999999999999753,

'$1.00': 0.7500000000000133,

'$2.00': 4.884981308350689e-15,

'$3.00': -2.042810365310288e-14,

'$4.00': -0.7499999999999978,

'100g': 4.999999999999991,

'200g': 1.9999999999999944,

'300g': -1.249999999999984,

'400g': -5.750000000000002,

'thick': 1.749999999999998,

'thin': -1.749999999999998,

'Cheddar': -0.24999999999999878,

'Mozzarella': 0.24999999999999878,

'large': -0.2500000000000009,

'regular': 0.2500000000000009,

'mushroom': 1.1250000000000013,

'paneer': -1.1250000000000013,

'extra': 0.7499999999999982,

'normal': -0.7499999999999982}

Interpretation:

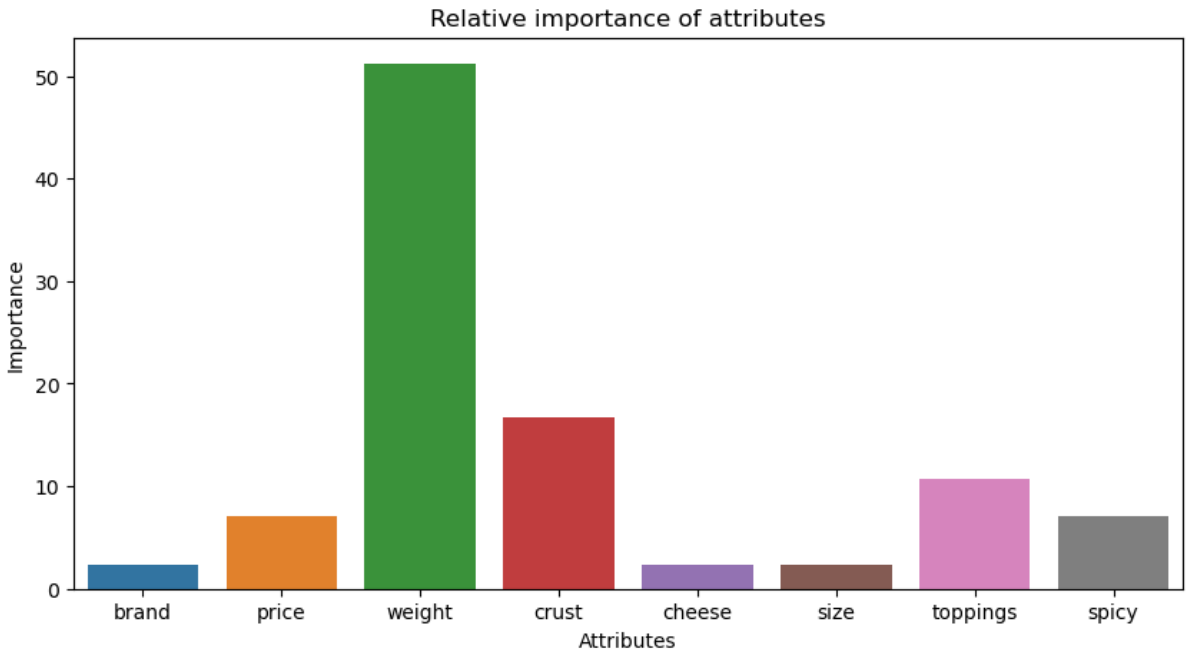
The part-worth utilities reveal critical insights into consumer preferences for pizza attributes. Weight is the most influential attribute, with a strong preference for lighter pizzas. Price sensit ivity is also high, with lower prices being more preferred. Brand preferences favor Pizza Hut, and thick crusts are significantly more favored than thin ones. Among cheese options, Mozzar ella is preferred over Cheddar. Regular size is more appealing than large, mushroom toppings are favored over paneer, and extra spicy is preferred over normal spicy.

