assignment3

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1 Author

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- Repository: https://github.com/HuberNicolas/python-data-processing-uts

2 Source

https://www.kaggle.com/datasets/mexwell/drug-consumption-classification

[1]:
```
# Imports

import random
import sys

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import plotly.graph_objects as go
import seaborn as sns
from scipy.stats import pearsonr
```

[2]:
```
# Constants
PATH = './data/drug_consumption.csv'
```

[3]:
```
# Dev variables
DEV = False
DEV_FRACTION = 0.01
RANDOM_STATE = 31011997
np.random.seed(RANDOM_STATE)
```

[4]:
```
# Explicitly define the order of the target column values
CATEGORIES_ORDER = ['cl0', 'cl1', 'cl2', 'cl3', 'cl4', 'cl5', 'cl6']
```

[5]:
```
# Mapping categories based on source
CATEGORIES = {
    'cl0': 'Never Used',
```

```
    'cl1': 'Used over a Decade Ago',
    'cl2': 'Used in Last Decade',
    'cl3': 'Used in Last Year',
    'cl4': 'Used in Last Month',
    'cl5': 'Used in Last Week',
    'cl6': 'Used in Last Day'
}
```

[6]:
```
COLUMNS_TYPE = {
    'ID': int,
    'Age': float,
    'Gender': float,
    'Education': float,
    'Country': float,
    'Ethnicity': float,
    'Nscore': float,
    'Escore': float,
    'Oscore': float,
    'Ascore': float,
    'Cscore': float,
    'Impulsive': float,
    'SS': float,
    'Alcohol': str,
    'Amphet': str,
    'Amyl': str,
    'Benzos': str,
    'Caff': str,
    'Cannabis': str,
    'Choc': str,
    'Coke': str,
    'Crack': str,
    'Ecstasy': str,
    'Heroin': str,
    'Ketamine': str,
    'Legalh': str,
    'LSD': str,
    'Meth': str,
    'Mushrooms': str,
    'Nicotine': str,
    'Semer': str,
    'VSA': str
}
```

[7]:
```
# Define columns for better clarity
RENAME_COLUMNS = {
    # Big Five
    # https://en.wikipedia.org/wiki/Big_Five_personality_traits
```

```
    'Nscore': 'Neuroticism_score',
    'Escore': 'Extraversion_score',
    'Oscore': 'Openness_score',
    'Ascore': 'Agreeableness_score',
    'Cscore': 'Conscientiousness_score',

    'Impulsive': 'Impulsive_score',
    'SS': 'Sensation_seeing_score'
}
```

3 Preparation: Load data

[8]:
```
# Load data
try:
    df = pd.read_csv(filepath_or_buffer=PATH, header=0)
except FileNotFoundError:
    print('The specified file path does not exist.')
except Exception as e:
    print(f'An unexpected error occurred: {e}')
```

[9]:
```
# For efficiency, using during development only
if DEV:
    # in dev mode, we reduce the data set quantity by sampling 10% to ease␣
 ↪development speed
    df = df.sample(frac=DEV_FRACTION, random_state=RANDOM_STATE)
else:
    pass
```

[10]:
```
# Display top rows
df.head(n=5)
```

[10]:
```
   ID      Age   Gender  Education  Country  Ethnicity   Nscore   Escore  \
0   1  0.49788  0.48246   -0.05921  0.96082    0.12600  0.31287 -0.57545
1   2 -0.07854 -0.48246    1.98437  0.96082   -0.31685 -0.67825  1.93886
2   3  0.49788 -0.48246   -0.05921  0.96082   -0.31685 -0.46725  0.80523
3   4 -0.95197  0.48246    1.16365  0.96082   -0.31685 -0.14882 -0.80615
4   5  0.49788  0.48246    1.98437  0.96082   -0.31685  0.73545 -1.63340

    Oscore   Ascore  …  Ecstasy Heroin  Ketamine Legalh  LSD Meth  \
0 -0.58331 -0.91699  …      CL0    CL0       CL0    CL0  CL0  CL0
1  1.43533  0.76096  …      CL4    CL0       CL2    CL0  CL2  CL3
2 -0.84732 -1.62090  …      CL0    CL0       CL0    CL0  CL0  CL0
3 -0.01928  0.59042  …      CL0    CL0       CL2    CL0  CL0  CL0
4 -0.45174 -0.30172  …      CL1    CL0       CL0    CL1  CL0  CL0

  Mushrooms Nicotine Semer  VSA
```

```
0        CL0       CL2    CL0   CL0
1        CL0       CL4    CL0   CL0
2        CL1       CL0    CL0   CL0
3        CL0       CL2    CL0   CL0
4        CL2       CL2    CL0   CL0

[5 rows x 32 columns]
```

3.1 Preprocessing

[11]:
```
# Defining and Applying Mappings: df values as keys will be mapped to values
# Using 'Attribute Information' on the Source Page: https://www.kaggle.com/
 ↪datasets/mexwell/drug-consumption-classification
```

3.1.1 Extract Mapping Information

[12]:
```
# Define the mapping for age values
age_mapping = {
    -0.95197: '18 - 24',
    -0.07854: '25 - 34',
    0.49788: '35 - 44',
    1.09449: '45 - 54',
    1.82213: '55 - 64',
    2.59171: '65+'
}
```

[13]:
```
# Define the mapping for gender values
gender_mapping = {
    0.48246: 'Female',
    -0.48246: 'Male'
}
```

[14]:
```
# Define the mapping for education values
education_mapping = {
    -2.43591: 'Left School Before 16 years',
    -1.73790: 'Left School at 16 years',
    -1.43719: 'Left School at 17 years',
    -1.22751: 'Left School at 18 years',
    -0.61113: 'Some College, No Certificate Or Degree',
    -0.05921: 'Professional Certificate/Diploma',
    0.45468: 'University Degree',
    1.16365: 'Masters Degree',
    1.98437: 'Doctorate Degree'
}
```

[15]:
```
# Define the mapping for country values
country_mapping = {
```

```
    -0.09765: 'Australia',
    0.24923: 'Canada',
    -0.46841: 'New Zealand',
    -0.28519: 'Other',
    0.21128: 'Republic of Ireland',
    0.96082: 'UK',
    -0.57009: 'USA'
}
```

[16]:
```
# Define the mapping for ethnicity values
ethnicity_mapping = {
    -0.50212: 'Asian',
    -1.10702: 'Black',
    1.90725: 'Mixed-Black/Asian',
    0.12600: 'Mixed-White/Asian',
    -0.22166: 'Mixed-White/Black',
    0.11440: 'Other',
    -0.31685: 'White'
}
```

[17]:
```
# Define the mapping for Nscore values
nscore_mapping = {
    -3.46436: 12,
    -3.15735: 13,
    -2.75696: 14,
    -2.52197: 15,
    -2.42317: 16,
    -2.34360: 17,
    -2.21844: 18,
    -2.05048: 19,
    -1.86962: 20,
    -1.69163: 21,
    -1.55078: 22,
    -1.43907: 23,
    -1.32828: 24,
    -1.19430: 25,
    -1.05308: 26,
    -0.92104: 27,
    -0.79151: 28,
    -0.67825: 29,
    -0.58016: 30,
    -0.46725: 31,
    -0.34799: 32,
    -0.24649: 33,
    -0.14882: 34,
    -0.05188: 35,
    0.04257: 36,
```

```
    0.13606: 37,
    0.22393: 38,
    0.31287: 39,
    0.41667: 40,
    0.52135: 41,
    0.62967: 42,
    0.73545: 43,
    0.82562: 44,
    0.91093: 45,
    1.02119: 46,
    1.13281: 47,
    1.23461: 48,
    1.37297: 49,
    1.49158: 50,
    1.60383: 51,
    1.72012: 52,
    1.83990: 53,
    1.98437: 54,
    2.12700: 55,
    2.28554: 56,
    2.46262: 57,
    2.61139: 58,
    2.82196: 59,
    3.27393: 60
}
```

[18]:
```
# Define the mapping for Escore values
escore_mapping = {
    -3.27393: 16,
    -3.00537: 17,
    -2.72827: 19,
    -2.53830: 20,
    -2.44904: 21,
    -2.32338: 22,
    -2.21069: 23,
    -2.11437: 24,
    -2.03972: 25,
    -1.92173: 26,
    -1.76250: 27,
    -1.63340: 28,
    -1.50796: 29,
    -1.37639: 30,
    -1.23177: 31,
    -1.09207: 32,
    -0.94779: 33,
    -0.80615: 34,
    -0.69509: 35,
```

```
    -0.57545: 36,
    -0.43999: 37,
    -0.30033: 38,
    -0.15487: 39,
    0.00332: 40,
    0.16767: 41,
    0.32197: 42,
    0.47617: 43,
    0.63779: 44,
    0.80523: 45,
    0.96248: 46,
    1.11406: 47,
    1.28610: 48,
    1.45421: 49,
    1.58487: 50,
    1.74091: 51,
    1.93886: 52,
    2.12700: 53,
    2.32338: 54,
    2.57309: 55,
    2.85950: 56,
    3.00537: 58,
    3.27393: 59
}
```

[19]:
```
# Define the mapping for Oscore values
oscore_mapping = {
    -3.27393: 24,
    -2.85950: 26,
    -2.63199: 28,
    -2.39883: 29,
    -2.21069: 30,
    -2.09015: 31,
    -1.97495: 32,
    -1.82919: 33,
    -1.68062: 34,
    -1.55521: 35,
    -1.42424: 36,
    -1.27553: 37,
    -1.11902: 38,
    -0.97631: 39,
    -0.84732: 40,
    -0.71727: 41,
    -0.58331: 42,
    -0.45174: 43,
    -0.31776: 44,
    -0.17779: 45,
```

```
    -0.01928: 46,
    0.14143: 47,
    0.29338: 48,
    0.44585: 49,
    0.58331: 50,
    0.72330: 51,
    0.88309: 52,
    1.06238: 53,
    1.24033: 54,
    1.43533: 55,
    1.65653: 56,
    1.88511: 57,
    1.15324: 58,
    2.44904: 59,
    2.90161: 60
}
```

[20]:

```
# Define the mapping for Ascore values
ascore_mapping = {
    -3.46436: 12,
    -3.15735: 16,
    -3.00537: 18,
    -2.90161: 23,
    -2.78793: 24,
    -2.70172: 25,
    -2.53830: 26,
    -2.35413: 27,
    -2.21844: 28,
    -2.07848: 29,
    -1.92595: 30,
    -1.77200: 31,
    -1.62090: 32,
    -1.47955: 33,
    -1.34289: 34,
    -1.21213: 35,
    -1.07533: 36,
    -0.91699: 37,
    -0.76096: 38,
    -0.60633: 39,
    -0.45321: 40,
    -0.30172: 41,
    -0.15487: 42,
    -0.01729: 43,
    0.13136: 44,
    0.28783: 45,
    0.43852: 46,
    0.59042: 47,
```

```
    0.76096: 48,
    0.94156: 49,
    1.11406: 50,
    1.28610: 51,
    1.45039: 52,
    1.61108: 53,
    1.81866: 54,
    2.03972: 55,
    2.23427: 56,
    2.46262: 57,
    2.75696: 58,
    3.15735: 59,
    3.46436: 60
}
```

[21]:

```
# Define the mapping for Cscore values
cscore_mapping = {
    -3.46436: 17,
    -3.15735: 19,
    -2.90161: 20,
    -2.72827: 21,
    -2.57309: 22,
    -2.42317: 23,
    -2.30408: 24,
    -2.18109: 25,
    -2.04506: 26,
    -1.92173: 27,
    -1.78169: 28,
    -1.64101: 29,
    -1.51840: 30,
    -1.38502: 31,
    -1.25773: 32,
    -1.13788: 33,
    -1.01450: 34,
    -0.89891: 35,
    -0.78155: 36,
    -0.65253: 37,
    -0.52745: 38,
    -0.40581: 39,
    -0.27607: 40,
    -0.14277: 41,
    -0.00665: 42,
    0.12331: 43,
    0.25953: 44,
    0.41594: 45,
    0.58489: 46,
    0.75830: 47,
```

```
    0.93949: 48,
    1.13407: 49,
    1.30612: 50,
    1.46191: 51,
    1.63088: 52,
    1.81175: 53,
    2.04506: 54,
    2.33337: 55,
    2.63199: 56,
    3.00537: 57,
    3.46436: 59
}
```

[22]:
```
# Define the mapping for impulsiveness values
impulsive_mapping = {
    -2.55524: 20,
    -1.37983: 276,
    -0.71126: 307,
    -0.21712: 355,
    0.19268: 257,
    0.52975: 216,
    0.88113: 195,
    1.29221: 148,
    1.86203: 104,
    2.90161: 7
}
```

[23]:
```
# Define the mapping for sensation values
sensation_mapping = {
    -2.07848: 71,
    -1.54858: 87,
    -1.18084: 132,
    -0.84637: 169,
    -0.52593: 211,
    -0.21575: 223,
    0.07987: 219,
    0.40148: 249,
    0.76540: 211,
    1.22470: 210,
    1.92173: 103
}
```

[24]:
```
# Define the mapping for drug use values
drug_use_mapping = {
    'CL0': 'Never Used',
    'CL1': 'Used over a Decade Ago',
    'CL2': 'Used in Last Decade',
```

```python
    'CL3': 'Used in Last Year',
    'CL4': 'Used in Last Month',
    'CL5': 'Used in Last Week',
    'CL6': 'Used in Last Day'
}

# List of columns that need this mapping
drug_columns = [
    'Alcohol', 'Amphet', 'Amyl', 'Benzos', 'Cannabis', 'Choc', 'Coke', 'Caff',
    'Crack', 'Ecstasy', 'Heroin', 'Ketamine', 'Legalh', 'LSD', 'Meth',
    'Mushrooms', 'Nicotine', 'Semer', 'VSA'
]
```

[25]:
```python
mappings = {
    'age_values': age_mapping,
    'gender_values': gender_mapping,
    'education_values': education_mapping,
    'country_values': country_mapping,
    'ethnicity_values': ethnicity_mapping
}
```

3.1.2 Apply Mapping Information

[26]:
```python
# Create the 'age_values' column using the mapping
df['age_values'] = df['Age'].map(age_mapping)
```

[27]:
```python
# Create the 'gender_values' column using the mapping
df['gender_values'] = df['Gender'].map(gender_mapping)
```

[28]:
```python
# Create the 'education_values' column using the mapping
df['education_values'] = df['Education'].map(education_mapping)
```

[29]:
```python
# Create the 'country_values' column using the mapping
df['country_values'] = df['Country'].map(country_mapping)
```

[30]:
```python
# Create the 'ethnicity_values' column using the mapping
df['ethnicity_values'] = df['Ethnicity'].map(ethnicity_mapping)
```

[31]:
```python
# Create the 'escore_values' column using the mapping
df['escore_values'] = df['Escore'].map(escore_mapping)
```

[32]:
```python
# Create the 'nscore_values' column using the mapping
df['nscore_values'] = df['Nscore'].map(nscore_mapping)
```

[33]:
```python
# Create the 'oscore_values' column using the mapping
df['oscore_values'] = df['Oscore'].map(oscore_mapping)
```

[34]:
```
# Create the 'ascore_values' column using the mapping
df['ascore_values'] = df['Ascore'].map(ascore_mapping)
```

[35]:
```
# Create the 'cscore_values' column using the mapping
df['cscore_values'] = df['Cscore'].map(cscore_mapping)
```

[36]:
```
# Create the 'impulsive_values' column using the mapping
df['impulsive_values'] = df['Impulsive'].map(impulsive_mapping)
```

[37]:
```
# Create the 'sensation_values' column using the mapping
df['sensation_values'] = df['SS'].map(sensation_mapping)
```

[38]:
```
# Apply the mapping to each of the drug columns
for col in drug_columns:
    df[f'{col}_values'] = df[col].map(drug_use_mapping)
```

[39]:
```
df.head()
```

[39]:
```
   ID      Age   Gender  Education  Country  Ethnicity   Nscore   Escore  \
0   1  0.49788  0.48246   -0.05921  0.96082    0.12600  0.31287 -0.57545
1   2 -0.07854 -0.48246    1.98437  0.96082   -0.31685 -0.67825  1.93886
2   3  0.49788 -0.48246   -0.05921  0.96082   -0.31685 -0.46725  0.80523
3   4 -0.95197  0.48246    1.16365  0.96082   -0.31685 -0.14882 -0.80615
4   5  0.49788  0.48246    1.98437  0.96082   -0.31685  0.73545 -1.63340

    Oscore   Ascore  …          Ecstasy_values Heroin_values  \
0 -0.58331 -0.91699  …              Never Used    Never Used
1  1.43533  0.76096  …      Used in Last Month    Never Used
2 -0.84732 -1.62090  …              Never Used    Never Used
3 -0.01928  0.59042  …              Never Used    Never Used
4 -0.45174 -0.30172  …  Used over a Decade Ago    Never Used

      Ketamine_values           Legalh_values           LSD_values  \
0          Never Used              Never Used           Never Used
1  Used in Last Decade             Never Used  Used in Last Decade
2          Never Used              Never Used           Never Used
3  Used in Last Decade             Never Used           Never Used
4          Never Used  Used over a Decade Ago           Never Used

         Meth_values        Mushrooms_values      Nicotine_values  \
0         Never Used              Never Used  Used in Last Decade
1  Used in Last Year              Never Used   Used in Last Month
2         Never Used  Used over a Decade Ago           Never Used
3         Never Used              Never Used  Used in Last Decade
4         Never Used     Used in Last Decade  Used in Last Decade

  Semer_values  VSA_values
```

```
0   Never Used  Never Used
1   Never Used  Never Used
2   Never Used  Never Used
3   Never Used  Never Used
4   Never Used  Never Used

[5 rows x 63 columns]
```

[40]:

```python
# Backup the df using a deepcopy
df_orig = df.copy(deep=True)
```

3.1.3 Filtering Columns

[41]:

```python
# Creating a list of columns to include
columns_to_include = ['ID'] + list(df.columns[df.columns.get_loc('VSA') + 1:])

# Creating a new df with the selected columns
df = df[columns_to_include]
print(df)
```

```
        ID age_values gender_values                         education_values  \
0        1    35 - 44        Female       Professional Certificate/Diploma
1        2    25 - 34          Male                      Doctorate Degree
2        3    35 - 44          Male       Professional Certificate/Diploma
3        4    18 - 24        Female                        Masters Degree
4        5    35 - 44        Female                      Doctorate Degree
…     …        …           …                                       …
1880  1884    18 - 24        Female  Some College, No Certificate Or Degree
1881  1885    18 - 24          Male  Some College, No Certificate Or Degree
1882  1886    25 - 34        Female                     University Degree
1883  1887    18 - 24        Female  Some College, No Certificate Or Degree
1884  1888    18 - 24          Male  Some College, No Certificate Or Degree

           country_values   ethnicity_values  escore_values  nscore_values  \
0                      UK  Mixed-White/Asian             36             39
1                      UK              White             52             29
2                      UK              White             45             31
3                      UK              White             34             34
4                      UK              White             28             43
…                    …                  …             …              …
1880                  USA              White             51             25
1881                  USA              White             51             33
1882                  USA              White             30             47
1883                  USA              White             26             45
1884  Republic of Ireland              White             53             31

      oscore_values  ascore_values  …          Ecstasy_values  \
0              42.0             37  …              Never Used
```

```
1             55.0              48  …      Used in Last Month
2             40.0              32  …              Never Used
3             46.0              47  …              Never Used
4             43.0              41  …  Used over a Decade Ago
…              …             …   …                     …
1880          57.0              48  …              Never Used
1881          50.0              48  …     Used in Last Decade
1882          37.0              31  …      Used in Last Month
1883          48.0              32  …       Used in Last Year
1884          56.0              50  …       Used in Last Year

     Heroin_values      Ketamine_values           Legalh_values  \
0       Never Used           Never Used              Never Used
1       Never Used  Used in Last Decade              Never Used
2       Never Used           Never Used              Never Used
3       Never Used  Used in Last Decade              Never Used
4       Never Used           Never Used  Used over a Decade Ago
…              …                  …                       …
1880    Never Used           Never Used       Used in Last Year
1881    Never Used           Never Used       Used in Last Year
1882    Never Used  Used in Last Decade              Never Used
1883    Never Used           Never Used       Used in Last Year
1884    Never Used           Never Used       Used in Last Year

              LSD_values         Meth_values        Mushrooms_values  \
0             Never Used          Never Used              Never Used
1    Used in Last Decade   Used in Last Year              Never Used
2             Never Used          Never Used  Used over a Decade Ago
3             Never Used          Never Used              Never Used
4             Never Used          Never Used     Used in Last Decade
…                    …                   …                       …
1880   Used in Last Year          Never Used              Never Used
1881   Used in Last Week  Used in Last Month      Used in Last Month
1882 Used in Last Decade          Never Used     Used in Last Decade
1883   Used in Last Year          Never Used       Used in Last Year
1884   Used in Last Year          Never Used       Used in Last Year

        Nicotine_values Semer_values          VSA_values
0    Used in Last Decade   Never Used          Never Used
1     Used in Last Month   Never Used          Never Used
2             Never Used   Never Used          Never Used
3    Used in Last Decade   Never Used          Never Used
4    Used in Last Decade   Never Used          Never Used
…                    …          …                   …
1880          Never Used   Never Used   Used in Last Week
1881   Used in Last Week   Never Used          Never Used
1882     Used in Last Day   Never Used          Never Used
1883  Used in Last Month   Never Used          Never Used
```

```
1884     Used in Last Day   Never Used  Used in Last Decade

[1885 rows x 32 columns]
```

3.1.4 Artificially introduce defects

[42]:
```
# Parameters for artificially defile the df
NUM_MISSING_COLUMNS = 4
NUM_OUTLIER_COLUMNS = 2

NUM_MISSING_VALUES_PER_ROW = 10
NUM_DUPLICATES_PER_ROW = 10
NUM_OUTLIERS_PER_ROW = 10
OUTLIERS_VARIATION = 3
```

[43]:
```
# Randomly select columns
# missing_columns = random.choices(df.columns, k=NUM_MISSING_COLUMNS)

# Hardcode candidates for missing values to make it more consistent
missing_columns = ['nscore_values', 'escore_values', 'oscore_values',␣
↪'ascore_values', 'cscore_values',
                   'impulsive_values', 'sensation_values']
missing_columns
```

[43]:
```
['nscore_values',
 'escore_values',
 'oscore_values',
 'ascore_values',
 'cscore_values',
 'impulsive_values',
 'sensation_values']
```

[44]:
```
# Define columns for outlier values
outlier_columns = random.choices(
    ['nscore_values', 'escore_values', 'oscore_values', 'ascore_values',␣
↪'cscore_values', 'impulsive_values',
     'sensation_values'], k=NUM_OUTLIER_COLUMNS)
outlier_columns
```

[44]:
```
['escore_values', 'sensation_values']
```

[45]:
```
# Missing value function
def introduce_missing_values(df, columns, num_missing, random_state=None):
    np.random.seed(random_state)
    df_copy = df.copy()

    for col in columns:
```

```
        missing_indices = np.random.choice(df_copy.index, num_missing,␣
↪replace=False)
        if df_copy[col].dtype == 'object':
            df_copy.loc[missing_indices, col] = ''
        else:
            df_copy.loc[missing_indices, col] = np.nan

    return df_copy
```

[46]:
```
# Artificially introduce missing values
df = introduce_missing_values(df, columns=missing_columns,␣
↪num_missing=NUM_MISSING_VALUES_PER_ROW,
                              random_state=RANDOM_STATE)
```

[47]:
```
def introduce_outliers(df, columns, num_outliers, variation=0,␣
↪random_state=None):
    np.random.seed(random_state)
    df_copy = df.copy()

    for col in columns:
        outlier_count = np.random.randint(max(0, num_outliers - variation),␣
↪num_outliers + variation + 1)
        outlier_indices = np.random.choice(df_copy.index, outlier_count,␣
↪replace=False)

        mean = df_copy[col].mean()
        std_dev = df_copy[col].std()

        # Introduce outliers as values far from the mean
        outliers = np.random.choice([mean + 3 * std_dev, mean - 3 * std_dev],␣
↪outlier_count)

        # Cast outliers to the same dtype as the column
        outliers = outliers.astype(df_copy[col].dtype)

        df_copy.loc[outlier_indices, col] = outliers

    return df_copy
```

[48]:
```
# Artificially introduce outliers
df = introduce_outliers(df, columns=outlier_columns,␣
↪num_outliers=NUM_OUTLIERS_PER_ROW, variation=OUTLIERS_VARIATION,
                        random_state=RANDOM_STATE)
```

[49]:
```
# Check how many rows were duplicated
df.shape
```

[49]: (1885, 32)

[50]:
```
def introduce_duplicate_rows(df, num_duplicates, random_state=None):
    np.random.seed(random_state)
    df_copy = df.copy()

    duplicate_indices = np.random.choice(df_copy.index, num_duplicates)
    duplicate_rows = df_copy.loc[duplicate_indices]
    df_copy = pd.concat([df_copy, duplicate_rows], ignore_index=True)

    return df_copy
```

[51]:
```
# Artificially introduce duplicates
df = introduce_duplicate_rows(df, num_duplicates=NUM_DUPLICATES_PER_ROW,␣
 ↪random_state=RANDOM_STATE)
```

[52]:
```
# Check how many rows were duplicated
df.shape
```

[52]: (1895, 32)

[53]:
```
df
```

[53]:
```
        ID age_values gender_values                    education_values  \
0        1    35 - 44        Female  Professional Certificate/Diploma
1        2    25 - 34          Male                    Doctorate Degree
2        3    35 - 44          Male  Professional Certificate/Diploma
3        4    18 - 24        Female                      Masters Degree
4        5    35 - 44        Female                    Doctorate Degree
…     …          …             …                                   …
1890   848    18 - 24        Female  Professional Certificate/Diploma
1891  1407    25 - 34        Female                   University Degree
1892   143    35 - 44          Male             Left School at 17 years
1893    37    35 - 44          Male                   University Degree
1894  1746    25 - 34        Female             Left School at 16 years

     country_values   ethnicity_values  escore_values  nscore_values  \
0                UK  Mixed-White/Asian           36.0           39.0
1                UK              White           52.0           29.0
2                UK              White           45.0           31.0
3                UK              White           34.0           34.0
4                UK              White           28.0           43.0
…               …                 …             …             …
1890         Canada              White           37.0           41.0
1891             UK              White           36.0           38.0
1892             UK              White           38.0           31.0
1893             UK              White           36.0           33.0
```

```
1894             UK              White          46.0           20.0

      oscore_values  ascore_values  …          Ecstasy_values  \
0              42.0           37.0  …              Never Used
1              55.0           48.0  …      Used in Last Month
2              40.0           32.0  …              Never Used
3              46.0           47.0  …              Never Used
4              43.0           41.0  …  Used over a Decade Ago
…             …            …  …                     …
1890           35.0           50.0  …       Used in Last Year
1891           35.0           46.0  …              Never Used
1892           37.0           45.0  …              Never Used
1893           45.0           43.0  …              Never Used
1894           39.0           56.0  …              Never Used

      Heroin_values      Ketamine_values           Legalh_values  \
0        Never Used           Never Used              Never Used
1        Never Used  Used in Last Decade              Never Used
2        Never Used           Never Used              Never Used
3        Never Used  Used in Last Decade              Never Used
4        Never Used           Never Used  Used over a Decade Ago
…             …                  …                     …
1890     Never Used           Never Used              Never Used
1891     Never Used           Never Used              Never Used
1892     Never Used           Never Used              Never Used
1893     Never Used           Never Used              Never Used
1894     Never Used           Never Used              Never Used

               LSD_values        Meth_values        Mushrooms_values  \
0              Never Used         Never Used              Never Used
1     Used in Last Decade  Used in Last Year              Never Used
2              Never Used         Never Used  Used over a Decade Ago
3              Never Used         Never Used              Never Used
4              Never Used         Never Used     Used in Last Decade
…                   …                …                     …
1890           Never Used         Never Used     Used in Last Decade
1891           Never Used         Never Used              Never Used
1892           Never Used         Never Used              Never Used
1893           Never Used         Never Used              Never Used
1894           Never Used         Never Used              Never Used

          Nicotine_values Semer_values  VSA_values
0     Used in Last Decade   Never Used  Never Used
1      Used in Last Month   Never Used  Never Used
2              Never Used   Never Used  Never Used
3     Used in Last Decade   Never Used  Never Used
4     Used in Last Decade   Never Used  Never Used
```

```
…                  …           …           …
1890     Used in Last Day   Never Used  Never Used
1891    Used in Last Year   Never Used  Never Used
1892    Used in Last Year   Never Used  Never Used
1893           Never Used   Never Used  Never Used
1894     Used in Last Day   Never Used  Never Used

[1895 rows x 32 columns]
```

4 TASK 1: Resolve data quality issues using Python and relevant Python packages

4.1 TASK 1.1: Missing values

[54]:
```python
# Function to count NaN and empty string values per column
def count_nulls(column):
    try:
        nan_count = column.isna().sum()
        empty_string_count = (column == '').sum()
        total_nulls = nan_count + empty_string_count
        return nan_count, empty_string_count, total_nulls
    except Exception as e:
        print(f'Error processing column: {column.name} - {e}')
        return None, None, None
```

[55]:
```python
# Columns with missing values
columns_with_missing_values = []

# Demonstrating advanced proficiency in resolving intricate data quality issues

# Apply the function to each column and display results
for column_name in df.columns:
    nan_count, empty_string_count, total_nulls = count_nulls(df[column_name])
    if nan_count is not None and empty_string_count is not None:
        # print(f"{column_name}: NaN: {nan_count}, '': {empty_string_count},␣
 ↪total null values: {total_nulls}") # DEBUG
        if total_nulls > 0:
            columns_with_missing_values.append(column_name)

columns_with_missing_values
```

[55]:
```
['escore_values',
 'nscore_values',
 'oscore_values',
 'ascore_values',
 'cscore_values',
```

 'impulsive_values',
 'sensation_values']

[56]:
```python
# Convert empty strings to NaN
df.replace('', np.nan)

# Demonstrating advanced proficiency in resolving intricate data quality issues

# Function to impute missing values with the median
def impute_median(df, columns_with_missing_values):
    for col in columns_with_missing_values:
        # Convert to numeric type if necessary
        df[col] = pd.to_numeric(df[col], errors='coerce')
        median = df[col].median()
        df[col] = df[col].fillna(median)
    return df
```

[57]:
```python
# Apply the function to the df
df = impute_median(df, columns_with_missing_values)
df
```

[57]:
```
        ID age_values gender_values                    education_values  \
0        1    35 - 44        Female  Professional Certificate/Diploma
1        2    25 - 34          Male                   Doctorate Degree
2        3    35 - 44          Male  Professional Certificate/Diploma
3        4    18 - 24        Female                     Masters Degree
4        5    35 - 44        Female                   Doctorate Degree
…     …          …            …                                …
1890   848    18 - 24        Female  Professional Certificate/Diploma
1891  1407    25 - 34        Female                  University Degree
1892   143    35 - 44          Male              Left School at 17 years
1893    37    35 - 44          Male                  University Degree
1894  1746    25 - 34        Female              Left School at 16 years

     country_values   ethnicity_values  escore_values  nscore_values  \
0                UK  Mixed-White/Asian           36.0           39.0
1                UK              White           52.0           29.0
2                UK              White           45.0           31.0
3                UK              White           34.0           34.0
4                UK              White           28.0           43.0
…             …                    …            …              …
1890         Canada              White           37.0           41.0
1891             UK              White           36.0           38.0
1892             UK              White           38.0           31.0
1893             UK              White           36.0           33.0
1894             UK              White           46.0           20.0
```

```
      oscore_values  ascore_values  …           Ecstasy_values  \
0              42.0           37.0  …               Never Used
1              55.0           48.0  …       Used in Last Month
2              40.0           32.0  …               Never Used
3              46.0           47.0  …               Never Used
4              43.0           41.0  …  Used over a Decade Ago
…               …             …  …                     …
1890           35.0           50.0  …        Used in Last Year
1891           35.0           46.0  …               Never Used
1892           37.0           45.0  …               Never Used
1893           45.0           43.0  …               Never Used
1894           39.0           56.0  …               Never Used

      Heroin_values      Ketamine_values           Legalh_values  \
0        Never Used           Never Used              Never Used
1        Never Used  Used in Last Decade              Never Used
2        Never Used           Never Used              Never Used
3        Never Used  Used in Last Decade              Never Used
4        Never Used           Never Used  Used over a Decade Ago
…             …                   …                     …
1890     Never Used           Never Used              Never Used
1891     Never Used           Never Used              Never Used
1892     Never Used           Never Used              Never Used
1893     Never Used           Never Used              Never Used
1894     Never Used           Never Used              Never Used

               LSD_values        Meth_values        Mushrooms_values  \
0              Never Used         Never Used              Never Used
1     Used in Last Decade  Used in Last Year              Never Used
2              Never Used         Never Used  Used over a Decade Ago
3              Never Used         Never Used              Never Used
4              Never Used         Never Used     Used in Last Decade
…                    …                 …                     …
1890           Never Used         Never Used     Used in Last Decade
1891           Never Used         Never Used              Never Used
1892           Never Used         Never Used              Never Used
1893           Never Used         Never Used              Never Used
1894           Never Used         Never Used              Never Used

          Nicotine_values Semer_values  VSA_values
0     Used in Last Decade   Never Used  Never Used
1      Used in Last Month   Never Used  Never Used
2              Never Used   Never Used  Never Used
3     Used in Last Decade   Never Used  Never Used
4     Used in Last Decade   Never Used  Never Used
…                    …          …          …
1890     Used in Last Day   Never Used  Never Used
```

```
1891    Used in Last Year   Never Used  Never Used
1892    Used in Last Year   Never Used  Never Used
1893           Never Used   Never Used  Never Used
1894     Used in Last Day   Never Used  Never Used

[1895 rows x 32 columns]
```

4.2 TASK 1.2: Duplicate values

[58]:
```python
# Find duplicate rows
duplicate_rows = df.duplicated()
```

[59]:
```python
# Demonstrating advanced proficiency in resolving intricate data quality issues
# Displaying duplicate
if duplicate_rows.any():
    # Print all duplicate rows if there are any
    print('Duplicate Rows Found:')
    print(df[duplicate_rows])

    # Remove duplicate rows
    df = df.drop_duplicates()
    print('Duplicates removed.')
    print(df.shape)
else:
    # Inform the user that no duplicate rows were found
    print('No duplicate rows were found in the data.')  # Detailed and␣
 ↪informative display of key dataset information.
```

```
Duplicate Rows Found:
        ID age_values gender_values                         education_values  \
1885   528    55 - 64          Male                    Left School at 18 years
1886   230    45 - 54        Female                          University Degree
1887   613    25 - 34          Male                          University Degree
1888   831    18 - 24          Male  Some College, No Certificate Or Degree
1889   566    45 - 54        Female  Some College, No Certificate Or Degree
1890   848    18 - 24        Female        Professional Certificate/Diploma
1891  1407    25 - 34        Female                          University Degree
1892   143    35 - 44          Male                    Left School at 17 years
1893    37    35 - 44          Male                          University Degree
1894  1746    25 - 34        Female                    Left School at 16 years

     country_values ethnicity_values  escore_values  nscore_values  \
1885             UK            White           43.0           20.0
1886             UK            White           49.0           26.0
1887             UK            White           42.0           29.0
1888            USA            White           44.0           37.0
1889             UK            White           37.0           31.0
1890         Canada            White           37.0           41.0
```

```
1891           UK          White          36.0          38.0
1892           UK          White          38.0          31.0
1893           UK          White          36.0          33.0
1894           UK          White          46.0          20.0

     oscore_values  ascore_values  …    Ecstasy_values  Heroin_values  \
1885          38.0           43.0  …        Never Used     Never Used
1886          47.0           49.0  …        Never Used     Never Used
1887          42.0           51.0  …        Never Used     Never Used
1888          57.0           51.0  …  Used in Last Year     Never Used
1889          46.0           44.0  …        Never Used     Never Used
1890          35.0           50.0  …  Used in Last Year     Never Used
1891          35.0           46.0  …        Never Used     Never Used
1892          37.0           45.0  …        Never Used     Never Used
1893          45.0           43.0  …        Never Used     Never Used
1894          39.0           56.0  …        Never Used     Never Used

     Ketamine_values      Legalh_values         LSD_values Meth_values  \
1885      Never Used         Never Used         Never Used  Never Used
1886      Never Used         Never Used         Never Used  Never Used
1887      Never Used  Used in Last Year         Never Used  Never Used
1888      Never Used         Never Used  Used in Last Week  Never Used
1889      Never Used         Never Used         Never Used  Never Used
1890      Never Used         Never Used         Never Used  Never Used
1891      Never Used         Never Used         Never Used  Never Used
1892      Never Used         Never Used         Never Used  Never Used
1893      Never Used         Never Used         Never Used  Never Used
1894      Never Used         Never Used         Never Used  Never Used

           Mushrooms_values         Nicotine_values Semer_values  \
1885             Never Used  Used over a Decade Ago   Never Used
1886             Never Used              Never Used   Never Used
1887     Used in Last Decade        Used in Last Day   Never Used
1888             Never Used      Used in Last Month   Never Used
1889  Used over a Decade Ago        Used in Last Day   Never Used
1890     Used in Last Decade        Used in Last Day   Never Used
1891             Never Used       Used in Last Year   Never Used
1892             Never Used       Used in Last Year   Never Used
1893             Never Used              Never Used   Never Used
1894             Never Used        Used in Last Day   Never Used

                 VSA_values
1885             Never Used
1886             Never Used
1887     Used in Last Decade
1888             Never Used
1889  Used over a Decade Ago
1890             Never Used
```

```
1891             Never Used
1892             Never Used
1893             Never Used
1894             Never Used

[10 rows x 32 columns]
Duplicates removed.
(1885, 32)
```

4.3 TASK 1.3: Outliers

[60]:

```python
# Function to detect outliers using the IQR method
def detect_outliers(column):
    if pd.api.types.is_numeric_dtype(column):
        Q1 = column.quantile(0.25)
        Q3 = column.quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        return (column < lower_bound) | (column > upper_bound)
    return pd.Series([False] * len(column))
```

[61]:

```python
# Function to impute outliers with the median
def impute_outliers_with_median(df, columns_with_outliers):
    for col in columns_with_outliers:
        median = df[col].median()
        outliers = detect_outliers(df[col])
        df.loc[outliers, col] = median
        print(f'Imputed outliers in column "{col}" with the median value:␣
 ↪{median}')
    return df
```

[62]:

```python
# Main function to iterate over columns and process outliers
# Demonstrating advanced proficiency in resolving intricate data quality issues
def process_outliers(df):

    columns_with_outliers = []

    for col in df.columns:
        if detect_outliers(df[col]).any():
            columns_with_outliers.append(col)
            print(f'Outliers detected in column "{col}"')
        else:
            print('No outliers found in column "{col}"')

    if columns_with_outliers:
        pass
```

```
        # df = impute_outliers_with_median(df, columns_with_outliers)
    else:
        print('No outliers to impute.')

    return df
```

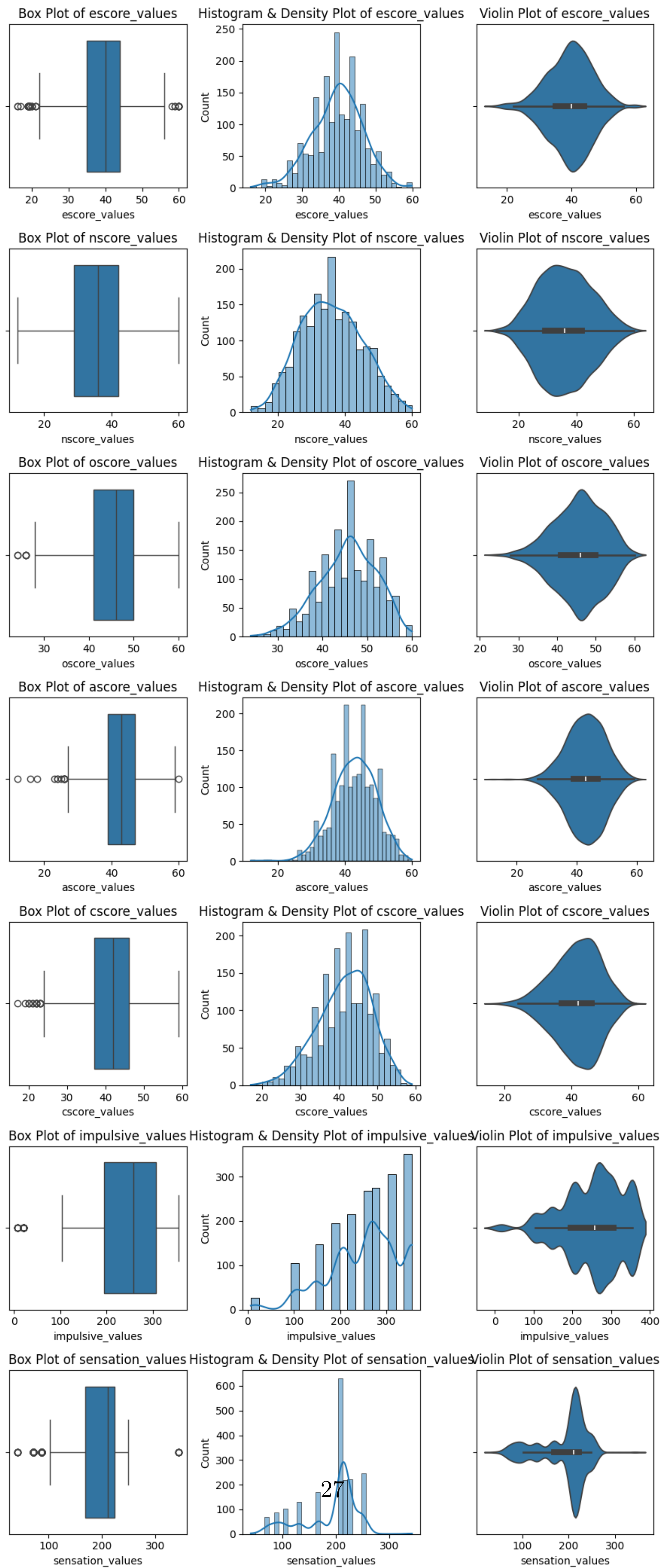
[63]:
```
df = process_outliers(df)
```

```
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
Outliers detected in column "escore_values"
No outliers found in column "{col}"
Outliers detected in column "oscore_values"
Outliers detected in column "ascore_values"
Outliers detected in column "cscore_values"
Outliers detected in column "impulsive_values"
Outliers detected in column "sensation_values"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
No outliers found in column "{col}"
```

