persona_analyzer

October 19, 2025

1 Persona Analysis

1.0.1 Comprehensive analysis of all persona variables with distributions, charts, and statistics

[27]:
```python
import json
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pathlib import Path
from collections import Counter
import warnings
warnings.filterwarnings('ignore')

# Set style for better visualizations
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")
plt.rcParams['figure.figsize'] = (12, 6)
plt.rcParams['font.family'] = 'DejaVu Sans'
```

1.1 1. Load JSON Files

[28]:
```python
# List of JSON file paths to analyze
json_files = [
    'personas/batch_output_1760799172.8845038.jsonl',
]



def load_file(file_path):
    try:
        with open(file_path, 'r', encoding='utf-8') as f:
            data = [json.loads(line) for line in f]
            return data
    except Exception as e:
        print(f"Error loading {file_path}: {e}")
        return []
```

```python
all_data = {}

for file in json_files:
    print(f"Loading file: {file}")
    data = load_file(file)
    all_data[file] = data
    print(f"  - Loaded {len(data)} batches from {file}")
    for i, batch in enumerate(data):
        print(f"    - Batch {i+1}: {len(batch)} personas")
```

```
Loading file: personas/batch_output_1760799172.8845038.jsonl
  - Loaded 20 batches from personas/batch_output_1760799172.8845038.jsonl
    - Batch 1: 10 personas
    - Batch 2: 10 personas
    - Batch 3: 10 personas
    - Batch 4: 10 personas
    - Batch 5: 10 personas
    - Batch 6: 10 personas
    - Batch 7: 10 personas
    - Batch 8: 10 personas
    - Batch 9: 10 personas
    - Batch 10: 10 personas
    - Batch 11: 10 personas
    - Batch 12: 10 personas
    - Batch 13: 10 personas
    - Batch 14: 10 personas
    - Batch 15: 10 personas
    - Batch 16: 10 personas
    - Batch 17: 10 personas
    - Batch 18: 10 personas
    - Batch 19: 10 personas
    - Batch 20: 10 personas
```

1.2 2. Flatten and Structure Data

[29]:

```python
# Flatten nested JSON structure into DataFrame
def flatten_persona(all_data):
    flat_personas = []
    for file in all_data:
        print(f"Processing file {file}...")
        for batch in all_data[file]:
            for persona in batch:
                flat_personas.append(persona)
    return flat_personas

flatten_persona_data = flatten_persona(all_data)
```

```python
print(f"\n  Total personas loaded: {len(flatten_persona_data)}")
```

```
Processing file personas/batch_output_1760799172.8845038.jsonl…

 Total personas loaded: 200
```

[30]:
```python
# Creating DataFrame
df = pd.DataFrame(flatten_persona_data)
print("\nDataFrame Info:")
print(df.info())
```

```
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 31 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   age                             200 non-null    int64
 1   gender                          200 non-null    object
 2   marital_status                  200 non-null    object
 3   children                        200 non-null    object
 4   living_situation                200 non-null    object
 5   general_health                  200 non-null    object
 6   chronic_disease                 199 non-null    object
 7   mobility                        200 non-null    object
 8   hearing_senses                  200 non-null    object
 9   vision_senses                   200 non-null    object
 10  daily_energy                    200 non-null    object
 11  personality_type                200 non-null    object
 12  cognitive_status                200 non-null    object
 13  dominant_emotion                200 non-null    object
 14  emotional_intelligence          200 non-null    object
 15  iq                              200 non-null    object
 16  attitude_toward_aging           200 non-null    object
 17  main_social_role                200 non-null    object
 18  social_support                  200 non-null    object
 19  social_participation            200 non-null    object
 20  income                          200 non-null    object
 21  economic_decile                 200 non-null    int64
 22  housing                         200 non-null    object
 23  religion_and_sect               200 non-null    object
 24  internalized_moral_traits       200 non-null    object
 25  religiosity_level               200 non-null    object
 26  ethnicity                       200 non-null    object
 27  language                        200 non-null    object
 28  important_personal_experiences  200 non-null    object
 29  life_satisfaction               200 non-null    object
```

```
 30  meaning_and_purpose_in_old_age  200 non-null    object
dtypes: int64(2), object(29)
memory usage: 48.6+ KB
None
```

1.3 3. Basic Statistics Overview

[31]:
```python
# Display first few rows
print("=" * 100)
print("SAMPLE DATA (First 3 Personas)")
print("=" * 100)
print(df.head(3).to_string())

# Basic statistics
print("\n" + "=" * 100)
print("BASIC STATISTICS")
print("=" * 100)
print(f"Total number of personas: {len(df)}")
print(f"Number of features: {df.shape[1]}")
print(f"\nMissing values per column:")
print(df.isnull().sum()[df.isnull().sum() > 0])

# Data types
print(f"\nData types:")
print(df.dtypes)
```

```
================================================================================
====================
SAMPLE DATA (First 3 Personas)
================================================================================
====================
   age  gender marital_status children    living_situation general_health
chronic_disease             mobility hearing_senses vision_senses daily_energy
personality_type    cognitive_status dominant_emotion emotional_intelligence
iq attitude_toward_aging main_social_role social_support social_participation
income   economic_decile   housing religion_and_sect
internalized_moral_traits religiosity_level ethnicity language
important_personal_experiences life_satisfaction meaning_and_purpose_in_old_age
0   72    Male         Married      2-3  Living with Family           Good
High Blood Pressure          Independent           Good          Good
Average             INTJ      Healthy Memory             Calm
High     High            Acceptance          Retired   Large Family
Active     Retirement Pension               7  Own Home       Shia Muslim
[Intellectual, Reserved, Prideful]          Average   Persian  Persian
Career Success         Satisfied                Helping Family
1   80  Female         Widowed       4+  Living with Family           Poor
Arthritis and Joint Pain  With Cane or Walker        Average          Poor
Low             ISFJ  Mild Forgetfulness             Sad                Average
```

```
Average            Acceptance      Grandmother   Large Family
Active  Dependent on Children               2  Own Home       Shia Muslim
[Traditional, Hospitable, Devout]             High     Azeri    Azeri
War Experience           Neutral                 Helping Family
2   69    Male        Married        4  Living with Family           Good
Type 2 Diabetes          Independent           Good       Average      Average
ESFP     Healthy Memory           Happy                  High  Average
Meaning-Seeking          Retired   Large Family              Active
Independent                 4  Own Home      Sunni Muslim         [Warm,
Generous, Practical]           Average   Kurdish  Kurdish              Economic
Hardship         Satisfied                 Helping Family

================================================================================
====================
BASIC STATISTICS
================================================================================
====================
Total number of personas: 200
Number of features: 31

Missing values per column:
chronic_disease    1
dtype: int64

Data types:
age                              int64
gender                          object
marital_status                  object
children                        object
living_situation                object
general_health                  object
chronic_disease                 object
mobility                        object
hearing_senses                  object
vision_senses                   object
daily_energy                    object
personality_type                object
cognitive_status                object
dominant_emotion                object
emotional_intelligence          object
iq                              object
attitude_toward_aging           object
main_social_role                object
social_support                  object
social_participation            object
income                          object
economic_decile                  int64
housing                         object
```

```
religion_and_sect                    object
internalized_moral_traits            object
religiosity_level                    object
ethnicity                            object
language                             object
important_personal_experiences       object
life_satisfaction                    object
meaning_and_purpose_in_old_age       object
dtype: object
```

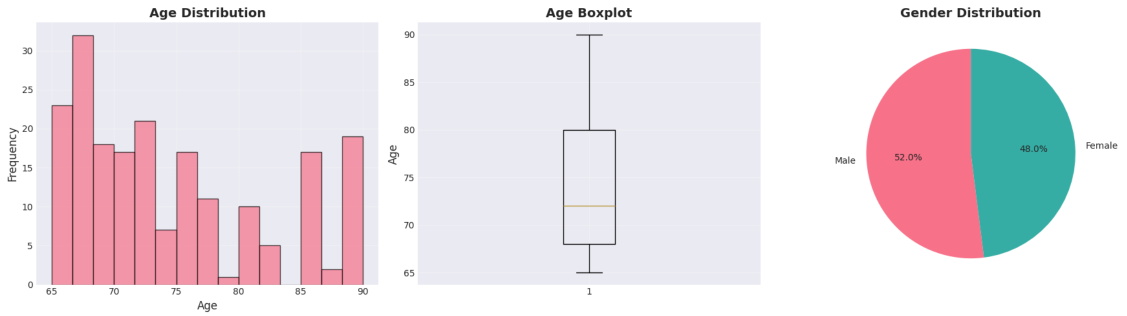
1.4 4. Demographic Analysis (Age & Gender)