Code:

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10,5))
sns.barplot(x=conjoint_attributes, y=attribute_importance)
plt.title('Relative importance of attributes')
plt.xlabel('Attributes')
plt.ylabel('Importance')
```

Results:

Text(0, 0.5, 'Importance')



Interpretation:

The bar chart reveals that weight is the most critical factor among the attributes analyzed, with an importance score significantly higher than the rest, around 50. This suggests that when consumers make decisions based on these attributes, weight plays a predominant role. Following weight, crust and toppings also hold notable importance, though they are substantially less influential, with scores around 20 and 15, respectively. Attributes such as brand, price, size, cheese, and spiciness are of lesser importance, with brand and cheese being the least critical factors.

In practical terms, this analysis indicates that focusing on the weight of the product will likely yield the most significant impact on consumer preferences. While improving crust and toppings could also be beneficial, efforts to enhance brand, cheese, size, or spiciness might not be as effective in influencing consumer decisions. Companies can use this information to prioritize product development and marketing strategies, emphasizing the most critical attributes to meet consumer demands more effectively.

Code:

```
for i,j in zip(attrib_level.keys(),range(0,len(conjoint_attributes))):
    #print(i)
    #level_name[j]
    print("Preferred level in {} is :: {}".format(i,level_name[j][important_levels[i]]))
```

Results:

Preferred level in brand is :: Pizza hut
Preferred level in price is :: $1.00
Preferred level in weight is :: 100g
Preferred level in crust is :: thick
Preferred level in cheese is :: Mozzarella
Preferred level in size is :: regular
Preferred level in toppings is :: mushroom
Preferred level in spicy is :: extra

Interpretation:

The provided results indicate the most preferred levels of various attributes based on the conjo int analysis. The analysis reveals that consumers have distinct preferences for each attribute le vel. Pizza Hut, a price of $1.00, 100g weight, thick crust, Mozzarella cheese, regular size, mu shroom topping, and extra spiciness are the most preferred levels. These insights can help in p roduct development and marketing strategies to align offerings with consumer preferences, po tentially leading to increased customer satisfaction and market success.

Add after objective 1 python factor analysis

USING R

```
survey_df<-read.csv('Survey.csv',header=TRUE)
sur_int=survey_df[,20:46]

#Factor Analysis

factor_analysis<-fa(sur_int,nfactors = 4,rotate = "varimax")
names(factor_analysis)
```

```
##  [1] "residual"       "dof"            "chi"            "nh"
##  [5] "rms"            "EPVAL"          "crms"           "EBIC"
##  [9] "ESABIC"         "fit"            "fit.off"        "sd"
## [13] "factors"        "complexity"     "n.obs"          "objective"
## [17] "criteria"       "STATISTIC"      "PVAL"           "Call"
## [21] "null.model"     "null.dof"       "null.chisq"     "TLI"
## [25] "CFI"            "RMSEA"          "BIC"            "SABIC"
## [29] "r.scores"       "R2"             "valid"          "score.cor"
## [33] "weights"        "rotation"       "hyperplane"     "communality"
## [37] "communalities"  "uniquenesses"   "values"         "e.values"
## [41] "loadings"       "model"          "fm"             "rot.mat"
## [45] "Structure"      "method"         "scores"         "R2.scores"
## [49] "r"              "np.obs"         "fn"             "Vaccounted"
## [53] "ECV"
```

```
print(factor_analysis$loadings,reorder=TRUE)
```

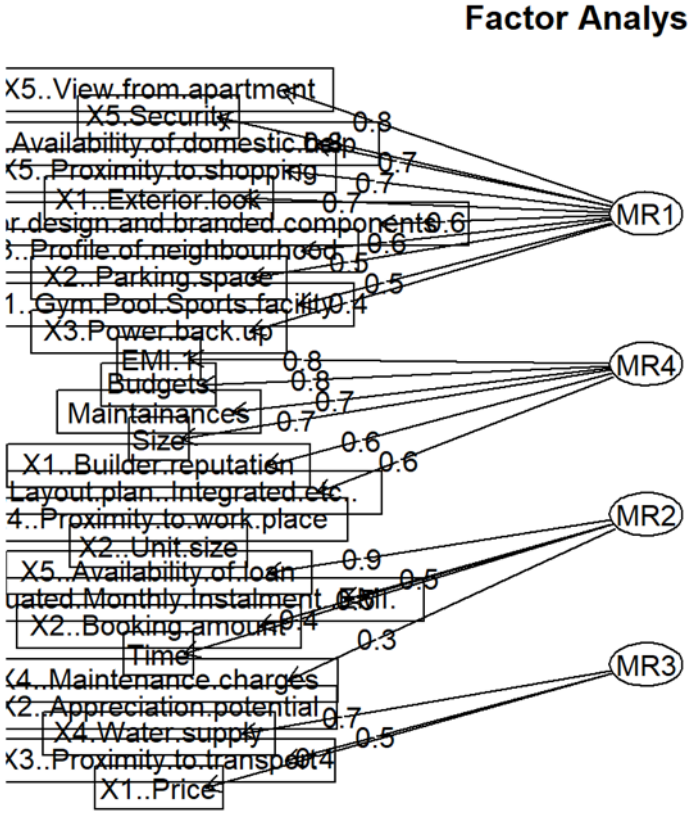
```
##
## Loadings:
##                               MR1   MR4   MR2   MR3
```