[64]:
```
# Get the list of numeric columns
numeric_df = df.select_dtypes(include=[np.number])
numeric_columns = numeric_df.columns.tolist()

# Get the list of categorical columns
categorical_columns = ['age_values', 'gender_values', 'education_values',␣
↪'country_values', 'ethnicity_values']
```

```
# Remove ID column since this is not considered to be an attribute
numeric_columns.remove('ID')
```

[65]:
```
# Set up the subplots grid
num_plots = len(numeric_columns)
num_cols = 3  # Three types of plots for each column: Box, Histogram & Density,␣
 ↪Violin

# Calculate the number of rows needed for all types of plots for each column
num_rows = len(numeric_columns)  # One row for each column type of plot

fig, axes = plt.subplots(num_rows, num_cols, figsize=(num_cols * 3, num_rows *␣
 ↪3))

# Flatten the axes array to make iteration easier
axes = axes.flatten()

# Iterate over each numeric column and plot each type in a separate cell
for i, col in enumerate(numeric_columns):
    # Demonstrating advanced proficiency in resolving intricate data quality␣
 ↪issues
    # using a comprehensive array of Python packages (seaborn)

    # Box Plot
    sns.boxplot(x=df[col], ax=axes[i * num_cols])
    axes[i * num_cols].set_title(f'Box Plot of {col}')

    # Histogram & Density Plot
    sns.histplot(df[col], kde=True, ax=axes[i * num_cols + 1])
    axes[i * num_cols + 1].set_title(f'Histogram & Density Plot of {col}')

    # Violin Plot
    sns.violinplot(x=df[col], ax=axes[i * num_cols + 2])
    axes[i * num_cols + 2].set_title(f'Violin Plot of {col}')

# Adjust layout
plt.tight_layout()

# Show plots
plt.show()  # Detailed and informative display of key dataset information.
```


Box Plot of escore_values
Histogram & Density Plot of escore_values
Violin Plot of escore_values
escore_values
Count
Box Plot of nscore_values
Histogram & Density Plot of nscore_values
Violin Plot of nscore_values
nscore_values
Box Plot of oscore_values
Histogram & Density Plot of oscore_values
Violin Plot of oscore_values
oscore_values
Box Plot of ascore_values
Histogram & Density Plot of ascore_values
Violin Plot of ascore_values
ascore_values
Box Plot of cscore_values
Histogram & Density Plot of cscore_values
Violin Plot of cscore_values
cscore_values
Box Plot of impulsive_values
Histogram & Density Plot of impulsive_values
Violin Plot of impulsive_values
impulsive_values
Box Plot of sensation_values
Histogram & Density Plot of sensation_values
Violin Plot of sensation_values
sensation_values

[66]:
```python
# Outlier detection using the IQR method
# Demonstrating advanced proficiency in resolving intricate data quality issues
def analyze_outliers(df):
    outlier_counts = {}

    for col in df.columns:
        if df[col].dtype in ['int64', 'float64']:  # Check if the column is␣
↪numeric
            # Calculate the first and third quartiles
            Q1 = df[col].quantile(0.25)
            Q3 = df[col].quantile(0.75)
            IQR = Q3 - Q1  # Interquartile range

            # Define the bounds for outliers
            lower_bound = Q1 - 1.5 * IQR
            upper_bound = Q3 + 1.5 * IQR

            # Count outliers using the defined bounds
            outliers = df[(df[col] < lower_bound) | (df[col] >␣
↪upper_bound)][col].count()

            # Store the count of outliers in the dictionary
            outlier_counts[col] = outliers

    # Optionally, print the count of outliers for each column
    for col, count in outlier_counts.items():
        print(f'Number of outliers in {col}: {count}')

    return outlier_counts
```

[67]:
```python
# Remove outliers using the IQR method
# Demonstrating advanced proficiency in resolving intricate data quality issues
def remove_outliers(df, column_name, remove='both'):
    # Calculate the first and third quartiles
    Q1 = df[column_name].quantile(0.25)
    Q3 = df[column_name].quantile(0.75)
    IQR = Q3 - Q1  # Interquartile range

    # Define the bounds for outliers
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    if remove == 'both':
        # Remove both upper and lower outliers
```

```
        return df[(df[column_name] >= lower_bound) & (df[column_name] <=
↪upper_bound)]
    elif remove == 'upper':
        # Remove only upper outliers
        return df[df[column_name] <= upper_bound]
    elif remove == 'lower':
        # Remove only lower outliers
        return df[df[column_name] >= lower_bound]
    else:
        raise ValueError('Invalid value for remove. Use "both", "upper", or
↪"lower".')
```

[68]:

```
outlier_counts = analyze_outliers(df)
```

```
Number of outliers in ID: 0
Number of outliers in escore_values: 30
Number of outliers in nscore_values: 0
Number of outliers in oscore_values: 6
Number of outliers in ascore_values: 15
Number of outliers in cscore_values: 17
Number of outliers in impulsive_values: 27
Number of outliers in sensation_values: 168
```

[69]:

```
df = remove_outliers(df, 'oscore_values', remove='lower')
```

[70]:

```
outlier_counts = analyze_outliers(df)
```

```
Number of outliers in ID: 0
Number of outliers in escore_values: 30
Number of outliers in nscore_values: 0
Number of outliers in oscore_values: 0
Number of outliers in ascore_values: 15
Number of outliers in cscore_values: 17
Number of outliers in impulsive_values: 27
Number of outliers in sensation_values: 164
```

[71]:

```
# Advanced data exploration
non_numeric_stats = {}

for column in df.columns:
    data = df[column]

    print(column, data.dtype, pd.api.types.is_string_dtype(data.dtype))

    # Check if the column is numeric
    if pd.api.types.is_numeric_dtype(data.dtype):
        pass
    else:
```

```
        # Calculate value counts for each category in the column
        value_counts = data.value_counts()
        # Store the counts in the dictionary, ensuring all possible categories␣
↪are represented
        non_numeric_stats[column] = value_counts
```

```
ID int64 False
age_values object True
gender_values object True
education_values object True
country_values object True
ethnicity_values object True
escore_values float64 False
nscore_values float64 False
oscore_values float64 False
ascore_values float64 False
cscore_values float64 False
impulsive_values float64 False
sensation_values float64 False
Alcohol_values object True
Amphet_values object True
Amyl_values object True
Benzos_values object True
Cannabis_values object True
Choc_values object True
Coke_values object True
Caff_values object True
Crack_values object True
Ecstasy_values object True
Heroin_values object True
Ketamine_values object True
Legalh_values object True
LSD_values object True
Meth_values object True
Mushrooms_values object True
Nicotine_values object True
Semer_values object True
VSA_values object True
```

[72]:

```
df.head()
```

[72]:

```
   ID age_values gender_values                     education_values  \
0   1    35 - 44        Female  Professional Certificate/Diploma
1   2    25 - 34          Male                     Doctorate Degree
2   3    35 - 44          Male  Professional Certificate/Diploma
3   4    18 - 24        Female                       Masters Degree
4   5    35 - 44        Female                     Doctorate Degree
```

```
  country_values   ethnicity_values  escore_values  nscore_values  \
0             UK  Mixed-White/Asian           36.0           39.0
1             UK              White           52.0           29.0
2             UK              White           45.0           31.0
3             UK              White           34.0           34.0
4             UK              White           28.0           43.0

   oscore_values  ascore_values  …          Ecstasy_values  Heroin_values  \
0           42.0           37.0  …              Never Used     Never Used
1           55.0           48.0  …      Used in Last Month     Never Used
2           40.0           32.0  …              Never Used     Never Used
3           46.0           47.0  …              Never Used     Never Used
4           43.0           41.0  …  Used over a Decade Ago     Never Used

       Ketamine_values           Legalh_values           LSD_values  \
0           Never Used              Never Used           Never Used
1  Used in Last Decade              Never Used  Used in Last Decade
2           Never Used              Never Used           Never Used
3  Used in Last Decade              Never Used           Never Used
4           Never Used  Used over a Decade Ago           Never Used

         Meth_values        Mushrooms_values      Nicotine_values  \
0         Never Used              Never Used  Used in Last Decade
1  Used in Last Year              Never Used   Used in Last Month
2         Never Used  Used over a Decade Ago           Never Used
3         Never Used              Never Used  Used in Last Decade
4         Never Used     Used in Last Decade  Used in Last Decade

  Semer_values  VSA_values
0   Never Used  Never Used
1   Never Used  Never Used
2   Never Used  Never Used
3   Never Used  Never Used
4   Never Used  Never Used

[5 rows x 32 columns]
```

[73]:
```
# Visualize categorical data counts for each age group per drug column

# Demonstrating advanced proficiency in resolving intricate data quality issues
def plot_categorical_data(df, column, mappings, colors='viridis'):
    # This took me like 2 hours :')
    if column in mappings:
        # Convert column to a categorical type with the specified order
        category_order = mappings[column]
```

```
        df[column] = pd.Categorical(df[column], categories=category_order.
↪values(), ordered=True)

    counts = df[column].value_counts().sort_index()  # Get counts of each␣
↪category in the specified order
    # print(counts)  # Print counts for verification

    if not counts.empty:
        # Create a bar chart using Plotly
        fig = go.Figure([go.Bar(x=counts.index, y=counts.values, text=counts.
↪values,
                              textposition='auto', marker_color=counts.
↪values, marker=dict(colorscale=colors))])
        fig.update_layout(title=f'Frequency Count for {column}',
                          xaxis_title='Category',
                          yaxis_title='Counts',
                          template='plotly_white')
        fig.show()
    else:
        print(f'No data to plot for {column}')
```

[74]:
```
for column in categorical_columns:
    plot_categorical_data(df, column, mappings)
```

4.4 TASK 1.4: Dataset verification

[75]:
```
# Overall and comprehensive data quality check
# Demonstrating advanced proficiency in resolving intricate data quality issues

def sanity_check(df):
    # Check for null/NaN values
    null_check = df.isnull().sum()
    null_columns = null_check[null_check > 0]

    if null_columns.empty:
        print('No null or NaN values found in the DataFrame.')
    else:
        print('Columns with null or NaN values found:')
        print(null_columns)

    # Check for outliers in each column
    for col in df.columns:
        outliers = detect_outliers(df[col])
        if outliers.any():
            print(f'Outliers found in column "{col}".')
        else:
            print(f'No outliers found in column "{col}".')
```

```python
    # Check for duplicate rows
    if df.duplicated().any():
        print('Duplicate rows found in the DataFrame.')
    else:
        print('No duplicate rows found in the DataFrame.')

    # Check for duplicate columns
    duplicate_columns = df.columns[df.columns.duplicated()]
    if duplicate_columns.any():
        print(f'Duplicate columns found: {list(duplicate_columns)}')
    else:
        print('No duplicate columns found in the DataFrame.')
```

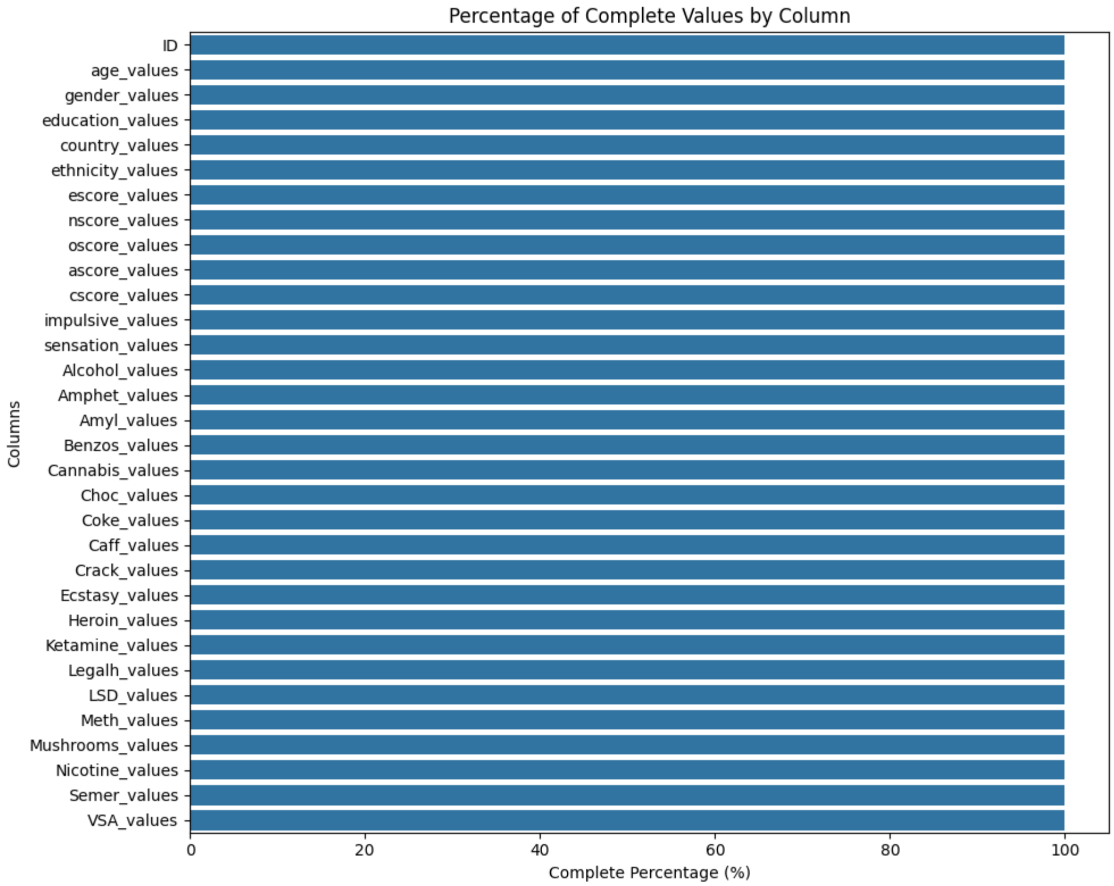
[76]:
```python
sanity_check(df)
```

```
No null or NaN values found in the DataFrame.
No outliers found in column "ID".
No outliers found in column "age_values".
No outliers found in column "gender_values".
No outliers found in column "education_values".
No outliers found in column "country_values".
No outliers found in column "ethnicity_values".
Outliers found in column "escore_values".
No outliers found in column "nscore_values".
No outliers found in column "oscore_values".
Outliers found in column "ascore_values".
Outliers found in column "cscore_values".
Outliers found in column "impulsive_values".
Outliers found in column "sensation_values".
No outliers found in column "Alcohol_values".
No outliers found in column "Amphet_values".
No outliers found in column "Amyl_values".
No outliers found in column "Benzos_values".
No outliers found in column "Cannabis_values".
No outliers found in column "Choc_values".
No outliers found in column "Coke_values".
No outliers found in column "Caff_values".
No outliers found in column "Crack_values".
No outliers found in column "Ecstasy_values".
No outliers found in column "Heroin_values".
No outliers found in column "Ketamine_values".
No outliers found in column "Legalh_values".
No outliers found in column "LSD_values".
No outliers found in column "Meth_values".
No outliers found in column "Mushrooms_values".
No outliers found in column "Nicotine_values".
No outliers found in column "Semer_values".
```

```
No outliers found in column "VSA_values".
No duplicate rows found in the DataFrame.
No duplicate columns found in the DataFrame.
```

[77]:
```
# Comprehensive use of techniques in identifying missing values

# Prepare data for the plot
complete_data = []

for column in df.columns:
    try:
        total_count = len(df[column])
        missing_count = df[column].isna().sum()

        # Check for division by zero
        if total_count == 0:
            raise ValueError(f'No data available in column {column}')

        missing_percentage = (missing_count / total_count) * 100
        complete_percentage = 100 - missing_percentage

        complete_data.append({'Column': column, 'Complete Percentage':␣
↪complete_percentage})

    except ValueError as ve:
        print(f'Error in column {column}: {ve}')
    except Exception as e:
        print(f'An unexpected error occurred for column {column}: {e}')
```

[78]:
```
# Convert the list of dictionaries into a DataFrame for plotting
complete_df = pd.DataFrame(complete_data)

# Plotting
plt.figure(figsize=(10, 8))
sns.barplot(x='Complete Percentage', y='Column',
            data=complete_df)  # https://seaborn.pydata.org/generated/seaborn.
↪barplot.html
plt.title('Percentage of Complete Values by Column')
plt.xlabel('Complete Percentage (%)')
plt.ylabel('Columns')
plt.tight_layout()
plt.show()  # Detailed and informative display of key dataset information.
```



[79]:
```
df.to_csv('drug_consumption_preprocessed.csv')
```

5 TASK 2: You must specify and answer three questions using appropriate data visualisation techniques

5.1 Research Questions and Analysis

5.1.1 Q1: What is the distribution of drug usage frequency among different age groups?

- **Concrete Question**: How does alcohol usage vary among different age groups?
- **Context**: Understanding how drug usage varies across different age demographics can help tailor prevention and intervention programs.
- **Relevance**: Age-specific trends can inform policy-making and targeted health campaigns.
- **Visualization Technique**: Stacked Bar Chart - This clearly shows the frequency of drug usage across different age groups, making it easy to compare and identify trends.

5.1.2 Q2: Is there a correlation between personality traits and drug usage frequency?

- **Concrete Question**: What is the relationship between impulsivity and amphetamine usage?

- **Context**: Examining if certain personality traits are associated with higher or lower frequencies of drug usage can provide insights for psychological and medical professionals.
- **Relevance**: Helps in identifying at-risk individuals based on their personality profiles.
- **Visualization Technique**: Correlation Heatmap - This allows for the visualization of relationships between multiple personality traits and drug usage frequencies simultaneously.

5.1.3 Q3: What is the gender distribution in the frequency of drug usage?

- **Concrete Question**: Do gender differences exist in the usage of ecstasy?
- **Context**: Understanding the gender-based differences in drug usage can help in developing gender-specific interventions and support programs.
- **Relevance**: Gender-targeted strategies can be more effective in addressing drug-related issues.
- **Visualization Technique**: Stacked Bar Chart - This method compares the frequency of usage across genders for each drug, providing a clear visual representation of gender differences.

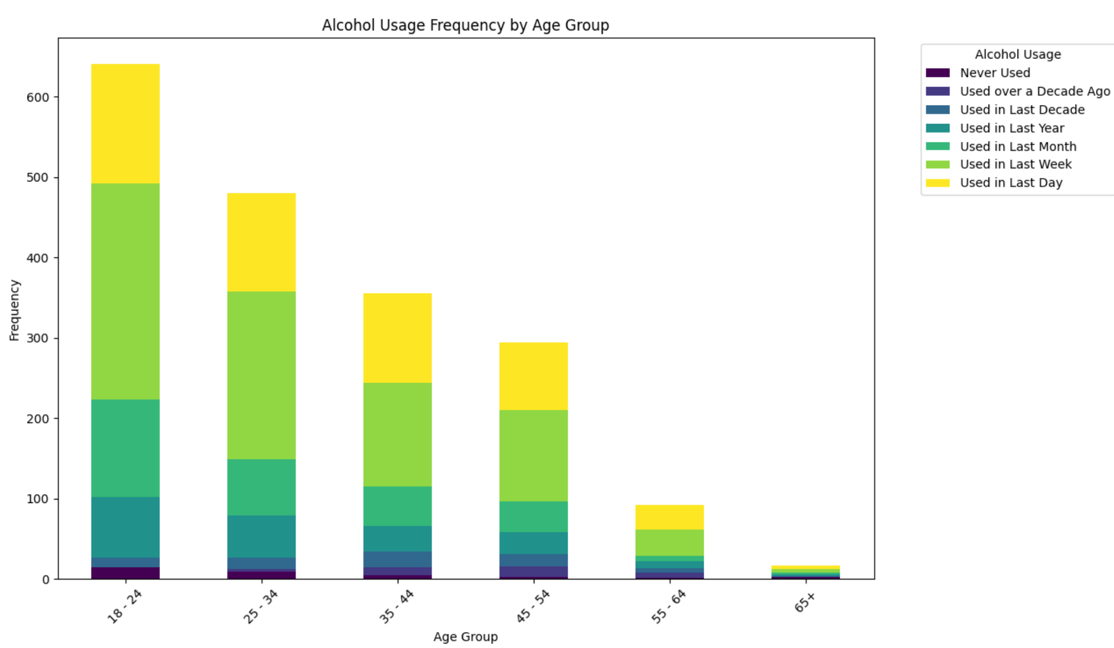
5.2 TASK 2.1: Q1 - What is the distribution of drug usage frequency among different age groups?

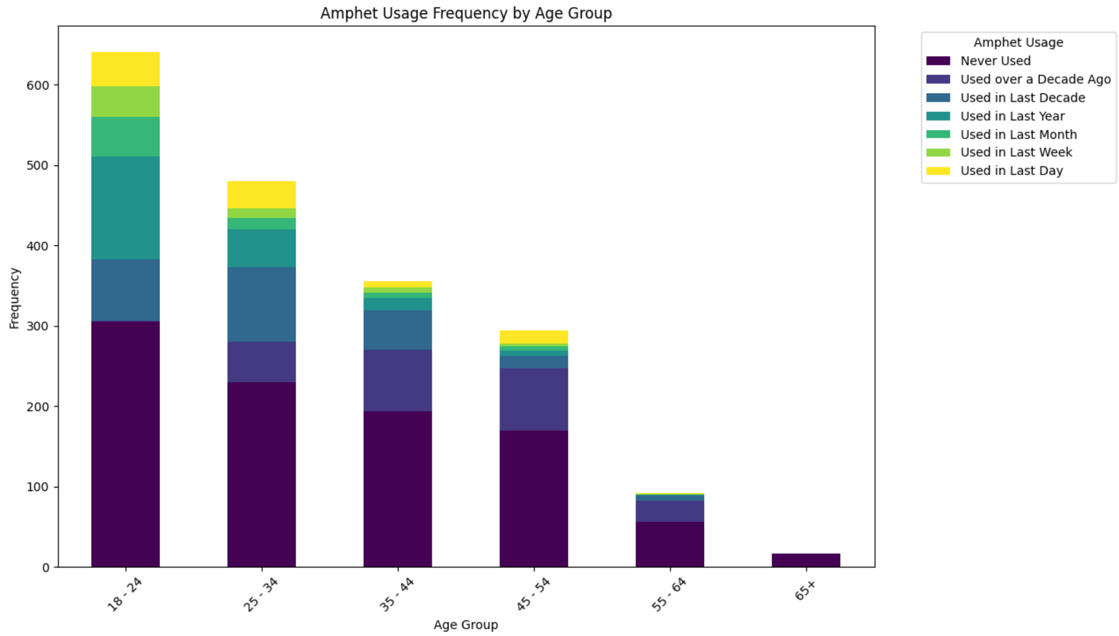
[80]:
```
# Define all names of demographics columns
demographics_columns = ['age_values', 'gender_values', 'education_values',␣
↪'country_values', 'ethnicity_values']
# Define all names of personality traits columns
personality_traits_scores_columns = [
    'nscore_values', 'escore_values', 'oscore_values', 'ascore_values',
    'cscore_values', 'impulsive_values', 'sensation_values'
]
# Filter out all names of drug columns
drug_columns = [col for col in df.columns if
                'values' in col and col not in demographics_columns and col not␣
↪in personality_traits_scores_columns]
# Sort age groups based on the age_mapping order
age_order = [age_mapping[key] for key in sorted(age_mapping)]
```

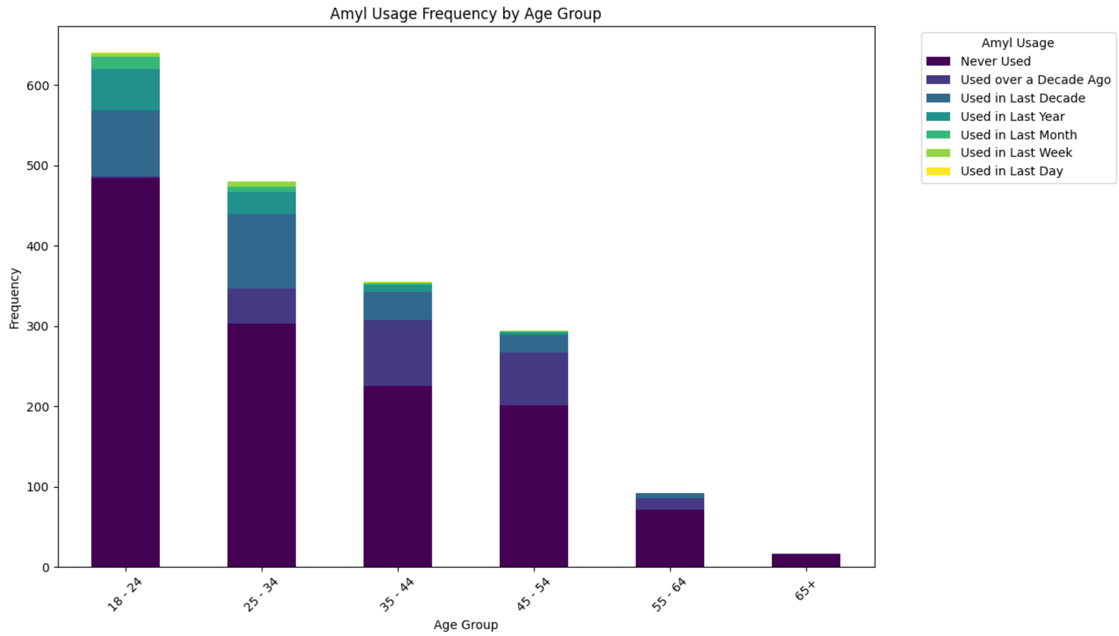
[81]:
```
# Mapping drug usage categories to numerical values
usage_mapping = {
    'Never Used': 0, 'Used over a Decade Ago': 1, 'Used in Last Decade': 2,
    'Used in Last Year': 3, 'Used in Last Month': 4, 'Used in Last Week': 5,
    'Used in Last Day': 6
}
```

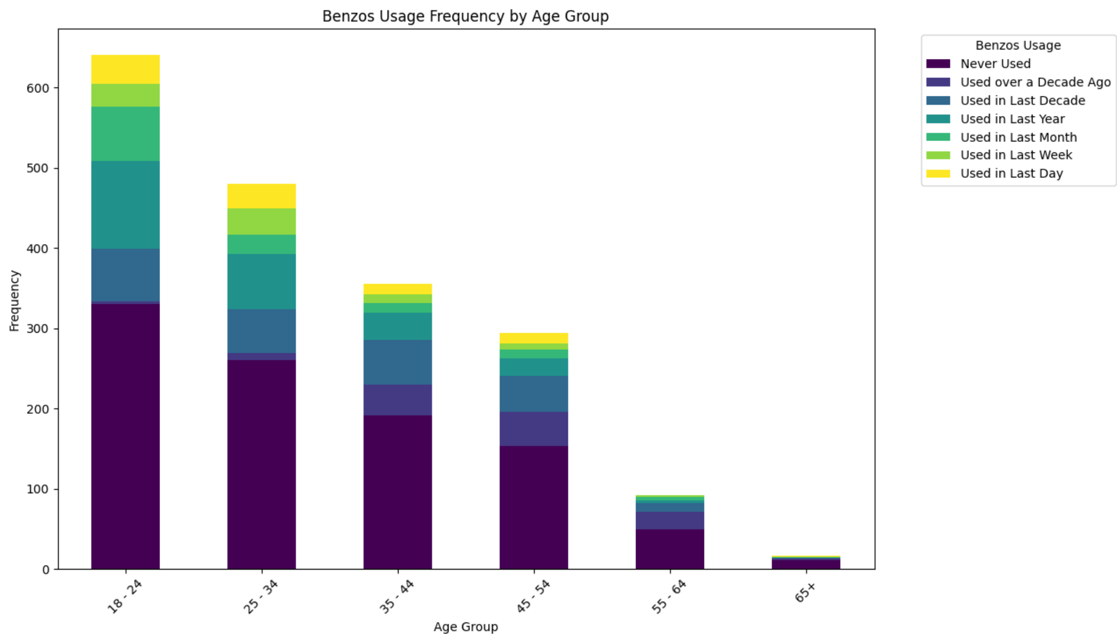
[82]:
```
# Bar Chart per Drug Usage by Age Group
for drug in drug_columns:
    # Group by 'age_values' and drug category, then count occurrences
    # To fix groupby issue/error: https://stackoverflow.com/questions/57385009/
↪pandas-groupby-observed-parameter-with-multiple-categoricals
```