[ ]:
```python
# AGE ANALYSIS
print("=" * 100)
print("AGE DISTRIBUTION")
print("=" * 100)
print(f"\nAge statistics:")
print(df['age'].describe())
print(f"\nAge range: {df['age'].min()} - {df['age'].max()}")
print(f"Most common age: {df['age'].mode()[0] if not df['age'].mode().empty␣
 ↪else 'N/A'}")

# Age distribution table
age_counts = df['age'].value_counts().sort_index()
print(f"\nAge frequency table:")
print(age_counts.to_string())

# GENDER ANALYSIS
print("\n" + "=" * 100)
print("GENDER DISTRIBUTION")
print("=" * 100)
gender_counts = df['gender'].value_counts()
gender_pct = df['gender'].value_counts(normalize=True) * 100
print(f"\nGender counts:")
for gender, count in gender_counts.items():
    print(f"  {gender}: {count} ({gender_pct[gender]:.2f}%)")

# Visualizations
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Age histogram
axes[0].hist(df['age'], bins=15, edgecolor='black', alpha=0.7)
axes[0].set_xlabel('Age', fontsize=12)
axes[0].set_ylabel('Frequency', fontsize=12)
axes[0].set_title('Age Distribution', fontsize=14, fontweight='bold')
axes[0].grid(True, alpha=0.3)
```

```python
# Age boxplot
axes[1].boxplot(df['age'], vert=True)
axes[1].set_ylabel('Age', fontsize=12)
axes[1].set_title('Age Boxplot', fontsize=14, fontweight='bold')
axes[1].grid(True, alpha=0.3)

# Gender pie chart
colors = sns.color_palette('husl', len(gender_counts))
axes[2].pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%',␣
↪colors=colors, startangle=90)
axes[2].set_title('Gender Distribution', fontsize=14, fontweight='bold')

plt.tight_layout()
plt.show()

# Age by Gender
print("\n" + "=" * 100)
print("AGE BY GENDER")
print("=" * 100)
age_by_gender = df.groupby('gender')['age'].describe()
print(age_by_gender.to_string())
```

```
================================================================================
====================
AGE DISTRIBUTION
================================================================================
====================

Age statistics:
count    200.000000
mean      74.480000
std        7.697784
min       65.000000
25%       68.000000
50%       72.000000
75%       80.000000
max       90.000000
Name: age, dtype: float64

Age range: 65 - 90
Most common age: 66

Age frequency table:
age
65     2
66    21
67    15
68    17
```

```
69     18
70     16
71      1
72     19
73      2
74      7
75     15
76      2
77      1
78     10
79      1
80      9
81      1
82      5
85     17
88      2
89      1
90     18

================================================================================
====================
GENDER DISTRIBUTION
================================================================================
====================

Gender counts:
  Male: 104 (52.00%)
  Female: 96 (48.00%)
```




```
================================================================================
====================
AGE BY GENDER
================================================================================
====================
        count        mean       std    min     25%    50%    75%    max
```

```
gender
Female   96.0  72.229167  6.58144  65.0  67.00  70.0  75.0  90.0
Male    104.0  76.557692  8.09030  66.0  69.75  74.0  85.0  90.0
```

1.5 5. Biological Component Analysis

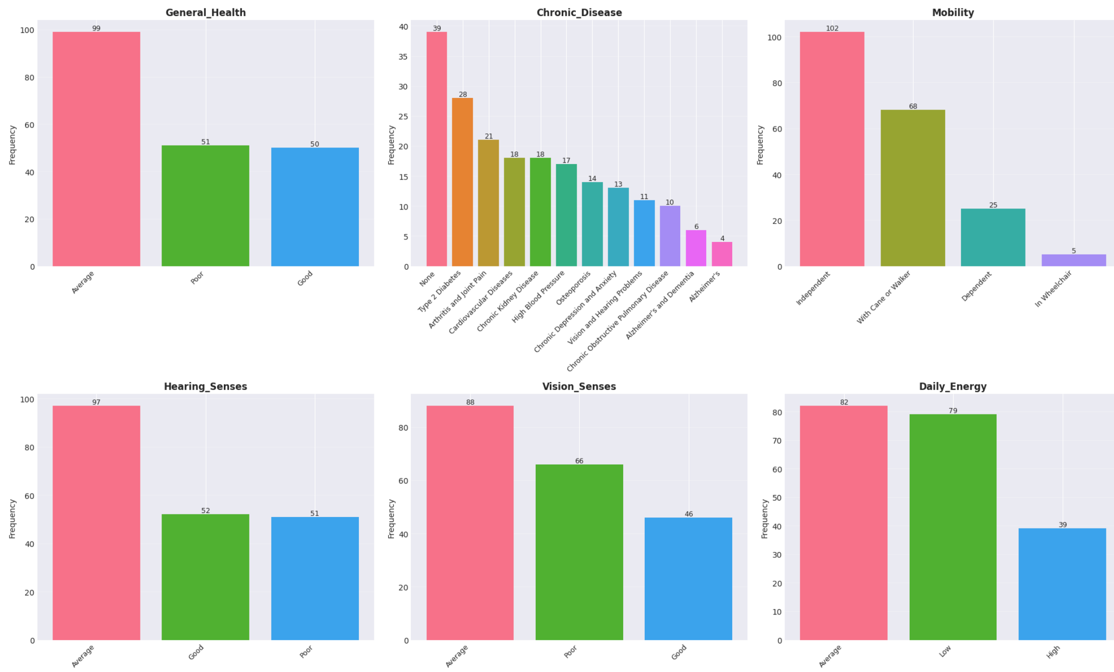
[35]:
```
# Biological component variables
bio_vars = ['general_health', 'chronic_disease', 'mobility', 'hearing_senses',␣
↪'vision_senses', 'daily_energy']

print("=" * 100)
print("BIOLOGICAL COMPONENT - COMPLETE ANALYSIS")
print("=" * 100)

# Analyze each biological variable
for var in bio_vars:
    print(f"\n{'=' * 100}")
    print(f"{var.upper()}")
    print(f"{'=' * 100}")

    # Clean data: remove None/NaN values
    clean_data = df[var].dropna()

    print(f"Total responses: {len(clean_data)} (Missing: {df[var].isnull().
↪sum()})")
    print(f"\nValue counts:")
    value_counts = clean_data.value_counts()
    value_pct = clean_data.value_counts(normalize=True) * 100

    for value, count in value_counts.items():
        print(f"  {value}: {count} ({value_pct[value]:.2f}%)")

    print(f"\nUnique values: {clean_data.nunique()}")
    print(f"Available values: {sorted(clean_data.unique().tolist())}")

# Visualizations
fig, axes = plt.subplots(2, 3, figsize=(20, 12))
axes = axes.flatten()

for idx, var in enumerate(bio_vars):
    clean_data = df[var].dropna()
    value_counts = clean_data.value_counts()

    # Bar chart
    axes[idx].bar(range(len(value_counts)), value_counts.values,
                  color=sns.color_palette('husl', len(value_counts)))
    axes[idx].set_xticks(range(len(value_counts)))
```

```
    axes[idx].set_xticklabels(value_counts.index, rotation=45, ha='right',␣
↪fontsize=9)
    axes[idx].set_ylabel('Frequency', fontsize=10)
    axes[idx].set_title(var.title(), fontsize=12, fontweight='bold')
    axes[idx].grid(True, alpha=0.3, axis='y')

    # Add value labels on bars
    for i, v in enumerate(value_counts.values):
        axes[idx].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

plt.tight_layout()
plt.show()

# Cross-tabulation: General Health vs Daily Energy
print("\n" + "=" * 100)
print("CROSS-TABULATION: General Health vs Daily Energy")
print("=" * 100)
crosstab = pd.crosstab(df['general_health'], df['daily_energy'], margins=True)
print(crosstab.to_string())

# Mobility vs General Health
print("\n" + "=" * 100)
print("CROSS-TABULATION: Mobility vs General Health")
print("=" * 100)
crosstab2 = pd.crosstab(df['mobility'], df['general_health'], margins=True)
print(crosstab2.to_string())
```

```
================================================================================
====================
BIOLOGICAL COMPONENT - COMPLETE ANALYSIS
================================================================================
====================

================================================================================
====================
GENERAL_HEALTH
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Average: 99 (49.50%)
  Poor: 51 (25.50%)
  Good: 50 (25.00%)

Unique values: 3
Available values: ['Average', 'Good', 'Poor']
```

```
================================================================================
====================
CHRONIC_DISEASE
================================================================================
====================
Total responses: 199 (Missing: 1)

Value counts:
  None: 39 (19.60%)
  Type 2 Diabetes: 28 (14.07%)
  Arthritis and Joint Pain: 21 (10.55%)
  Cardiovascular Diseases: 18 (9.05%)
  Chronic Kidney Disease: 18 (9.05%)
  High Blood Pressure: 17 (8.54%)
  Osteoporosis: 14 (7.04%)
  Chronic Depression and Anxiety: 13 (6.53%)
  Vision and Hearing Problems: 11 (5.53%)
  Chronic Obstructive Pulmonary Disease: 10 (5.03%)
  Alzheimer's and Dementia: 6 (3.02%)
  Alzheimer's: 4 (2.01%)

Unique values: 12
Available values: ["Alzheimer's", "Alzheimer's and Dementia", 'Arthritis and
Joint Pain', 'Cardiovascular Diseases', 'Chronic Depression and Anxiety',
'Chronic Kidney Disease', 'Chronic Obstructive Pulmonary Disease', 'High Blood
Pressure', 'None', 'Osteoporosis', 'Type 2 Diabetes', 'Vision and Hearing
Problems']

================================================================================
====================
MOBILITY
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Independent: 102 (51.00%)
  With Cane or Walker: 68 (34.00%)
  Dependent: 25 (12.50%)
  In Wheelchair: 5 (2.50%)

Unique values: 4
Available values: ['Dependent', 'In Wheelchair', 'Independent', 'With Cane or
Walker']

================================================================================
====================
HEARING_SENSES
```

```
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Average: 97 (48.50%)
  Good: 52 (26.00%)
  Poor: 51 (25.50%)

Unique values: 3
Available values: ['Average', 'Good', 'Poor']

================================================================================
====================
VISION_SENSES
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Average: 88 (44.00%)
  Poor: 66 (33.00%)
  Good: 46 (23.00%)

Unique values: 3
Available values: ['Average', 'Good', 'Poor']

================================================================================
====================
DAILY_ENERGY
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Average: 82 (41.00%)
  Low: 79 (39.50%)
  High: 39 (19.50%)

Unique values: 3
Available values: ['Average', 'High', 'Low']
```




```
================================================================================
====================
CROSS-TABULATION: General Health vs Daily Energy
================================================================================
====================
daily_energy    Average  High  Low  All
general_health
Average              70     1   28   99
Good                 12    38    0   50
Poor                  0     0   51   51
All                  82    39   79  200

================================================================================
====================
CROSS-TABULATION: Mobility vs General Health
================================================================================
====================
general_health       Average  Good  Poor  All
mobility
Dependent                  0     0    25   25
In Wheelchair              1     0     4    5
Independent               53    48     1  102
With Cane or Walker       45     2    21   68
All                       99    50    51  200
```