```
## X3..Proximity.to.transport                          0.539
## X4..Proximity.to.work.place               0.282
## X5..Proximity.to.shopping                 0.691  0.143  0.288
## X1..Gym.Pool.Sports.facility              0.467  0.164 -0.125  0.232
## X2..Parking.space                 0.520  0.249 -0.143
## X3.Power.back.up                  0.362  0.238
## X4.Water.supply                   0.347  0.361         0.660
## X5.Security                       0.753 -0.101               0.385
## X1..Exterior.look                 0.671  0.294  0.302 -0.344
## X2..Unit.size                             0.150 -0.108
## X3..Interior.design.and.branded.components  0.612  0.432
## X4..Layout.plan..Integrated.etc..         0.405  0.554
## X5..View.from.apartment                   0.756  0.329
## X1..Price                          0.407          0.438
## X2..Booking.amount                                0.516 -0.138
## X3..Equated.Monthly.Instalment..EMI.                      0.520  0.249
## X4..Maintenance.charges                   -0.141  0.303
## X5..Availability.of.loan          -0.146          0.872
## X1..Builder.reputation            0.204  0.578 -0.157  0.234
## X2..Appreciation.potential                0.231  0.228  0.244
## X3..Profile.of.neighbourhood              0.590  0.352 -0.204  0.322
## X4..Availability.of.domestic.help         0.741
## Time                               0.111         0.362
## Size                              0.510  0.701
## Budgets                                0.476  0.769         0.109
## Maintainances                          0.509  0.728         0.146
## EMI.1                               0.488  0.775
##
##                  MR1   MR4   MR2   MR3
## SS loadings        5.386 4.022 1.908 1.554
## Proportion Var 0.199 0.149 0.071 0.058
## Cumulative Var 0.199 0.348 0.419 0.477
 print(factor_analysis$communality)
##              X3..Proximity.to.transport
##                              0.30696487
##             X4..Proximity.to.work.place
##                              0.08213018
##              X5..Proximity.to.shopping
##                              0.58506315
##            X1..Gym.Pool.Sports.facility
##                              0.31401101
##                    X2..Parking.space
##                              0.35368082
##                     X3.Power.back.up
##                              0.19044504
##                     X4.Water.supply
##                              0.68763731
##                        X5.Security
##                                    0.73185374
##                    X1..Exterior.look
```