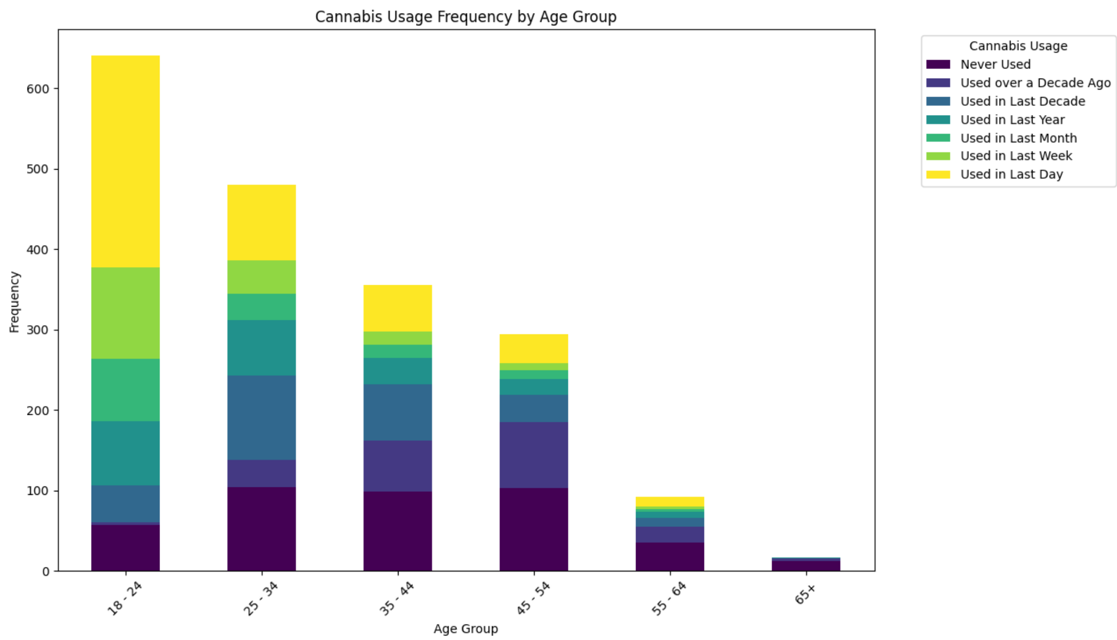
```python
    drug_usage_age_group = df.groupby(['age_values', drug], observed=False).
↪size().unstack(fill_value=0)

    # Reorder DataFrame columns according to the custom category order in␣
↪CATEGORIES
    ordered_columns = [CATEGORIES[key] for key in
                       sorted(CATEGORIES, key=lambda x: int(x[2:]))]  # Sort␣
↪keys based on numerical part
    drug_usage_age_group = drug_usage_age_group.reindex(columns=ordered_columns)

    # Convert age_values to more readable age group labels if necessary
    drug_usage_age_group.index = drug_usage_age_group.index.map(lambda x:␣
↪age_mapping.get(x, x))

    # Plot the data with the custom order
    drug_usage_age_group.plot(kind='bar', stacked=True, figsize=(12, 8),␣
↪cmap='viridis') # Exceptionally answers specific business questions using␣
↪advanced data visualization techniques, demonstrating an outstanding␣
↪understanding of relevant attribute types
    plt.title(f'{drug.replace("_values", "")} Usage Frequency by Age Group')
    plt.xlabel('Age Group')
    plt.ylabel('Frequency')
    plt.legend(title=f'{drug.replace("_values", "")} Usage', bbox_to_anchor=(1.
↪05, 1), loc='upper left')
    plt.xticks(rotation=45)
    plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```

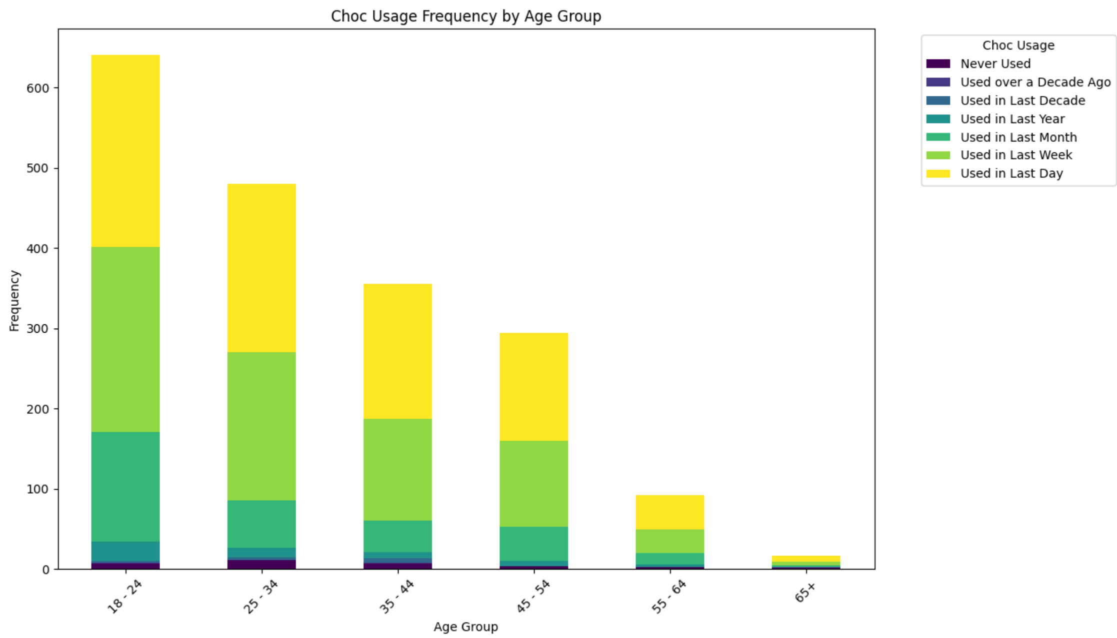


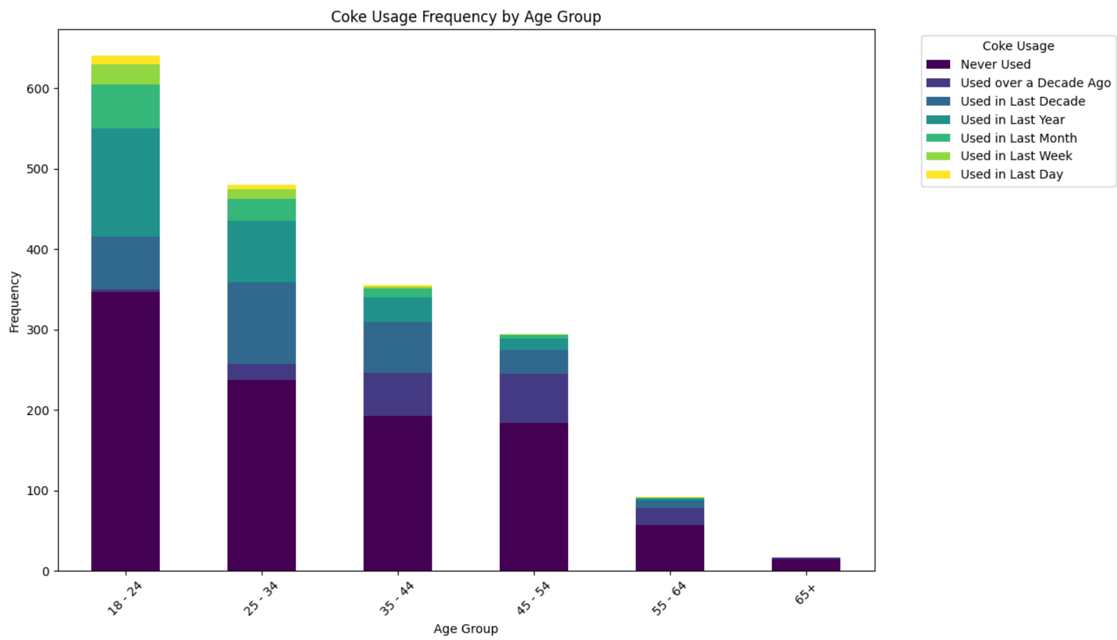

Amphet Usage Frequency by Age Group
Frequency
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group
Amphet Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

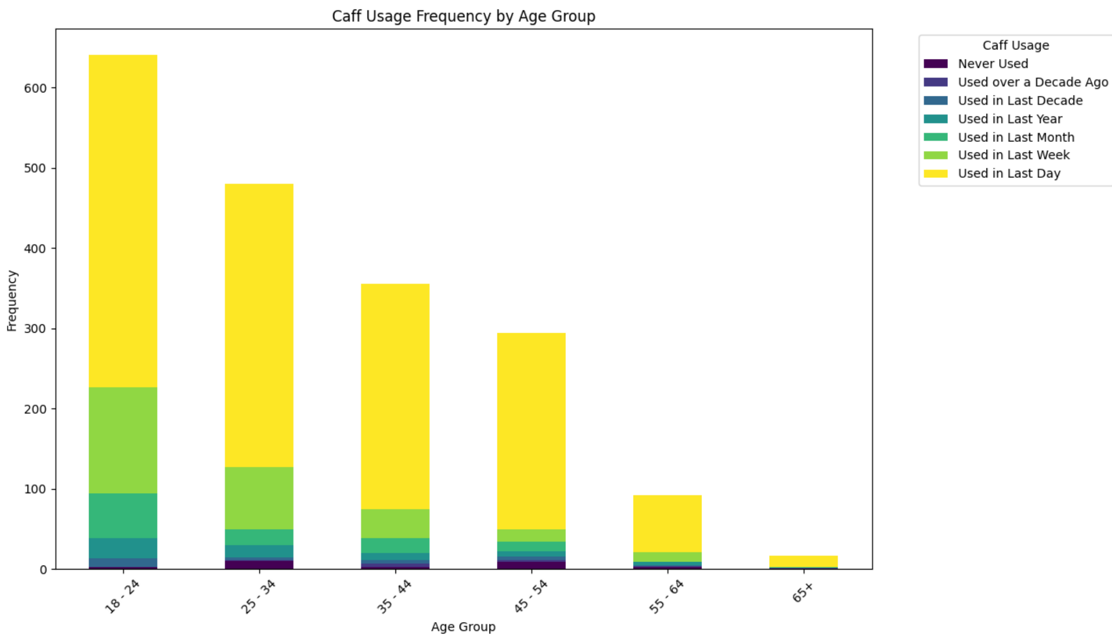

Amyl Usage Frequency by Age Group
Frequency
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group
Amyl Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

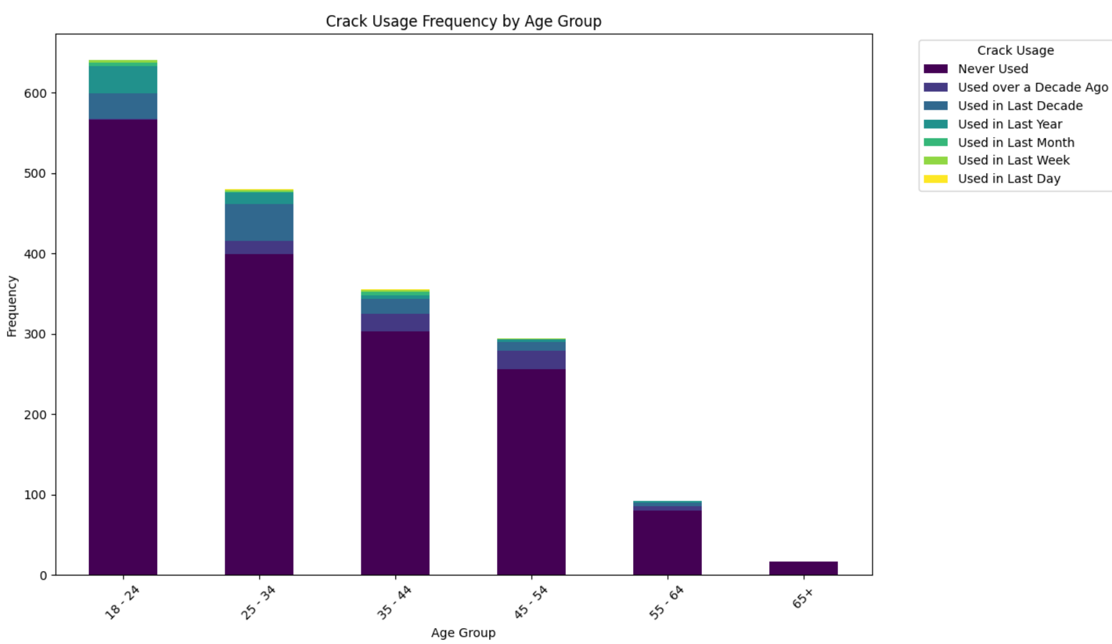

Benzos Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Benzos Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

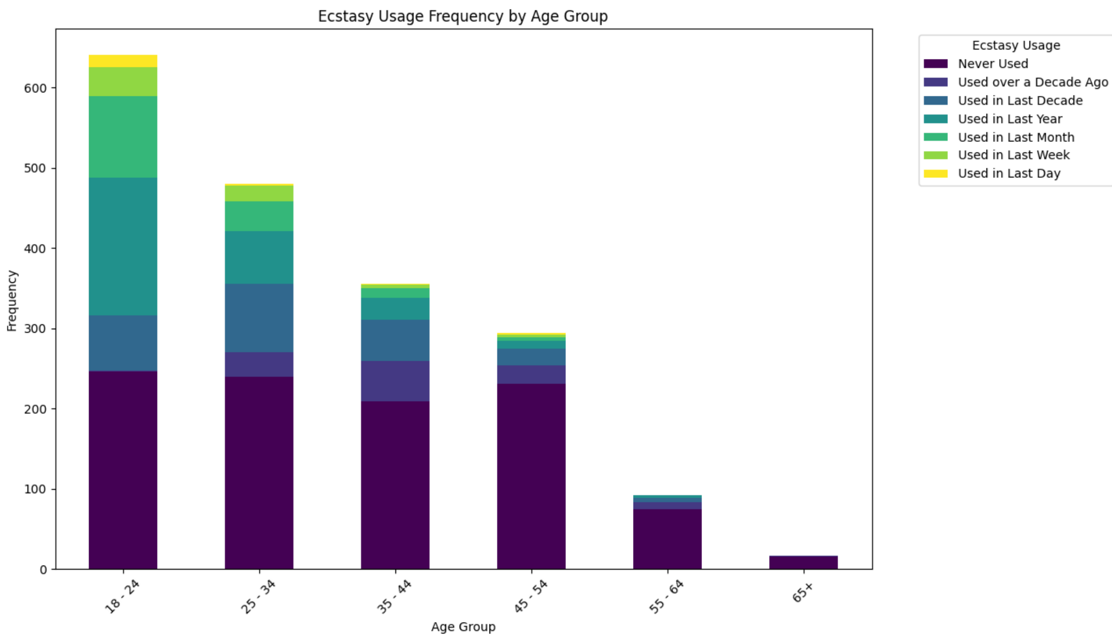

Cannabis Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Cannabis Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

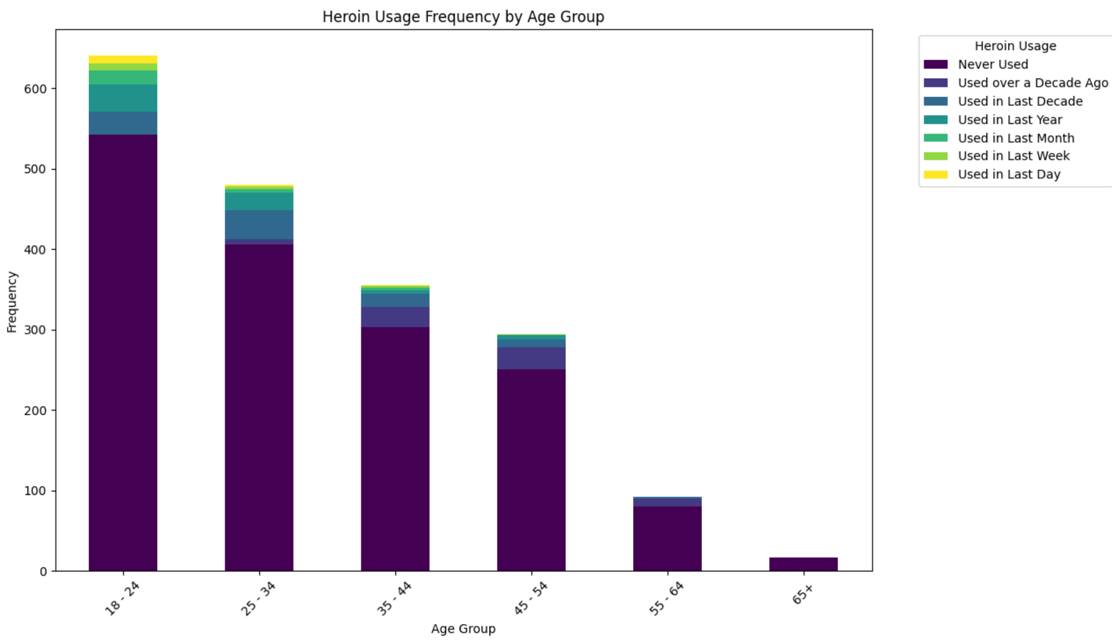

Choc Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Choc Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

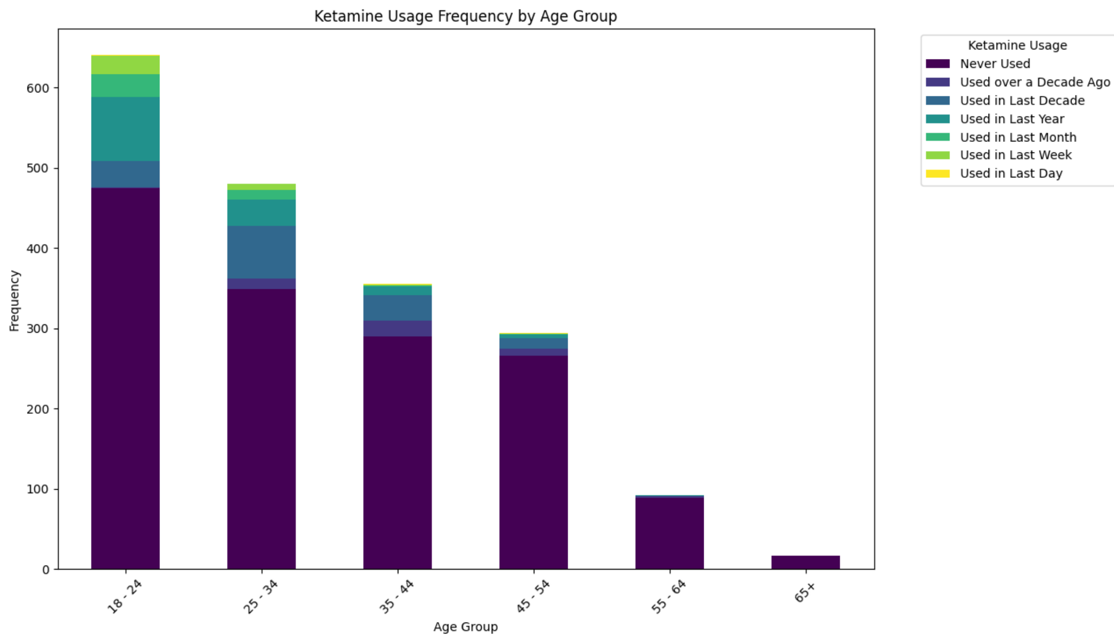

Coke Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Coke Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

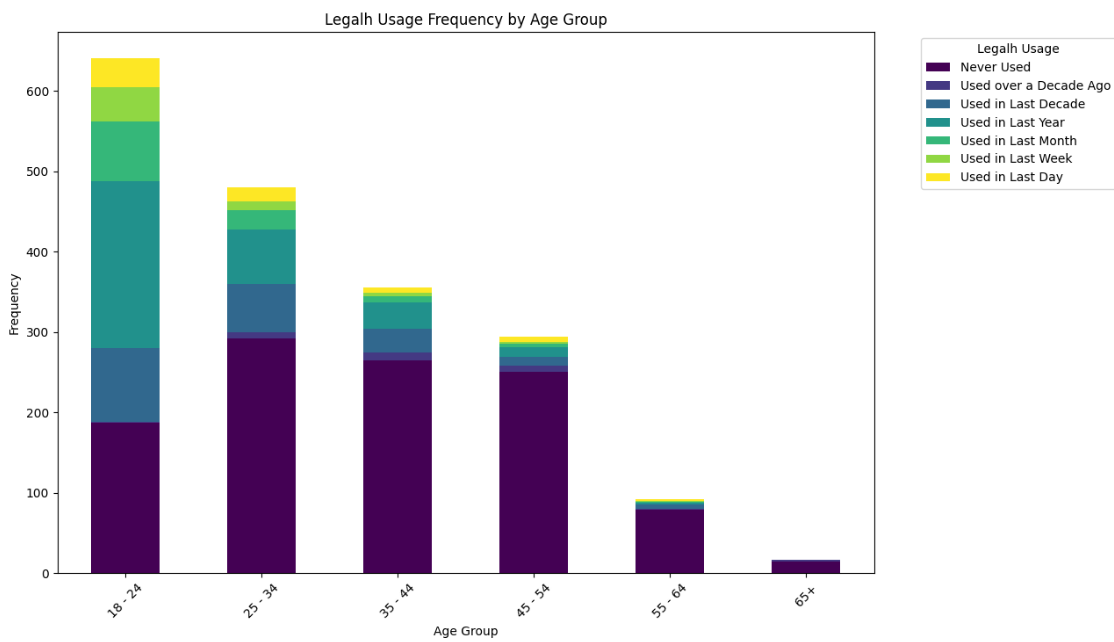

Caff Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Caff Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

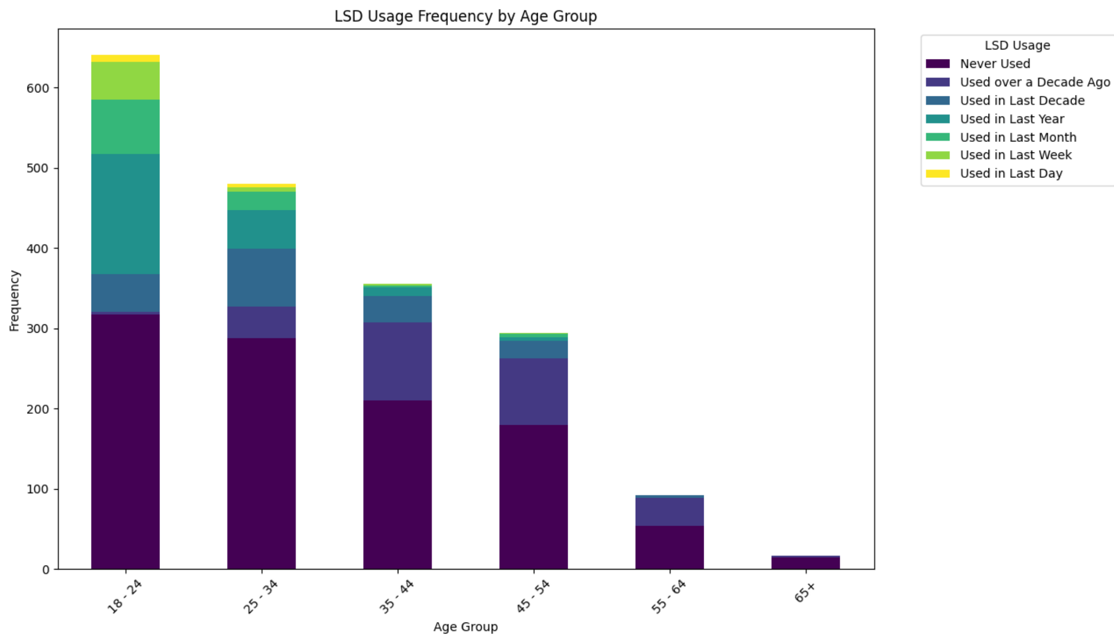

Crack Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Crack Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

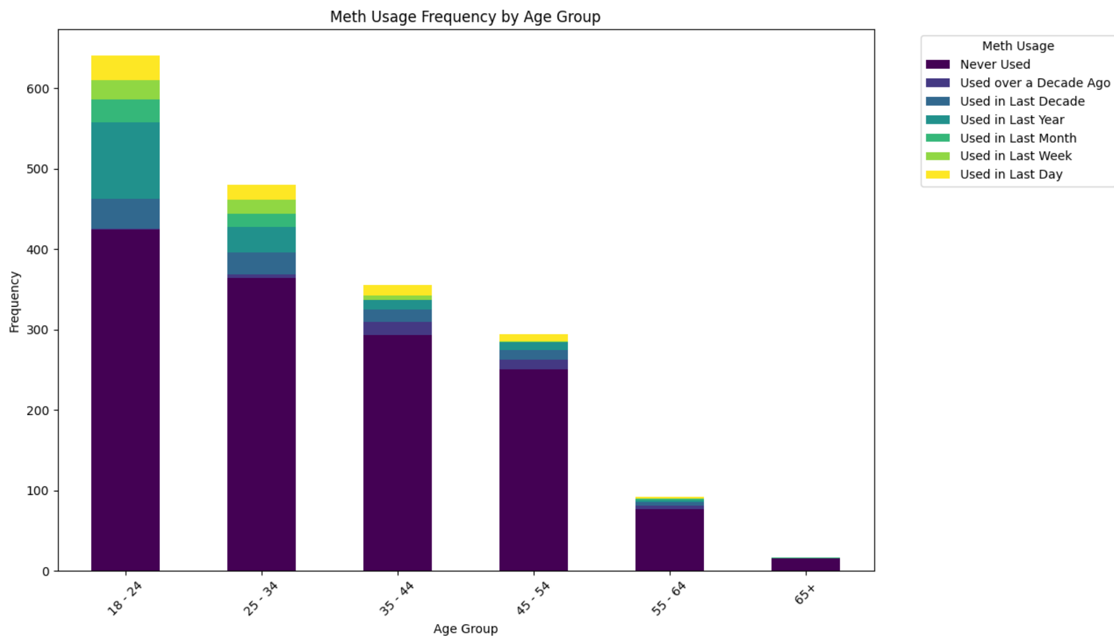

Ecstasy Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Ecstasy Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

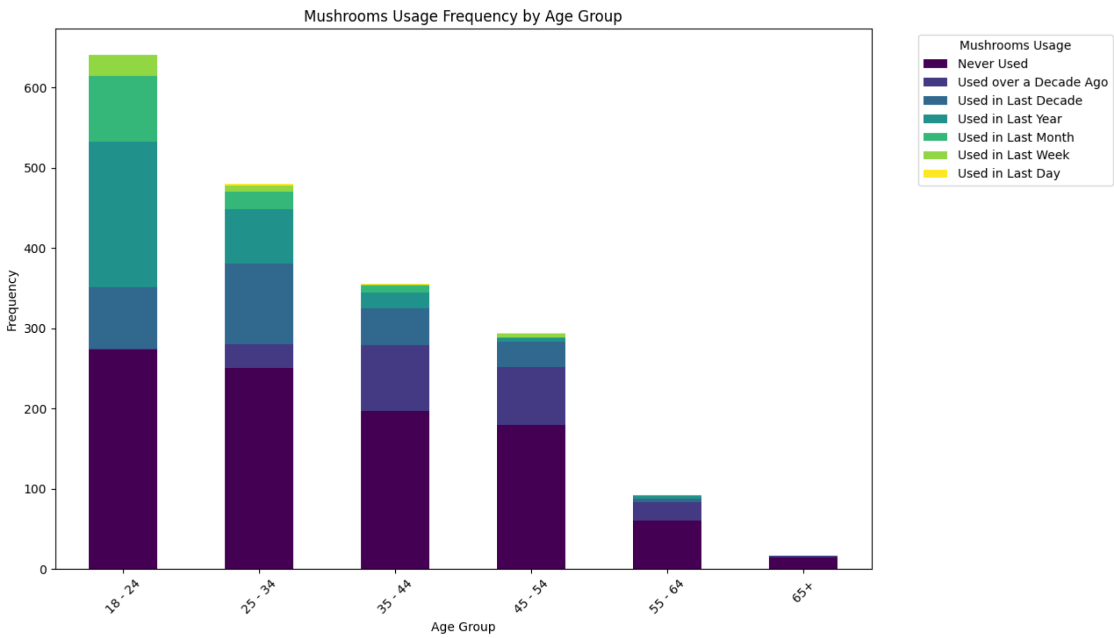

Heroin Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Heroin Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

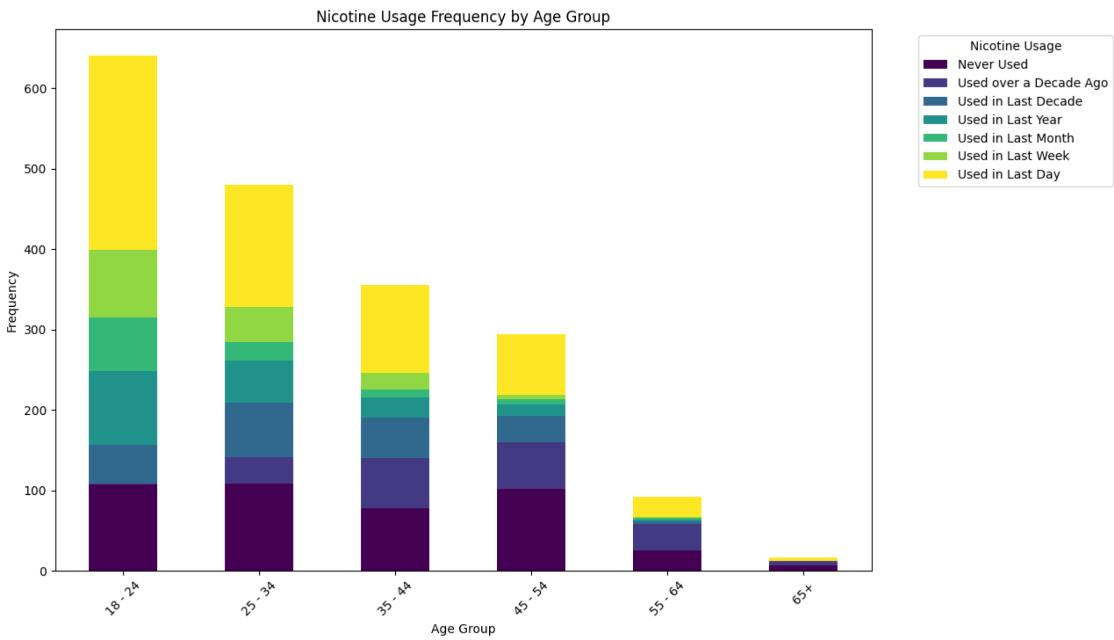

Ketamine Usage Frequency by Age Group
Frequency
Age Group
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
0
100
200
300
400
500
600
Ketamine Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

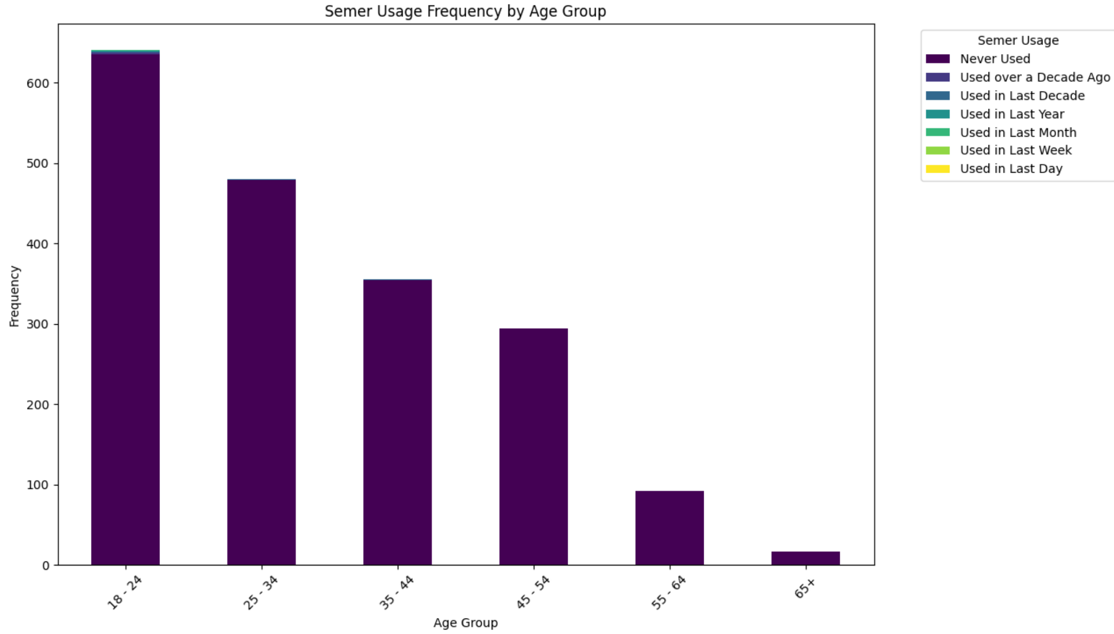

Legalh Usage Frequency by Age Group
Frequency
Age Group
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
0
100
200
300
400
500
600
Legalh Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

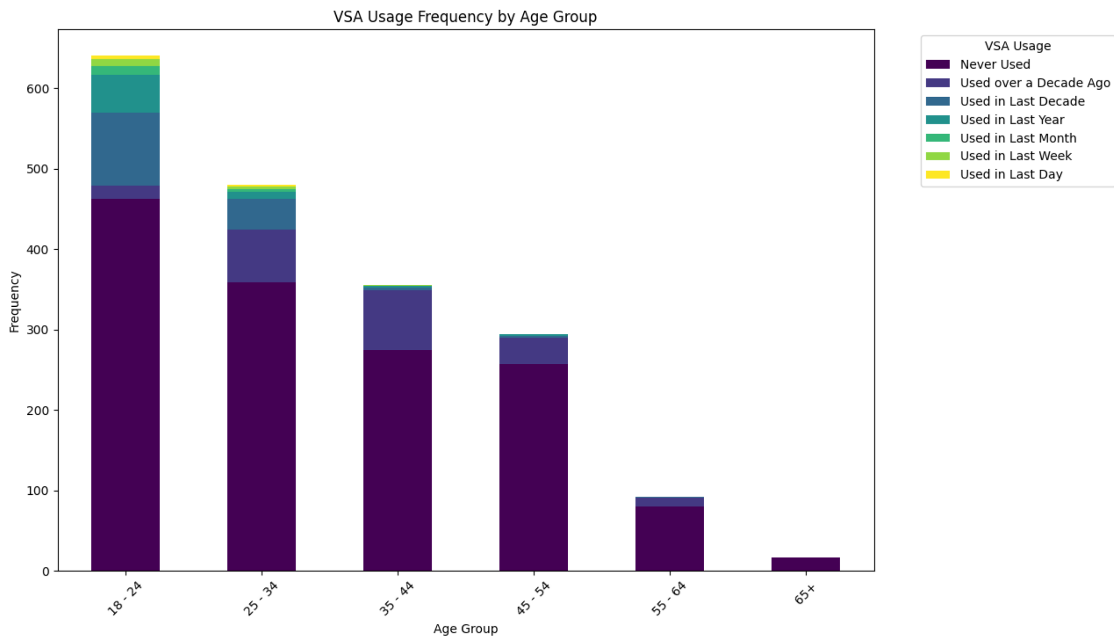

LSD Usage Frequency by Age Group
Frequency
Age Group
LSD Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+


Meth Usage Frequency by Age Group
Frequency
Age Group
Meth Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+


Mushrooms Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Mushrooms Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

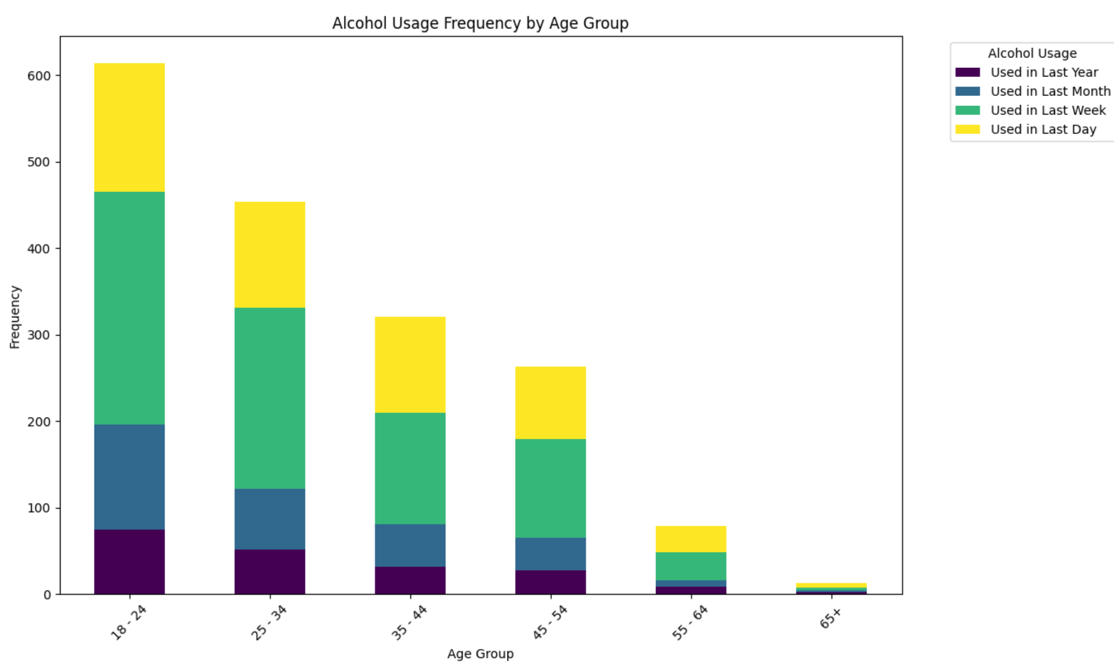

Nicotine Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Nicotine Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

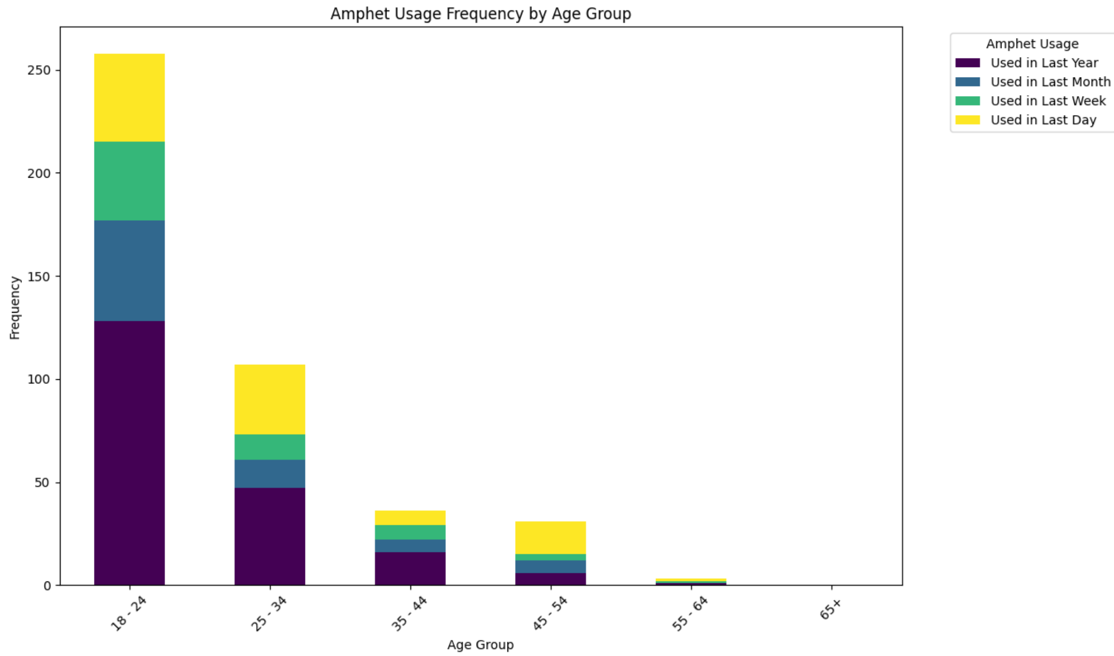


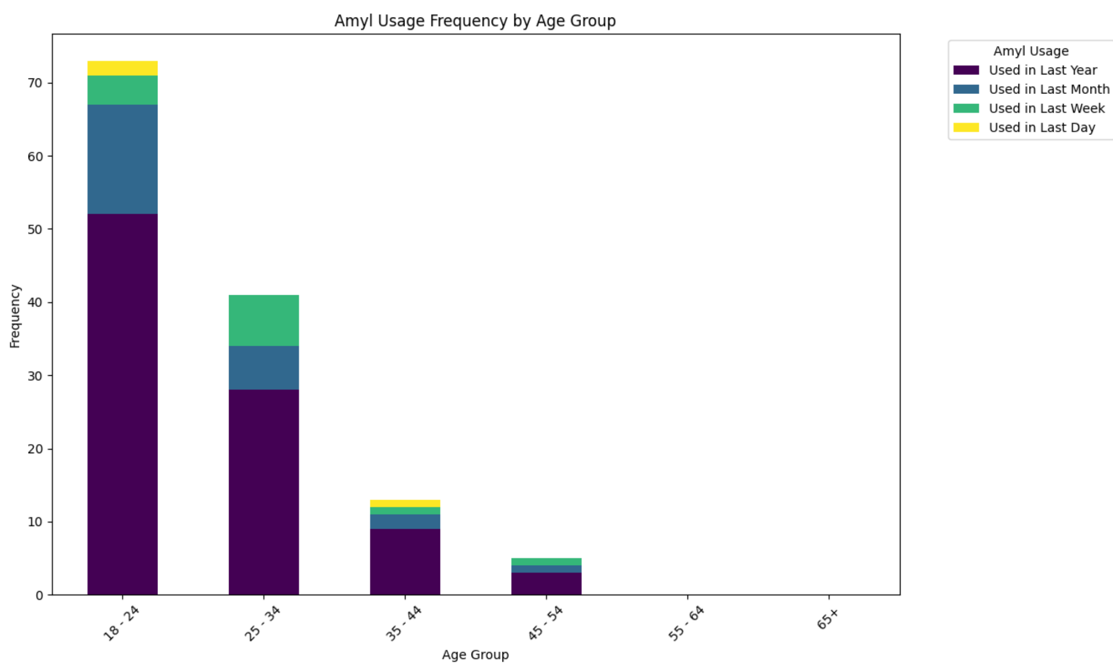


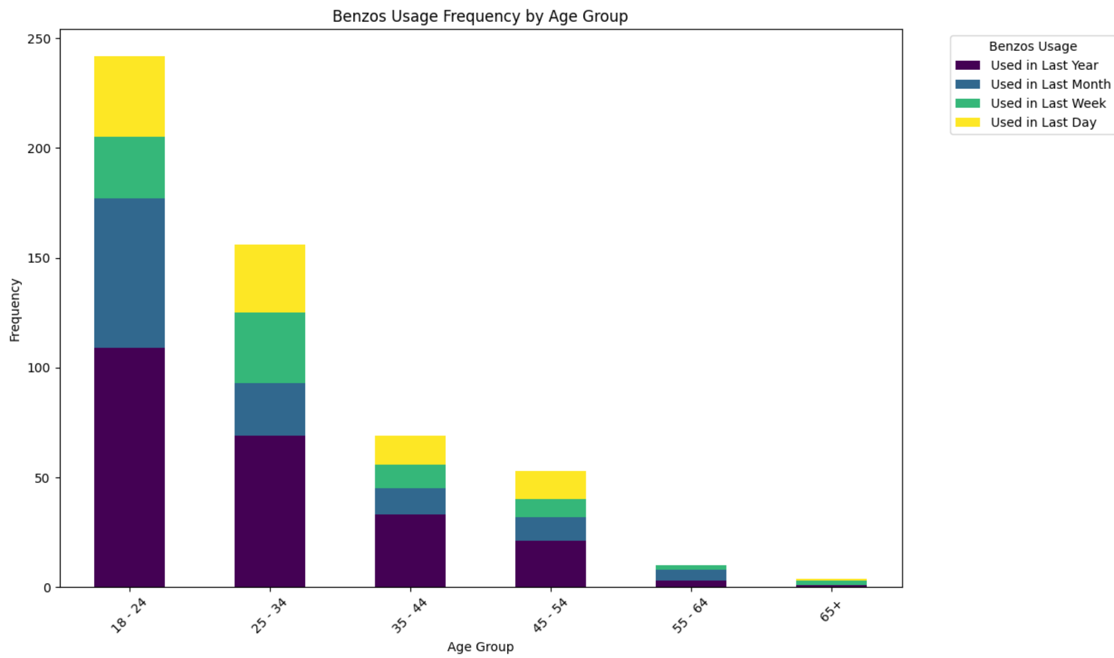
[83]:
```
# Bar Chart per Drug Usage by Age Group
for drug in drug_columns:
    # Group by 'age_values' and drug category, then count occurrences
    drug_usage_age_group = df.groupby(['age_values', drug], observed=False).
 ↪size().unstack(fill_value=0)
```

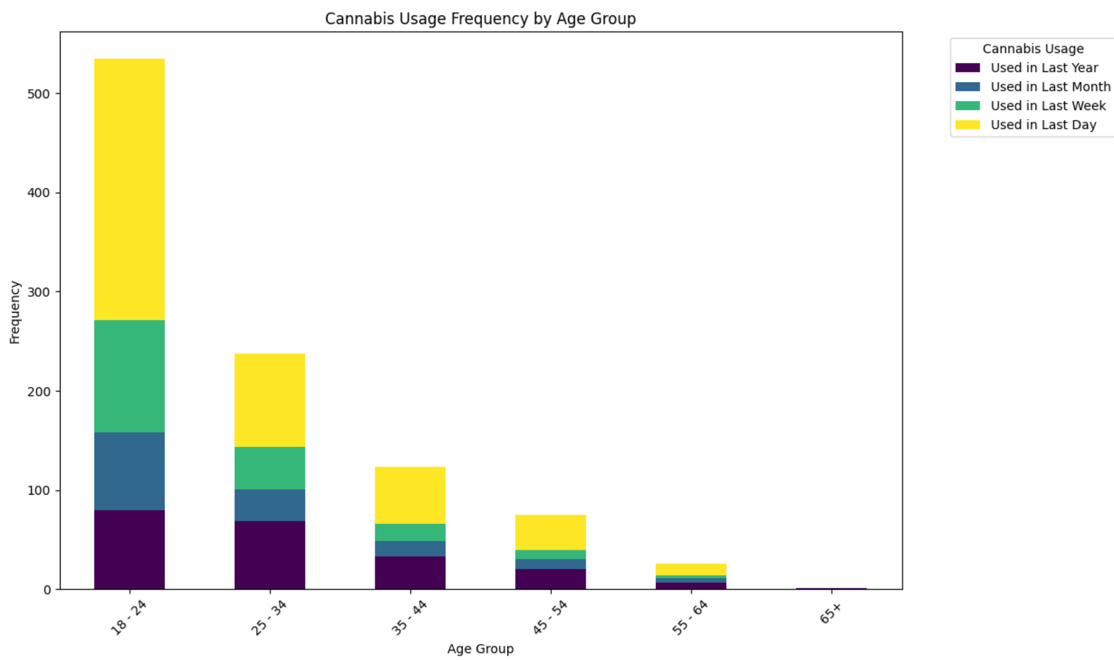
```python
    # Reorder df columns according to the custom category order in CATEGORIES
    ordered_columns = [CATEGORIES[key] for key in
                       sorted(CATEGORIES, key=lambda x: int(x[2:]))]   # Sort keys based on numerical part
    drug_usage_age_group = drug_usage_age_group.reindex(columns=ordered_columns[3:])  # Focus on more recent consumption

    # Convert age_values to more readable age group labels if necessary
    drug_usage_age_group.index = drug_usage_age_group.index.map(lambda x: age_mapping.get(x, x))