1.6 6. Psychological Component Analysis

[37]:
```python
# Psychological component variables
psych_vars = ['personality_type', 'cognitive_status', 'dominant_emotion',
              'emotional_intelligence', 'iq', 'attitude_toward_aging']

print("=" * 100)
print("PSYCHOLOGICAL COMPONENT - COMPLETE ANALYSIS")
print("=" * 100)

# Analyze each psychological variable
for var in psych_vars:
    print(f"\n{'=' * 100}")
    print(f"{var.upper()}")
    print(f"{'=' * 100}")

    # Clean data: remove None/NaN values
    clean_data = df[var].dropna()

    print(f"Total responses: {len(clean_data)} (Missing: {df[var].isnull().
 ↪sum()})")
    print(f"\nValue counts:")
    value_counts = clean_data.value_counts()
    value_pct = clean_data.value_counts(normalize=True) * 100

    for value, count in value_counts.items():
        print(f"  {value}: {count} ({value_pct[value]:.2f}%)")

    print(f"\nUnique values: {clean_data.nunique()}")
    print(f"Available values: {sorted(clean_data.unique().tolist())}")

# Visualizations
fig, axes = plt.subplots(2, 3, figsize=(20, 12))
axes = axes.flatten()

for idx, var in enumerate(psych_vars):
    clean_data = df[var].dropna()
    value_counts = clean_data.value_counts()

    # Bar chart
    axes[idx].bar(range(len(value_counts)), value_counts.values,
                  color=sns.color_palette('Set2', len(value_counts)))
    axes[idx].set_xticks(range(len(value_counts)))
    axes[idx].set_xticklabels(value_counts.index, rotation=45, ha='right',␣
 ↪fontsize=9)
    axes[idx].set_ylabel('Frequency', fontsize=10)
    axes[idx].set_title(var.title(), fontsize=12, fontweight='bold')
```

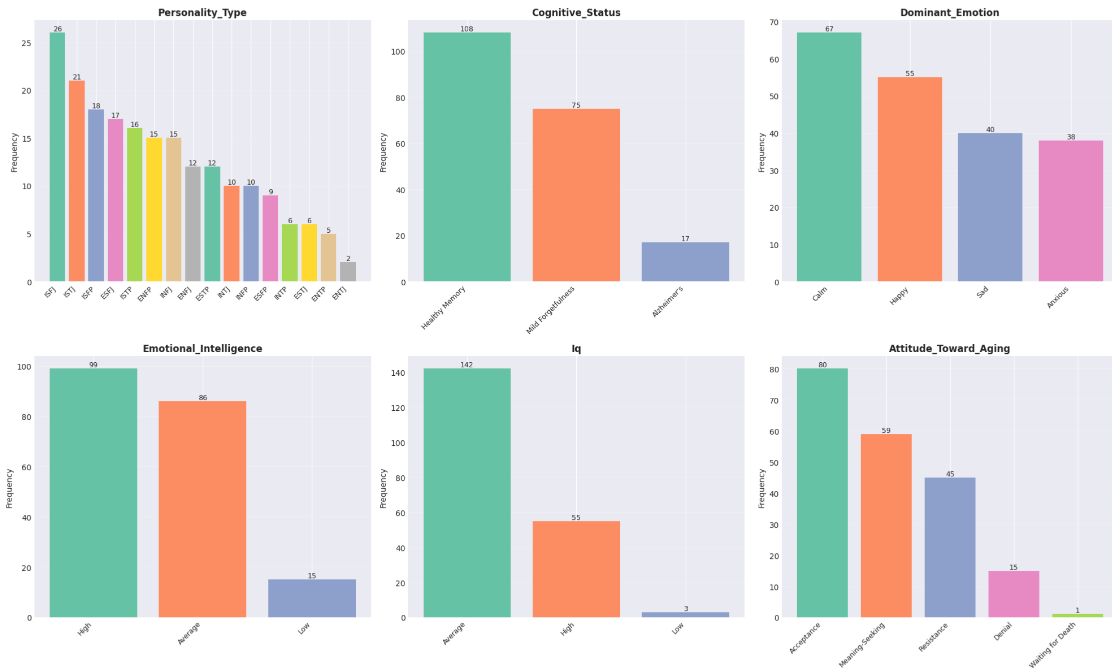
```python
    axes[idx].grid(True, alpha=0.3, axis='y')

    # Add value labels on bars
    for i, v in enumerate(value_counts.values):
        axes[idx].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

plt.tight_layout()
plt.show()

# MBTI Personality Type Analysis
print("\n" + "=" * 100)
print("MBTI PERSONALITY TYPE BREAKDOWN")
print("=" * 100)
mbti_data = df['personality_type'].dropna()
print(f"Total MBTI entries: {len(mbti_data)}")
print(f"\nMBTI Distribution:")
print(mbti_data.value_counts().to_string())

# Analyze MBTI dimensions
if len(mbti_data) > 0:
    print(f"\nMBTI Dimension Analysis:")
    mbti_list = mbti_data.tolist()

    # Extract dimensions
    e_i = [p[0] for p in mbti_list if len(p) == 4]
    s_n = [p[1] for p in mbti_list if len(p) == 4]
    t_f = [p[2] for p in mbti_list if len(p) == 4]
    j_p = [p[3] for p in mbti_list if len(p) == 4]

    print(f"  E vs I: E={e_i.count('E')}, I={e_i.count('I')}")
    print(f"  S vs N: S={s_n.count('S')}, N={s_n.count('N')}")
    print(f"  T vs F: T={t_f.count('T')}, F={t_f.count('F')}")
    print(f"  J vs P: J={j_p.count('J')}, P={j_p.count('P')}")

# Cognitive Status vs Dominant Emotion
print("\n" + "=" * 100)
print("CROSS-TABULATION: Cognitive Status vs Dominant Emotion")
print("=" * 100)
crosstab = pd.crosstab(df['cognitive_status'], df['dominant_emotion'],␣
↪margins=True)
print(crosstab.to_string())
```

```
================================================================================
====================
PSYCHOLOGICAL COMPONENT - COMPLETE ANALYSIS
================================================================================
====================
```

```
================================================================================
====================
PERSONALITY_TYPE
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  ISFJ: 26 (13.00%)
  ISTJ: 21 (10.50%)
  ISFP: 18 (9.00%)
  ESFJ: 17 (8.50%)
  ISTP: 16 (8.00%)
  ENFP: 15 (7.50%)
  INFJ: 15 (7.50%)
  ENFJ: 12 (6.00%)
  ESTP: 12 (6.00%)
  INTJ: 10 (5.00%)
  INFP: 10 (5.00%)
  ESFP: 9 (4.50%)
  INTP: 6 (3.00%)
  ESTJ: 6 (3.00%)
  ENTP: 5 (2.50%)
  ENTJ: 2 (1.00%)

Unique values: 16
Available values: ['ENFJ', 'ENFP', 'ENTJ', 'ENTP', 'ESFJ', 'ESFP', 'ESTJ',
'ESTP', 'INFJ', 'INFP', 'INTJ', 'INTP', 'ISFJ', 'ISFP', 'ISTJ', 'ISTP']

================================================================================
====================
COGNITIVE_STATUS
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Healthy Memory: 108 (54.00%)
  Mild Forgetfulness: 75 (37.50%)
  Alzheimer's: 17 (8.50%)

Unique values: 3
Available values: ["Alzheimer's", 'Healthy Memory', 'Mild Forgetfulness']

================================================================================
====================
DOMINANT_EMOTION
================================================================================
```

```
====================
Total responses: 200 (Missing: 0)

Value counts:
  Calm: 67 (33.50%)
  Happy: 55 (27.50%)
  Sad: 40 (20.00%)
  Anxious: 38 (19.00%)

Unique values: 4
Available values: ['Anxious', 'Calm', 'Happy', 'Sad']

================================================================================
====================
EMOTIONAL_INTELLIGENCE
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  High: 99 (49.50%)
  Average: 86 (43.00%)
  Low: 15 (7.50%)

Unique values: 3
Available values: ['Average', 'High', 'Low']

================================================================================
====================
IQ
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Average: 142 (71.00%)
  High: 55 (27.50%)
  Low: 3 (1.50%)

Unique values: 3
Available values: ['Average', 'High', 'Low']

================================================================================
====================
ATTITUDE_TOWARD_AGING
================================================================================
====================
Total responses: 200 (Missing: 0)
```

```
Value counts:
  Acceptance: 80 (40.00%)
  Meaning-Seeking: 59 (29.50%)
  Resistance: 45 (22.50%)
  Denial: 15 (7.50%)
  Waiting for Death: 1 (0.50%)

Unique values: 5
Available values: ['Acceptance', 'Denial', 'Meaning-Seeking', 'Resistance',
'Waiting for Death']
```




```
====================================================================================================
MBTI PERSONALITY TYPE BREAKDOWN
====================================================================================================
Total MBTI entries: 200

MBTI Distribution:
personality_type
ISFJ    26
ISTJ    21
ISFP    18
ESFJ    17
```

```
ISTP    16
ENFP    15
INFJ    15
ENFJ    12
ESTP    12
INTJ    10
INFP    10
ESFP     9
INTP     6
ESTJ     6
ENTP     5
ENTJ     2

MBTI Dimension Analysis:
  E vs I: E=78, I=122
  S vs N: S=125, N=75
  T vs F: T=78, F=122
  J vs P: J=109, P=91

================================================================================
====================
CROSS-TABULATION: Cognitive Status vs Dominant Emotion
================================================================================
====================
dominant_emotion    Anxious  Calm  Happy  Sad  All
cognitive_status
Alzheimer's               6     1      0   10   17
Healthy Memory           16    40     50    2  108
Mild Forgetfulness       16    26      5   28   75
All                      38    67     55   40  200
```