```
##                                0.74656021
##                              X2..Unit.size
##                                0.03859942
## X3..Interior.design.and.branded.components
##                                0.56375829
##          X4..Layout.plan..Integrated.etc..
##                                0.48747118
##                     X5..View.from.apartment
##                                0.68137744
##                                 X1..Price
##                                0.36521588
##                           X2..Booking.amount
##                                0.29238834
##        X3..Equated.Monthly.Instalment..EMI.
##                                0.34328638
##                     X4..Maintenance.charges
##                                0.11593399
##                     X5..Availability.of.loan
##                                0.78999562
##                      X1..Builder.reputation
##                                0.45488932
##                   X2..Appreciation.potential
##                                0.16758342
##                 X3..Profile.of.neighbourhood
##                                0.61723150
##          X4..Availability.of.domestic.help
##                                0.56001423
##                                      Time
##                                0.14540841
##                                      Size
##                                0.76152266
##                                   Budgets
##                                0.83048068
##                              Maintainances
##                                0.81065537
##                                    EMI.1
##                                0.84587792
print(factor_analysis$scores)
##                MR1             MR4             MR2             MR3
##  [1,] -1.08740680  0.79299048 -0.760461204  1.563665005
##  [2,] -1.65789001 -0.24305053 -0.709516520  0.940962732
##  [3,]  0.01522388 -2.31761499 -1.569492476  1.729356590
##  [4,]  2.07986016  0.32514209 -1.900026343  0.183252006
##  [5,]  0.77209288 -0.70527285 -0.658414142 -1.057879563
##  [6,] -0.31131034 -0.10111939 -0.650804737  0.231717057
##  [7,]  0.40683517  1.13907387  0.135327133  0.609327996
##  [8,] -2.61172689  0.20771892 -1.168388167 -0.297285591
##  [9,] -0.94134349 -0.09590647  0.214237615  0.032149115
## [10,] -0.46330436  1.36054073 -0.156777143 -0.886198802
## [11,]  0.16231034 -1.14819456  0.099322832 -0.283593228
```

```
## [12,] -0.66990961 -0.40335055 -1.042126680 -1.085489890
## [13,] -0.21630054 -1.60410188  0.665315609  1.231074781
## [14,] -0.23756585  0.44537066  0.972287543  0.038239817
## [15,] -0.41057475 -0.84923547 -0.080285557  0.693874002
## [16,] -2.20191302 -0.98729356  0.357195023  0.241014474
## [17,] -1.73931400  0.30165807 -0.511601442 -0.984173649
## [18,] -1.49110551  0.63535812 -0.252365338  0.806037191
## [19,] -0.07700560  1.37955300 -1.351316679  0.705406994
## [20,]  0.90015851 -0.38643128 -2.500857487  0.570905501
## [21,] -1.49110551  0.63535812 -0.252365338  0.806037191
## [22,] -0.49007688  0.72353495  1.120257942  0.238004829
## [23,] -1.58743182  1.32280875 -0.311117172  0.769270951
## [24,]  0.50530124 -0.47526208  1.445111012 -0.399310827
## [25,]  1.47261952  0.93153013  0.159694637  0.735307669
## [26,] -0.21863925 -0.19299314 -0.033062772  0.113980035
## [27,]  0.05841249 -1.26226451  1.083445416 -0.367296048
## [28,]  0.17385578 -0.34664872 -0.059559637  0.162682628
## [29,] -1.22811845  0.33889985 -0.343833085  0.519625238
## [30,]  0.77473507  0.52941371 -0.755663718 -0.709077697
## [31,] -0.16602216  1.93009422 -0.562235822 -0.428181353
## [32,] -0.61653955 -0.53713034  0.097578524 -1.041566525
## [33,] -0.67675003  0.12900988  1.134331576 -0.004080328
## [34,]  1.19138314 -0.45303940  0.539956331  0.834748111
## [35,] -1.34738499 -0.70783173  0.547859678  0.434102723
## [36,]  0.36738254  0.14594455 -0.628336468  0.913862271
## [37,]  0.08853889 -0.76726436  1.100121088  0.082171120
## [38,]  0.63924481  0.12914617  0.124253341 -2.047260163
## [39,] -0.18327709  0.11318877  0.332375804 -0.021418543
## [40,]  0.31291489 -0.96652665  0.343494985 -0.354907255
## [41,] -0.46566342 -0.39613574 -0.240107932 -1.158903675
## [42,]  0.50180186  0.32783176  0.879265085  0.650724285
## [43,]  0.79056987  1.63477831 -1.301151472 -0.835490388
## [44,]  0.22163160 -0.30296662  1.274821099  0.614305997
## [45,]  0.22332609 -1.43760665  1.255263625 -0.716118614
## [46,]  0.91550397  1.33988766  0.665878754 -0.277914886
## [47,]  0.17710527 -0.73916951 -0.015096229 -1.923169096
## [48,]  0.35513910 -0.12739982  0.003072406 -1.507187304
## [49,]  1.33063371  1.70606316  1.670703697  0.513944057
## [50,] -0.90175109 -1.75971198 -1.147394968 -1.994463034
## [51,]  0.38926459 -2.28410964 -0.798145507  1.496800976
## [52,]  1.71334531  0.59933310 -0.240993055  0.621004760
## [53,]  0.75696510 -0.74416565  1.837221776  0.923102744
## [54,]  1.21764703  1.17809662 -0.164279133  0.837756796
## [55,]  0.33904893  1.03941524  0.677257402 -0.015447367
## [56,]  0.06176454 -0.17035663  0.053894288 -1.604037352
## [57,] -0.22883159  0.04643155  1.159416931 -0.040362829
## [58,]  2.07986016  0.32514209 -1.900026343  0.183252006
## [59,]  0.37879647  1.91109491  1.420283145  0.035137693
## [60,]  0.48716896 -0.49476036  1.295029809  0.364744905
## [61,]  0.39865454  0.50896029 -0.621730643  0.916240899
```