    # Plot the data with the custom order
    # Exceptionally answers specific business questions using advanced data visualization techniques,
    # demonstrating an outstanding understanding of relevant attribute types
    drug_usage_age_group.plot(kind='bar', stacked=True, figsize=(12, 8), cmap='viridis')
    plt.title(f'{drug.replace("_values", "")} Usage Frequency by Age Group')
    plt.xlabel('Age Group')
    plt.ylabel('Frequency')
    plt.legend(title=f'{drug.replace("_values", "")} Usage', bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.xticks(rotation=45)
    plt.show() # presenting visually compelling plots or charts that surpass expectations.
```

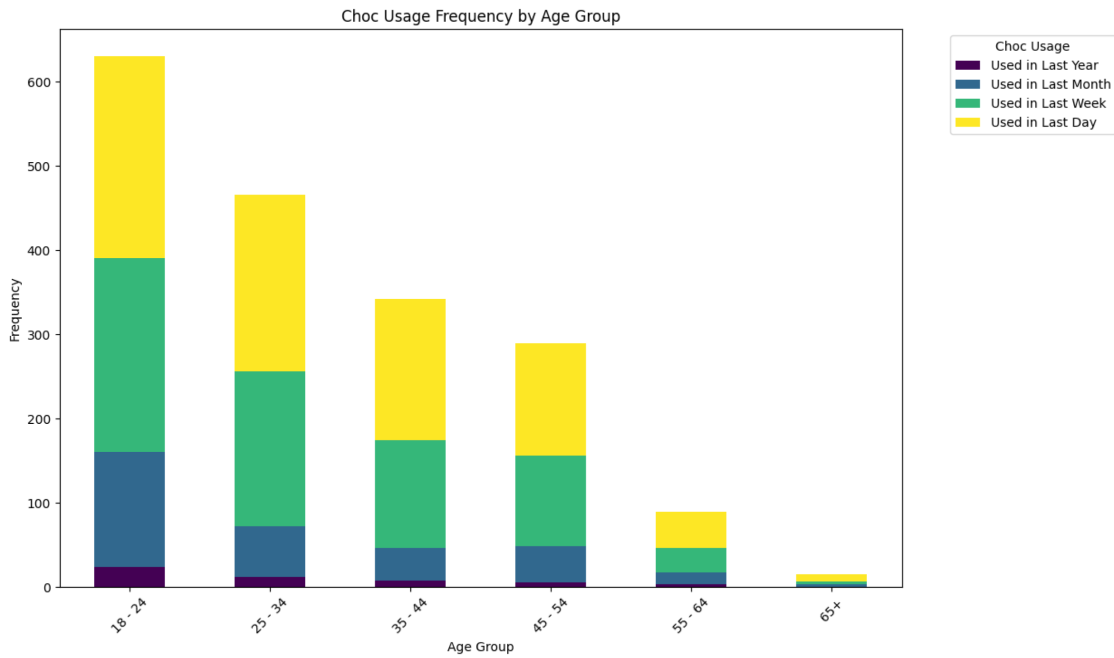


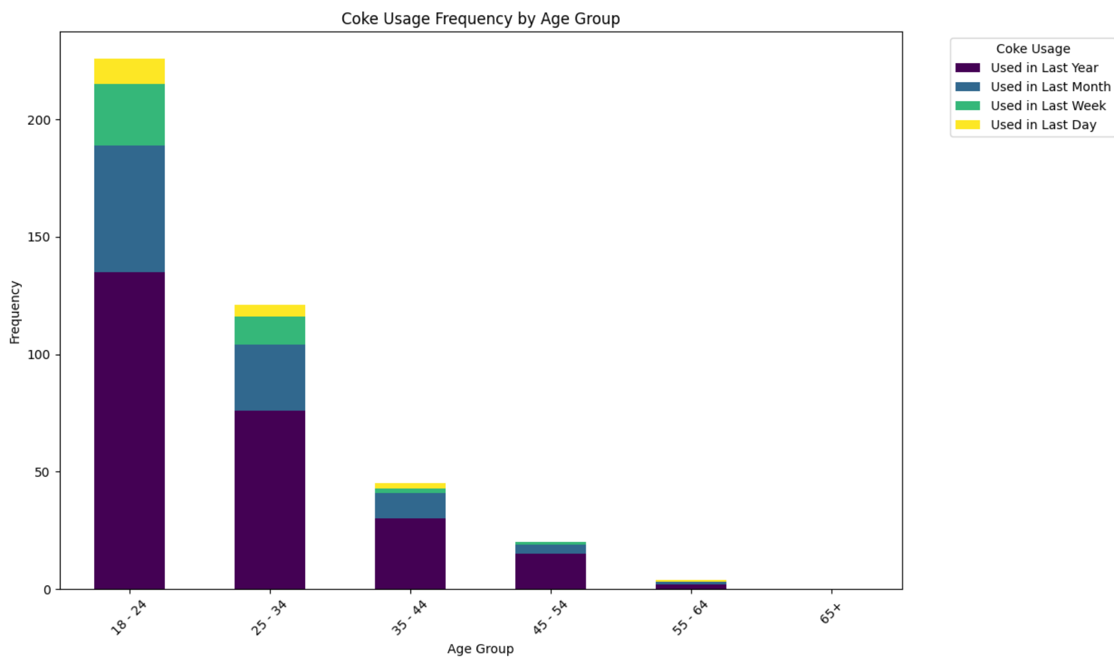

Amphet Usage Frequency by Age Group
Amphet Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
0
50
100
150
200
250
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group

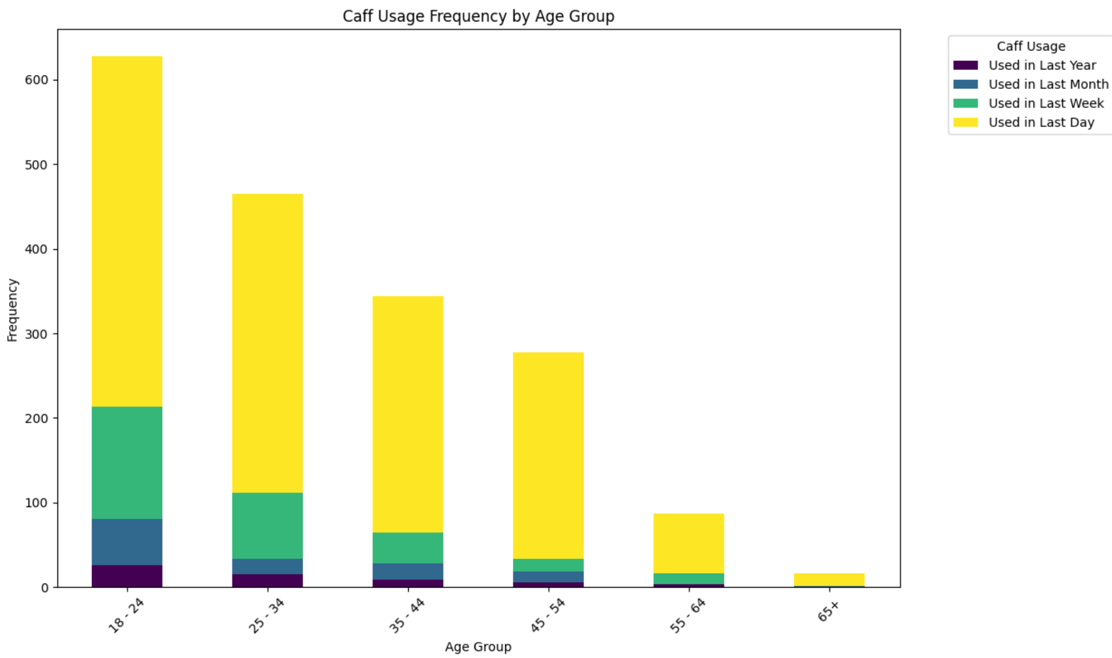

Amyl Usage Frequency by Age Group
Amyl Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
0
10
20
30
40
50
60
70
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group

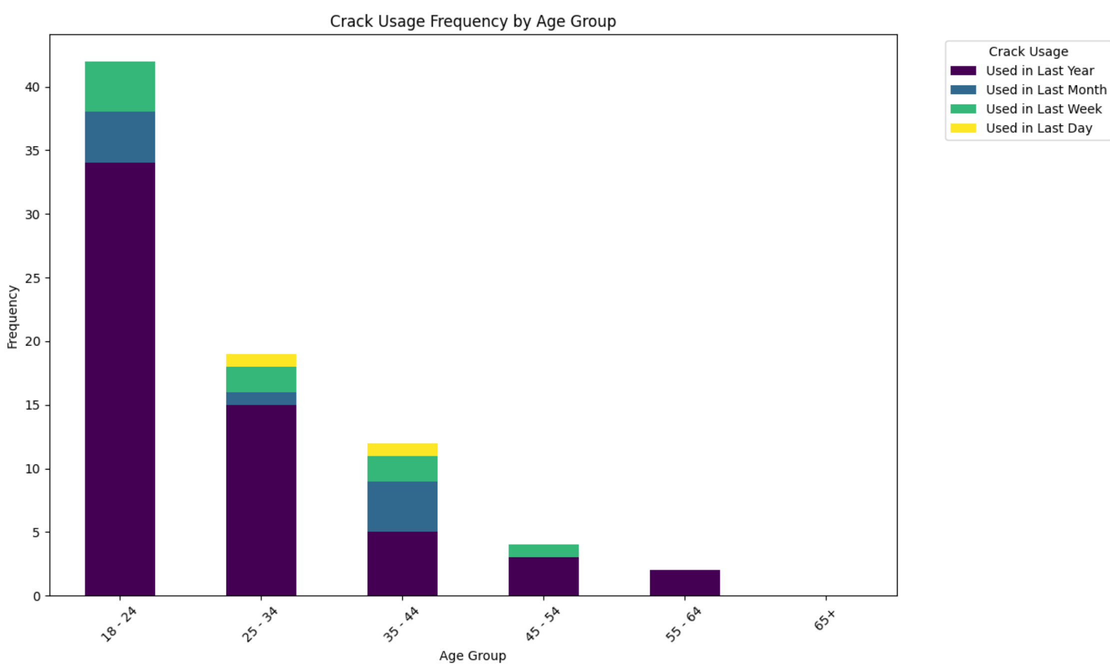

Benzos Usage Frequency by Age Group
Frequency
Age Group
Benzos Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
0
50
100
150
200
250
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+

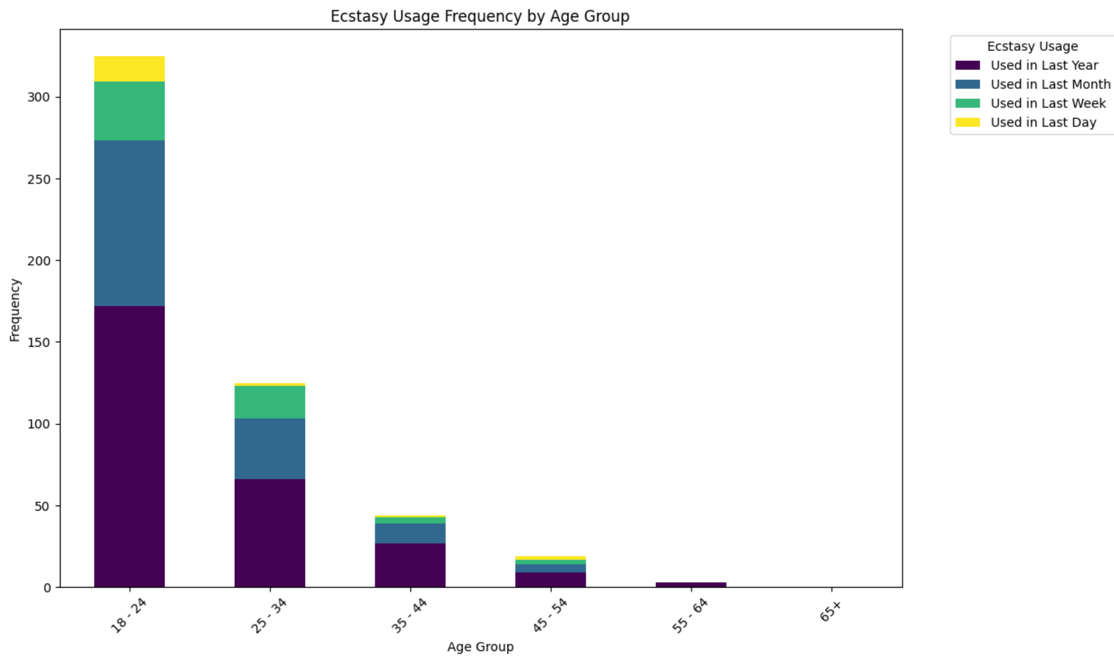

Cannabis Usage Frequency by Age Group
Frequency
Age Group
Cannabis Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
0
100
200
300
400
500
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+


Choc Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Choc Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

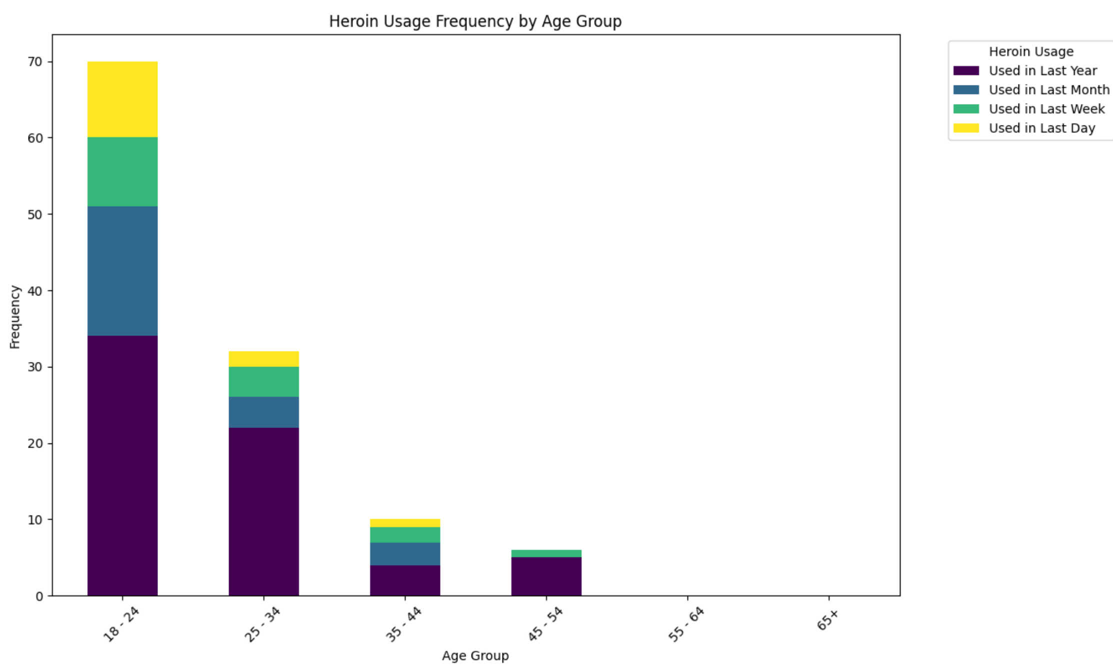

Coke Usage Frequency by Age Group
Frequency
Age Group
0
50
100
150
200
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Coke Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Caff Usage Frequency by Age Group
Frequency
Age Group
0
100
200
300
400
500
600
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Caff Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

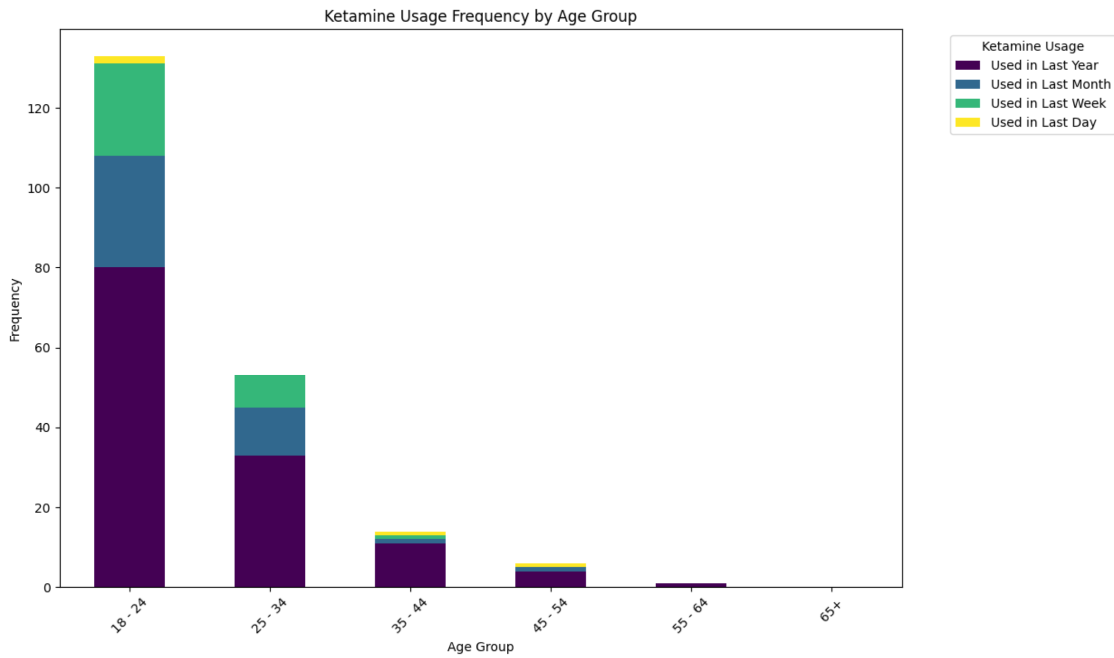

Crack Usage Frequency by Age Group
Frequency
Age Group
0
5
10
15
20
25
30
35
40
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Crack Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

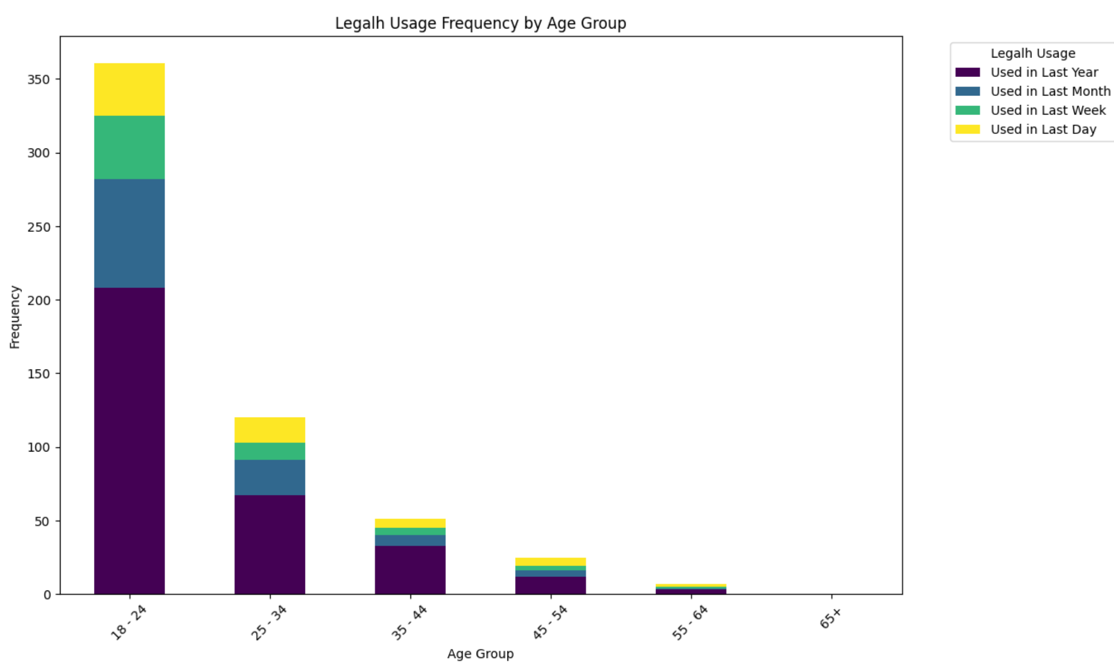


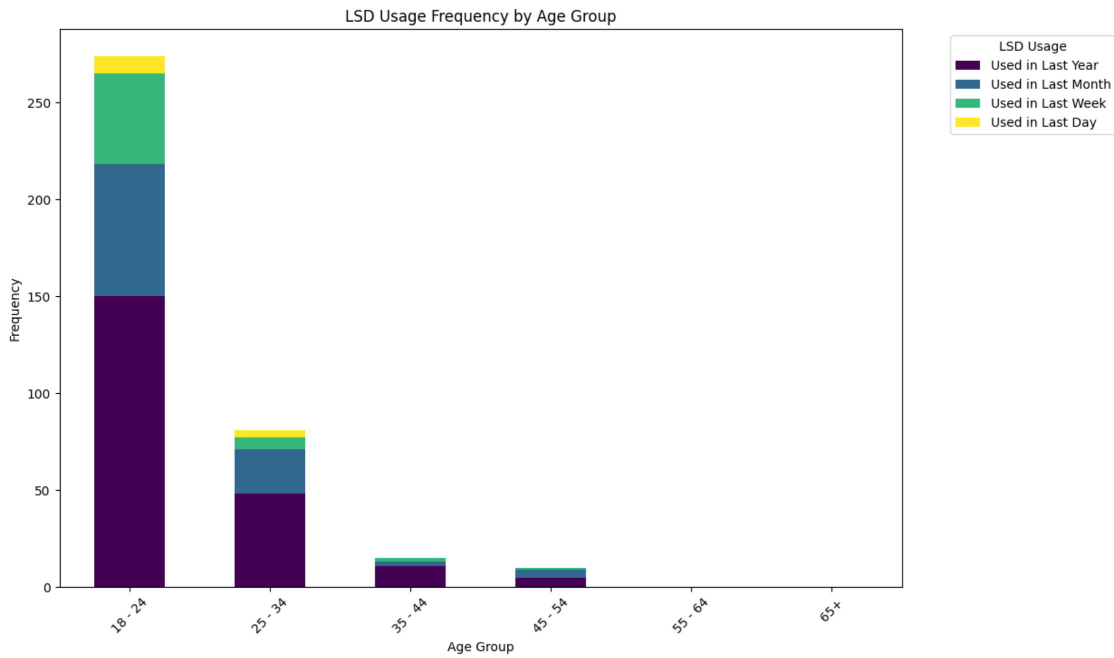
Ecstasy Usage Frequency by Age Group
Ecstasy Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
0
50
100
150
200
250
300
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group

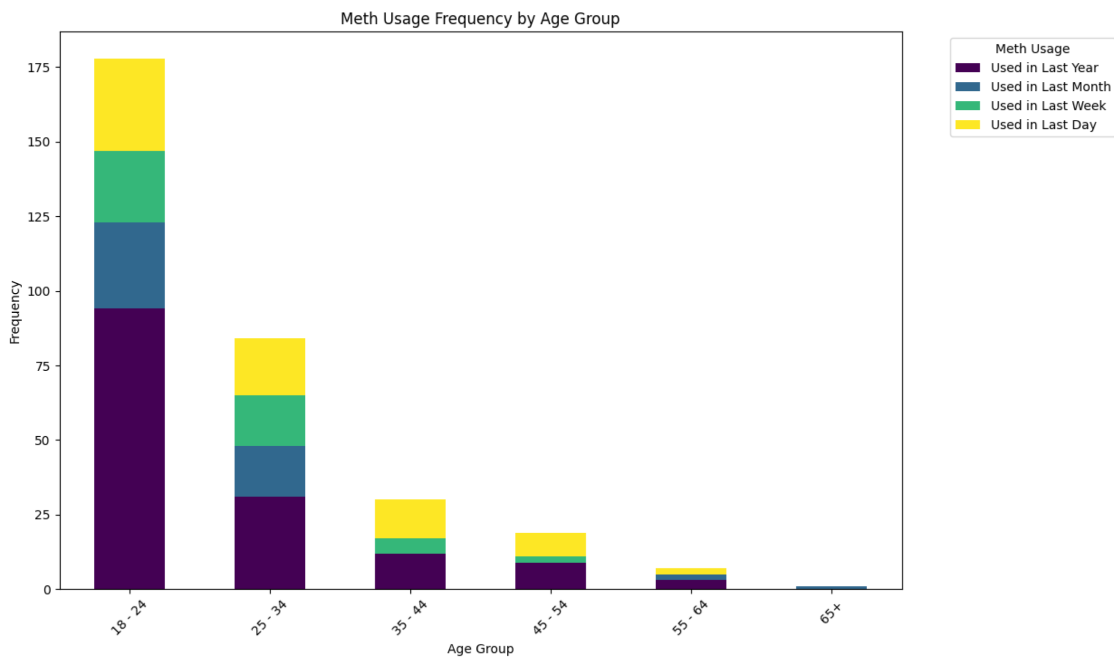


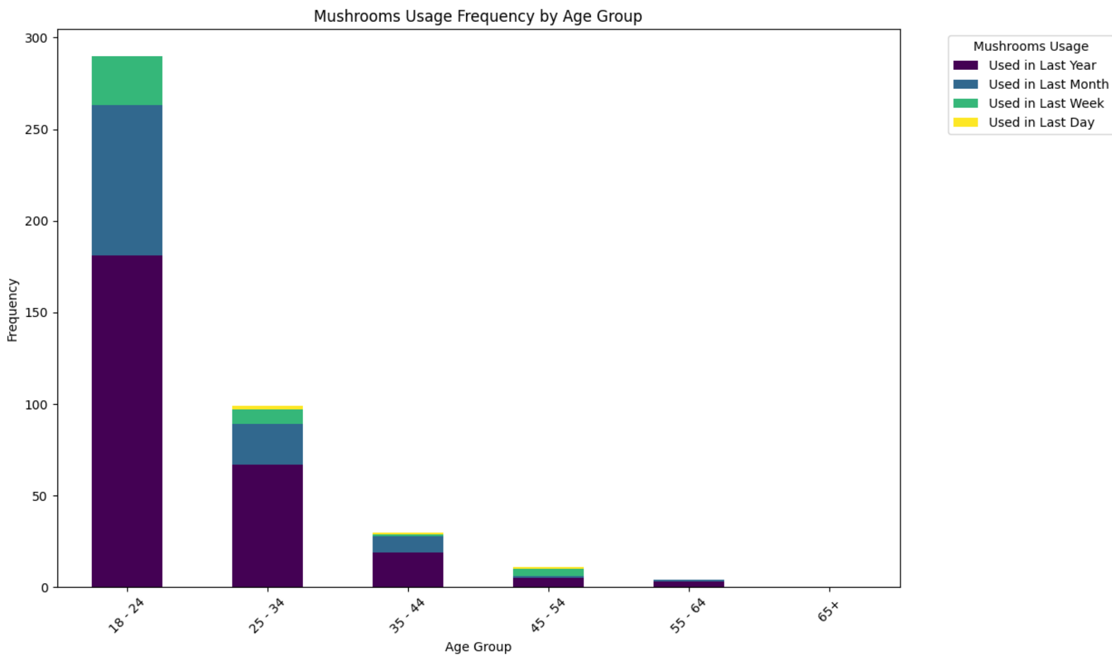
Heroin Usage Frequency by Age Group
Heroin Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
0
10
20
30
40
50
60
70
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group

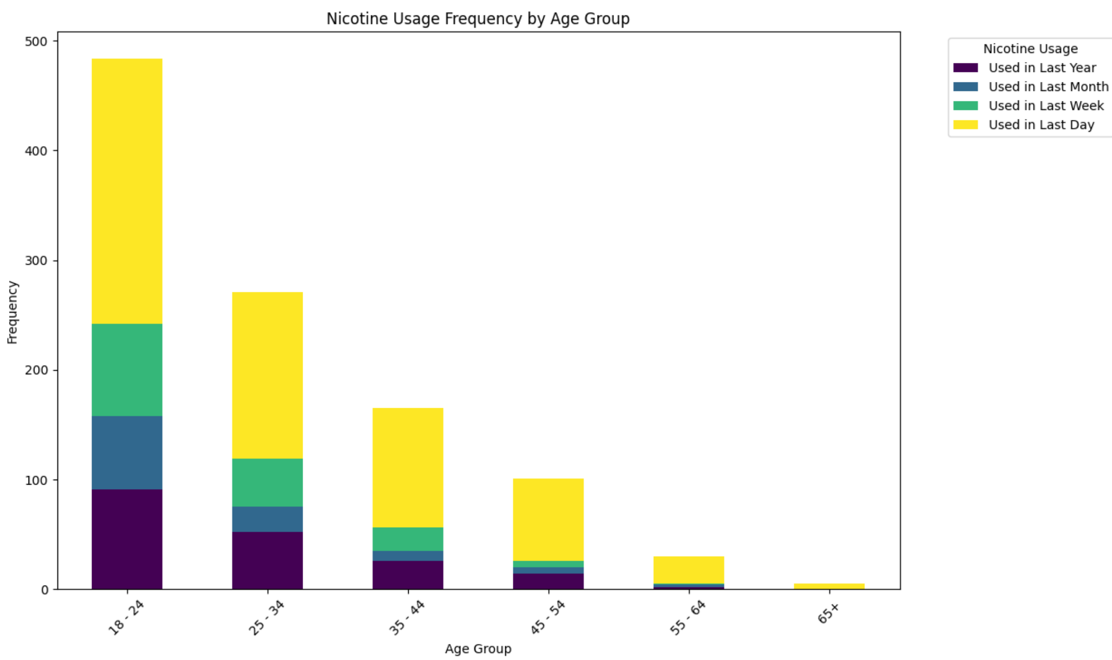

Ketamine Usage Frequency by Age Group
Ketamine Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
0
20
40
60
80
100
120
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group

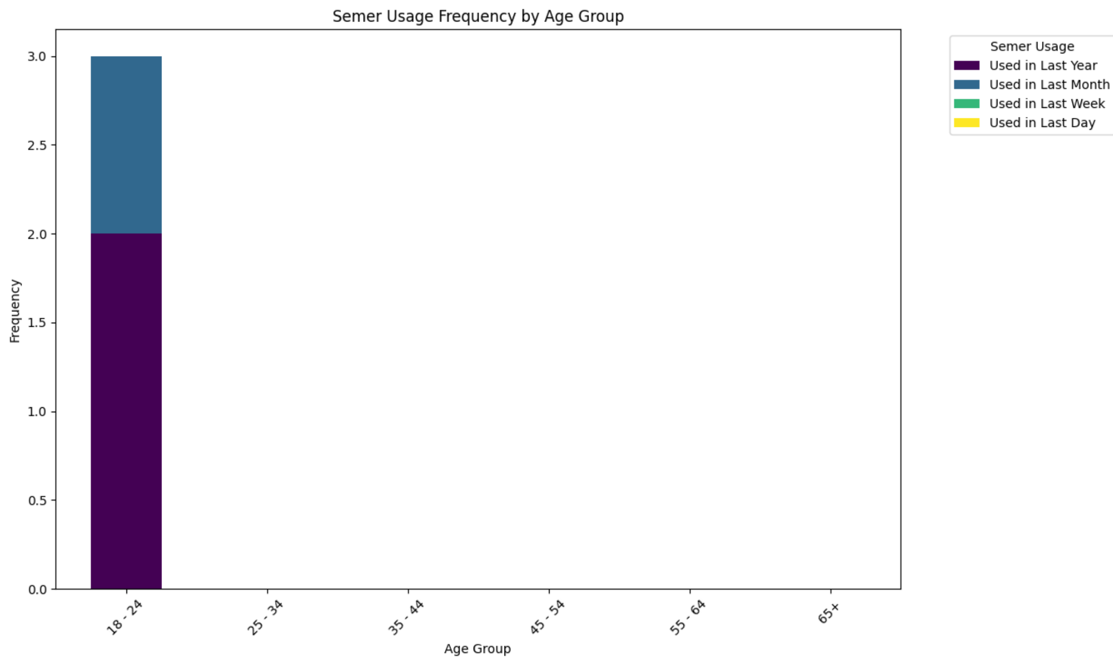

Legalh Usage Frequency by Age Group
Legalh Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
0
50
100
150
200
250
300
350
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group

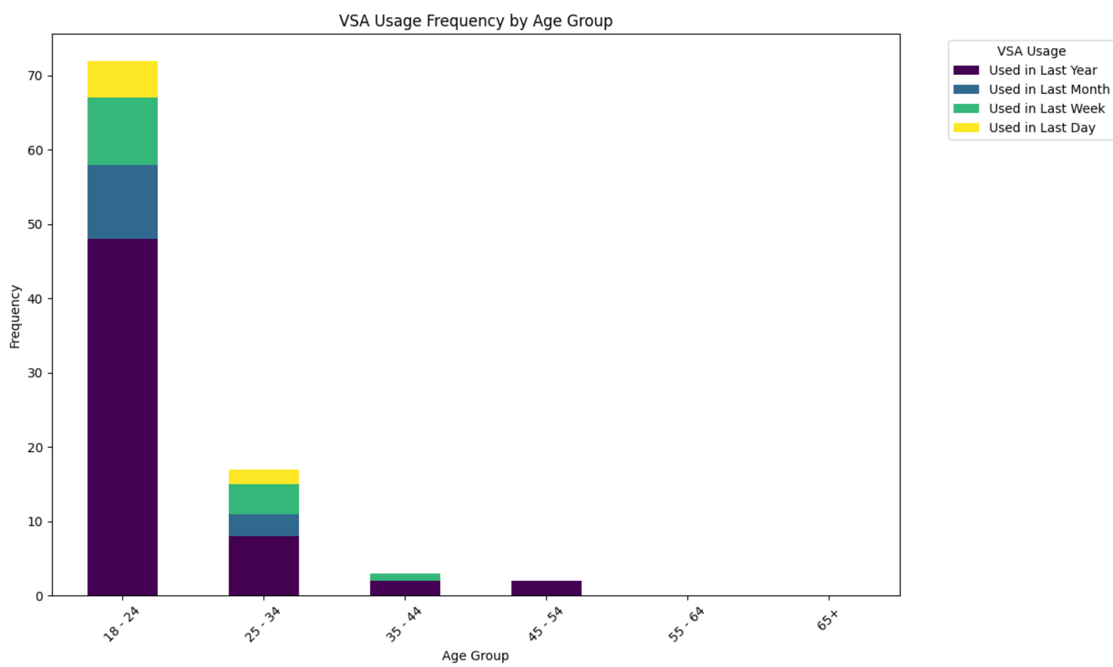

LSD Usage Frequency by Age Group
Frequency
0
50
100
150
200
250
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group
LSD Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Meth Usage Frequency by Age Group
Frequency
0
25
50
75
100
125
150
175
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Age Group
Meth Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Mushrooms Usage Frequency by Age Group
Mushrooms Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
Age Group
0
50
100
150
200
250
300
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+

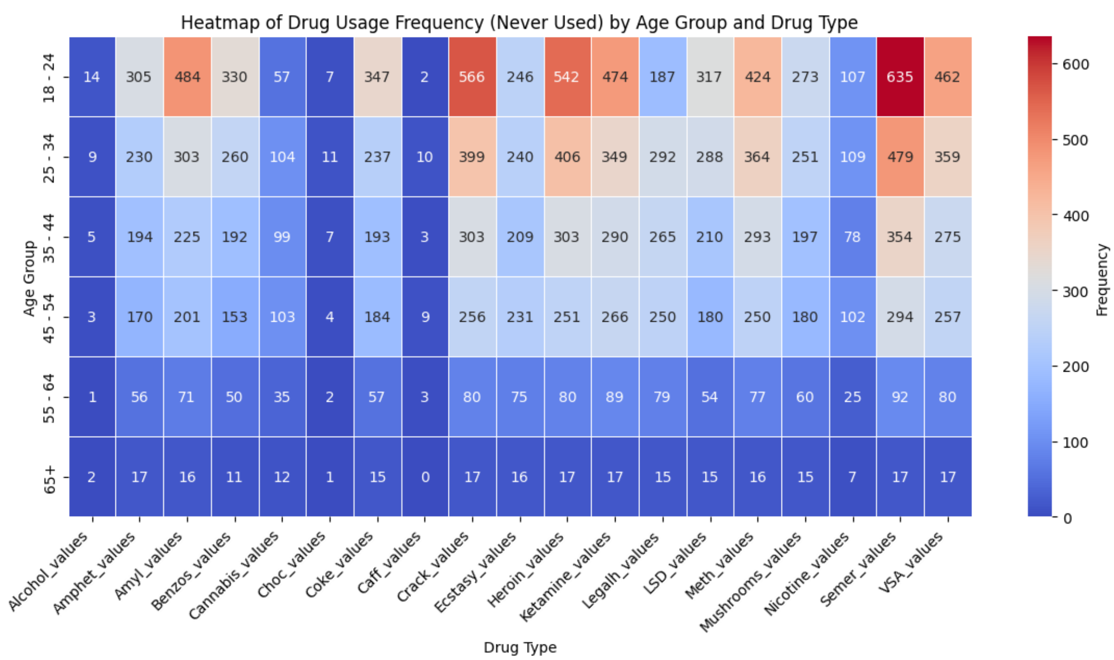

Nicotine Usage Frequency by Age Group
Nicotine Usage
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Frequency
Age Group
0
100
200
300
400
500
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+

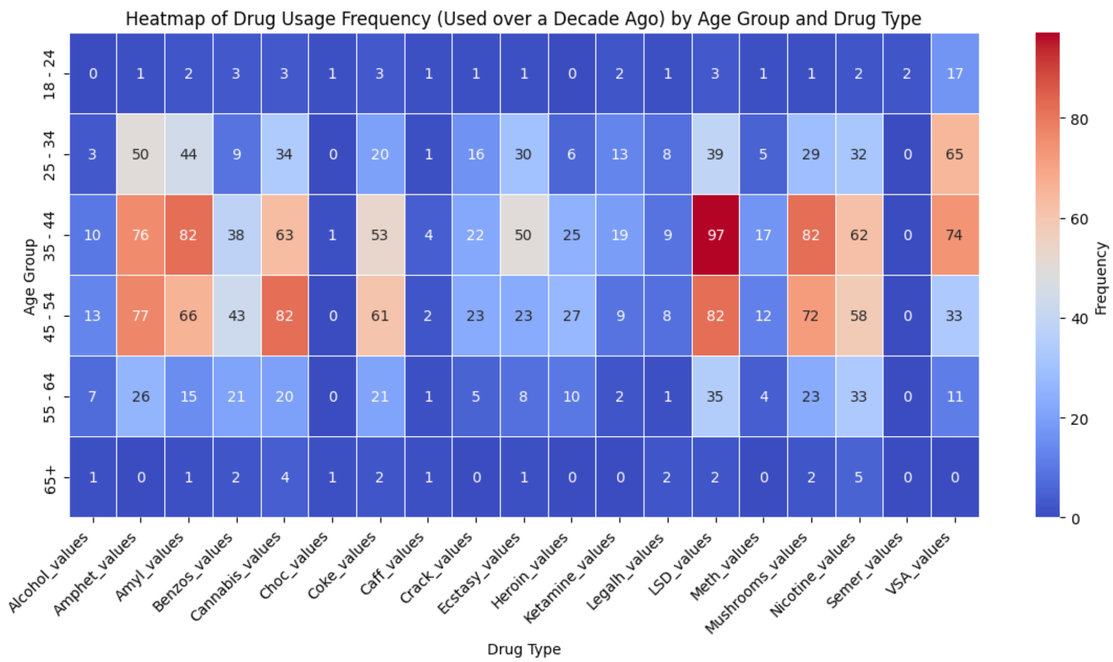


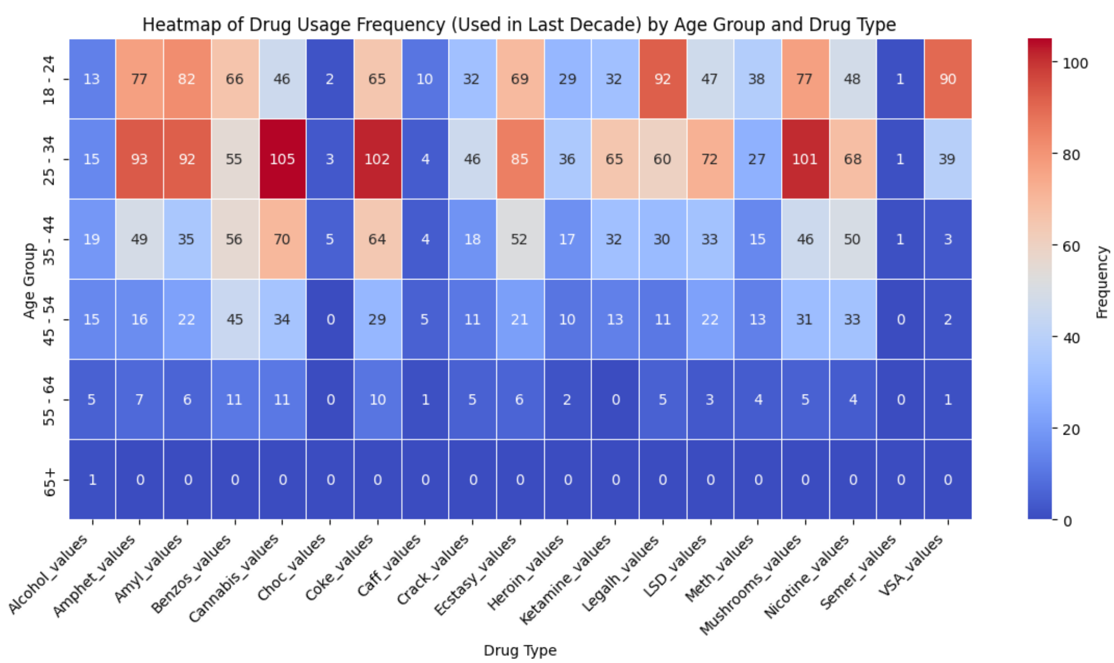


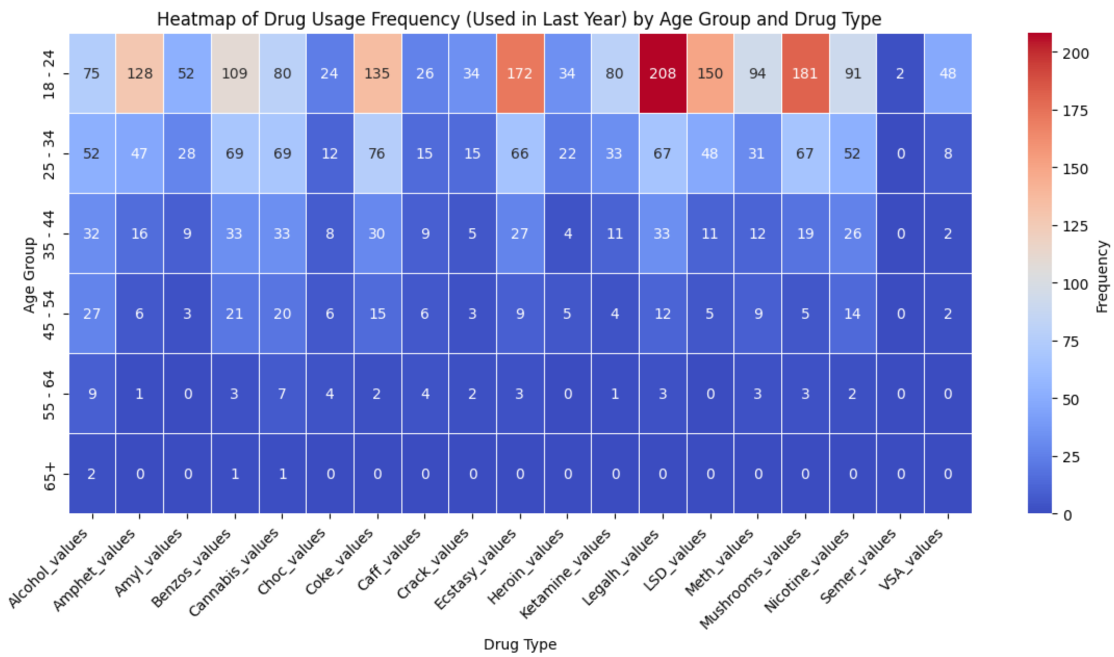
[84]:
```
# Initialize the usage matrix for all age groups
usage_matrix = pd.DataFrame(0, index=age_order, columns=drug_columns)

# Iterate over all drug usage categories
```

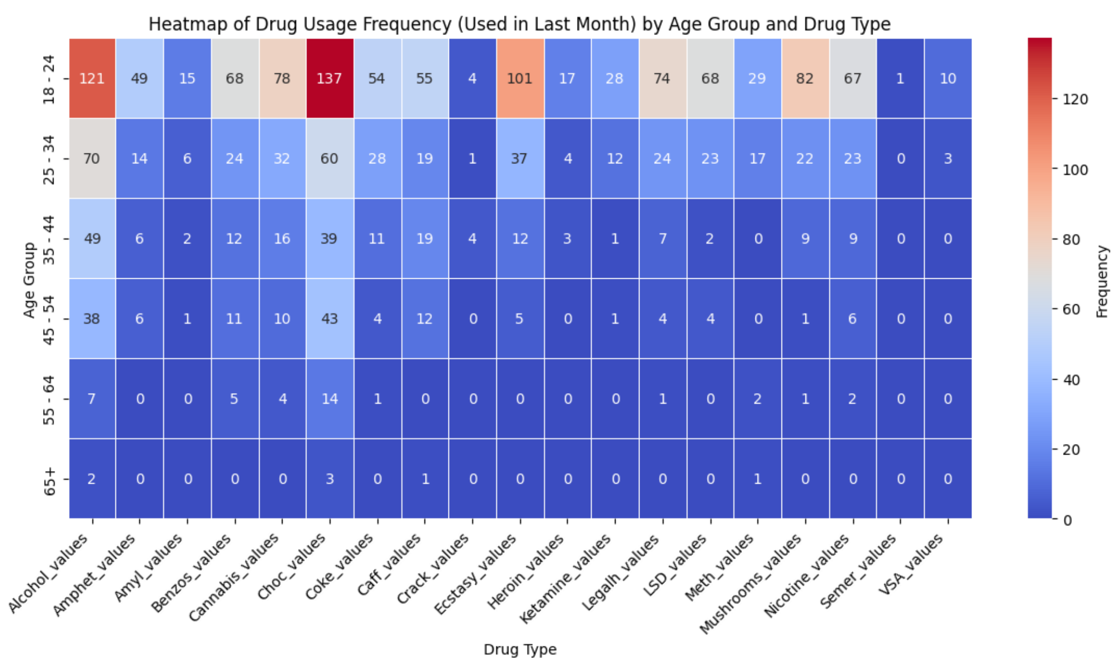
```
for category in CATEGORIES.values():
    # Populate the usage matrix
    for age_key, age_group in age_mapping.items():
        age_group_data = df[df['age_values'] == age_group]
        for drug in drug_columns:
            usage_counts = age_group_data[drug].value_counts()
            # Aggregate the counts for the category e.g., 'Used in Last Day'
            usage_matrix.loc[age_group, drug] = usage_counts.get(category, 0)