1.7 7. Social Component Analysis

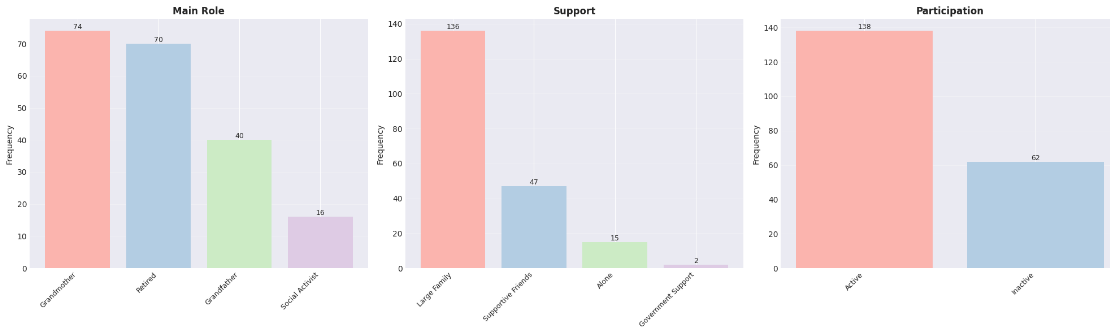
[ ]:
```python
# Social component variables
social_vars = ['main_social_role', 'social_support', 'social_participation']

print("=" * 100)
print("SOCIAL COMPONENT - COMPLETE ANALYSIS")
print("=" * 100)

# Analyze each social variable
for var in social_vars:
    print(f"\n{'=' * 100}")
    print(f"{var.upper()}")
    print(f"{'=' * 100}")

    # Clean data: remove None/NaN values
```

```
    clean_data = df[var].dropna()

    print(f"Total responses: {len(clean_data)} (Missing: {df[var].isnull().
↪sum()})")
    print(f"\nValue counts:")
    value_counts = clean_data.value_counts()
    value_pct = clean_data.value_counts(normalize=True) * 100

    for value, count in value_counts.items():
        print(f"  {value}: {count} ({value_pct[value]:.2f}%)")

    print(f"\nUnique values: {clean_data.nunique()}")
    print(f"Available values: {sorted(clean_data.unique().tolist())}")

# Visualizations
fig, axes = plt.subplots(1, 3, figsize=(20, 6))

for idx, var in enumerate(social_vars):
    clean_data = df[var].dropna()
    value_counts = clean_data.value_counts()

    # Bar chart
    axes[idx].bar(range(len(value_counts)), value_counts.values,
                  color=sns.color_palette('Pastel1', len(value_counts)))
    axes[idx].set_xticks(range(len(value_counts)))
    axes[idx].set_xticklabels(value_counts.index, rotation=45, ha='right',␣
↪fontsize=9)
    axes[idx].set_ylabel('Frequency', fontsize=10)
    axes[idx].set_title(var.title(), fontsize=12, fontweight='bold')
    axes[idx].grid(True, alpha=0.3, axis='y')

    # Add value labels on bars
    for i, v in enumerate(value_counts.values):
        axes[idx].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

plt.tight_layout()
plt.show()

# Cross-tabulation: Social Support vs Social Participation
print("\n" + "=" * 100)
print("CROSS-TABULATION: Social Support vs Social Participation")
print("=" * 100)
crosstab = pd.crosstab(df['social_support'], df['social_participation'],␣
↪margins=True)
print(crosstab.to_string())
```

```
================================================================================
```

```
====================
SOCIAL COMPONENT - COMPLETE ANALYSIS
================================================================================
====================

================================================================================
====================
MAIN_ROLE
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Grandmother: 74 (37.00%)
  Retired: 70 (35.00%)
  Grandfather: 40 (20.00%)
  Social Activist: 16 (8.00%)

Unique values: 4
Available values: ['Grandfather', 'Grandmother', 'Retired', 'Social Activist']

================================================================================
====================
SUPPORT
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Large Family: 136 (68.00%)
  Supportive Friends: 47 (23.50%)
  Alone: 15 (7.50%)
  Government Support: 2 (1.00%)

Unique values: 4
Available values: ['Alone', 'Government Support', 'Large Family', 'Supportive
Friends']

================================================================================
====================
PARTICIPATION
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Active: 138 (69.00%)
  Inactive: 62 (31.00%)
```

```
Unique values: 2
Available values: ['Active', 'Inactive']
```




```
================================================================================
====================
CROSS-TABULATION: Social Support vs Social Participation
================================================================================
====================
social_participation  Active  Inactive  All
social_support
Alone                      0        15   15
Government Support         0         2    2
Large Family             100        36  136
Supportive Friends        38         9   47
All                      138        62  200
```