```
## [62,]  1.02880489 -0.53217806 -0.324344947 -0.536515244
## [63,]  0.55333998  0.32835840  0.287153746 -1.800184342
## [64,]  0.88018917 -1.03348860 -2.071607668  1.000393277
## [65,] -1.01984153  0.47603663  0.065394221  0.223342305
## [66,]  0.07673477 -1.18721184  1.882530700  0.517698157
## [67,]  0.75269908 -0.13343187  0.419948744 -1.153611285
## [68,] -0.46566342 -0.39613574 -0.240107932 -1.158903675
## [69,] -0.51167697  0.39647496 -0.389565410 -0.621282159
```



Interpretation

The factor analysis conducted on the survey data reveals interesting insights into the underlying structure of the factors.

Factor Loadings

Factor loadings represent the correlation between the observed variables and the latent factors. The four factors (MR1, MR2, MR3, MR4) can be interpreted as follows based on the loadings:

MR1:

- High loadings on "X5..Security," "X1..Exterior.look," "X5..View.from.apartment," "X4..Availability.of.domestic.help," "Size," "Budgets," and "Maintainances."
- This factor can be interpreted as "Safety and Aesthetic Appeal."

MR2:

- High loadings on "X5..Availability.of.loan," "X2..Booking.amount," "X3..Equated.Monthly.Instalment..EMI."
- This factor seems to capture "Financial Aspects."

MR3:

- High loadings on "X4.Water.supply," "X5.Security," "X1..Price."
- This factor could be interpreted as "Basic Amenities and Security."

MR4:

- High loadings on "Size," "Budgets," "Maintainances," and "EMI.1."
- This factor might represent "Space and Maintenance Costs."

Communalities

Communalities indicate how much of the variance in each variable is explained by the factors. Higher communalities (closer to 1) suggest that the variable is well explained by the factors.

- Variables like "X5.Security," "X1..Exterior.look," "Size," "Budgets," "Maintainances," and "EMI.1" have high communalities, indicating they are well explained by the factors.
- Variables like "X4..Proximity.to.work.place," "X2..Unit.size," and "X3.Power.back.up" have lower communalities, suggesting they are not as well explained by the factors.

Factor Scores

Factor scores are the individual scores of each observation on the identified factors. These scores can be used for further analysis, such as clustering or regression.

Proportion of Variance Explained

The four factors explain approximately 47.7% of the total variance in the data, which is a decent amount considering the complexity of the dataset.

Interpretation Summary

1. **MR1 (Safety and Aesthetic Appeal):** This factor highlights the importance of security, aesthetic appeal of the exterior look, view from the apartment, availability of domestic help, and size of the unit.
2. **MR2 (Financial Aspects):** This factor captures the financial considerations such as loan availability, booking amount, and EMI.
3. **MR3 (Basic Amenities and Security):** This factor emphasizes the necessity of basic amenities like water supply and security, along with the price of the unit.
4. **MR4 (Space and Maintenance Costs):** This factor reflects the importance of unit size, maintenance costs, and budgets.