    # Plotting the combined heatmap for all age groups
    plt.figure(figsize=(14, 6))  # Adjust size as necessary
    # Format: https://stackoverflow.com/a/65020192
    # Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
    # demonstrating an outstanding understanding of relevant attribute types
    sns.heatmap(usage_matrix, annot=True, fmt='g', cmap='coolwarm',␣
↪cbar_kws={'label': 'Frequency'}, linewidths=0.5)
    plt.title(f'Heatmap of Drug Usage Frequency ({category}) by Age Group and␣
↪Drug Type')
    plt.xlabel('Drug Type')
    plt.ylabel('Age Group')
    plt.xticks(rotation=45, ha='right')
    plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```

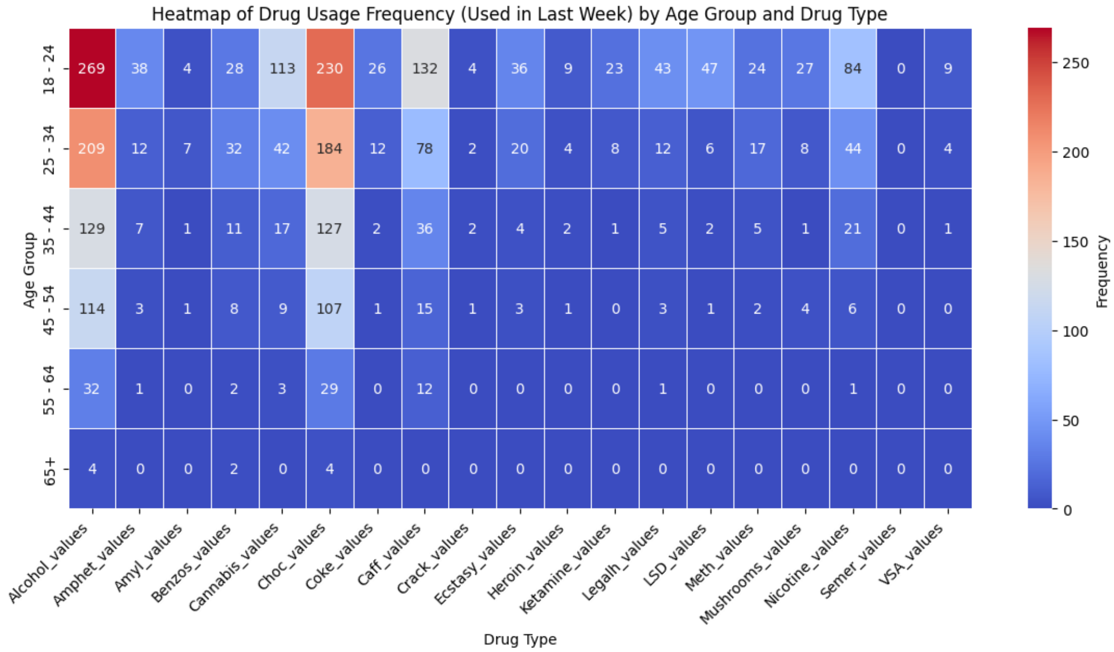


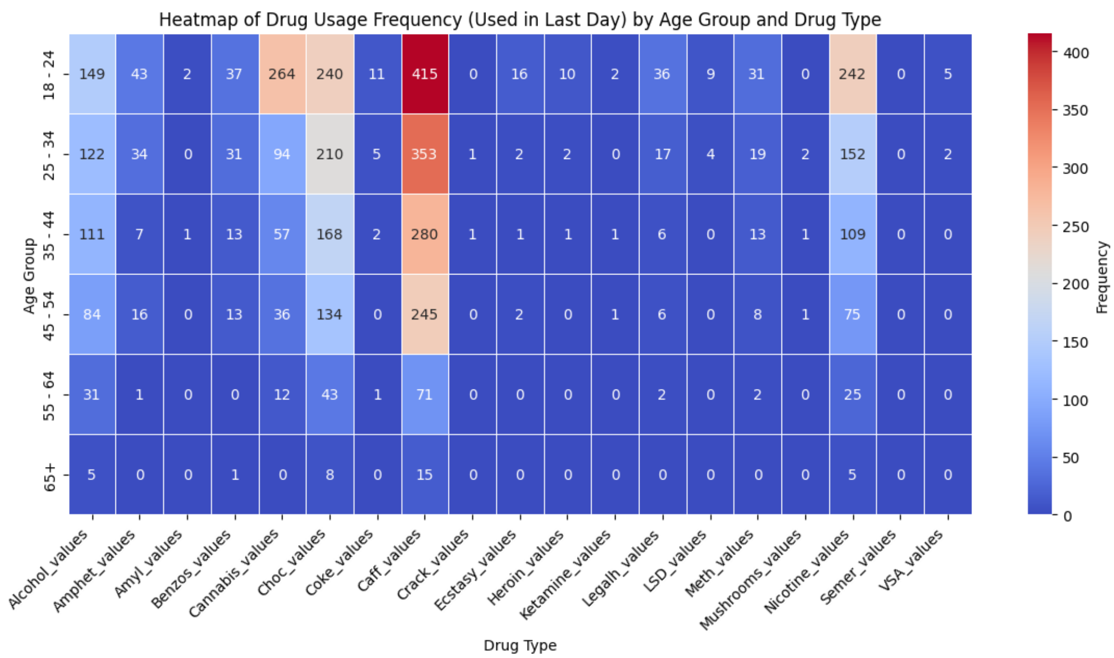

Heatmap of Drug Usage Frequency (Used over a Decade Ago) by Age Group and Drug Type
Age Group
Drug Type
Frequency
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Alcohol_values
Amphet_values
Amyl_values
Benzos_values
Cannabis_values
Choc_values
Coke_values
Caff_values
Crack_values
Ecstasy_values
Heroin_values
Ketamine_values
Legalh_values
LSD_values
Meth_values
Mushrooms_values
Nicotine_values
Semer_values
VSA_values
0 1 2 3 3 1 3 1 1 1 0 2 1 3 1 1 2 2 17
3 50 44 9 34 0 20 1 16 30 6 13 8 39 5 29 32 0 65
10 76 82 38 63 1 53 4 22 50 25 19 9 97 17 82 62 0 74
13 77 66 43 82 0 61 2 23 23 27 9 8 82 12 72 58 0 33
7 26 15 21 20 0 21 1 5 8 10 2 1 35 4 23 33 0 11
1 0 1 2 4 1 2 1 0 1 0 0 2 2 0 2 5 0 0
0
20
40
60
80


Heatmap of Drug Usage Frequency (Used in Last Decade) by Age Group and Drug Type
Age Group
Drug Type
Frequency
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Alcohol_values
Amphet_values
Amyl_values
Benzos_values
Cannabis_values
Choc_values
Coke_values
Caff_values
Crack_values
Ecstasy_values
Heroin_values
Ketamine_values
Legalh_values
LSD_values
Meth_values
Mushrooms_values
Nicotine_values
Semer_values
VSA_values
13 77 82 66 46 2 65 10 32 69 29 32 92 47 38 77 48 1 90
15 93 92 55 105 3 102 4 46 85 36 65 60 72 27 101 68 1 39
19 49 35 56 70 5 64 4 18 52 17 32 30 33 15 46 50 1 3
15 16 22 45 34 0 29 5 11 21 10 13 11 22 13 31 33 0 2
5 7 6 11 11 0 10 1 5 6 2 0 5 3 4 5 4 0 1
1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
20
40
60
80
100


Heatmap of Drug Usage Frequency (Used in Last Year) by Age Group and Drug Type
Age Group
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
75 128 52 109 80 24 135 26 34 172 34 80 208 150 94 181 91 2 48
52 47 28 69 69 12 76 15 15 66 22 33 67 48 31 67 52 0 8
32 16 9 33 33 8 30 9 5 27 4 11 33 11 12 19 26 0 2
27 6 3 21 20 6 15 6 3 9 5 4 12 5 9 5 14 0 2
9 1 0 3 7 4 2 4 2 3 0 1 3 0 3 3 2 0 0
2 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Alcohol_values
Amphet_values
Amyl_values
Benzos_values
Cannabis_values
Choc_values
Coke_values
Caff_values
Crack_values
Ecstasy_values
Heroin_values
Ketamine_values
Legalh_values
LSD_values
Meth_values
Mushrooms_values
Nicotine_values
Semer_values
VSA_values
Drug Type
Frequency
0
25
50
75
100
125
150
175
200


Heatmap of Drug Usage Frequency (Used in Last Month) by Age Group and Drug Type
Age Group
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
121 49 15 68 78 137 54 55 4 101 17 28 74 68 29 82 67 1 10
70 14 6 24 32 60 28 19 1 37 4 12 24 23 17 22 23 0 3
49 6 2 12 16 39 11 19 4 12 3 1 7 2 0 9 9 0 0
38 6 1 11 10 43 4 12 0 5 0 1 4 4 0 1 6 0 0
7 0 0 5 4 14 1 0 0 0 0 0 1 0 2 1 2 0 0
2 0 0 0 0 3 0 1 0 0 0 0 0 0 1 0 0 0 0
Alcohol_values
Amphet_values
Amyl_values
Benzos_values
Cannabis_values
Choc_values
Coke_values
Caff_values
Crack_values
Ecstasy_values
Heroin_values
Ketamine_values
Legalh_values
LSD_values
Meth_values
Mushrooms_values
Nicotine_values
Semer_values
VSA_values
Drug Type
Frequency
0
20
40
60
80
100
120





[85]:
```python
# Iterate over each category in the dictionary CATEGORIES, whose values may␣
↪represent specific groups of interest
# Iterate over all drug usage categories
for category in CATEGORIES.values():
```

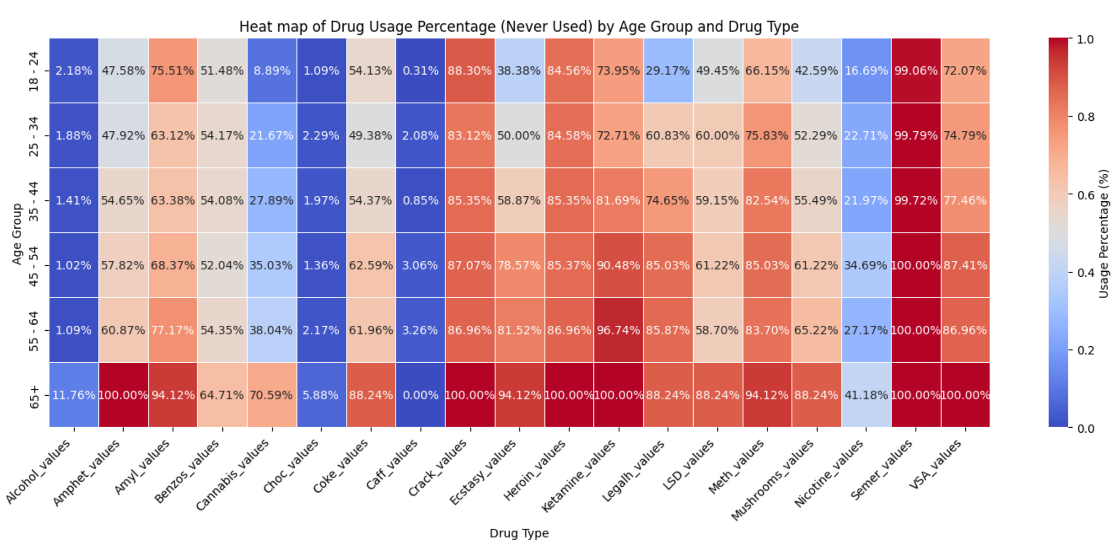
```
    # Populate the usage matrix with percentages
    for age_key, age_group in age_mapping.items():
        # Filter the df to include only data for the current age group
        age_group_data = df[df['age_values'] == age_group]
        # Total number of respondents in this age group
        total_respondents = age_group_data.shape[0]

        # Iterate over the columns in the df that correspond to different drugs
        for drug in drug_columns:
            # Get the count of each category's usage within the specified drug␣
↪column
            usage_counts = age_group_data[drug].value_counts()
            if total_respondents > 0:
                # Calculate the percentage of respondents using the drug␣
↪categorized under 'category'
                usage_percentage = (usage_counts.get(category, 0) /␣
↪total_respondents)
                # Update the corresponding cell in the usage matrix with the␣
↪calculated percentage
                usage_matrix.loc[age_group, drug] = usage_percentage
            else:
                # If there are no respondents in this age group, set usage␣
↪percentage to 0 to avoid division by zero
                usage_matrix.loc[age_group, drug] = 0

    # Plotting the combined heatmap for each drug usage category
    plt.figure(figsize=(18, 6))  # Set the size of the figure
    # Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
    # demonstrating an outstanding understanding of relevant attribute types
    sns.heatmap(usage_matrix, annot=True, fmt='.2%', cmap='coolwarm',␣
↪cbar_kws={'label': 'Usage Percentage (%)'},
                linewidths=0.5)

    plt.title(f'Heat map of Drug Usage Percentage ({category}) by Age Group and␣
↪Drug Type')
    plt.xlabel('Drug Type')
    plt.ylabel('Age Group')
    # Rotate x-axis labels for better readability
    plt.xticks(rotation=45, ha='right')
    plt.show()
```

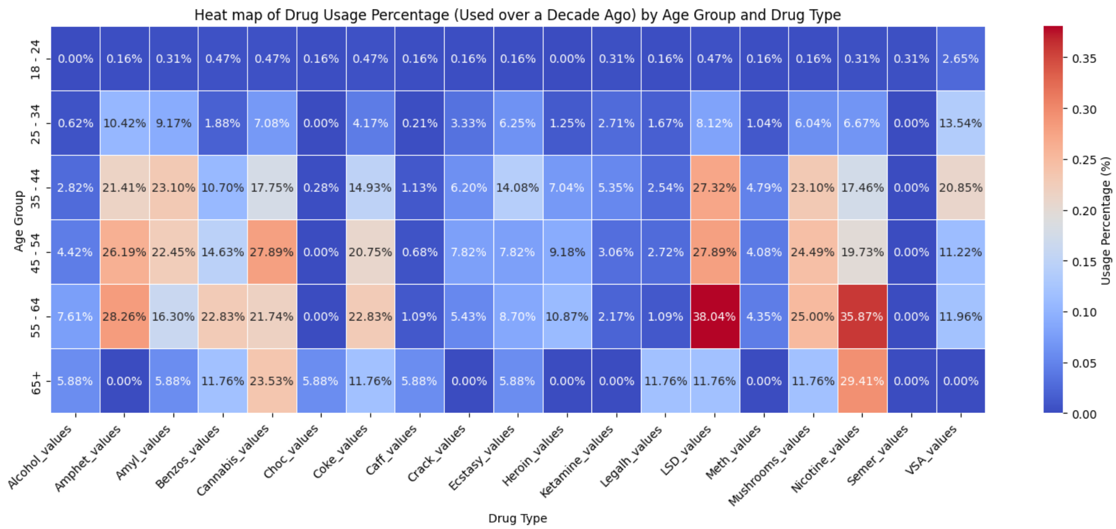
```
/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.0218408736349454' has dtype incompatible with
```

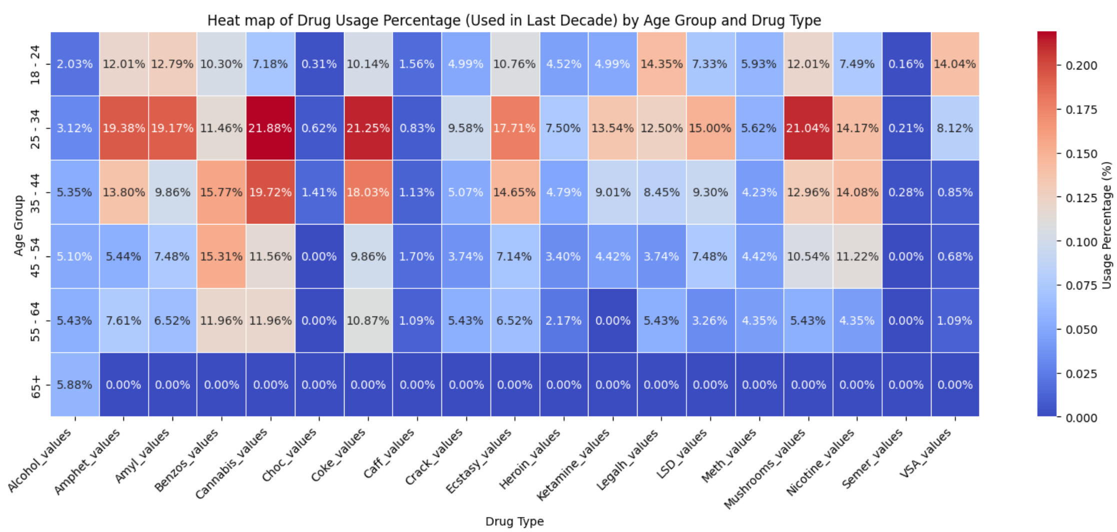
```
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.47581903276131043' has dtype incompatible
with int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.7550702028081123' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.514820592823713' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.08892355694227769' has dtype incompatible
with int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.0109204368174727' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.5413416536661466' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
```

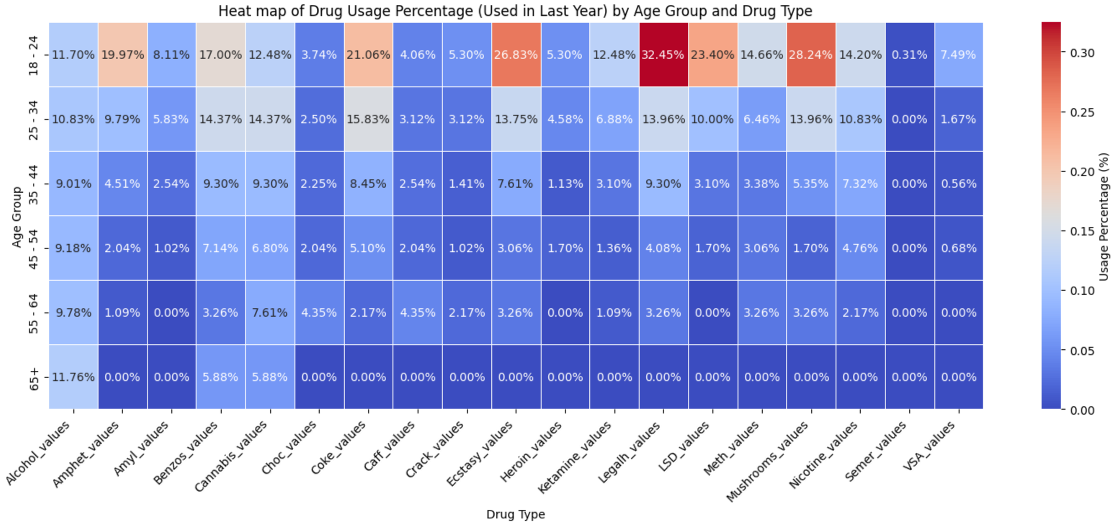
```
future version of pandas. Value '0.0031201248049922' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.8829953198127926' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.3837753510140406' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.8455538221528861' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.7394695787831513' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.2917316692667707' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.49453978159126366' has dtype incompatible
with int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:
```

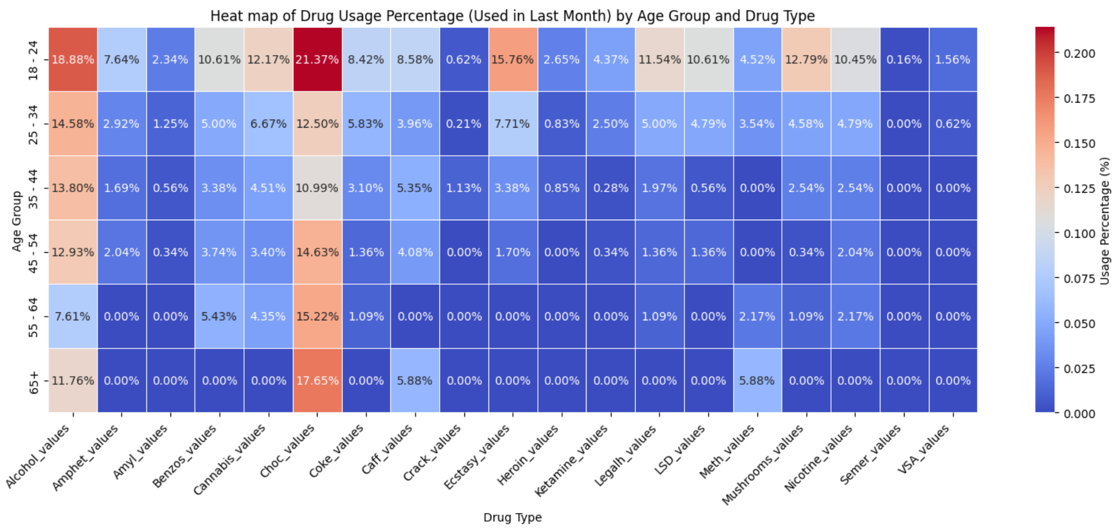
```
Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.6614664586583463' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.42589703588143524' has dtype incompatible
with int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.1669266770670827' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.9906396255850234' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.

/var/folders/ck/vgxn_9f907d122j56f3203gm0000gn/T/ipykernel_22891/34385846.py:19:
FutureWarning:

Setting an item of incompatible dtype is deprecated and will raise an error in a
future version of pandas. Value '0.7207488299531981' has dtype incompatible with
int64, please explicitly cast to a compatible dtype first.
```

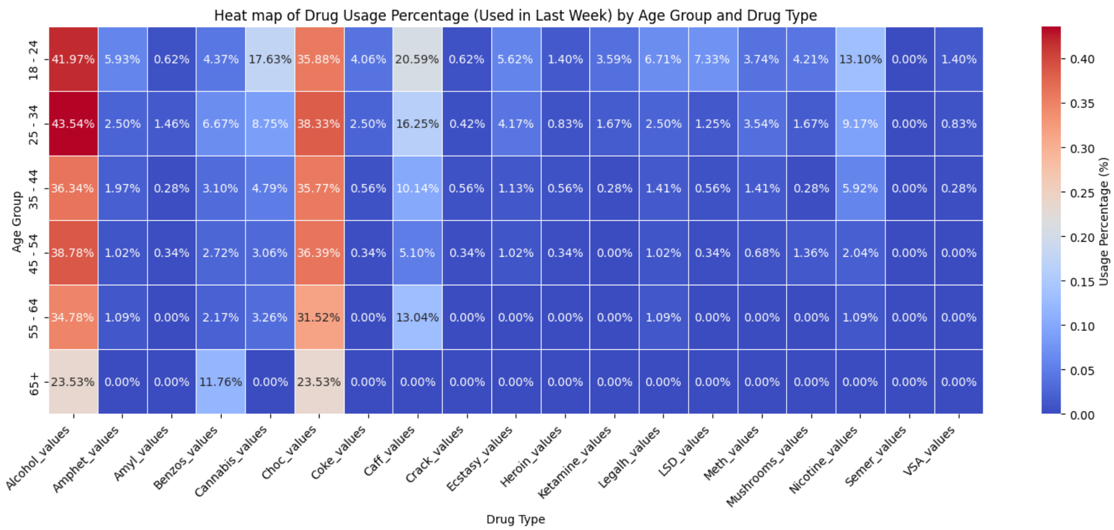


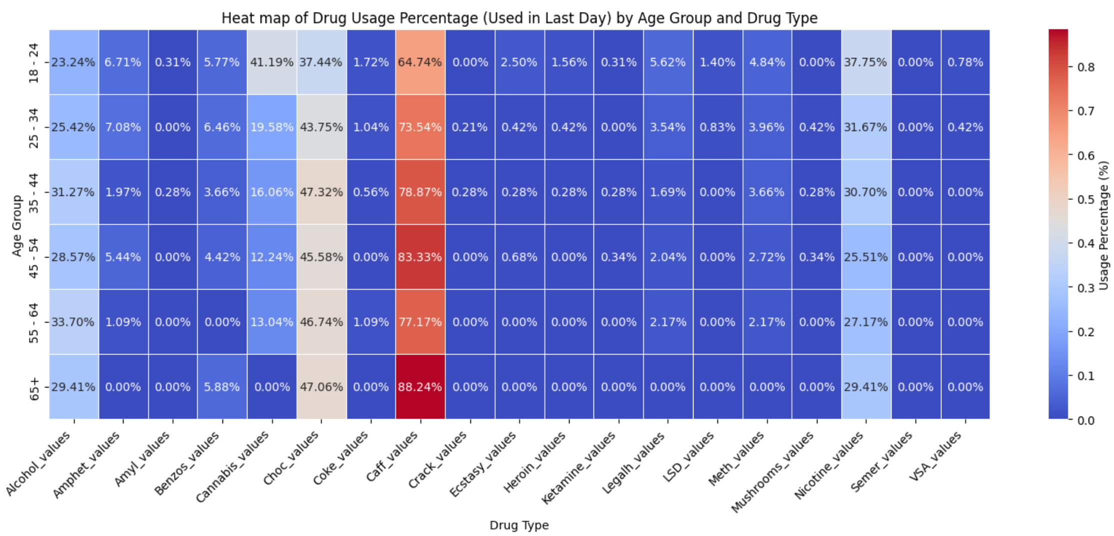

Heat map of Drug Usage Percentage (Used over a Decade Ago) by Age Group and Drug Type
Age Group
Drug Type
Usage Percentage (%)


Heat map of Drug Usage Percentage (Used in Last Decade) by Age Group and Drug Type
Age Group
Drug Type
Usage Percentage (%)

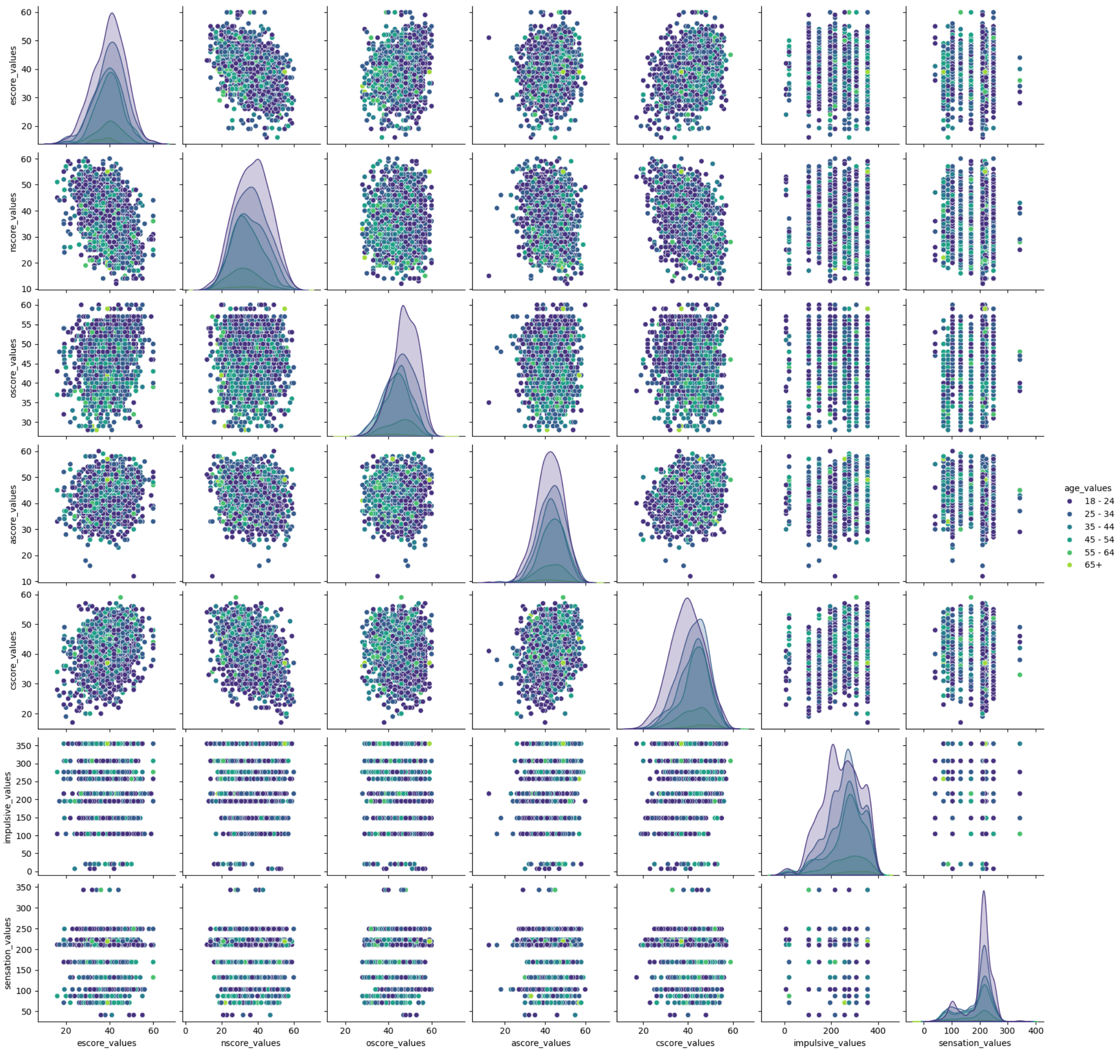

Heat map of Drug Usage Percentage (Used in Last Year) by Age Group and Drug Type
Age Group
Drug Type
Usage Percentage (%)
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Alcohol_values
Amphet_values
Amyl_values
Benzos_values
Cannabis_values
Choc_values
Coke_values
Caff_values
Crack_values
Ecstasy_values
Heroin_values
Ketamine_values
Legalh_values
LSD_values
Meth_values
Mushrooms_values
Nicotine_values
Semer_values
VSA_values
11.70% 19.97% 8.11% 17.00% 12.48% 3.74% 21.06% 4.06% 5.30% 26.83% 5.30% 12.48% 32.45% 23.40% 14.66% 28.24% 14.20% 0.31% 7.49%
10.83% 9.79% 5.83% 14.37% 14.37% 2.50% 15.83% 3.12% 3.12% 13.75% 4.58% 6.88% 13.96% 10.00% 6.46% 13.96% 10.83% 0.00% 1.67%
9.01% 4.51% 2.54% 9.30% 9.30% 2.25% 8.45% 2.54% 1.41% 7.61% 1.13% 3.10% 9.30% 3.10% 3.38% 5.35% 7.32% 0.00% 0.56%
9.18% 2.04% 1.02% 7.14% 6.80% 2.04% 5.10% 2.04% 1.02% 3.06% 1.70% 1.36% 4.08% 1.70% 3.06% 1.70% 4.76% 0.00% 0.68%
9.78% 1.09% 0.00% 3.26% 7.61% 4.35% 2.17% 4.35% 2.17% 3.26% 0.00% 1.09% 3.26% 0.00% 3.26% 3.26% 2.17% 0.00% 0.00%
11.76% 0.00% 0.00% 5.88% 5.88% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00%
0.00
0.05
0.10
0.15
0.20
0.25
0.30


Heat map of Drug Usage Percentage (Used in Last Month) by Age Group and Drug Type
Age Group
Drug Type
Usage Percentage (%)
18 - 24
25 - 34
35 - 44
45 - 54
55 - 64
65+
Alcohol_values
Amphet_values
Amyl_values
Benzos_values
Cannabis_values
Choc_values
Coke_values
Caff_values
Crack_values
Ecstasy_values
Heroin_values
Ketamine_values
Legalh_values
LSD_values
Meth_values
Mushrooms_values
Nicotine_values
Semer_values
VSA_values
18.88% 7.64% 2.34% 10.61% 12.17% 21.37% 8.42% 8.58% 0.62% 15.76% 2.65% 4.37% 11.54% 10.61% 4.52% 12.79% 10.45% 0.16% 1.56%
14.58% 2.92% 1.25% 5.00% 6.67% 12.50% 5.83% 3.96% 0.21% 7.71% 0.83% 2.50% 5.00% 4.79% 3.54% 4.58% 4.79% 0.00% 0.62%
13.80% 1.69% 0.56% 3.38% 4.51% 10.99% 3.10% 5.35% 1.13% 3.38% 0.85% 0.28% 1.97% 0.56% 0.00% 2.54% 2.54% 0.00% 0.00%
12.93% 2.04% 0.34% 3.74% 3.40% 14.63% 1.36% 4.08% 0.00% 1.70% 0.00% 0.34% 1.36% 1.36% 0.00% 0.34% 2.04% 0.00% 0.00%
7.61% 0.00% 0.00% 5.43% 4.35% 15.22% 1.09% 0.00% 0.00% 0.00% 0.00% 0.00% 1.09% 0.00% 2.17% 1.09% 2.17% 0.00% 0.00%
11.76% 0.00% 0.00% 0.00% 0.00% 17.65% 0.00% 5.88% 0.00% 0.00% 0.00% 0.00% 0.00% 0.00% 5.88% 0.00% 0.00% 0.00% 0.00%
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200

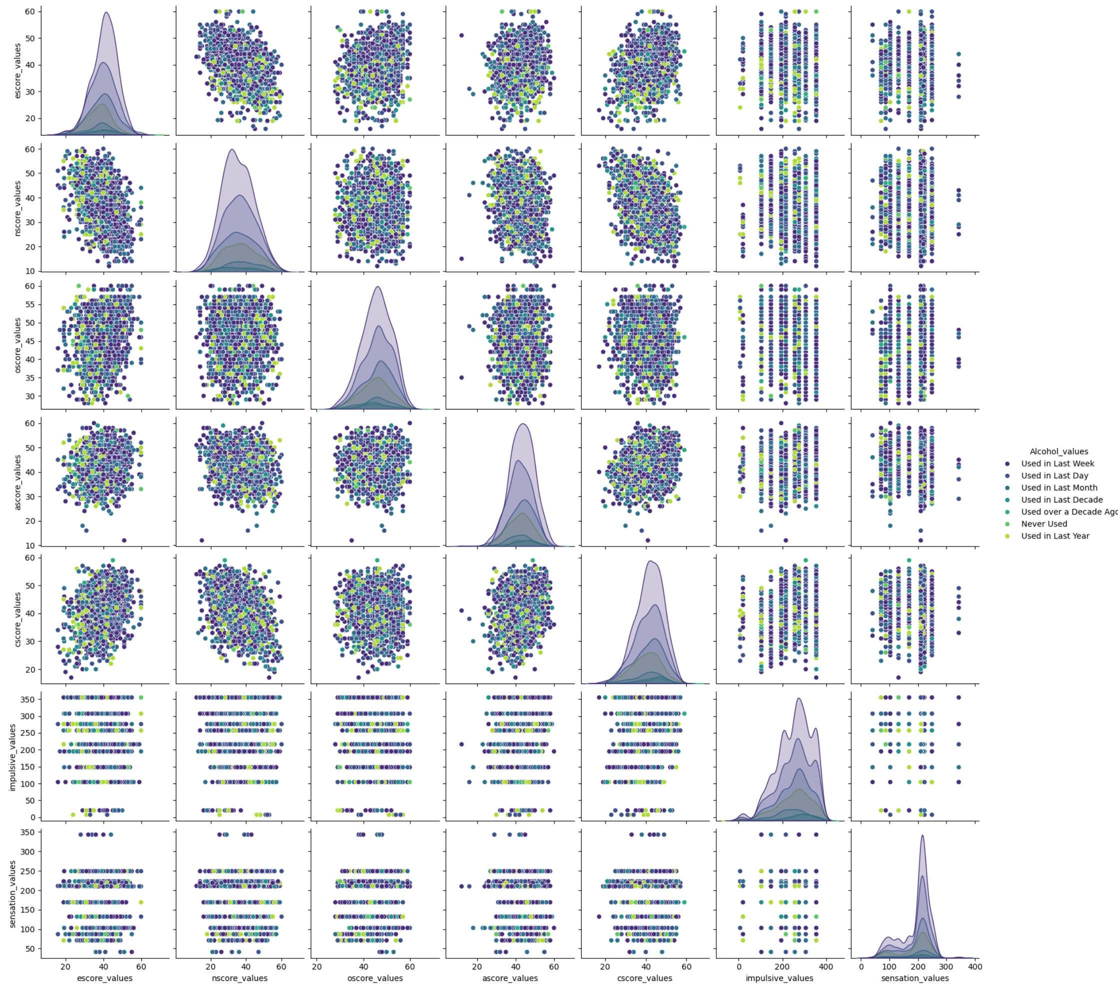




[86]:
```python
# Pair plot with age class
# Exceptionally answers specific business questions using advanced data
↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.pairplot(df.loc[:, df.columns!='ID'], hue='age_values', palette='viridis')
plt.show() # presenting visually compelling plots or charts that surpass
↪expectations.
```



[87]:
```
# Pair plot with alcohol usage class
# Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.pairplot(df.loc[:, df.columns!='ID'], hue='Alcohol_values',␣
↪palette='viridis')
plt.show()
```



5.2.1 Analysis:

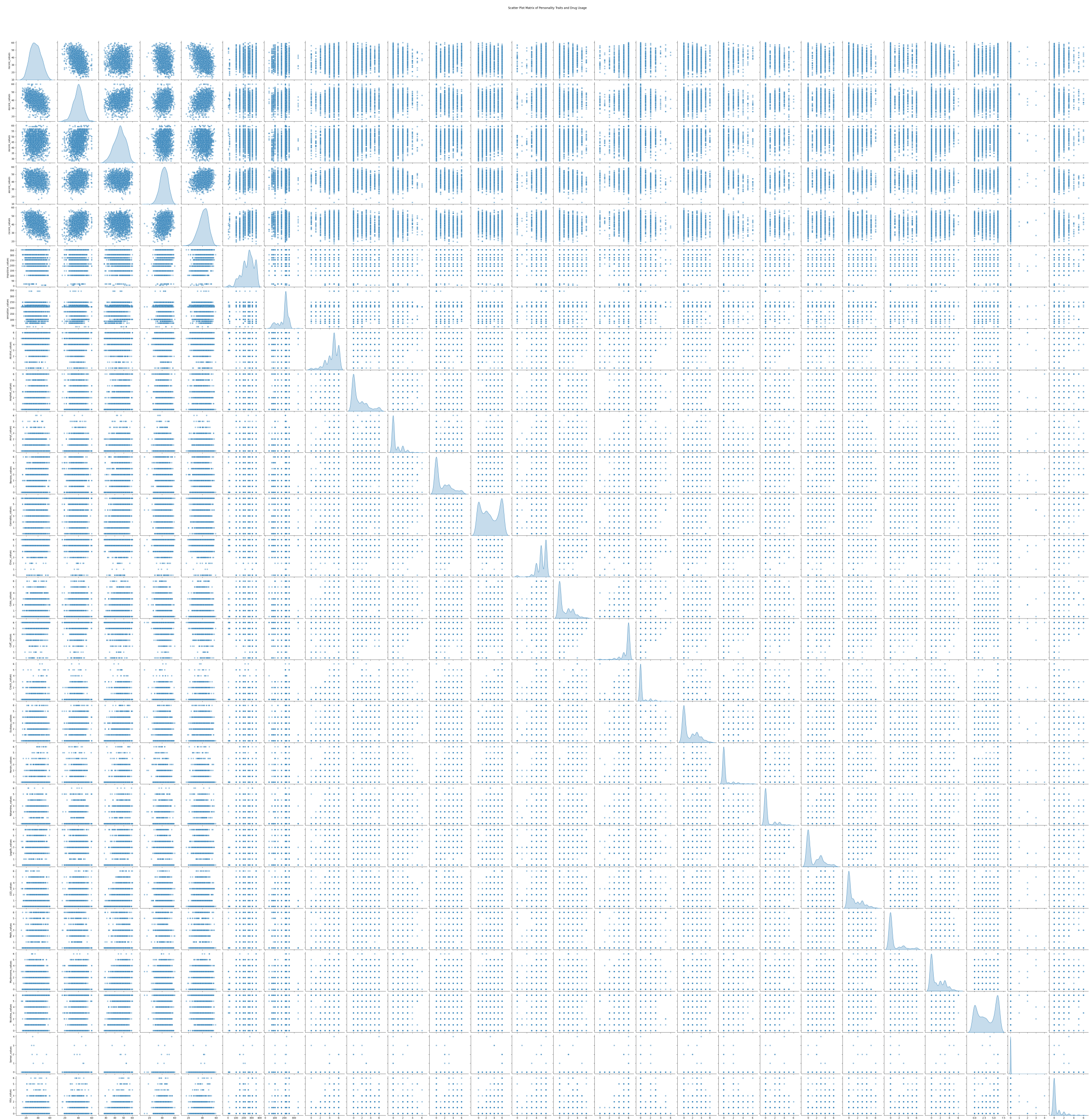
The stacked bar charts reveal distinct patterns in drug usage frequency across age groups. For instance: - **Alcohol**: Higher recent usage is observed in younger age groups (18-24 and 25-34). - **Cannabis**: Also shows higher recent usage in younger demographics, with a notable decline in older age groups. - **Caffeine**: Exhibits consistent high usage across all age groups, reflecting its widespread acceptance.

These trends highlight the need for age-specific strategies in drug prevention and intervention programs.