1.8 8. Economic Component Analysis

[39]:
```python
# Economic component variables
econ_vars = ['income', 'economic_decile', 'housing']

print("=" * 100)
print("ECONOMIC COMPONENT - COMPLETE ANALYSIS")
print("=" * 100)

# Analyze each economic variable
for var in econ_vars:
    print(f"\n{'=' * 100}")
    print(f"{var.upper()}")
    print(f"{'=' * 100}")

    # Clean data: remove None/NaN values
    clean_data = df[var].dropna()
```

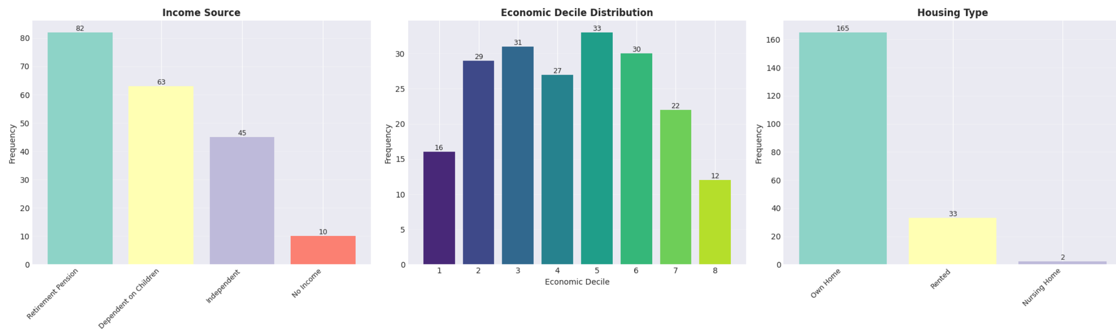
```python
    print(f"Total responses: {len(clean_data)} (Missing: {df[var].isnull().
↪sum()})")

    # For numeric data (economic_decile)
    if var == 'economic_decile':
        print(f"\nStatistics:")
        print(clean_data.describe())
        print(f"\nValue counts:")
        value_counts = clean_data.value_counts().sort_index()
    else:
        print(f"\nValue counts:")
        value_counts = clean_data.value_counts()

    value_pct = value_counts / len(clean_data) * 100

    for value, count in value_counts.items():
        print(f"  {value}: {count} ({value_pct[value]:.2f}%)")

    print(f"\nUnique values: {clean_data.nunique()}")
    if var != 'econ_decile':
        print(f"Available values: {sorted(clean_data.unique().tolist())}")

# Visualizations
fig, axes = plt.subplots(1, 3, figsize=(20, 6))

# Income
clean_data = df['income'].dropna()
value_counts = clean_data.value_counts()
axes[0].bar(range(len(value_counts)), value_counts.values,
            color=sns.color_palette('Set3', len(value_counts)))
axes[0].set_xticks(range(len(value_counts)))
axes[0].set_xticklabels(value_counts.index, rotation=45, ha='right', fontsize=9)
axes[0].set_ylabel('Frequency', fontsize=10)
axes[0].set_title('Income Source', fontsize=12, fontweight='bold')
axes[0].grid(True, alpha=0.3, axis='y')
for i, v in enumerate(value_counts.values):
    axes[0].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

# Economic Decile
clean_data = df['economic_decile'].dropna()
value_counts = clean_data.value_counts().sort_index()
axes[1].bar(value_counts.index, value_counts.values,
            color=sns.color_palette('viridis', len(value_counts)))
axes[1].set_xlabel('Economic Decile', fontsize=10)
axes[1].set_ylabel('Frequency', fontsize=10)
```

```python
axes[1].set_title('Economic Decile Distribution', fontsize=12,␣
↪fontweight='bold')
axes[1].grid(True, alpha=0.3, axis='y')
for i, v in zip(value_counts.index, value_counts.values):
    axes[1].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

# Housing
clean_data = df['housing'].dropna()
value_counts = clean_data.value_counts()
axes[2].bar(range(len(value_counts)), value_counts.values,
            color=sns.color_palette('Set3', len(value_counts)))
axes[2].set_xticks(range(len(value_counts)))
axes[2].set_xticklabels(value_counts.index, rotation=45, ha='right', fontsize=9)
axes[2].set_ylabel('Frequency', fontsize=10)
axes[2].set_title('Housing Type', fontsize=12, fontweight='bold')
axes[2].grid(True, alpha=0.3, axis='y')
for i, v in enumerate(value_counts.values):
    axes[2].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

plt.tight_layout()
plt.show()

# Cross-tabulation: Income vs Housing
print("\n" + "=" * 100)
print("CROSS-TABULATION: Income vs Housing")
print("=" * 100)
crosstab = pd.crosstab(df['income'], df['housing'], margins=True)
print(crosstab.to_string())

# Economic Decile statistics by Income
print("\n" + "=" * 100)
print("ECONOMIC DECILE BY INCOME SOURCE")
print("=" * 100)
decile_by_income = df.groupby('income')['economic_decile'].describe()
print(decile_by_income.to_string())
```

```
================================================================================
====================
ECONOMIC COMPONENT - COMPLETE ANALYSIS
================================================================================
====================

================================================================================
====================
INCOME
================================================================================
====================
Total responses: 200 (Missing: 0)
```

```
Value counts:
  Retirement Pension: 82 (41.00%)
  Dependent on Children: 63 (31.50%)
  Independent: 45 (22.50%)
  No Income: 10 (5.00%)

Unique values: 4
Available values: ['Dependent on Children', 'Independent', 'No Income',
'Retirement Pension']

================================================================================
====================
ECONOMIC_DECILE
================================================================================
====================
Total responses: 200 (Missing: 0)

Statistics:
count    200.000000
mean       4.350000
std        2.016888
min        1.000000
25%        3.000000
50%        4.000000
75%        6.000000
max        8.000000
Name: economic_decile, dtype: float64

Value counts:
  1: 16 (8.00%)
  2: 29 (14.50%)
  3: 31 (15.50%)
  4: 27 (13.50%)
  5: 33 (16.50%)
  6: 30 (15.00%)
  7: 22 (11.00%)
  8: 12 (6.00%)

Unique values: 8
Available values: [1, 2, 3, 4, 5, 6, 7, 8]

================================================================================
====================
HOUSING
================================================================================
====================
Total responses: 200 (Missing: 0)
```

```
Value counts:
  Own Home: 165 (82.50%)
  Rented: 33 (16.50%)
  Nursing Home: 2 (1.00%)

Unique values: 3
Available values: ['Nursing Home', 'Own Home', 'Rented']
```




```
================================================================================
====================
CROSS-TABULATION: Income vs Housing
================================================================================
====================
```

housing	Nursing Home	Own Home	Rented	All
income				
Dependent on Children	0	53	10	63
Independent	0	35	10	45
No Income	1	5	4	10
Retirement Pension	1	72	9	82
All	2	165	33	200

```
================================================================================
====================
ECONOMIC DECILE BY INCOME SOURCE
================================================================================
====================
```

	count	mean	std	min	25%	50%	75%	max
income								
Dependent on Children	63.0	2.746032	1.269598	1.0	2.00	3.0	4.0	6.0
Independent	45.0	6.044444	1.223920	4.0	5.00	6.0	7.0	8.0
No Income	10.0	1.900000	0.737865	1.0	1.25	2.0	2.0	3.0
Retirement Pension	82.0	4.951220	1.784034	2.0	3.25	5.0	6.0	8.0