5.3 TASK 2.2: Q2 - Is there a correlation between personality traits and drug usage frequency?

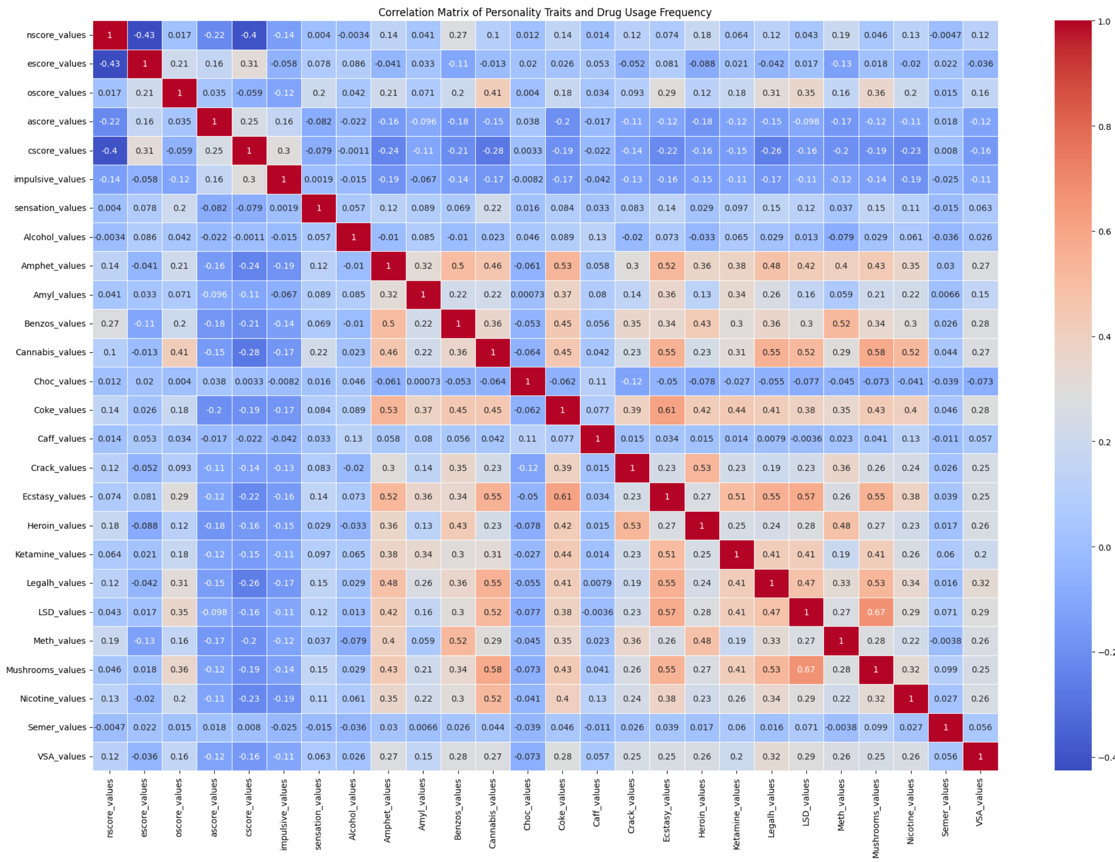
[88]:
```
# Preprocessing: Ensuring personality traits and drug usage columns are numeric
# Make a copy of the dataframe for mapping and conversion
data_mapped = df.copy()

# Apply the mapping to the drug usage columns
for col in drug_columns:
    data_mapped[col] = data_mapped[col].map(usage_mapping)

# Convert all relevant columns to numeric, coercing errors
for col in personality_traits_scores_columns + drug_columns:
    data_mapped[col] = pd.to_numeric(data_mapped[col], errors='coerce')

# Drop rows with missing values in the relevant columns
data_mapped_clean = data_mapped.dropna(subset=personality_traits_scores_columns␣
 ↪+ drug_columns)
```

[89]:
```
# Scatter Plot Matrix (Pairs Plot)
sns.pairplot(data_mapped_clean[personality_traits_scores_columns +␣
 ↪drug_columns], diag_kind='kde', kind='scatter',
             plot_kws={'alpha': 0.5})
plt.suptitle('Scatter Plot Matrix of Personality Traits and Drug Usage', y=1.02)
plt.show()
```



[90]:
```python
# Correlation Matrix with Heat map
correlation_matrix_clean = data_mapped_clean[personality_traits_scores_columns␣
 ↪+ drug_columns].corr()
plt.figure(figsize=(24, 16))
# Exceptionally answers specific business questions using advanced data␣
 ↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.heatmap(correlation_matrix_clean, annot=True, cmap='coolwarm', linewidths=0.
 ↪5)
plt.title('Correlation Matrix of Personality Traits and Drug Usage Frequency')
```

```
plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```



[91]:
```
# Apply the mapping to the drug usage columns
for col in drug_columns:
    df.loc[:, col] = df[col].map(usage_mapping)

# Ensure all relevant columns are numeric
for col in personality_traits_scores_columns + drug_columns:
    df.loc[:, col] = pd.to_numeric(df[col], errors='coerce')

# Drop rows with missing values in the selected columns
data_clean = df.dropna(subset=personality_traits_scores_columns + drug_columns)

# Calculate the correlation matrix
correlation_matrix = data_clean[personality_traits_scores_columns +␣
↪drug_columns].corr()
```

[92]:
```
# Function to calculate p-values
def calculate_pvalues(df):
```

```
    # Initialize a df to store p-values with the same columns as the input df.
    columns_pvalues = pd.DataFrame(columns=df.columns)
    p_values_matrix = columns_pvalues.transpose().join(columns_pvalues,␣
 ↪how='outer')

    try:
        # Iterate over each combination of columns to calculate the p-value.
        for row_col in df.columns:
            for col_col in df.columns:
                # Check for columns with only NaN values or only one unique␣
 ↪value.
                if (df[row_col].isnull().all() or df[col_col].isnull().all() or
                        len(df[row_col].unique()) <= 1 or len(df[col_col].
 ↪unique()) <= 1):
                    p_values_matrix.loc[row_col, col_col] = None
                else:
                    # Calculate the Pearson correlation p-value, rounding to 4␣
 ↪decimal places.
                    p_value = pearsonr(df[row_col].dropna(), df[col_col].
 ↪dropna())[1]
                    p_values_matrix.loc[row_col, col_col] = round(p_value, 4)
    except Exception as e:
        print(f"An error occurred while calculating p-values: {e}")
        return None

    return p_values_matrix
```

[93]:
```
# Calculate p-values for the correlations
pvalues = calculate_pvalues(data_clean[personality_traits_scores_columns +␣
 ↪drug_columns])

# Display the correlation matrix and p-values
print('Correlation Matrix:\n', correlation_matrix)
print('\nP-Values Matrix:\n', pvalues)
```

```
Correlation Matrix:
                    nscore_values  escore_values  oscore_values  ascore_values  \
nscore_values           1.000000      -0.426282       0.017496      -0.216593
escore_values          -0.426282       1.000000       0.213604       0.161470
oscore_values           0.017496       0.213604       1.000000       0.035290
ascore_values          -0.216593       0.161470       0.035290       1.000000
cscore_values          -0.398768       0.310206      -0.058959       0.250090
impulsive_values       -0.140776      -0.057977      -0.116153       0.161733
sensation_values        0.004036       0.077550       0.203656      -0.081683
Alcohol_values         -0.003362       0.085910       0.042386      -0.021889
Amphet_values           0.135564      -0.040807       0.214022      -0.157710
Amyl_values             0.040909       0.032543       0.070800      -0.095507
```

```
Benzos_values           0.274599      -0.113566       0.198489      -0.175409
Cannabis_values         0.102512      -0.013295       0.412245      -0.153998
Choc_values             0.012031       0.020403       0.003961       0.038432
Coke_values             0.144977       0.026257       0.176186      -0.201972
Caff_values             0.014421       0.053264       0.034371      -0.017119
Crack_values            0.116359      -0.051704       0.092511      -0.112849
Ecstasy_values          0.074168       0.080898       0.294675      -0.118138
Heroin_values           0.178590      -0.087714       0.117000      -0.179755
Ketamine_values         0.064186       0.020925       0.179477      -0.116749
Legalh_values           0.120252      -0.042202       0.306167      -0.146385
LSD_values              0.042558       0.017199       0.351376      -0.098169
Meth_values             0.188026      -0.133078       0.158483      -0.168429
Mushrooms_values        0.046484       0.017966       0.358467      -0.120387
Nicotine_values         0.130254      -0.020485       0.198731      -0.114659
Semer_values           -0.004684       0.021517       0.015456       0.017825
VSA_values              0.118556      -0.036431       0.157053      -0.119565

                  cscore_values  impulsive_values  sensation_values  \
nscore_values         -0.398768         -0.140776          0.004036
escore_values          0.310206         -0.057977          0.077550
oscore_values         -0.058959         -0.116153          0.203656
ascore_values          0.250090          0.161733         -0.081683
cscore_values          1.000000          0.296740         -0.079489
impulsive_values       0.296740          1.000000          0.001921
sensation_values      -0.079489          0.001921          1.000000
Alcohol_values        -0.001083         -0.015175          0.057263
Amphet_values         -0.239148         -0.190182          0.124204
Amyl_values           -0.114146         -0.067360          0.088525
Benzos_values         -0.207290         -0.137599          0.069360
Cannabis_values       -0.279231         -0.171572          0.221052
Choc_values            0.003326         -0.008235          0.015687
Coke_values           -0.194920         -0.171485          0.084392
Caff_values           -0.021641         -0.042066          0.032946
Crack_values          -0.135004         -0.134767          0.082656
Ecstasy_values        -0.216616         -0.157064          0.143951
Heroin_values         -0.163454         -0.148248          0.029442
Ketamine_values       -0.152871         -0.113015          0.097479
Legalh_values         -0.258477         -0.167144          0.146043
LSD_values            -0.161002         -0.106836          0.123797
Meth_values           -0.195394         -0.121611          0.036976
Mushrooms_values      -0.192862         -0.135654          0.154596
Nicotine_values       -0.229790         -0.190333          0.109070
Semer_values           0.008028         -0.025157         -0.014738
VSA_values            -0.162322         -0.108445          0.063011

                  Alcohol_values  Amphet_values  Amyl_values  …  \
nscore_values          -0.003362       0.135564     0.040909  …
escore_values           0.085910      -0.040807     0.032543  …
```

oscore_values	0.042386	0.214022	0.070800	…
ascore_values	-0.021889	-0.157710	-0.095507	…
cscore_values	-0.001083	-0.239148	-0.114146	…
impulsive_values	-0.015175	-0.190182	-0.067360	…
sensation_values	0.057263	0.124204	0.088525	…
Alcohol_values	1.000000	-0.010169	0.085450	…
Amphet_values	-0.010169	1.000000	0.317518	…
Amyl_values	0.085450	0.317518	1.000000	…
Benzos_values	-0.010233	0.499381	0.220477	…
Cannabis_values	0.023422	0.457373	0.220545	…
Choc_values	0.045564	-0.061143	0.000729	…
Coke_values	0.089391	0.532640	0.374506	…
Caff_values	0.126551	0.058208	0.079986	…
Crack_values	-0.019697	0.295130	0.143111	…
Ecstasy_values	0.073301	0.521387	0.356814	…
Heroin_values	-0.033374	0.361854	0.130161	…
Ketamine_values	0.064584	0.375117	0.338023	…
Legalh_values	0.028858	0.476587	0.262292	…
LSD_values	0.012691	0.420789	0.161349	…
Meth_values	-0.078942	0.395788	0.058526	…
Mushrooms_values	0.028519	0.429467	0.214004	…
Nicotine_values	0.060834	0.351802	0.223382	…
Semer_values	-0.036080	0.029713	0.006572	…
VSA_values	0.025559	0.271748	0.154282	…

	Ecstasy_values	Heroin_values	Ketamine_values	\
nscore_values	0.074168	0.178590	0.064186	
escore_values	0.080898	-0.087714	0.020925	
oscore_values	0.294675	0.117000	0.179477	
ascore_values	-0.118138	-0.179755	-0.116749	
cscore_values	-0.216616	-0.163454	-0.152871	
impulsive_values	-0.157064	-0.148248	-0.113015	
sensation_values	0.143951	0.029442	0.097479	
Alcohol_values	0.073301	-0.033374	0.064584	
Amphet_values	0.521387	0.361854	0.375117	
Amyl_values	0.356814	0.130161	0.338023	
Benzos_values	0.342832	0.427763	0.300114	
Cannabis_values	0.552516	0.233256	0.309891	
Choc_values	-0.049516	-0.077728	-0.027271	
Coke_values	0.609946	0.424655	0.439511	
Caff_values	0.034326	0.015226	0.013734	
Crack_values	0.232557	0.526926	0.230725	
Ecstasy_values	1.000000	0.265967	0.507147	
Heroin_values	0.265967	1.000000	0.250868	
Ketamine_values	0.507147	0.250868	1.000000	
Legalh_values	0.554973	0.241602	0.413323	
LSD_values	0.571132	0.279097	0.410969	
Meth_values	0.259047	0.478885	0.188749	

```
Mushrooms_values      0.548400       0.267700         0.412616
Nicotine_values       0.380524       0.225008         0.256039
Semer_values          0.039139       0.016894         0.059669
VSA_values            0.253497       0.256761         0.198435

                  Legalh_values  LSD_values  Meth_values  Mushrooms_values  \
nscore_values          0.120252    0.042558     0.188026          0.046484
escore_values         -0.042202    0.017199    -0.133078          0.017966
oscore_values          0.306167    0.351376     0.158483          0.358467
ascore_values         -0.146385   -0.098169    -0.168429         -0.120387
cscore_values         -0.258477   -0.161002    -0.195394         -0.192862
impulsive_values      -0.167144   -0.106836    -0.121611         -0.135654
sensation_values       0.146043    0.123797     0.036976          0.154596
Alcohol_values         0.028858    0.012691    -0.078942          0.028519
Amphet_values          0.476587    0.420789     0.395788          0.429467
Amyl_values            0.262292    0.161349     0.058526          0.214004
Benzos_values          0.358030    0.303349     0.518122          0.344943
Cannabis_values        0.553959    0.520839     0.293753          0.579882
Choc_values           -0.054537   -0.077453    -0.044753         -0.072782
Coke_values            0.413272    0.383533     0.345316          0.426918
Caff_values            0.007878   -0.003626     0.023378          0.041268
Crack_values           0.193986    0.229790     0.356384          0.261011
Ecstasy_values         0.554973    0.571132     0.259047          0.548400
Heroin_values          0.241602    0.279097     0.478885          0.267700
Ketamine_values        0.413323    0.410969     0.188749          0.412616
Legalh_values          1.000000    0.471239     0.325316          0.530902
LSD_values             0.471239    1.000000     0.267284          0.668226
Meth_values            0.325316    0.267284     1.000000          0.277664
Mushrooms_values       0.530902    0.668226     0.277664          1.000000
Nicotine_values        0.342646    0.293266     0.220128          0.324612
Semer_values           0.015864    0.071185    -0.003822          0.099069
VSA_values             0.320792    0.287321     0.260421          0.246207

                  Nicotine_values  Semer_values  VSA_values
nscore_values            0.130254     -0.004684    0.118556
escore_values           -0.020485      0.021517   -0.036431
oscore_values            0.198731      0.015456    0.157053
ascore_values           -0.114659      0.017825   -0.119565
cscore_values           -0.229790      0.008028   -0.162322
impulsive_values        -0.190333     -0.025157   -0.108445
sensation_values         0.109070     -0.014738    0.063011
Alcohol_values           0.060834     -0.036080    0.025559
Amphet_values            0.351802      0.029713    0.271748
Amyl_values              0.223382      0.006572    0.154282
Benzos_values            0.302845      0.026105    0.276185
Cannabis_values          0.515911      0.043922    0.273478
Choc_values             -0.041459     -0.039440   -0.073294
Coke_values              0.402182      0.046468    0.283765
```

```
Caff_values           0.126371    -0.010999    0.057300
Crack_values          0.241727     0.026375    0.250956
Ecstasy_values        0.380524     0.039139    0.253497
Heroin_values         0.225008     0.016894    0.256761
Ketamine_values       0.256039     0.059669    0.198435
Legalh_values         0.342646     0.015864    0.320792
LSD_values            0.293266     0.071185    0.287321
Meth_values           0.220128    -0.003822    0.260421
Mushrooms_values      0.324612     0.099069    0.246207
Nicotine_values       1.000000     0.026855    0.255802
Semer_values          0.026855     1.000000    0.056207
VSA_values            0.255802     0.056207    1.000000

[26 rows x 26 columns]

P-Values Matrix:
                  nscore_values escore_values oscore_values ascore_values  \
Alcohol_values           0.8842        0.0002        0.0662         0.343
Amphet_values               0.0         0.077           0.0           0.0
Amyl_values              0.0763        0.1585        0.0021           0.0
Benzos_values               0.0           0.0           0.0           0.0
Caff_values              0.5321        0.0209        0.1364        0.4583
Cannabis_values             0.0        0.5647           0.0           0.0
Choc_values              0.6022        0.3767        0.8638        0.0958
Coke_values                 0.0        0.2553           0.0           0.0
Crack_values                0.0         0.025        0.0001           0.0
Ecstasy_values           0.0013        0.0004           0.0           0.0
Heroin_values               0.0        0.0001           0.0           0.0
Ketamine_values          0.0054        0.3647           0.0           0.0
LSD_values               0.0651        0.4562           0.0           0.0
Legalh_values               0.0        0.0674           0.0           0.0
Meth_values                 0.0           0.0           0.0           0.0
Mushrooms_values         0.0439        0.4364           0.0           0.0
Nicotine_values             0.0        0.3748           0.0           0.0
Semer_values             0.8392        0.3512        0.5031          0.44
VSA_values                  0.0        0.1144           0.0           0.0
ascore_values               0.0           0.0        0.1262           0.0
cscore_values               0.0           0.0        0.0106           0.0
escore_values               0.0           0.0           0.0           0.0
impulsive_values            0.0         0.012           0.0           0.0
nscore_values               0.0           0.0        0.4485           0.0
oscore_values            0.4485           0.0           0.0        0.1262
sensation_values         0.8612        0.0008           0.0        0.0004

                 cscore_values impulsive_values sensation_values  \
Alcohol_values          0.9626           0.5109            0.013
Amphet_values              0.0              0.0              0.0
Amyl_values                0.0           0.0035           0.0001
```

Benzos_values	0.0	0.0	0.0026
Caff_values	0.3485	0.0683	0.1534
Cannabis_values	0.0	0.0	0.0
Choc_values	0.8854	0.7213	0.4968
Coke_values	0.0	0.0	0.0002
Crack_values	0.0	0.0	0.0003
Ecstasy_values	0.0	0.0	0.0
Heroin_values	0.0	0.0	0.2021
Ketamine_values	0.0	0.0	0.0
LSD_values	0.0	0.0	0.0
Legalh_values	0.0	0.0	0.0
Meth_values	0.0	0.0	0.1091
Mushrooms_values	0.0	0.0	0.0
Nicotine_values	0.0	0.0	0.0
Semer_values	0.728	0.2757	0.5232
VSA_values	0.0	0.0	0.0063
ascore_values	0.0	0.0	0.0004
cscore_values	0.0	0.0	0.0006
escore_values	0.0	0.012	0.0008
impulsive_values	0.0	0.0	0.9337
nscore_values	0.0	0.0	0.8612
oscore_values	0.0106	0.0	0.0
sensation_values	0.0006	0.9337	0.0

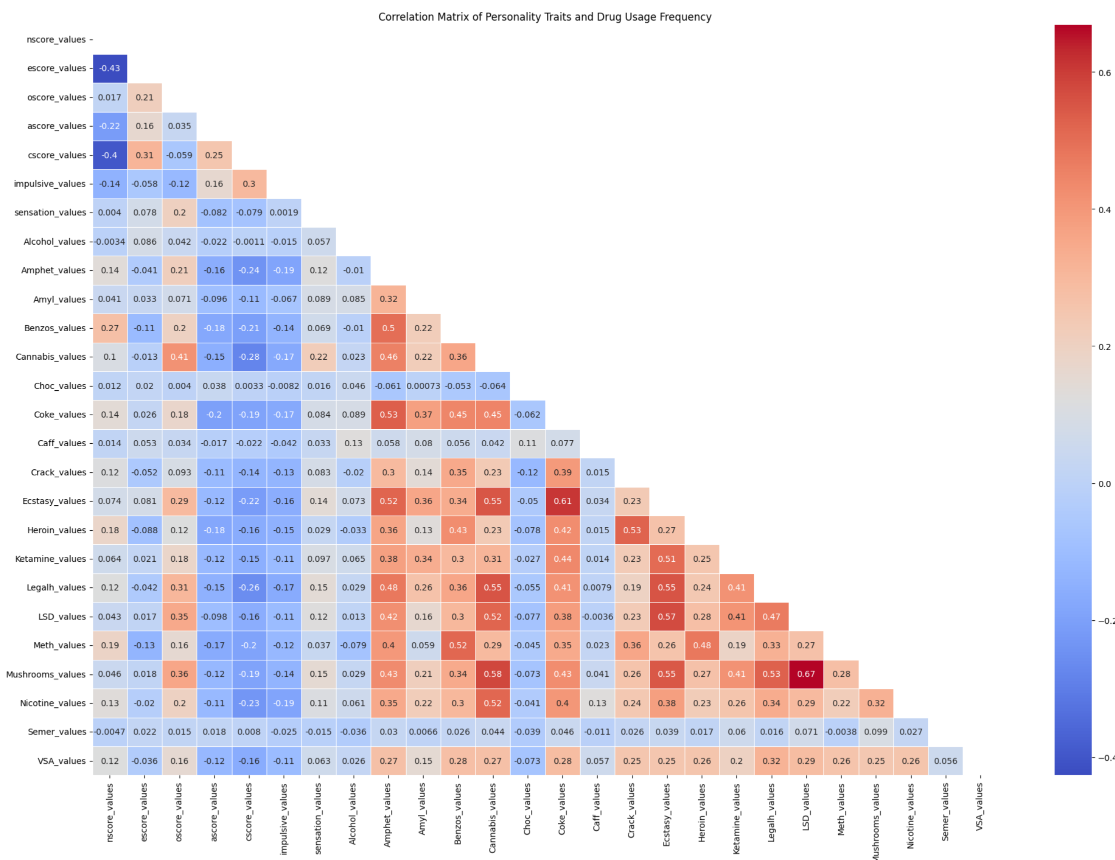
	Alcohol_values	Amphet_values	Amyl_values	…	Ecstasy_values	\
Alcohol_values	0.0	0.6596	0.0002	…	0.0015	
Amphet_values	0.6596	0.0	0.0	…	0.0	
Amyl_values	0.0002	0.0	0.0	…	0.0	
Benzos_values	0.6576	0.0	0.0	…	0.0	
Caff_values	0.0	0.0116	0.0005	…	0.1369	
Cannabis_values	0.3102	0.0	0.0	…	0.0	
Choc_values	0.0483	0.008	0.9748	…	0.0319	
Coke_values	0.0001	0.0	0.0	…	0.0	
Crack_values	0.3935	0.0	0.0	…	0.0	
Ecstasy_values	0.0015	0.0	0.0	…	0.0	
Heroin_values	0.1481	0.0	0.0	…	0.0	
Ketamine_values	0.0051	0.0	0.0	…	0.0	
LSD_values	0.5825	0.0	0.0	…	0.0	
Legalh_values	0.2112	0.0	0.0	…	0.0	
Meth_values	0.0006	0.0	0.0112	…	0.0	
Mushrooms_values	0.2166	0.0	0.0	…	0.0	
Nicotine_values	0.0083	0.0	0.0	…	0.0	
Semer_values	0.1179	0.198	0.7759	…	0.0899	
VSA_values	0.2681	0.0	0.0	…	0.0	
ascore_values	0.343	0.0	0.0	…	0.0	
cscore_values	0.9626	0.0	0.0	…	0.0	
escore_values	0.0002	0.077	0.1585	…	0.0004	
impulsive_values	0.5109	0.0	0.0035	…	0.0	

```
nscore_values          0.8842           0.0      0.0763  …         0.0013
oscore_values          0.0662           0.0      0.0021  …            0.0
sensation_values        0.013           0.0      0.0001  …            0.0

                 Heroin_values Ketamine_values Legalh_values LSD_values  \
Alcohol_values          0.1481          0.0051        0.2112     0.5825
Amphet_values              0.0             0.0           0.0        0.0
Amyl_values                0.0             0.0           0.0        0.0
Benzos_values              0.0             0.0           0.0        0.0
Caff_values             0.5095          0.5519        0.7329     0.8752
Cannabis_values            0.0             0.0           0.0        0.0
Choc_values             0.0007          0.2374        0.0181     0.0008
Coke_values                0.0             0.0           0.0        0.0
Crack_values               0.0             0.0           0.0        0.0
Ecstasy_values             0.0             0.0           0.0        0.0
Heroin_values              0.0             0.0           0.0        0.0
Ketamine_values            0.0             0.0           0.0        0.0
LSD_values                 0.0             0.0           0.0        0.0
Legalh_values              0.0             0.0           0.0        0.0
Meth_values                0.0             0.0           0.0        0.0
Mushrooms_values           0.0             0.0           0.0        0.0
Nicotine_values            0.0             0.0           0.0        0.0
Semer_values            0.4643          0.0097        0.4919      0.002
VSA_values                 0.0             0.0           0.0        0.0
ascore_values              0.0             0.0           0.0        0.0
cscore_values              0.0             0.0           0.0        0.0
escore_values           0.0001          0.3647        0.0674     0.4562
impulsive_values           0.0             0.0           0.0        0.0
nscore_values              0.0          0.0054           0.0     0.0651
oscore_values              0.0             0.0           0.0        0.0
sensation_values        0.2021             0.0           0.0        0.0

                 Meth_values Mushrooms_values Nicotine_values Semer_values  \
Alcohol_values        0.0006           0.2166          0.0083       0.1179
Amphet_values            0.0              0.0             0.0        0.198
Amyl_values           0.0112              0.0             0.0       0.7759
Benzos_values            0.0              0.0             0.0        0.258
Caff_values           0.3111           0.0737             0.0       0.6337
Cannabis_values          0.0              0.0             0.0        0.057
Choc_values           0.0524           0.0016          0.0724       0.0874
Coke_values              0.0              0.0             0.0        0.044
Crack_values             0.0              0.0             0.0       0.2531
Ecstasy_values           0.0              0.0             0.0       0.0899
Heroin_values            0.0              0.0             0.0       0.4643
Ketamine_values          0.0              0.0             0.0       0.0097
LSD_values               0.0              0.0             0.0        0.002
Legalh_values            0.0              0.0             0.0       0.4919
Meth_values              0.0              0.0             0.0       0.8685
```

```
Mushrooms_values        0.0          0.0          0.0      0.0
Nicotine_values         0.0          0.0          0.0   0.2446
Semer_values         0.8685          0.0       0.2446      0.0
VSA_values              0.0          0.0          0.0   0.0148
ascore_values           0.0          0.0          0.0     0.44
cscore_values           0.0          0.0          0.0    0.728
escore_values           0.0       0.4364       0.3748   0.3512
impulsive_values        0.0          0.0          0.0   0.2757
nscore_values           0.0       0.0439          0.0   0.8392
oscore_values           0.0          0.0          0.0   0.5031
sensation_values     0.1091          0.0          0.0   0.5232

                  VSA_values
Alcohol_values        0.2681
Amphet_values            0.0
Amyl_values              0.0
Benzos_values            0.0
Caff_values            0.013
Cannabis_values          0.0
Choc_values           0.0015
Coke_values              0.0
Crack_values             0.0
Ecstasy_values           0.0
Heroin_values            0.0
Ketamine_values          0.0
LSD_values               0.0
Legalh_values            0.0
Meth_values              0.0
Mushrooms_values         0.0
Nicotine_values          0.0
Semer_values          0.0148
VSA_values               0.0
ascore_values            0.0
cscore_values            0.0
escore_values         0.1144
impulsive_values         0.0
nscore_values            0.0
oscore_values            0.0
sensation_values      0.0063

[26 rows x 26 columns]
```

[94]:
```
# Prepare mask to only show lower diagonal triangle in heat map
# Creating mask for heat map: https://stackoverflow.com/questions/57414771/
↪how-to-plot-only-the-lower-triangle-of-a-seaborn-heatmap
mask = np.zeros_like(correlation_matrix, dtype=bool)
mask[np.triu_indices_from(mask)] = True
```

```
# Plot the correlation matrix with heatmap
plt.figure(figsize=(24, 16))
# Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.heatmap(correlation_matrix, mask=mask, annot=True, cmap='coolwarm',␣
↪linewidths=0.5)
plt.title('Correlation Matrix of Personality Traits and Drug Usage Frequency')
plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```



[95]:
```
# Separate heat map only showing personality traits to increase usability
correlation_matrix_personality_traits =␣
↪correlation_matrix[personality_traits_scores_columns]
correlation_matrix_personality_traits = correlation_matrix_personality_traits.
↪loc[personality_traits_scores_columns]
correlation_matrix_personality_traits
```

[95]:

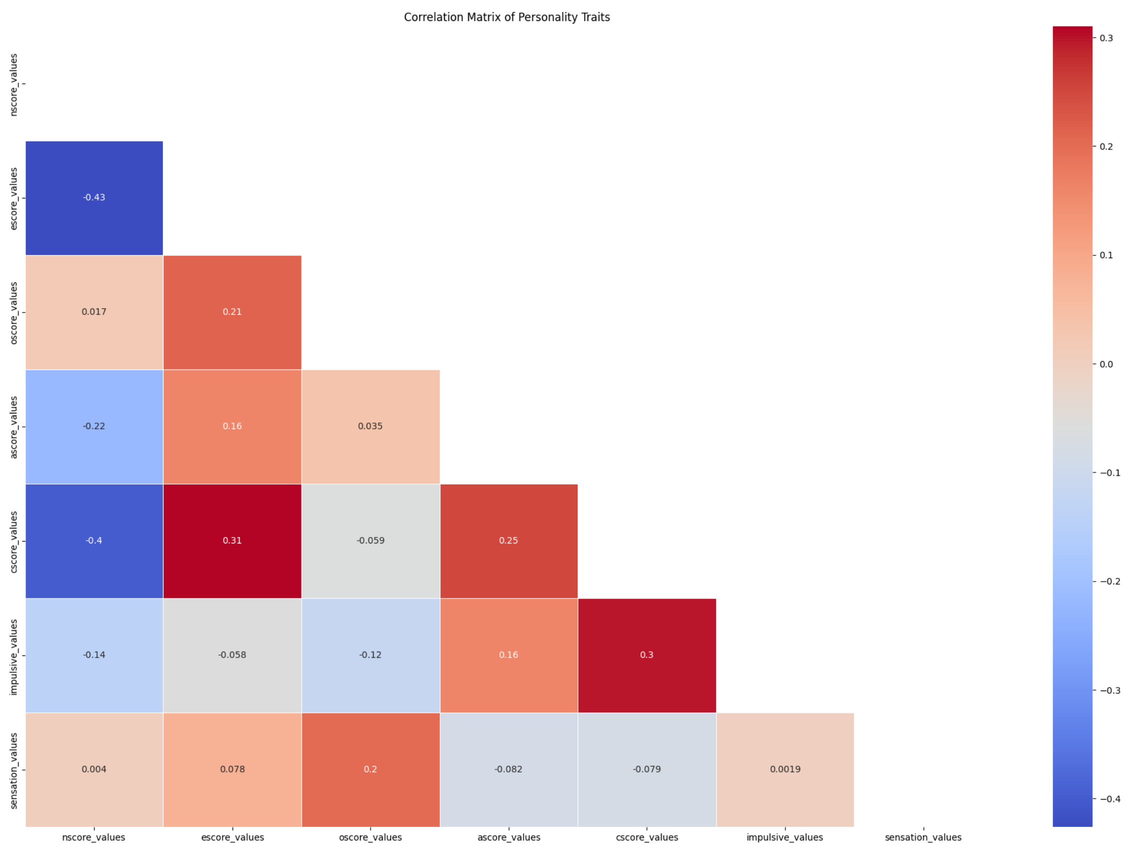
```
                   nscore_values  escore_values  oscore_values  ascore_values  \
nscore_values           1.000000      -0.426282       0.017496      -0.216593
escore_values          -0.426282       1.000000       0.213604       0.161470
oscore_values           0.017496       0.213604       1.000000       0.035290
ascore_values          -0.216593       0.161470       0.035290       1.000000
cscore_values          -0.398768       0.310206      -0.058959       0.250090
impulsive_values       -0.140776      -0.057977      -0.116153       0.161733
sensation_values        0.004036       0.077550       0.203656      -0.081683

                   cscore_values  impulsive_values  sensation_values
nscore_values          -0.398768         -0.140776          0.004036
escore_values           0.310206         -0.057977          0.077550
oscore_values          -0.058959         -0.116153          0.203656
ascore_values           0.250090          0.161733         -0.081683
cscore_values           1.000000          0.296740         -0.079489
impulsive_values        0.296740          1.000000          0.001921
sensation_values       -0.079489          0.001921          1.000000
```

[96]:

```
# Prepare mask to only show lower diagonal triangle in heat map
mask = np.zeros_like(correlation_matrix_personality_traits, dtype=bool)
mask[np.triu_indices_from(mask)] = True
```

[97]:

```
# Plot the correlation matrix with heatmap for personalty traits
plt.figure(figsize=(24, 16))
# Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.heatmap(correlation_matrix_personality_traits, mask=mask, annot=True,␣
↪cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix of Personality Traits ')
plt.show()
```



[98]:
```python
# Separate heat map only showing drug usage to increase usability
correlation_matrix_drugs = correlation_matrix[drug_columns]
correlation_matrix_drugs = correlation_matrix_drugs.loc[drug_columns]
correlation_matrix_drugs
```

[98]:
```
                  Alcohol_values  Amphet_values  Amyl_values  Benzos_values  \
Alcohol_values          1.000000      -0.010169     0.085450      -0.010233
Amphet_values          -0.010169       1.000000     0.317518       0.499381
Amyl_values             0.085450       0.317518     1.000000       0.220477
Benzos_values          -0.010233       0.499381     0.220477       1.000000
Cannabis_values         0.023422       0.457373     0.220545       0.357383
Choc_values             0.045564      -0.061143     0.000729      -0.052533
Coke_values             0.089391       0.532640     0.374506       0.445307
Caff_values             0.126551       0.058208     0.079986       0.055862
Crack_values           -0.019697       0.295130     0.143111       0.348196
Ecstasy_values          0.073301       0.521387     0.356814       0.342832
Heroin_values          -0.033374       0.361854     0.130161       0.427763
Ketamine_values         0.064584       0.375117     0.338023       0.300114
Legalh_values           0.028858       0.476587     0.262292       0.358030
LSD_values              0.012691       0.420789     0.161349       0.303349
```

Meth_values	-0.078942	0.395788	0.058526	0.518122
Mushrooms_values	0.028519	0.429467	0.214004	0.344943
Nicotine_values	0.060834	0.351802	0.223382	0.302845
Semer_values	-0.036080	0.029713	0.006572	0.026105
VSA_values	0.025559	0.271748	0.154282	0.276185

	Cannabis_values	Choc_values	Coke_values	Caff_values \
Alcohol_values	0.023422	0.045564	0.089391	0.126551
Amphet_values	0.457373	-0.061143	0.532640	0.058208
Amyl_values	0.220545	0.000729	0.374506	0.079986
Benzos_values	0.357383	-0.052533	0.445307	0.055862
Cannabis_values	1.000000	-0.064032	0.448739	0.041578
Choc_values	-0.064032	1.000000	-0.062333	0.114660
Coke_values	0.448739	-0.062333	1.000000	0.077411
Caff_values	0.041578	0.114660	0.077411	1.000000
Crack_values	0.234233	-0.117590	0.390782	0.015085
Ecstasy_values	0.552516	-0.049516	0.609946	0.034326
Heroin_values	0.233256	-0.077728	0.424655	0.015226
Ketamine_values	0.309891	-0.027271	0.439511	0.013734
Legalh_values	0.553959	-0.054537	0.413272	0.007878
LSD_values	0.520839	-0.077453	0.383533	-0.003626
Meth_values	0.293753	-0.044753	0.345316	0.023378
Mushrooms_values	0.579882	-0.072782	0.426918	0.041268
Nicotine_values	0.515911	-0.041459	0.402182	0.126371
Semer_values	0.043922	-0.039440	0.046468	-0.010999
VSA_values	0.273478	-0.073294	0.283765	0.057300

	Crack_values	Ecstasy_values	Heroin_values \
Alcohol_values	-0.019697	0.073301	-0.033374
Amphet_values	0.295130	0.521387	0.361854
Amyl_values	0.143111	0.356814	0.130161
Benzos_values	0.348196	0.342832	0.427763
Cannabis_values	0.234233	0.552516	0.233256
Choc_values	-0.117590	-0.049516	-0.077728
Coke_values	0.390782	0.609946	0.424655
Caff_values	0.015085	0.034326	0.015226
Crack_values	1.000000	0.232557	0.526926
Ecstasy_values	0.232557	1.000000	0.265967
Heroin_values	0.526926	0.265967	1.000000
Ketamine_values	0.230725	0.507147	0.250868
Legalh_values	0.193986	0.554973	0.241602
LSD_values	0.229790	0.571132	0.279097
Meth_values	0.356384	0.259047	0.478885
Mushrooms_values	0.261011	0.548400	0.267700
Nicotine_values	0.241727	0.380524	0.225008
Semer_values	0.026375	0.039139	0.016894
VSA_values	0.250956	0.253497	0.256761

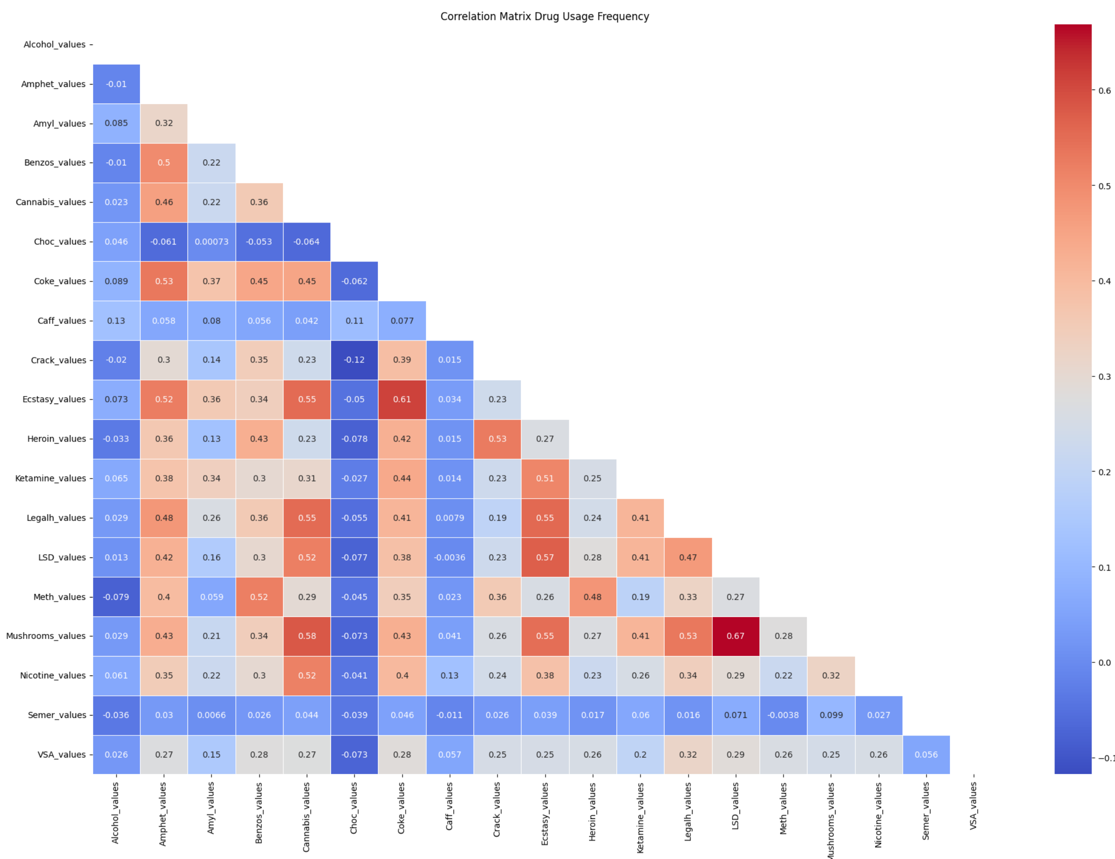
```
                  Ketamine_values  Legalh_values  LSD_values  Meth_values  \
Alcohol_values           0.064584       0.028858    0.012691    -0.078942
Amphet_values            0.375117       0.476587    0.420789     0.395788
Amyl_values              0.338023       0.262292    0.161349     0.058526
Benzos_values            0.300114       0.358030    0.303349     0.518122
Cannabis_values          0.309891       0.553959    0.520839     0.293753
Choc_values             -0.027271      -0.054537   -0.077453    -0.044753
Coke_values              0.439511       0.413272    0.383533     0.345316
Caff_values              0.013734       0.007878   -0.003626     0.023378
Crack_values             0.230725       0.193986    0.229790     0.356384
Ecstasy_values           0.507147       0.554973    0.571132     0.259047
Heroin_values            0.250868       0.241602    0.279097     0.478885
Ketamine_values          1.000000       0.413323    0.410969     0.188749
Legalh_values            0.413323       1.000000    0.471239     0.325316
LSD_values               0.410969       0.471239    1.000000     0.267284
Meth_values              0.188749       0.325316    0.267284     1.000000
Mushrooms_values         0.412616       0.530902    0.668226     0.277664
Nicotine_values          0.256039       0.342646    0.293266     0.220128
Semer_values             0.059669       0.015864    0.071185    -0.003822
VSA_values               0.198435       0.320792    0.287321     0.260421

                  Mushrooms_values  Nicotine_values  Semer_values  VSA_values
Alcohol_values            0.028519         0.060834     -0.036080    0.025559
Amphet_values             0.429467         0.351802      0.029713    0.271748
Amyl_values               0.214004         0.223382      0.006572    0.154282
Benzos_values             0.344943         0.302845      0.026105    0.276185
Cannabis_values           0.579882         0.515911      0.043922    0.273478
Choc_values              -0.072782        -0.041459     -0.039440   -0.073294
Coke_values               0.426918         0.402182      0.046468    0.283765
Caff_values               0.041268         0.126371     -0.010999    0.057300
Crack_values              0.261011         0.241727      0.026375    0.250956
Ecstasy_values            0.548400         0.380524      0.039139    0.253497
Heroin_values             0.267700         0.225008      0.016894    0.256761
Ketamine_values           0.412616         0.256039      0.059669    0.198435
Legalh_values             0.530902         0.342646      0.015864    0.320792
LSD_values                0.668226         0.293266      0.071185    0.287321
Meth_values               0.277664         0.220128     -0.003822    0.260421
Mushrooms_values          1.000000         0.324612      0.099069    0.246207
Nicotine_values           0.324612         1.000000      0.026855    0.255802
Semer_values              0.099069         0.026855      1.000000    0.056207
VSA_values                0.246207         0.255802      0.056207    1.000000
```

[99]:

```
# Prepare mask to only show lower diagonal triangle in heat map
mask = np.zeros_like(correlation_matrix_drugs, dtype=bool)
mask[np.triu_indices_from(mask)] = True
```

[100]:

```
# Plot the correlation matrix with heat map for drug usage
plt.figure(figsize=(24, 16))
# Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.heatmap(correlation_matrix_drugs, mask=mask, annot=True, cmap='coolwarm',␣
↪linewidths=0.5)
plt.title('Correlation Matrix Drug Usage Frequency')
plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```



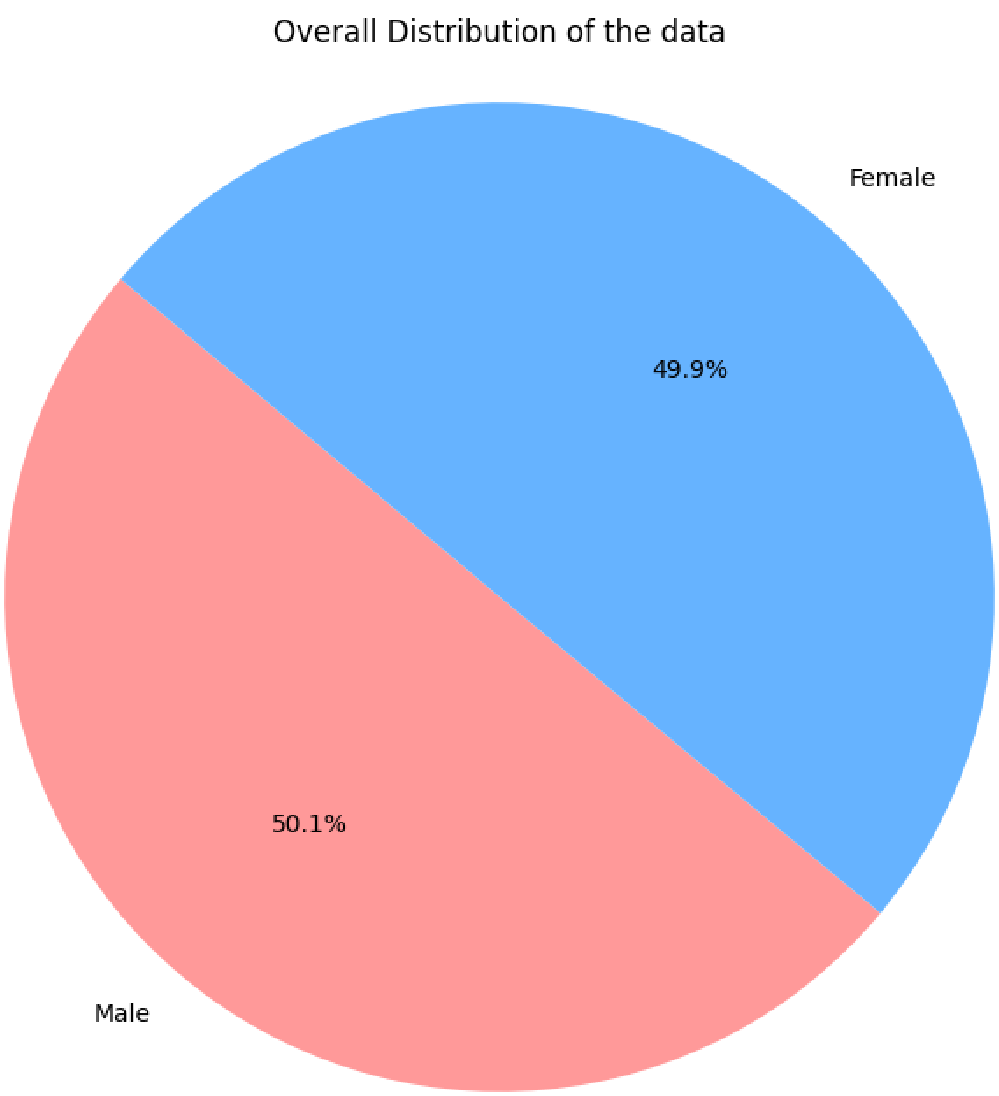
5.3.1 Analysis:

The correlation heatmap illustrates several interesting relationships: - **High Openness (Oscore) and High Drug Usage**: Drugs such as cannabis and LSD show positive correlations with high openness scores. - **High Impulsivity and Higher Drug Usage**: Notably, impulsivity is positively correlated with the usage of cocaine and ecstasy, indicating that individuals with higher impulsivity scores might be more prone to using these substances. - **Conscientiousness (Cscore) and Lower Drug Usage**: High conscientiousness is generally associated with lower frequencies of drug use.

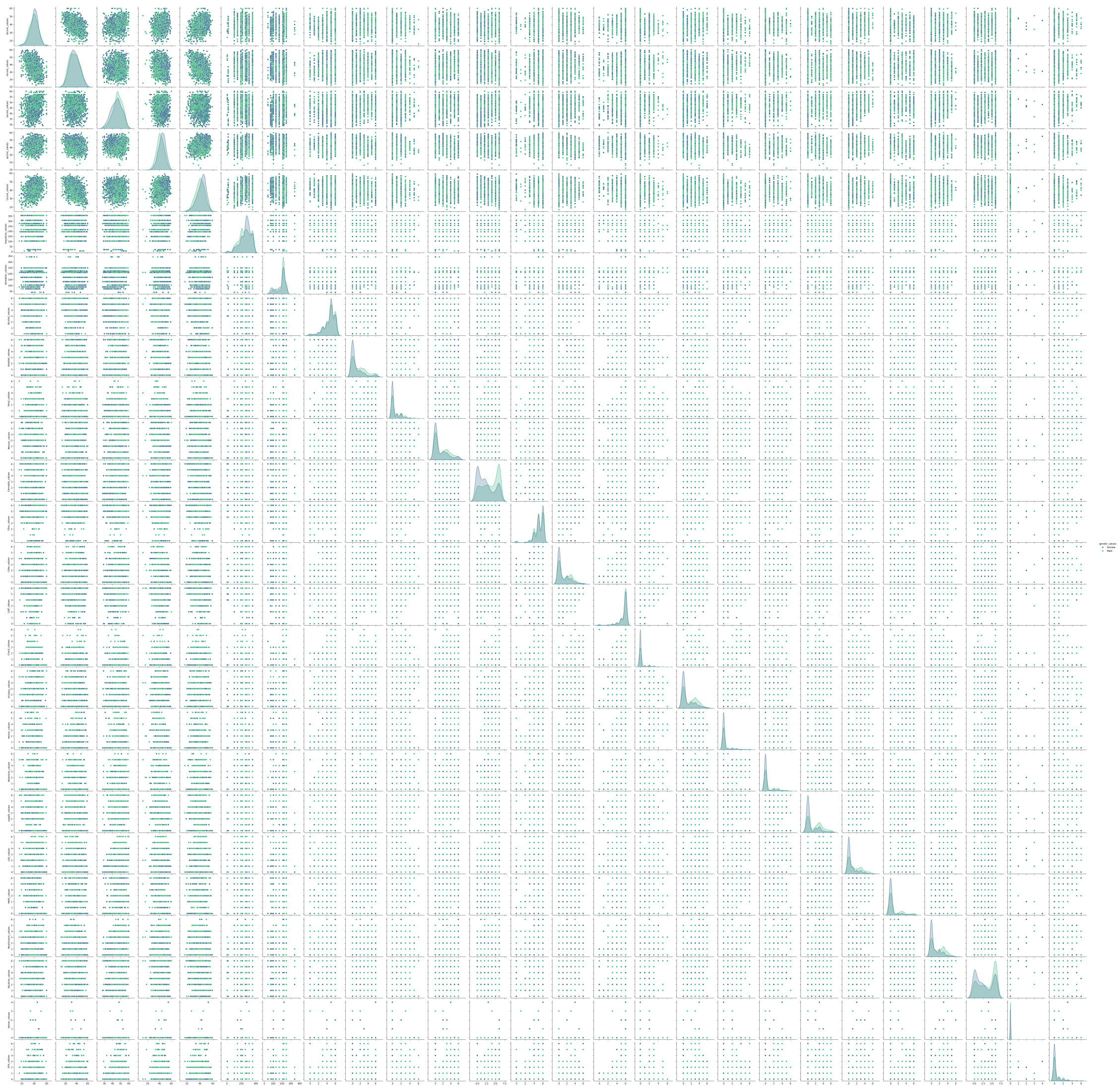
These insights can guide psychological interventions and help in tailoring support for individuals based on their personality traits.

5.4 TASK 2.3: Q3 - What is the gender distribution in the frequency of drug usage?

[101]:
```
# Visualize gender distribution across the whole dataset
gender_distribution = df['gender_values'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(gender_distribution, labels=gender_distribution.index, autopct='%1.
↪1f%%', startangle=140,
        colors=['#ff9999', '#66b3ff', '#99ff99', '#ffcc99'])
plt.title('Overall Distribution of the data')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```

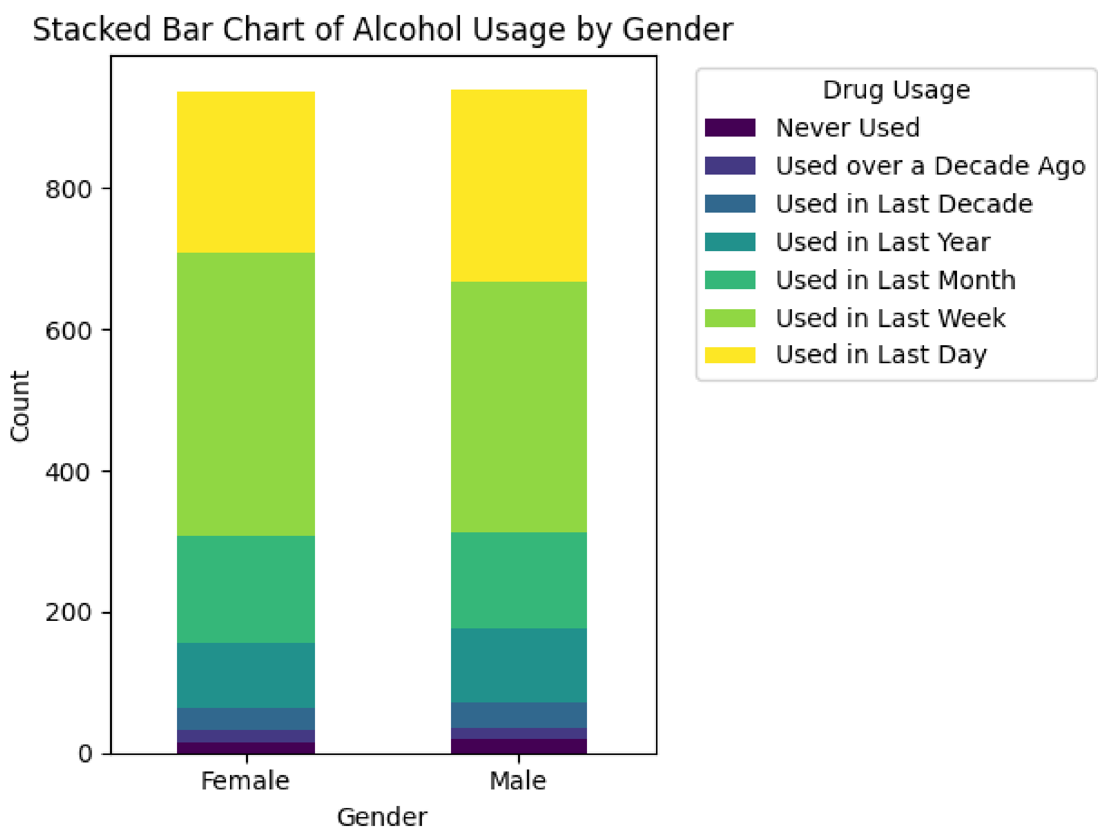


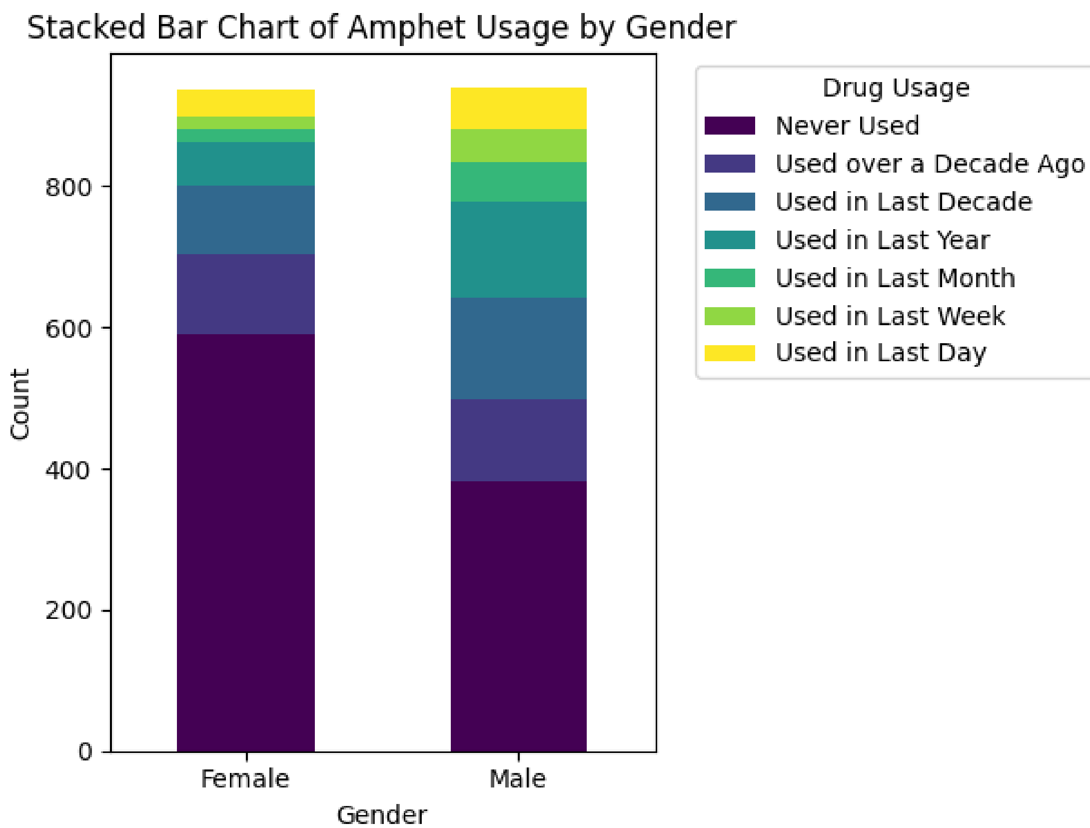
[102]:
```
# Pair plot with gender class
# Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
# demonstrating an outstanding understanding of relevant attribute types
sns.pairplot(df.loc[:, df.columns!='ID'], hue='gender_values',␣
↪palette='viridis')
plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```

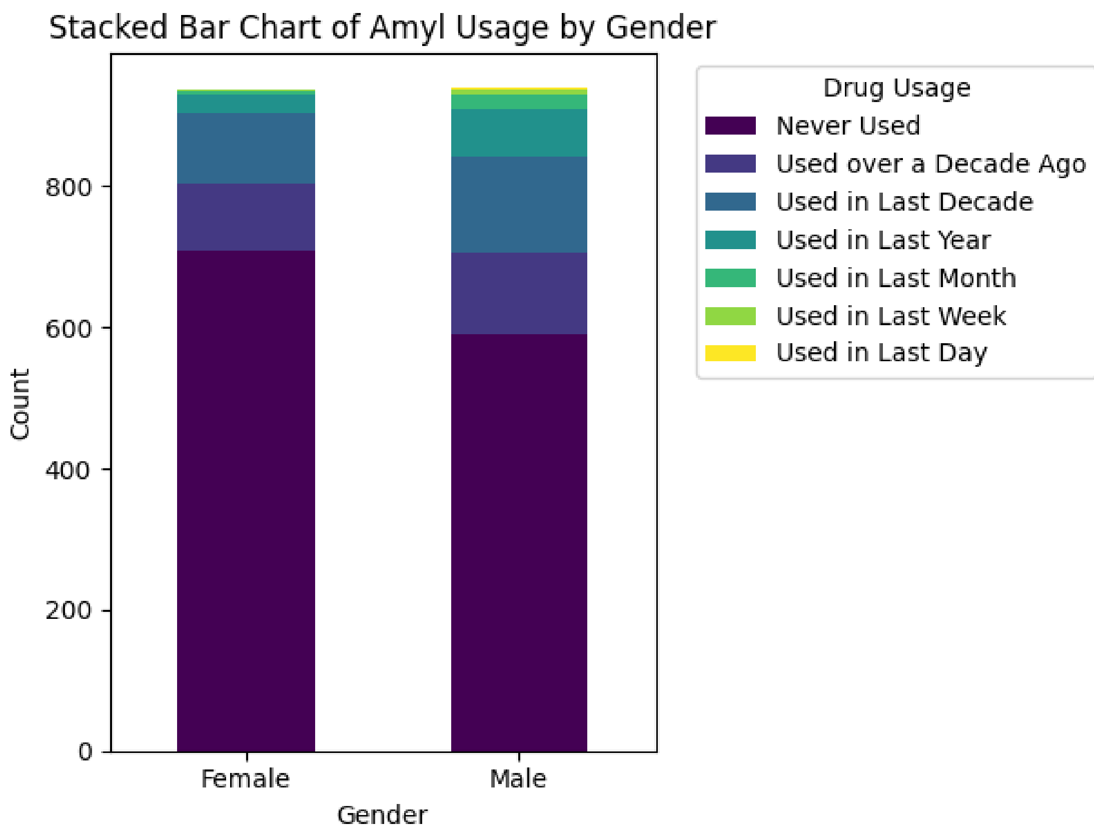


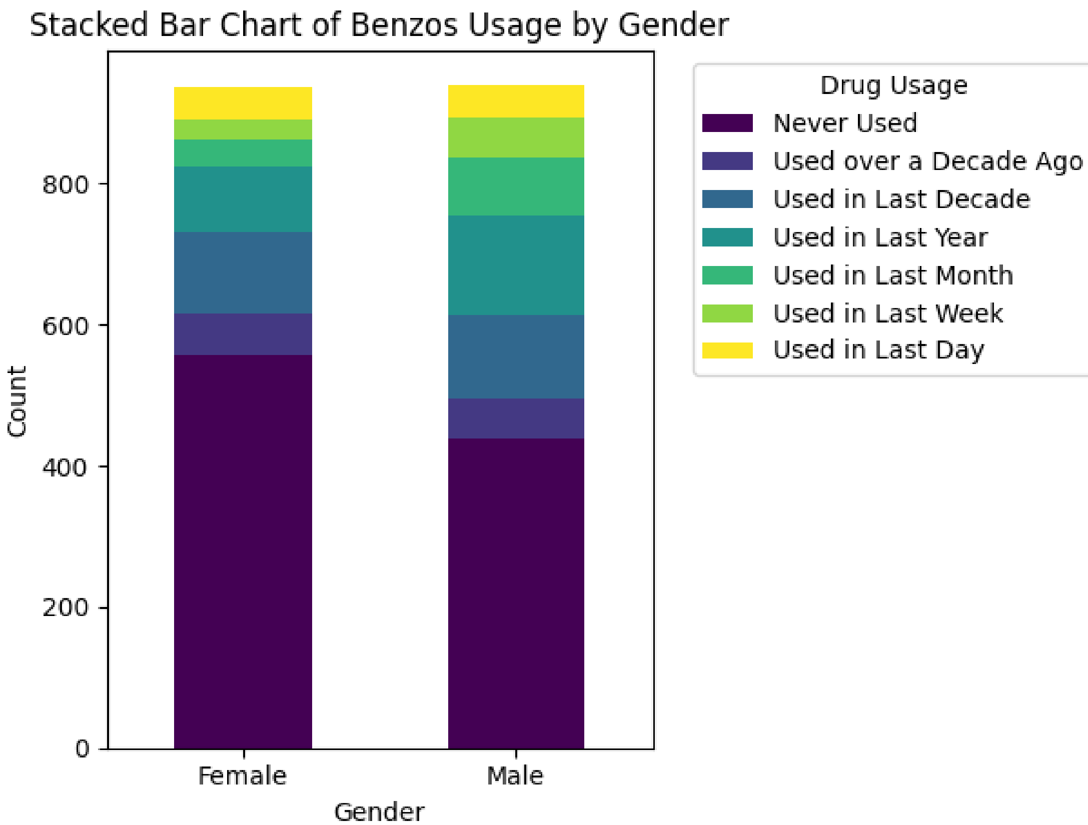
[103]:
```python
# Prepare ordered category list for consistent plotting and legend
category_order = [CATEGORIES[key] for key in sorted(CATEGORIES.keys())]
for drug in drug_columns:
    # Prepare data for plotting
    plot_data = df.groupby(['gender_values', drug], observed=True).size().
 ↪unstack(fill_value=0)

    # Convert the columns to descriptive labels for the plot only
    plot_data = plot_data.rename(columns=CATEGORIES)

    # Create a stacked bar chart
    # Exceptionally answers specific business questions using advanced data␣
 ↪visualization techniques,
```

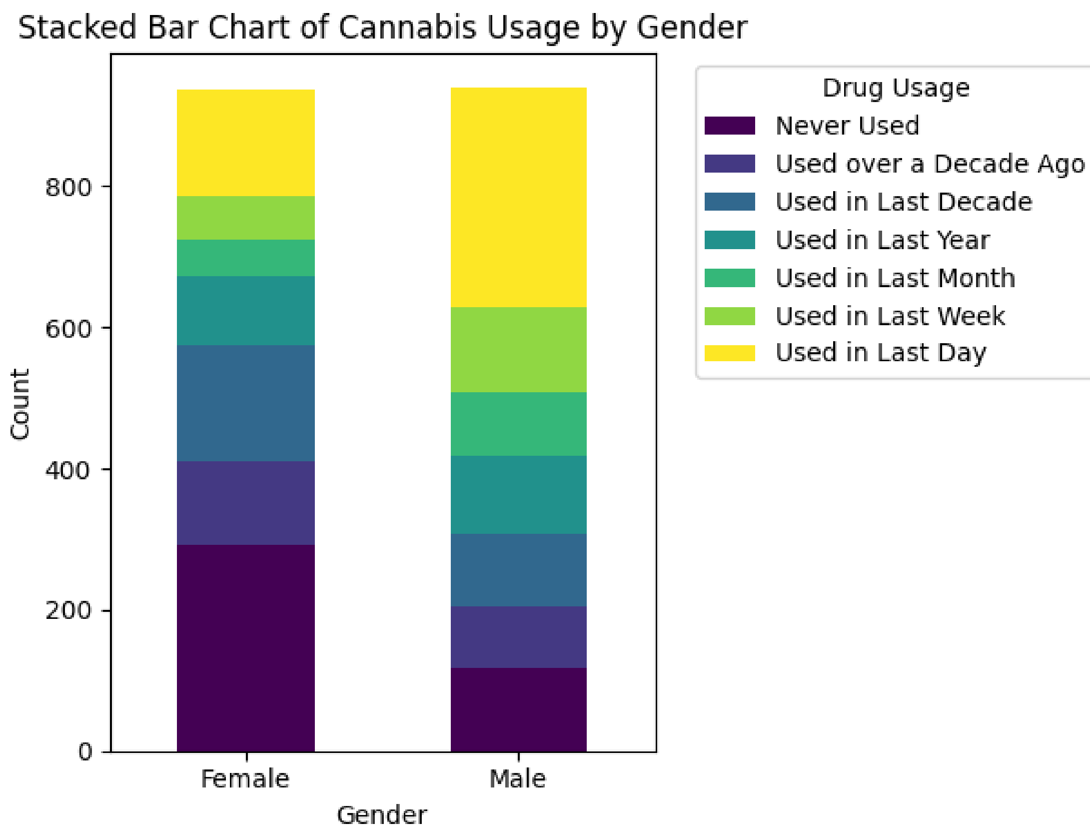
```
    # demonstrating an outstanding understanding of relevant attribute types
    ax = plot_data.plot(kind='bar', stacked=True, colormap='viridis')
    plt.title(f'Stacked Bar Chart of {drug.replace("_values", "")} Usage by␣
↪Gender')
    plt.xlabel('Gender')
    plt.ylabel('Count')
    plt.xticks(rotation=0)  # Keep the gender labels horizontal for readability

    # Set legend directly using the category order
    plt.legend(category_order, title='Drug Usage', bbox_to_anchor=(1.05, 1),␣
↪loc='upper left')

    plt.tight_layout()
    plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```

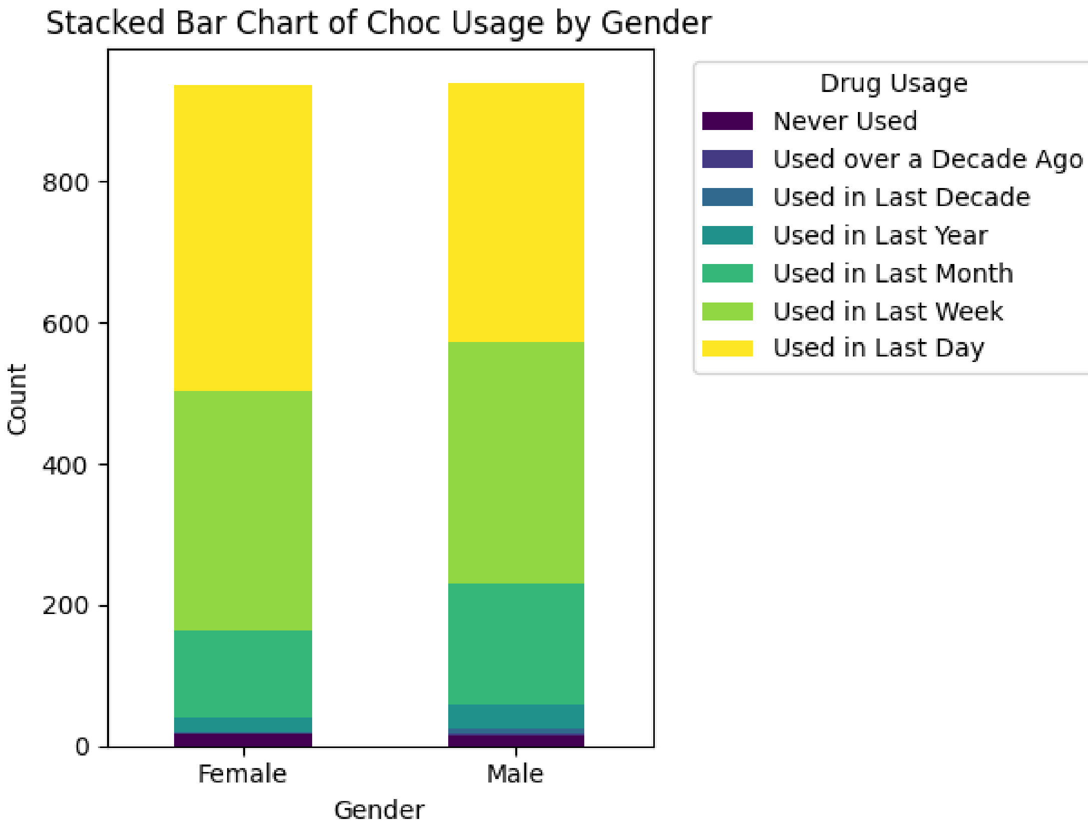


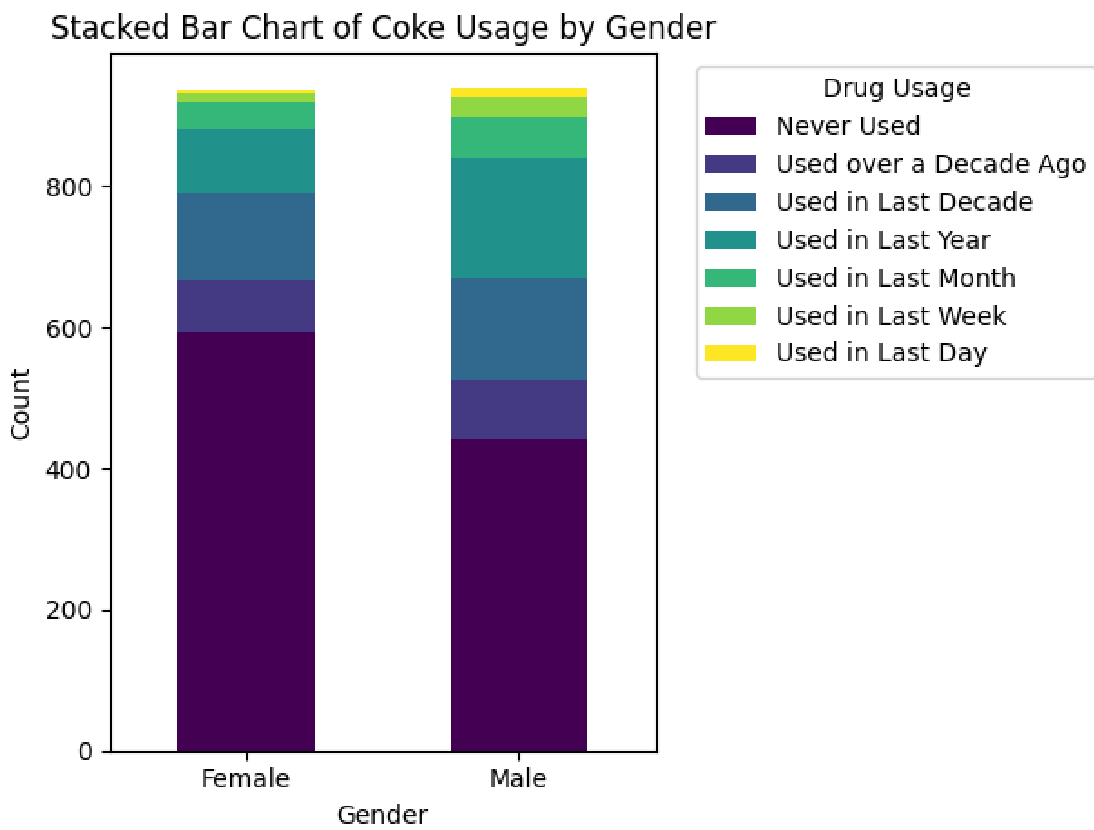

Stacked Bar Chart of Amphet Usage by Gender
Count
Gender
Female
Male
0
200
400
600
800
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

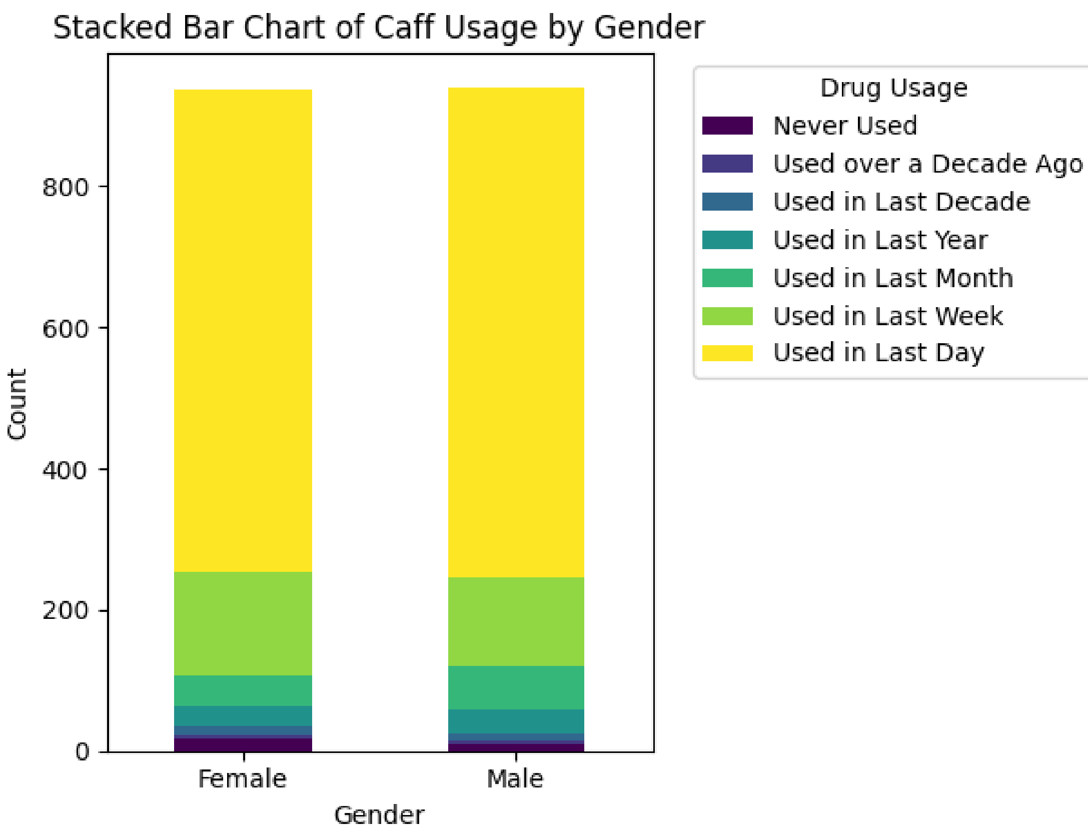

Stacked Bar Chart of Amyl Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

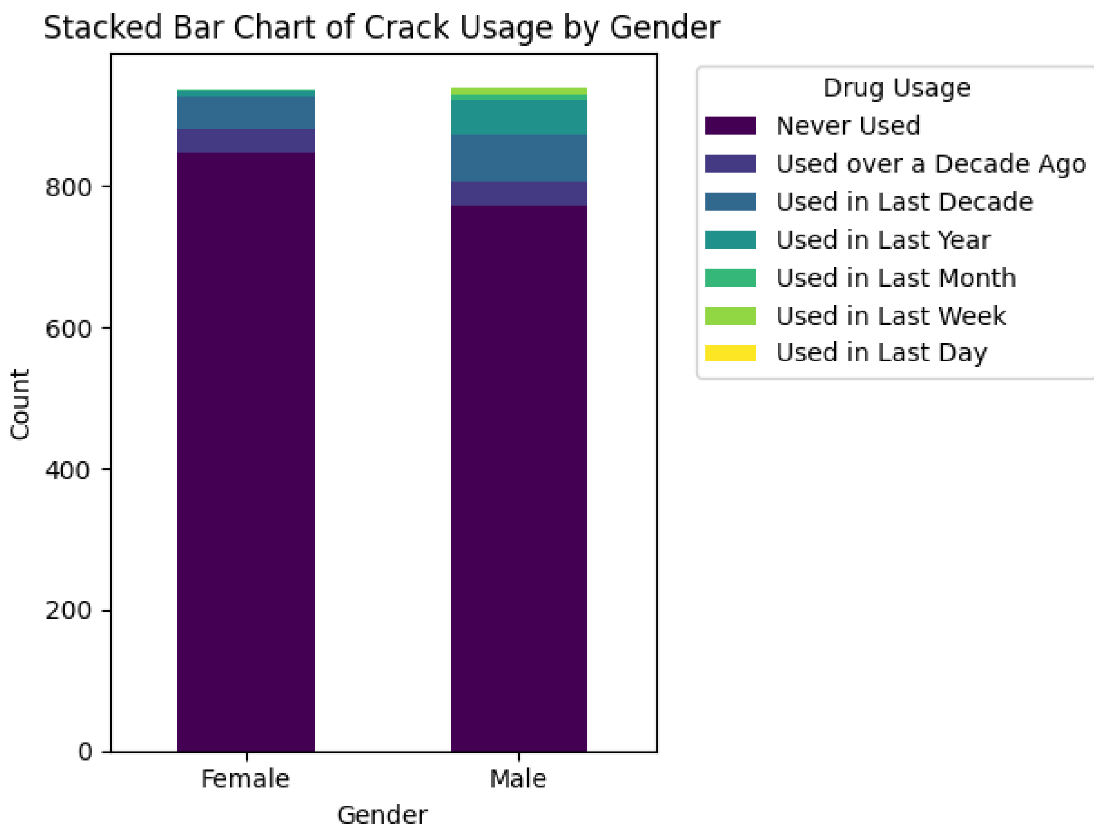

Stacked Bar Chart of Benzos Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Stacked Bar Chart of Cannabis Usage by Gender
Count
800
600
400
200
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

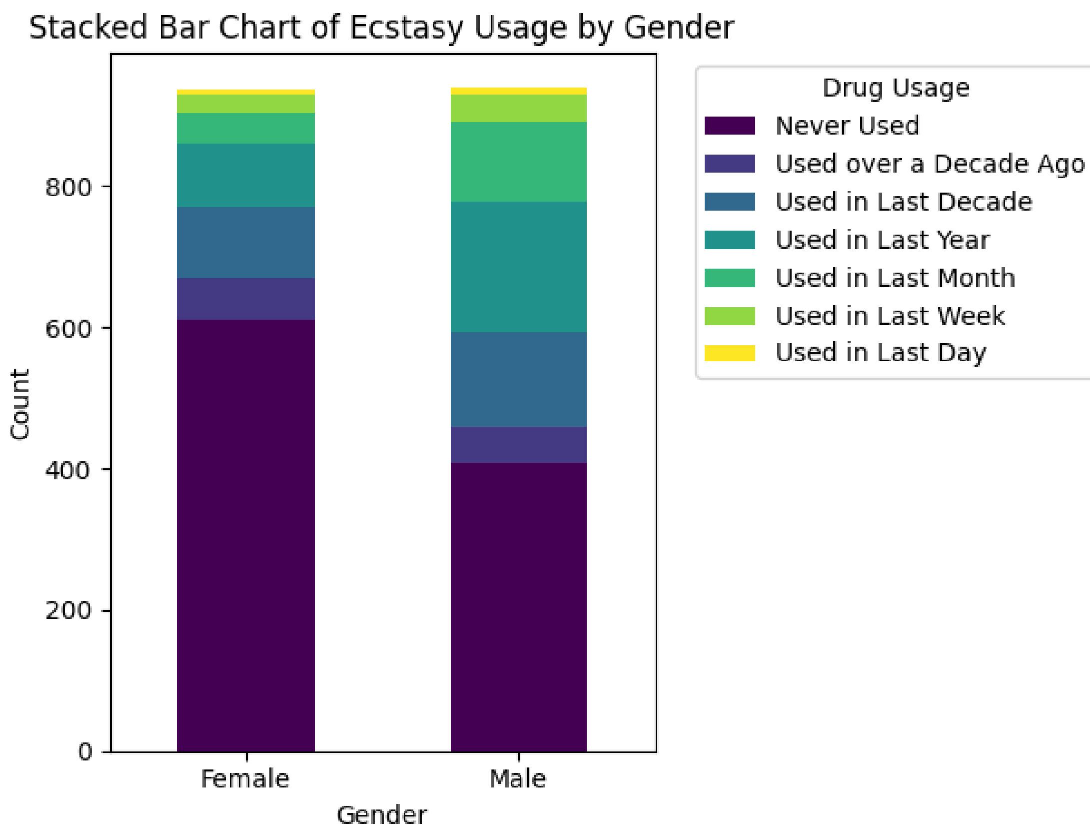

Stacked Bar Chart of Choc Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

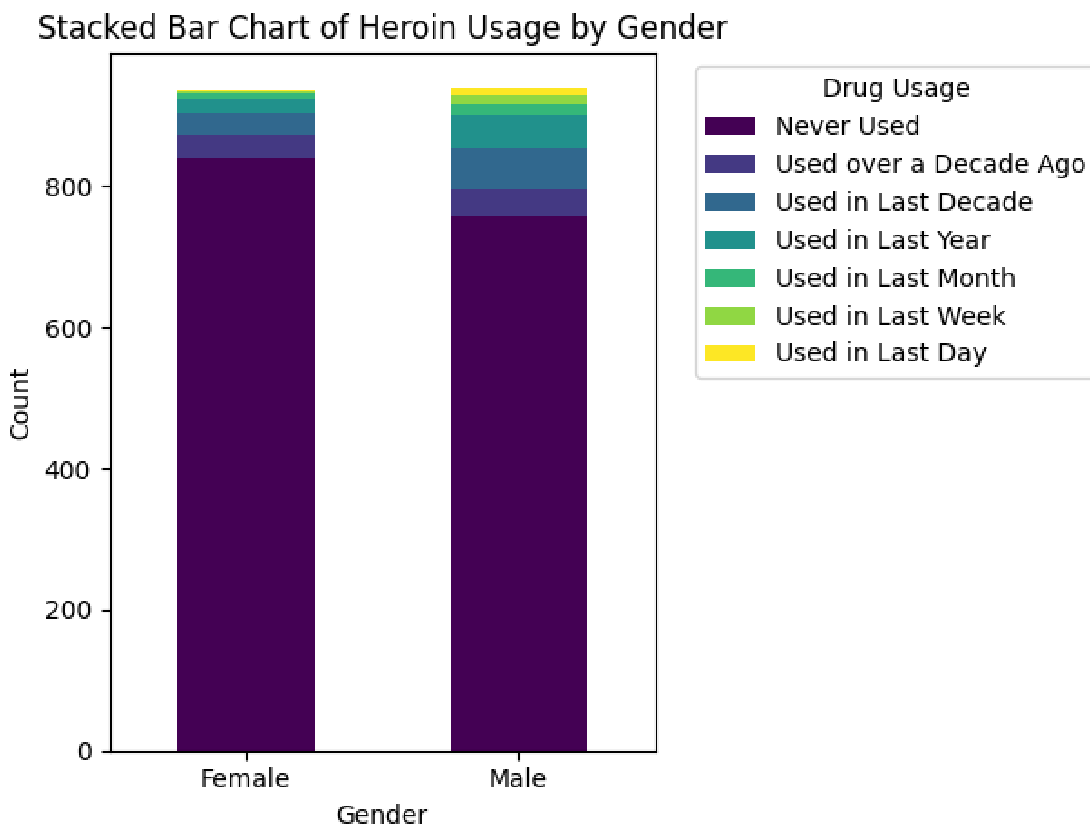

Stacked Bar Chart of Coke Usage by Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Count
0
200
400
600
800
Female
Male
Gender