1.9 9. Cultural & Value Component Analysis

[41]:
```
# Cultural component variables (excluding internalized_moral_traits which is a␣
↪list)
cultural_vars = ['religion_and_sect', 'religiosity_level', 'ethnicity',␣
↪'language']

print("=" * 100)
print("CULTURAL & VALUE COMPONENT - COMPLETE ANALYSIS")
print("=" * 100)

# Analyze each cultural variable
for var in cultural_vars:
    print(f"\n{'=' * 100}")
    print(f"{var.upper()}")
    print(f"{'=' * 100}")

    # Clean data: remove None/NaN values
    clean_data = df[var].dropna()

    print(f"Total responses: {len(clean_data)} (Missing: {df[var].isnull().
↪sum()})")
    print(f"\nValue counts:")
    value_counts = clean_data.value_counts()
    value_pct = clean_data.value_counts(normalize=True) * 100

    for value, count in value_counts.items():
        print(f"  {value}: {count} ({value_pct[value]:.2f}%)")

    print(f"\nUnique values: {clean_data.nunique()}")
    print(f"Available values: {sorted(clean_data.unique().tolist())}")

# MORAL TRAITS ANALYSIS (List variable)
print("\n" + "=" * 100)
print("MORAL TRAITS (LIST VARIABLE)")
print("=" * 100)

# Extract all moral traits from lists
all_moral_traits = []
for traits_list in df['internalized_moral_traits'].dropna():
    if isinstance(traits_list, list):
        all_moral_traits.extend(traits_list)

if all_moral_traits:
    moral_counts = Counter(all_moral_traits)
    print(f"Total moral trait entries: {len(all_moral_traits)}")
    print(f"Unique moral traits: {len(moral_counts)}")
```

```python
    print(f"\nMoral traits frequency:")
    for trait, count in moral_counts.most_common():
        pct = (count / len(all_moral_traits)) * 100
        print(f"  {trait}: {count} ({pct:.2f}%)")
    print(f"\nAll unique moral traits: {sorted(moral_counts.keys())}")

# Visualizations
fig, axes = plt.subplots(2, 3, figsize=(20, 12))
axes = axes.flatten()

# Plot first 5 cultural variables
for idx, var in enumerate(cultural_vars):
    clean_data = df[var].dropna()
    value_counts = clean_data.value_counts()

    # Bar chart
    axes[idx].bar(range(len(value_counts)), value_counts.values,
                  color=sns.color_palette('Spectral', len(value_counts)))
    axes[idx].set_xticks(range(len(value_counts)))
    axes[idx].set_xticklabels(value_counts.index, rotation=45, ha='right',␣
↪fontsize=9)
    axes[idx].set_ylabel('Frequency', fontsize=10)
    axes[idx].set_title(var.title(), fontsize=12, fontweight='bold')
    axes[idx].grid(True, alpha=0.3, axis='y')

    # Add value labels on bars
    for i, v in enumerate(value_counts.values):
        axes[idx].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

# Plot moral traits in the 6th subplot
if all_moral_traits:
    moral_counts_series = pd.Series(moral_counts).sort_values(ascending=False).
↪head(15)
    axes[4].barh(range(len(moral_counts_series)), moral_counts_series.values,
                 color=sns.color_palette('coolwarm', len(moral_counts_series)))
    axes[4].set_yticks(range(len(moral_counts_series)))
    axes[4].set_yticklabels(moral_counts_series.index, fontsize=9)
    axes[4].set_xlabel('Frequency', fontsize=10)
    axes[4].set_title('Top 15 Moral Traits', fontsize=12, fontweight='bold')
    axes[4].grid(True, alpha=0.3, axis='x')
    axes[4].invert_yaxis()

plt.tight_layout()
plt.show()

# Cross-tabulation: Religion vs Religiosity Level
print("\n" + "=" * 100)
```

```python
print("CROSS-TABULATION: Religion vs Religiosity Level")
print("=" * 100)
crosstab = pd.crosstab(df['religion_and_sect'], df['religiosity_level'],␣
↪margins=True)
print(crosstab.to_string())

# Ethnicity vs Language
print("\n" + "=" * 100)
print("CROSS-TABULATION: Ethnicity vs Language")
print("=" * 100)
crosstab2 = pd.crosstab(df['ethnicity'], df['language'], margins=True)
print(crosstab2.to_string())
```

```
================================================================================
====================
CULTURAL & VALUE COMPONENT - COMPLETE ANALYSIS
================================================================================
====================

================================================================================
====================
RELIGION_AND_SECT
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Shia Muslim: 126 (63.00%)
  Sunni Muslim: 54 (27.00%)
  Jewish: 11 (5.50%)
  Zoroastrian: 5 (2.50%)
  Christian: 4 (2.00%)

Unique values: 5
Available values: ['Christian', 'Jewish', 'Shia Muslim', 'Sunni Muslim',
'Zoroastrian']

================================================================================
====================
RELIGIOSITY_LEVEL
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Average: 107 (53.50%)
  High: 75 (37.50%)
  Low: 18 (9.00%)
```

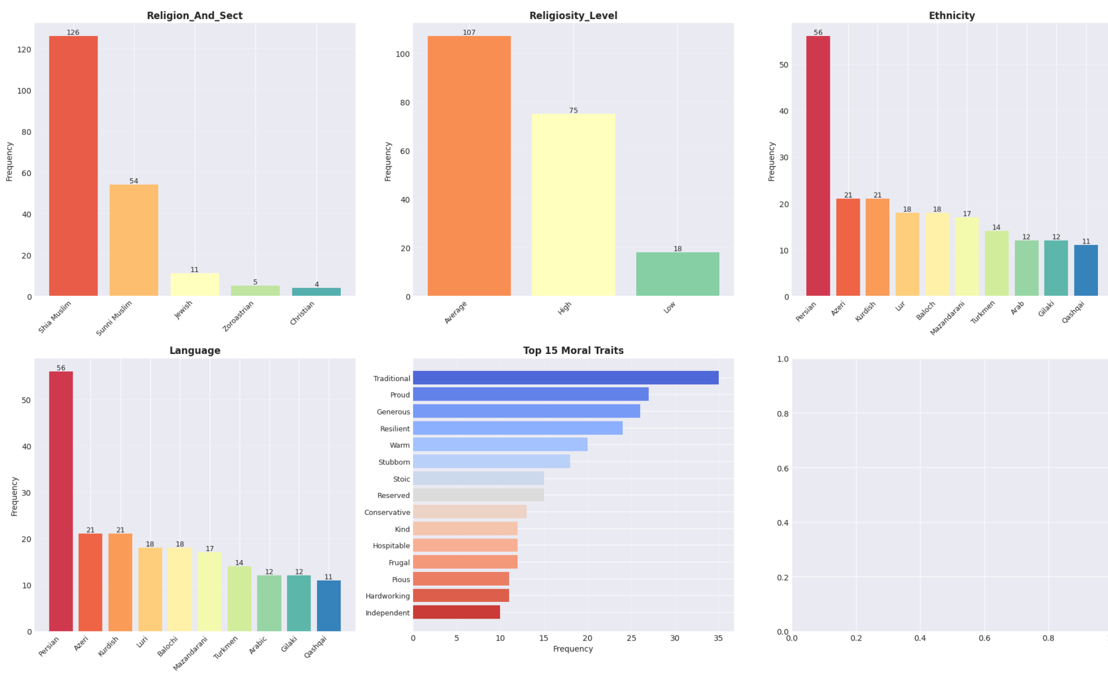
```
Unique values: 3
Available values: ['Average', 'High', 'Low']

================================================================================
====================
ETHNICITY
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Persian: 56 (28.00%)
  Azeri: 21 (10.50%)
  Kurdish: 21 (10.50%)
  Lur: 18 (9.00%)
  Baloch: 18 (9.00%)
  Mazandarani: 17 (8.50%)
  Turkmen: 14 (7.00%)
  Arab: 12 (6.00%)
  Gilaki: 12 (6.00%)
  Qashqai: 11 (5.50%)

Unique values: 10
Available values: ['Arab', 'Azeri', 'Baloch', 'Gilaki', 'Kurdish', 'Lur',
'Mazandarani', 'Persian', 'Qashqai', 'Turkmen']

================================================================================
====================
LANGUAGE
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Persian: 56 (28.00%)
  Azeri: 21 (10.50%)
  Kurdish: 21 (10.50%)
  Luri: 18 (9.00%)
  Balochi: 18 (9.00%)
  Mazandarani: 17 (8.50%)
  Turkmen: 14 (7.00%)
  Arabic: 12 (6.00%)
  Gilaki: 12 (6.00%)
  Qashqai: 11 (5.50%)

Unique values: 10
Available values: ['Arabic', 'Azeri', 'Balochi', 'Gilaki', 'Kurdish', 'Luri',
```

```
'Mazandarani', 'Persian', 'Qashqai', 'Turkmen']

================================================================================
====================
MORAL TRAITS (LIST VARIABLE)
================================================================================
====================
Total moral trait entries: 568
Unique moral traits: 144

Moral traits frequency:
  Traditional: 35 (6.16%)
  Proud: 27 (4.75%)
  Generous: 26 (4.58%)
  Resilient: 24 (4.23%)
  Warm: 20 (3.52%)
  Stubborn: 18 (3.17%)
  Reserved: 15 (2.64%)
  Stoic: 15 (2.64%)
  Conservative: 13 (2.29%)
  Hospitable: 12 (2.11%)
  Kind: 12 (2.11%)
  Frugal: 12 (2.11%)
  Hardworking: 11 (1.94%)
  Pious: 11 (1.94%)
  Practical: 10 (1.76%)
  Independent: 10 (1.76%)
  Hospitality: 10 (1.76%)
  Pragmatic: 9 (1.58%)
  Curious: 9 (1.58%)
  Devout: 8 (1.41%)
  Respectful: 8 (1.41%)
  Outspoken: 8 (1.41%)
  Loyal: 7 (1.23%)
  Open-minded: 7 (1.23%)
  Compassionate: 7 (1.23%)
  Community-oriented: 5 (0.88%)
  Protective: 5 (0.88%)
  Nurturing: 5 (0.88%)
  Religious: 5 (0.88%)
  stubborn: 5 (0.88%)
  Dutiful: 5 (0.88%)
  Principled: 5 (0.88%)
  Idealistic: 4 (0.70%)
  Skeptical: 4 (0.70%)
  Authoritative: 4 (0.70%)
  Superstitious: 4 (0.70%)
  Faithful: 4 (0.70%)
```

Optimistic: 4 (0.70%)
Talkative: 4 (0.70%)
Suspicious: 4 (0.70%)
Empathetic: 4 (0.70%)
Pride: 4 (0.70%)
Intellectual: 3 (0.53%)
Prideful: 3 (0.53%)
Hot-tempered: 3 (0.53%)
hardworking: 3 (0.53%)
proud: 3 (0.53%)
hospitable: 3 (0.53%)
Diligent: 3 (0.53%)
Private: 3 (0.53%)
Forgetful: 3 (0.53%)
Bitter: 3 (0.53%)
Reflective: 3 (0.53%)
Piety: 3 (0.53%)
Resilience: 3 (0.53%)
Family-oriented: 3 (0.53%)
Artistic: 2 (0.35%)
Community-minded: 2 (0.35%)
Distrustful: 2 (0.35%)
devout: 2 (0.35%)
generous: 2 (0.35%)
traditional: 2 (0.35%)
superstitious: 2 (0.35%)
Sociable: 2 (0.35%)
Patient: 2 (0.35%)
Honest: 2 (0.35%)
Organized: 2 (0.35%)
Quiet: 2 (0.35%)
Stoicism: 2 (0.35%)
Warmth: 2 (0.35%)
Traditionalism: 2 (0.35%)
Progressive: 2 (0.35%)
Introverted: 2 (0.35%)
Nonconformist: 2 (0.35%)
Witty: 2 (0.35%)
Gentle: 1 (0.18%)
Gruff: 1 (0.18%)
Altruistic: 1 (0.18%)
Aloof: 1 (0.18%)
principled: 1 (0.18%)
intellectual: 1 (0.18%)
fair: 1 (0.18%)
resilient: 1 (0.18%)
fatalistic: 1 (0.18%)
stoic: 1 (0.18%)

distrustful: 1 (0.18%)
honest: 1 (0.18%)
modest: 1 (0.18%)
empathetic: 1 (0.18%)
idealistic: 1 (0.18%)
private: 1 (0.18%)
patient: 1 (0.18%)
learned: 1 (0.18%)
charitable: 1 (0.18%)
nostalgic: 1 (0.18%)
Cultured: 1 (0.18%)
Tolerance: 1 (0.18%)
Charismatic: 1 (0.18%)
Loving: 1 (0.18%)
Pessimistic: 1 (0.18%)
Mistrustful: 1 (0.18%)
Thoughtful: 1 (0.18%)
Resourceful: 1 (0.18%)
Authoritarian: 1 (0.18%)
Charitable: 1 (0.18%)
Family-Oriented: 1 (0.18%)
Cynical: 1 (0.18%)
Humble: 1 (0.18%)
Responsibility: 1 (0.18%)
Modesty: 1 (0.18%)
Generosity: 1 (0.18%)
Fatalism: 1 (0.18%)
Independence: 1 (0.18%)
Skepticism: 1 (0.18%)
Discipline: 1 (0.18%)
Ambition: 1 (0.18%)
Intellectualism: 1 (0.18%)
Pragmatism: 1 (0.18%)
Privacy: 1 (0.18%)
Assertive: 1 (0.18%)
Honorable: 1 (0.18%)
Creative: 1 (0.18%)
Brave: 1 (0.18%)
Curiosity: 1 (0.18%)
Integrity: 1 (0.18%)
Wise: 1 (0.18%)
Courageous: 1 (0.18%)
Communal: 1 (0.18%)
Gossipy: 1 (0.18%)
Cautious: 1 (0.18%)
Energetic: 1 (0.18%)
Respect for tradition: 1 (0.18%)
Frugality: 1 (0.18%)

```
  Melancholic: 1 (0.18%)
  Trusting: 1 (0.18%)
  Fatalistic: 1 (0.18%)
  Withdrawn: 1 (0.18%)
  Cultural: 1 (0.18%)
  Storyteller: 1 (0.18%)
  Humorous: 1 (0.18%)
  Modest: 1 (0.18%)
  Bold: 1 (0.18%)
  Community-leader: 1 (0.18%)
  Cheerful: 1 (0.18%)

All unique moral traits: ['Aloof', 'Altruistic', 'Ambition', 'Artistic',
'Assertive', 'Authoritarian', 'Authoritative', 'Bitter', 'Bold', 'Brave',
'Cautious', 'Charismatic', 'Charitable', 'Cheerful', 'Communal', 'Community-
leader', 'Community-minded', 'Community-oriented', 'Compassionate',
'Conservative', 'Courageous', 'Creative', 'Cultural', 'Cultured', 'Curiosity',
'Curious', 'Cynical', 'Devout', 'Diligent', 'Discipline', 'Distrustful',
'Dutiful', 'Empathetic', 'Energetic', 'Faithful', 'Family-Oriented', 'Family-
oriented', 'Fatalism', 'Fatalistic', 'Forgetful', 'Frugal', 'Frugality',
'Generosity', 'Generous', 'Gentle', 'Gossipy', 'Gruff', 'Hardworking', 'Honest',
'Honorable', 'Hospitable', 'Hospitality', 'Hot-tempered', 'Humble', 'Humorous',
'Idealistic', 'Independence', 'Independent', 'Integrity', 'Intellectual',
'Intellectualism', 'Introverted', 'Kind', 'Loving', 'Loyal', 'Melancholic',
'Mistrustful', 'Modest', 'Modesty', 'Nonconformist', 'Nurturing', 'Open-minded',
'Optimistic', 'Organized', 'Outspoken', 'Patient', 'Pessimistic', 'Piety',
'Pious', 'Practical', 'Pragmatic', 'Pragmatism', 'Pride', 'Prideful',
'Principled', 'Privacy', 'Private', 'Progressive', 'Protective', 'Proud',
'Quiet', 'Reflective', 'Religious', 'Reserved', 'Resilience', 'Resilient',
'Resourceful', 'Respect for tradition', 'Respectful', 'Responsibility',
'Skeptical', 'Skepticism', 'Sociable', 'Stoic', 'Stoicism', 'Storyteller',
'Stubborn', 'Superstitious', 'Suspicious', 'Talkative', 'Thoughtful',
'Tolerance', 'Traditional', 'Traditionalism', 'Trusting', 'Warm', 'Warmth',
'Wise', 'Withdrawn', 'Witty', 'charitable', 'devout', 'distrustful',
'empathetic', 'fair', 'fatalistic', 'generous', 'hardworking', 'honest',
'hospitable', 'idealistic', 'intellectual', 'learned', 'modest', 'nostalgic',
'patient', 'principled', 'private', 'proud', 'resilient', 'stoic', 'stubborn',
'superstitious', 'traditional']
```




```
================================================================================
====================
CROSS-TABULATION: Religion vs Religiosity Level
================================================================================
====================
religiosity_level  Average  High  Low  All
religion_and_sect
Christian                3     1    0    4
Jewish                   7     4    0   11
Shia Muslim             66    45   15  126
Sunni Muslim            26    25    3   54
Zoroastrian              5     0    0    5
All                    107    75   18  200

================================================================================
====================
CROSS-TABULATION: Ethnicity vs Language
================================================================================
====================
language     Arabic  Azeri  Balochi  Gilaki  Kurdish  Luri  Mazandarani  Persian
Qashqai  Turkmen  All
ethnicity
Arab             12      0        0       0        0     0            0        0
0         0   12
Azeri             0     21        0       0        0     0            0        0
```

```
0         0   21
Baloch              0       0        18        0         0      0            0         0
0         0   18
Gilaki              0       0         0       12         0      0            0         0
0         0   12
Kurdish             0       0         0        0        21      0            0         0
0         0   21
Lur                 0       0         0        0         0     18            0         0
0         0   18
Mazandarani         0       0         0        0         0      0           17         0
0         0   17
Persian             0       0         0        0         0      0            0        56
0         0   56
Qashqai             0       0         0        0         0      0            0         0
11         0   11
Turkmen             0       0         0        0         0      0            0         0
0        14   14
All                12      21        18       12        21     18           17        56
11        14  200
```

1.10 10. Contextual Component Analysis

[48]:
```python
# Contextual component variables (excluding list variables)
context_vars = ['life_satisfaction', 'meaning_and_purpose_in_old_age']

print("=" * 100)
print("CONTEXTUAL COMPONENT - COMPLETE ANALYSIS")
print("=" * 100)

# Analyze each contextual variable
for var in context_vars:
    print(f"\n{'=' * 100}")
    print(f"{var.upper()}")
    print(f"{'=' * 100}")

    # Clean data: remove None/NaN values
    clean_data = df[var].dropna()

    print(f"Total responses: {len(clean_data)} (Missing: {df[var].isnull().
 ↪sum()})")
    print(f"\nValue counts:")
    value_counts = clean_data.value_counts()
    value_pct = clean_data.value_counts(normalize=True) * 100

    for value, count in value_counts.items():
        print(f"  {value}: {count} ({value_pct[value]:.2f}%)")
```

```
    print(f"\nUnique values: {clean_data.nunique()}")
    print(f"Available values: {sorted(clean_data.unique().tolist())}")

# PERSONAL EXPERIENCES ANALYSIS (List variable)
print("\n" + "=" * 100)
print("PERSONAL EXPERIENCES (LIST VARIABLE)")
print("=" * 100)

# Extract all personal experiences from lists
all_personal_experiences = []
for exp_list in df['important_personal_experiences'].dropna():
    if isinstance(exp_list, list):
        all_personal_experiences.extend(exp_list)

if all_personal_experiences:
    exp_counts = Counter(all_personal_experiences)
    print(f"Total personal experience entries: {len(all_personal_experiences)}")
    print(f"Unique personal experiences: {len(exp_counts)}")
    print(f"\nPersonal experiences frequency:")
    for exp, count in exp_counts.most_common():
        pct = (count / len(all_personal_experiences)) * 100
        print(f"  {exp}: {count} ({pct:.2f}%)")
    print(f"\nAll unique personal experiences: {sorted(exp_counts.keys())}")

# HISTORICAL EVENTS ANALYSIS (List variable)
print("\n" + "=" * 100)
print("HISTORICAL EVENTS (LIST VARIABLE)")
print("=" * 100)

# Visualizations
fig, axes = plt.subplots(1, 3, figsize=(20, 6))

# Life Satisfaction
clean_data = df['life_satisfaction'].dropna()
value_counts = clean_data.value_counts()
axes[0].bar(range(len(value_counts)), value_counts.values,
              color=sns.color_palette('Set1', len(value_counts)))
axes[0].set_xticks(range(len(value_counts)))
axes[0].set_xticklabels(value_counts.index, rotation=45, ha='right', fontsize=9)
axes[0].set_ylabel('Frequency', fontsize=10)
axes[0].set_title('Life Satisfaction', fontsize=12, fontweight='bold')
axes[0].grid(True, alpha=0.3, axis='y')
for i, v in enumerate(value_counts.values):
    axes[0].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

# Meaning and Purpose
clean_data = df['meaning_and_purpose_in_old_age'].dropna()
```

```python
value_counts = clean_data.value_counts()
axes[1].bar(range(len(value_counts)), value_counts.values,
              color=sns.color_palette('Set2', len(value_counts)))
axes[1].set_xticks(range(len(value_counts)))
axes[1].set_xticklabels(value_counts.index, rotation=45, ha='right', fontsize=9)
axes[1].set_ylabel('Frequency', fontsize=10)
axes[1].set_title('Meaning and Purpose', fontsize=12, fontweight='bold')
axes[1].grid(True, alpha=0.3, axis='y')
for i, v in enumerate(value_counts.values):
    axes[1].text(i, v, str(v), ha='center', va='bottom', fontsize=9)

# Personal Experiences
if all_personal_experiences:
    exp_counts_series = pd.Series(exp_counts).sort_values(ascending=False).
 ↪head(10)
    axes[2].barh(range(len(exp_counts_series)), exp_counts_series.values,
                   color=sns.color_palette('viridis', len(exp_counts_series)))
    axes[2].set_yticks(range(len(exp_counts_series)))
    axes[2].set_yticklabels(exp_counts_series.index, fontsize=9)
    axes[2].set_xlabel('Frequency', fontsize=10)
    axes[2].set_title('Top 10 Personal Experiences', fontsize=12,␣
 ↪fontweight='bold')
    axes[2].grid(True, alpha=0.3, axis='x')
    axes[2].invert_yaxis()


plt.tight_layout()
plt.show()

# Cross-tabulation: Life Satisfaction vs Meaning and Purpose
print("\n" + "=" * 100)
print("CROSS-TABULATION: Life Satisfaction vs Meaning and Purpose")
print("=" * 100)
crosstab = pd.crosstab(df['life_satisfaction'],␣
 ↪df['meaning_and_purpose_in_old_age'], margins=True)
print(crosstab.to_string())
```

```
================================================================================
====================
CONTEXTUAL COMPONENT - COMPLETE ANALYSIS
================================================================================
====================

================================================================================
====================
LIFE_SATISFACTION
================================================================================
```

```
====================
Total responses: 200 (Missing: 0)

Value counts:
  Satisfied: 81 (40.50%)
  Neutral: 68 (34.00%)
  Dissatisfied: 51 (25.50%)

Unique values: 3
Available values: ['Dissatisfied', 'Neutral', 'Satisfied']

================================================================================
====================
MEANING_AND_PURPOSE_IN_OLD_AGE
================================================================================
====================
Total responses: 200 (Missing: 0)

Value counts:
  Helping Family: 106 (53.00%)
  Spiritual Activities: 45 (22.50%)
  Waiting for Death: 35 (17.50%)
  Pleasure-Seeking: 13 (6.50%)
  Meaning-Seeking: 1 (0.50%)

Unique values: 5
Available values: ['Helping Family', 'Meaning-Seeking', 'Pleasure-Seeking',
'Spiritual Activities', 'Waiting for Death']

================================================================================
====================
PERSONAL EXPERIENCES (LIST VARIABLE)
================================================================================
====================
Total personal experience entries: 129
Unique personal experiences: 8

Personal experiences frequency:
  Loss of Loved Ones: 29 (22.48%)
  Economic Hardship: 26 (20.16%)
  Educational Achievement: 22 (17.05%)
  Career Success: 21 (16.28%)
  War Experience: 17 (13.18%)
  Battle with Serious Illness (e.g., Cancer, Chronic Disease): 6 (4.65%)
  Immigration: 6 (4.65%)
  Battle with Serious Illness: 2 (1.55%)

All unique personal experiences: ['Battle with Serious Illness', 'Battle with
```

```
Serious Illness (e.g., Cancer, Chronic Disease)', 'Career Success', 'Economic
Hardship', 'Educational Achievement', 'Immigration', 'Loss of Loved Ones', 'War
Experience']

================================================================================
====================
HISTORICAL EVENTS (LIST VARIABLE)
================================================================================
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```

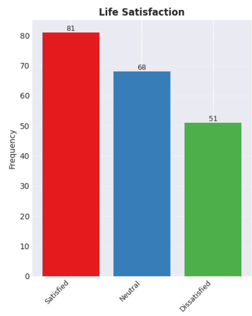

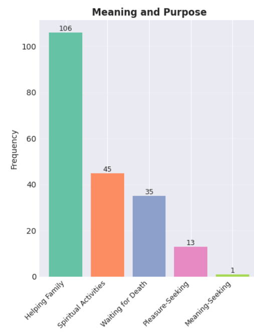

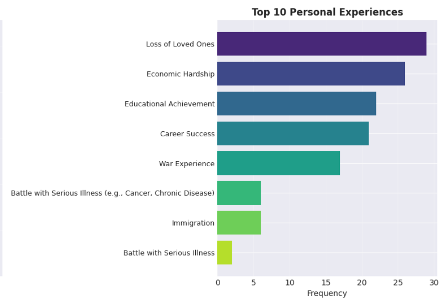


```
================================================================================
====================
CROSS-TABULATION: Life Satisfaction vs Meaning and Purpose
================================================================================
====================
meaning_and_purpose_in_old_age  Helping Family  Meaning-Seeking  Pleasure-
Seeking  Spiritual Activities  Waiting for Death  All
life_satisfaction
Dissatisfied                                11                0
3                     10                  27   51
Neutral                                     36                0
2                     22                   8   68
Satisfied                                   59                1
8                     13                   0   81
All                                        106                1
13                     45                  35  200
```