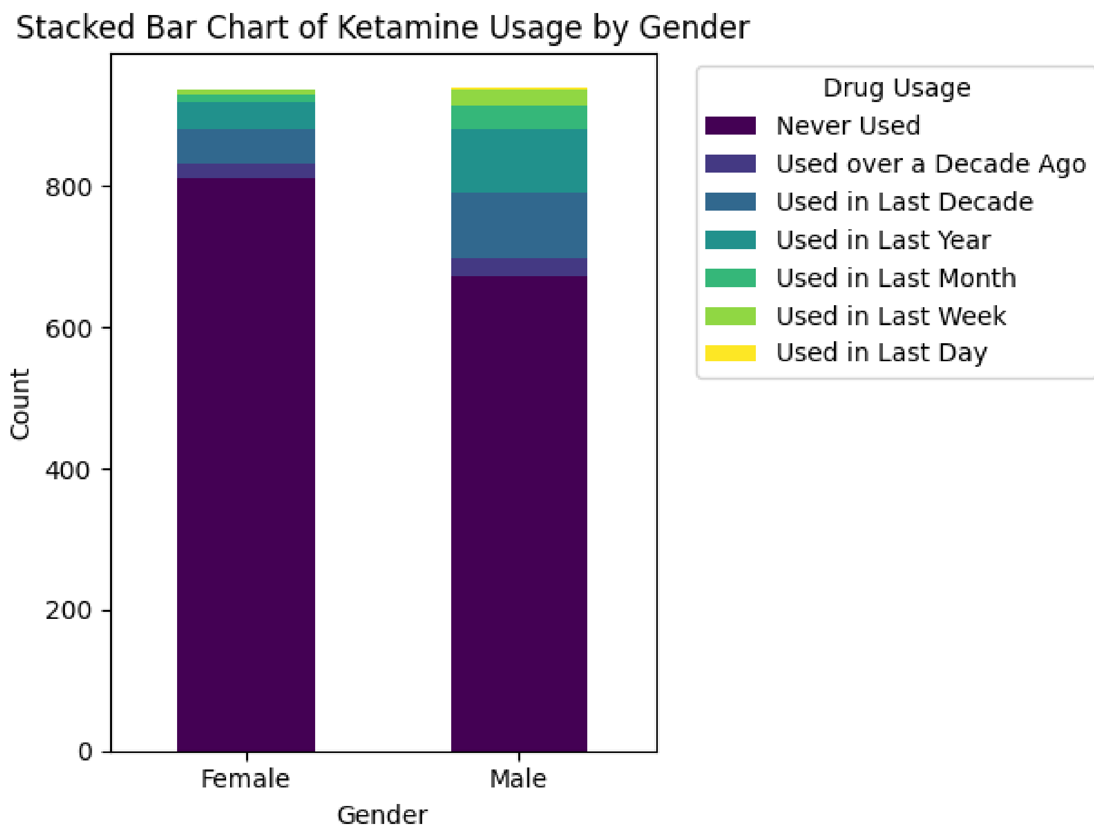

Stacked Bar Chart of Caff Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

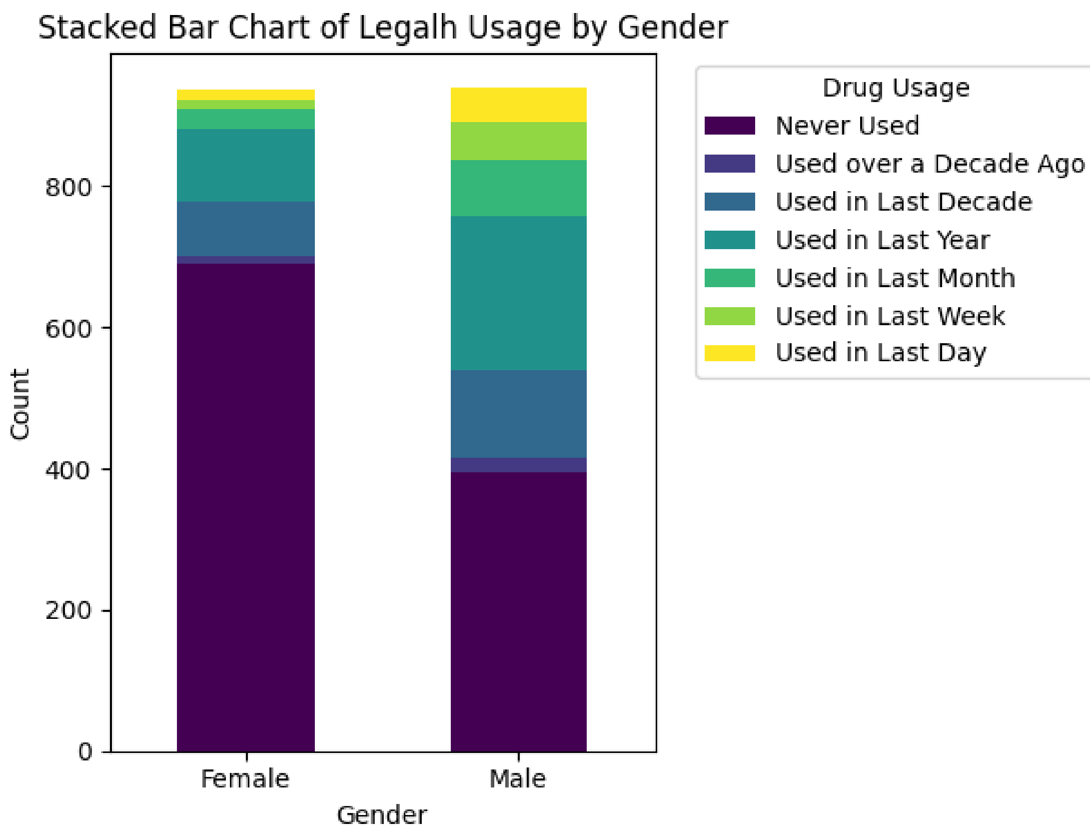


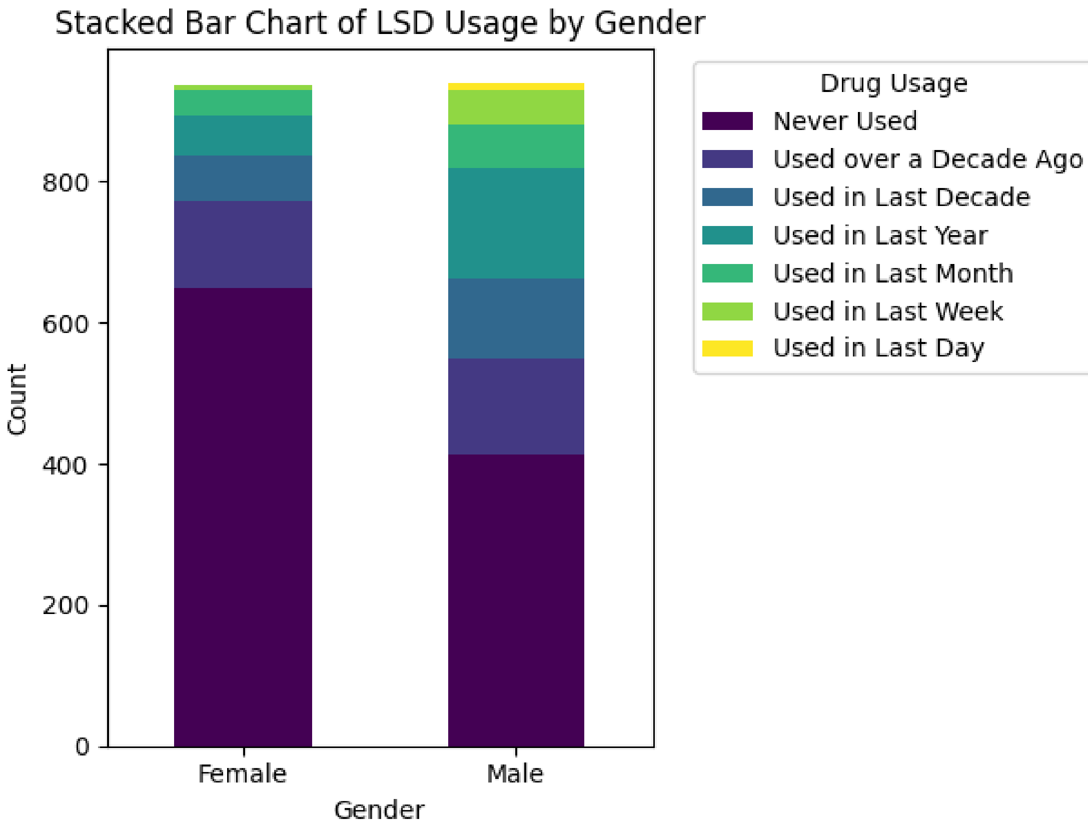
Stacked Bar Chart of Crack Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

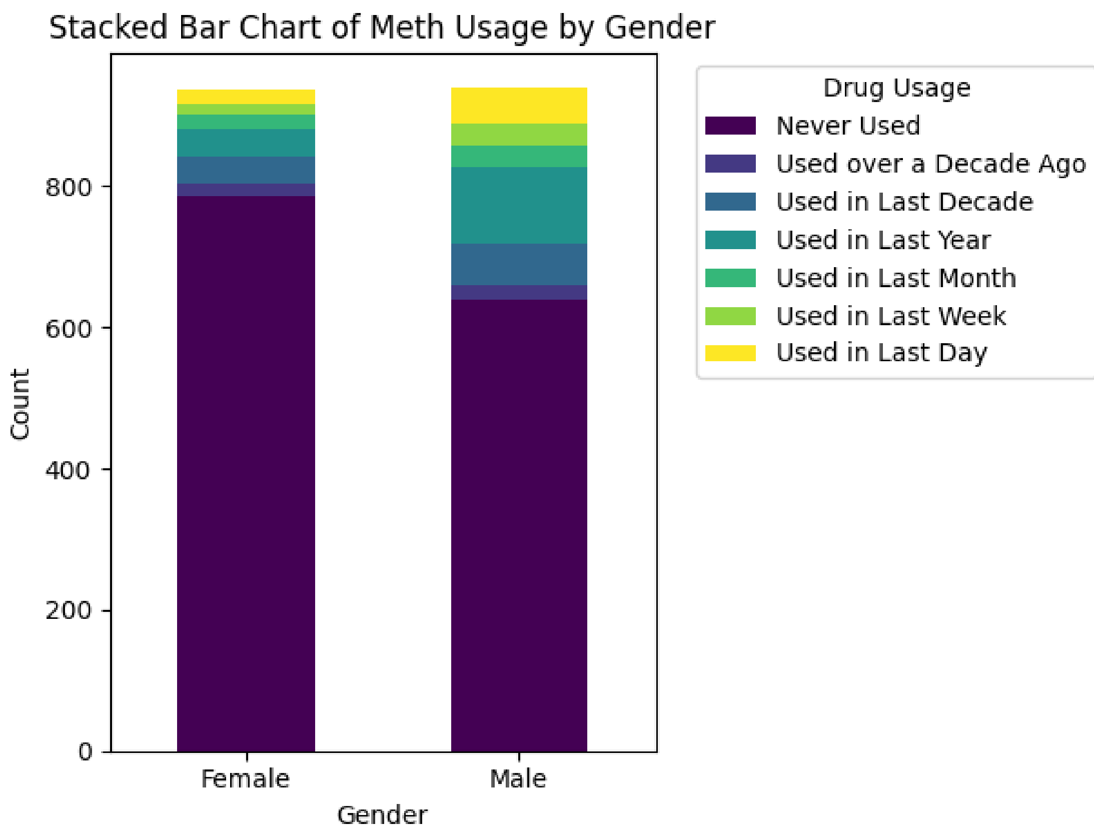

Stacked Bar Chart of Ecstasy Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Stacked Bar Chart of Heroin Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

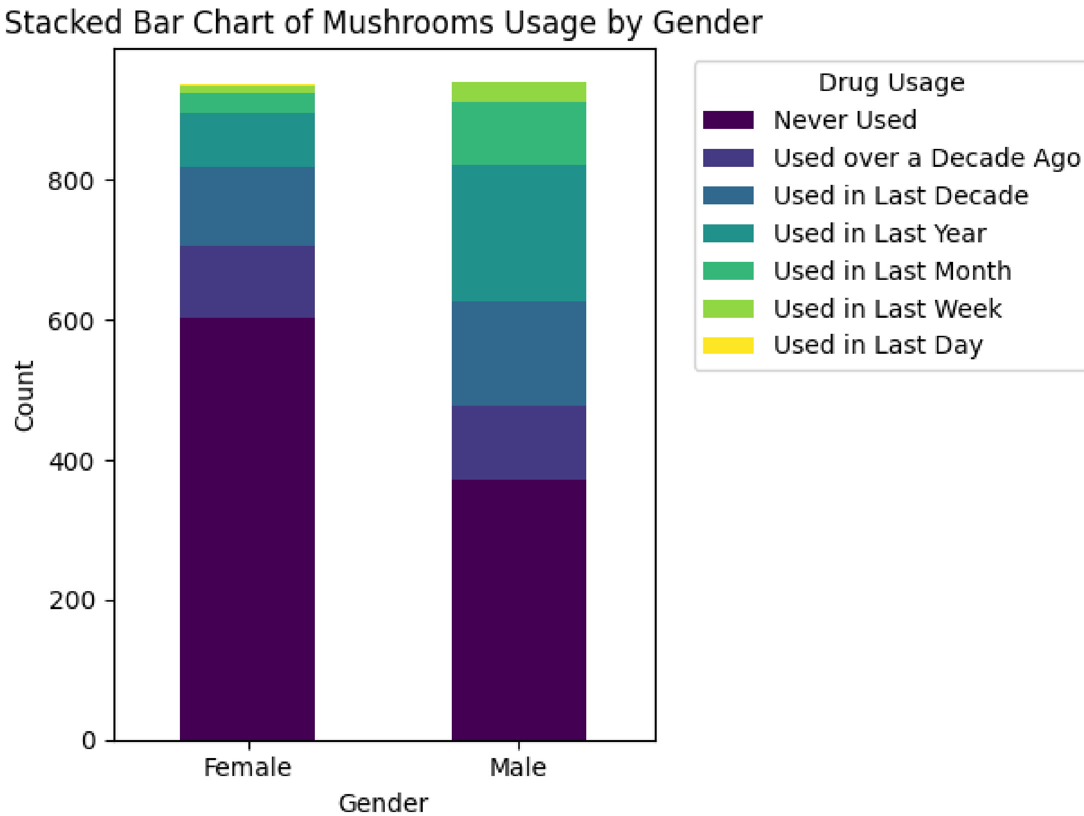

Stacked Bar Chart of Ketamine Usage by Gender
Count
800
600
400
200
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

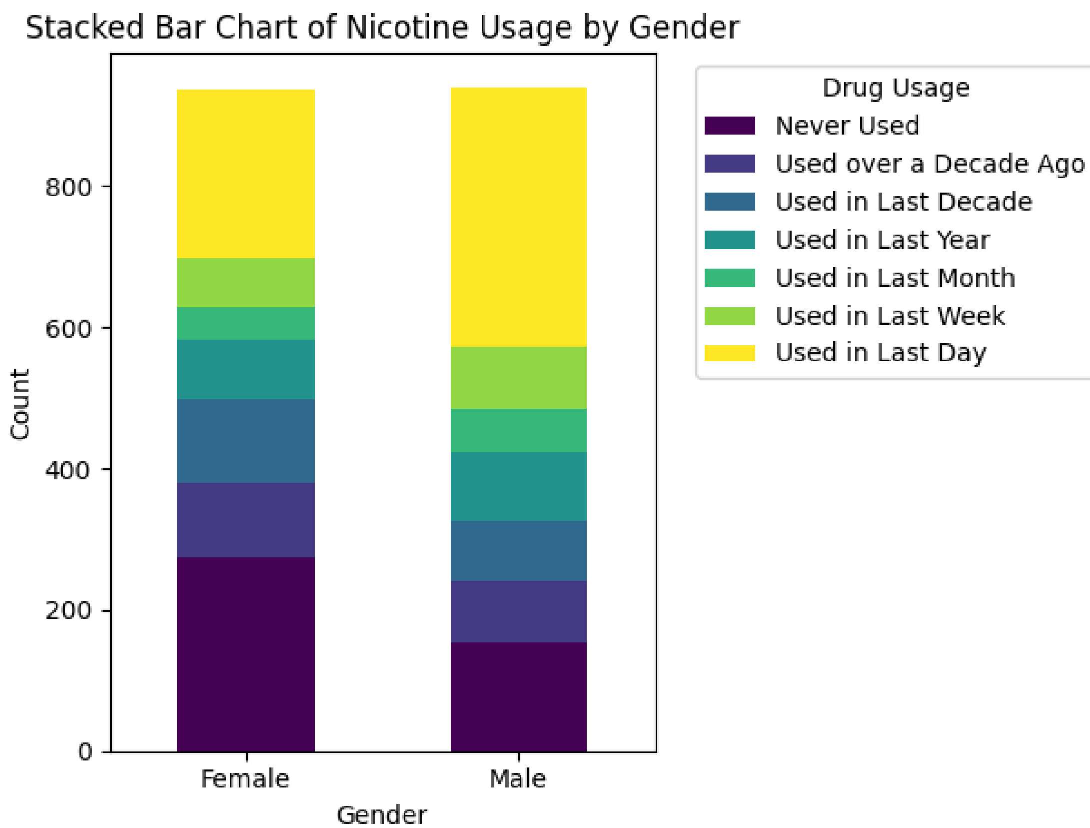

Stacked Bar Chart of Legalh Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

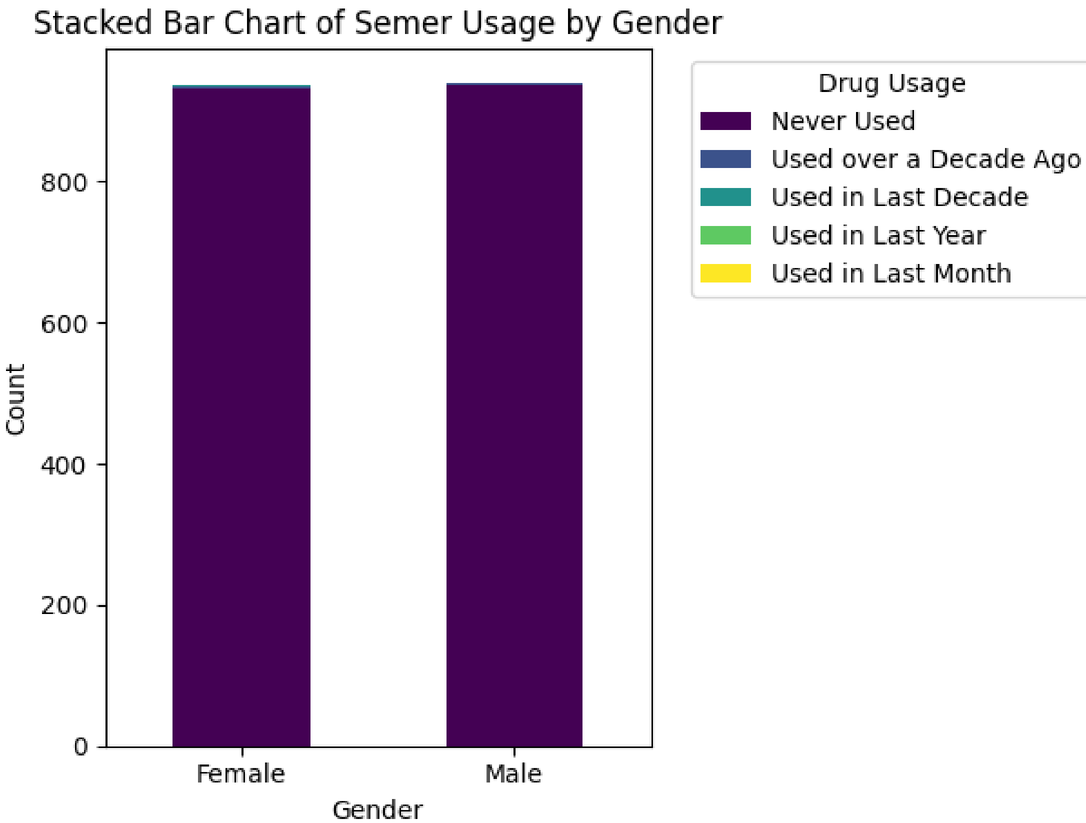

Stacked Bar Chart of LSD Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

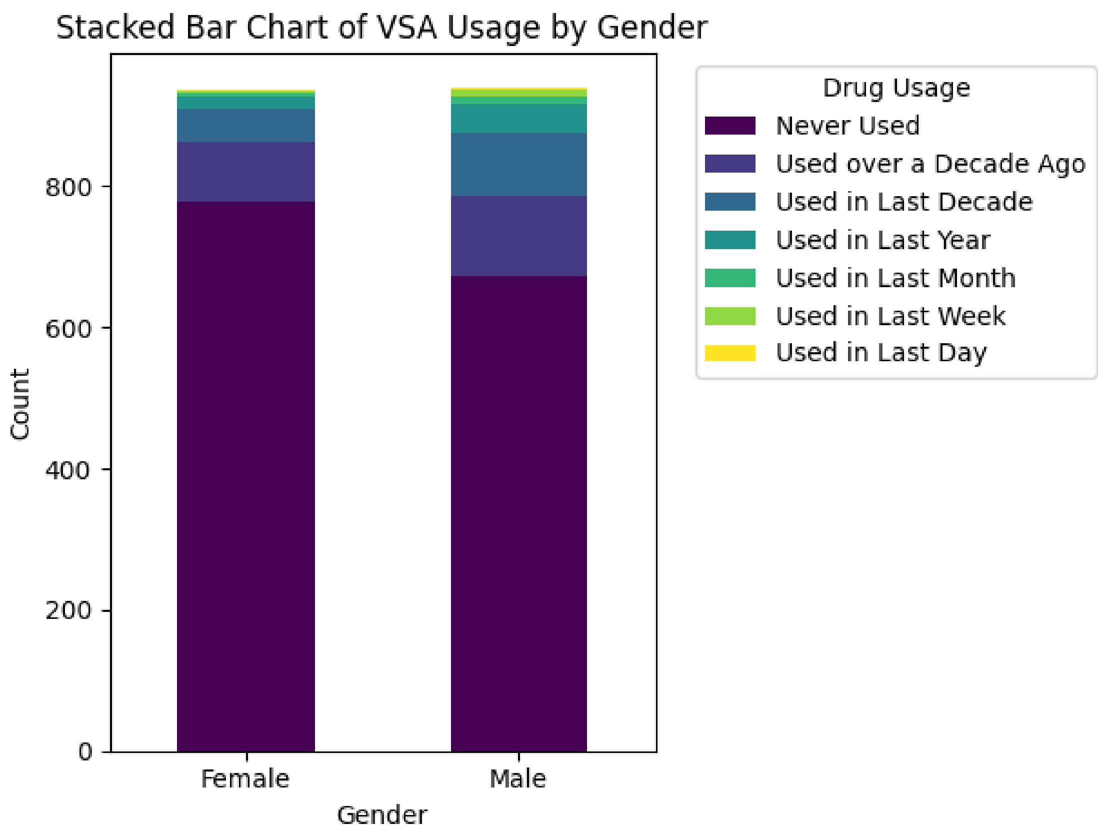


Stacked Bar Chart of Meth Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Stacked Bar Chart of Mushrooms Usage by Gender
Count
0
200
400
600
800
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Stacked Bar Chart of Nicotine Usage by Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day
Count
0
200
400
600
800
Female
Male
Gender

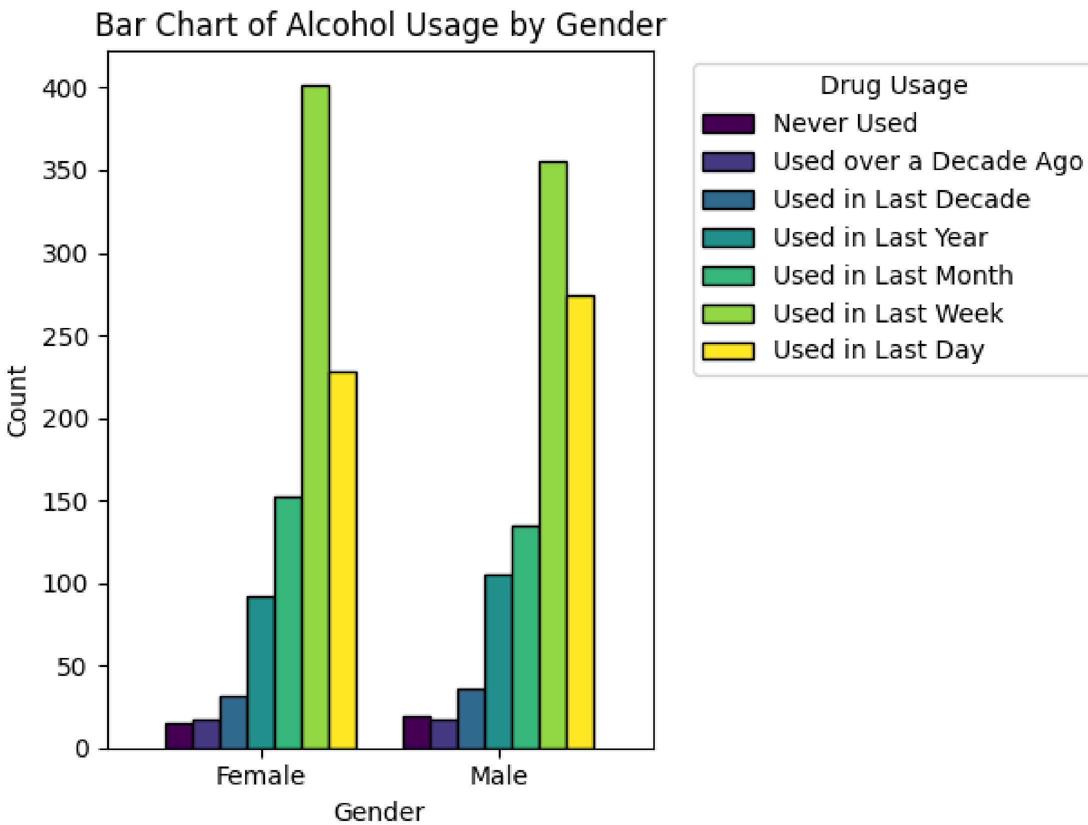

Stacked Bar Chart of Semer Usage by Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Count
800
600
400
200
0
Female
Male
Gender

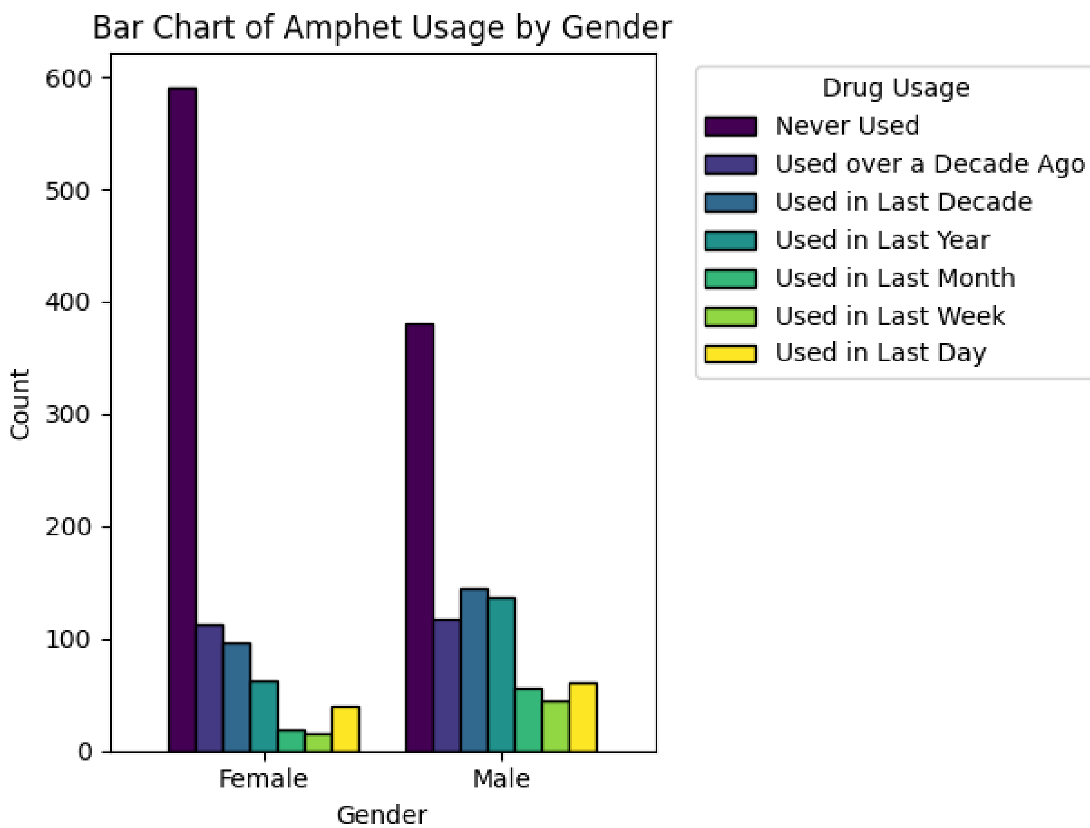


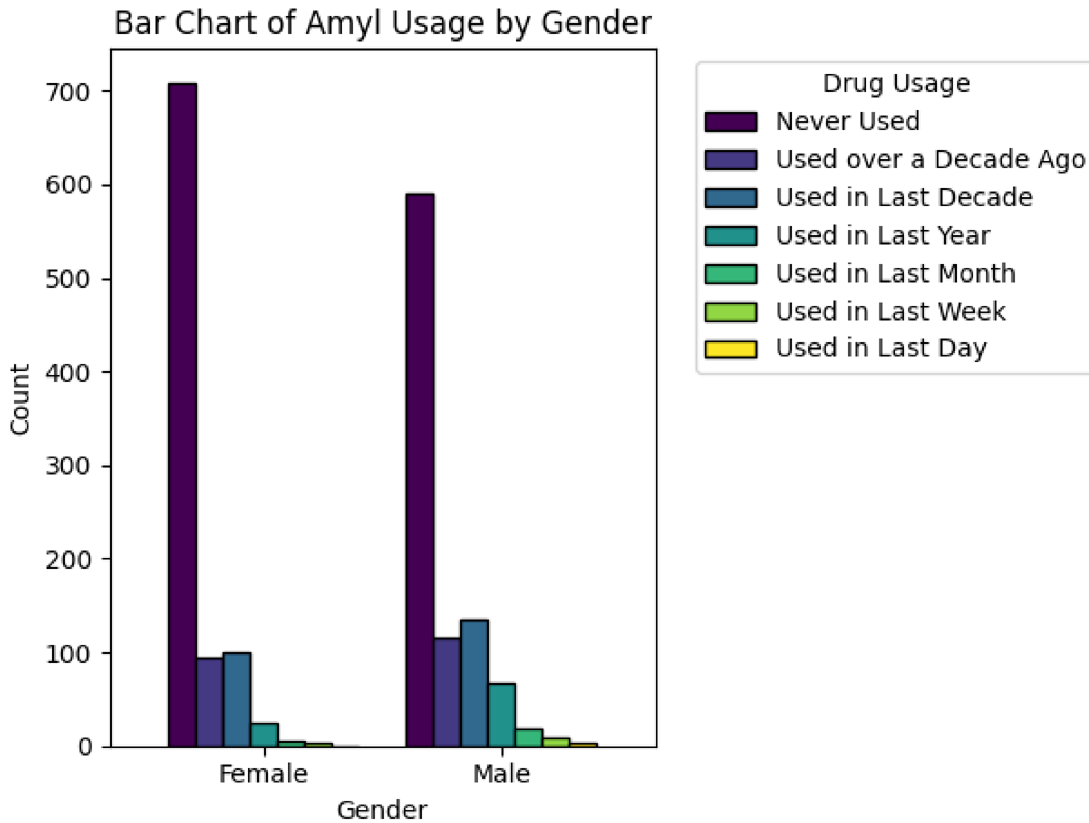
[104]:

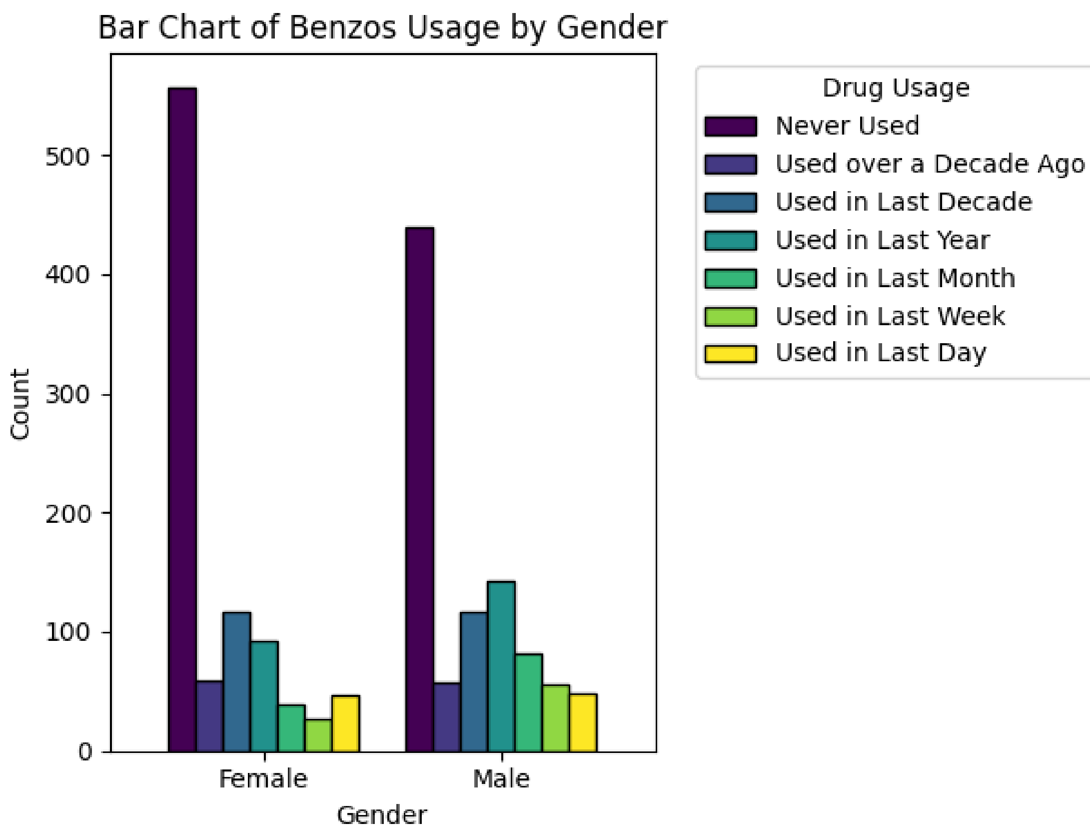
```
# Bar chart per drug usage by age group for each gender
for drug in drug_columns:
    # Prepare data for plotting
    plot_data = df.groupby(['gender_values', drug], observed=True).size().
↪unstack(fill_value=0)

    # Convert the columns to descriptive labels for the plot only
    plot_data = plot_data.rename(columns=CATEGORIES)

    # Plotting as grouped bars instead of stacked
    # Exceptionally answers specific business questions using advanced data␣
↪visualization techniques,
    # demonstrating an outstanding understanding of relevant attribute types
    ax = plot_data.plot(kind='bar', width=0.8, colormap='viridis', position=0.
↪5, edgecolor='black')
    plt.title(f'Bar Chart of {drug.replace("_values", "")} Usage by Gender')
    plt.xlabel('Gender')
    plt.ylabel('Count')
    plt.xticks(rotation=0)  # Keep the gender labels horizontal for readability
```

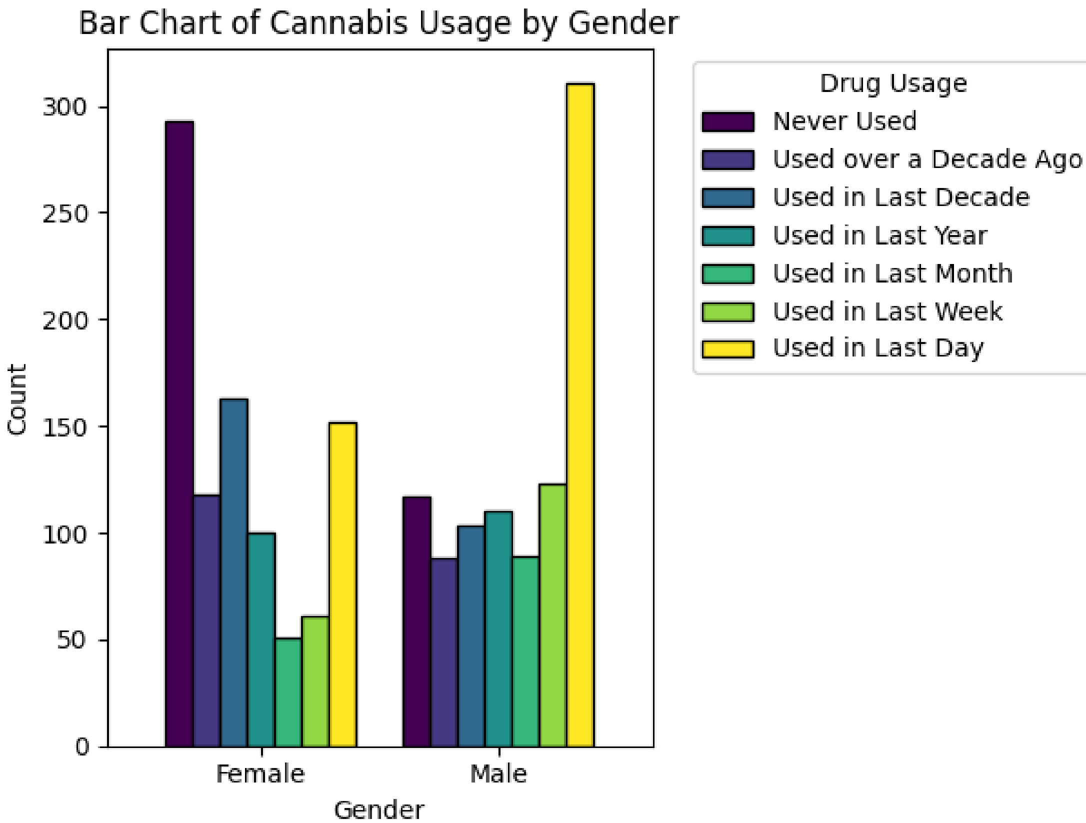
```
    # Set legend directly using the category order
    plt.legend(category_order, title='Drug Usage', bbox_to_anchor=(1.05, 1),␣
↪loc='upper left')

    plt.tight_layout()
    plt.show() # presenting visually compelling plots or charts that surpass␣
↪expectations.
```

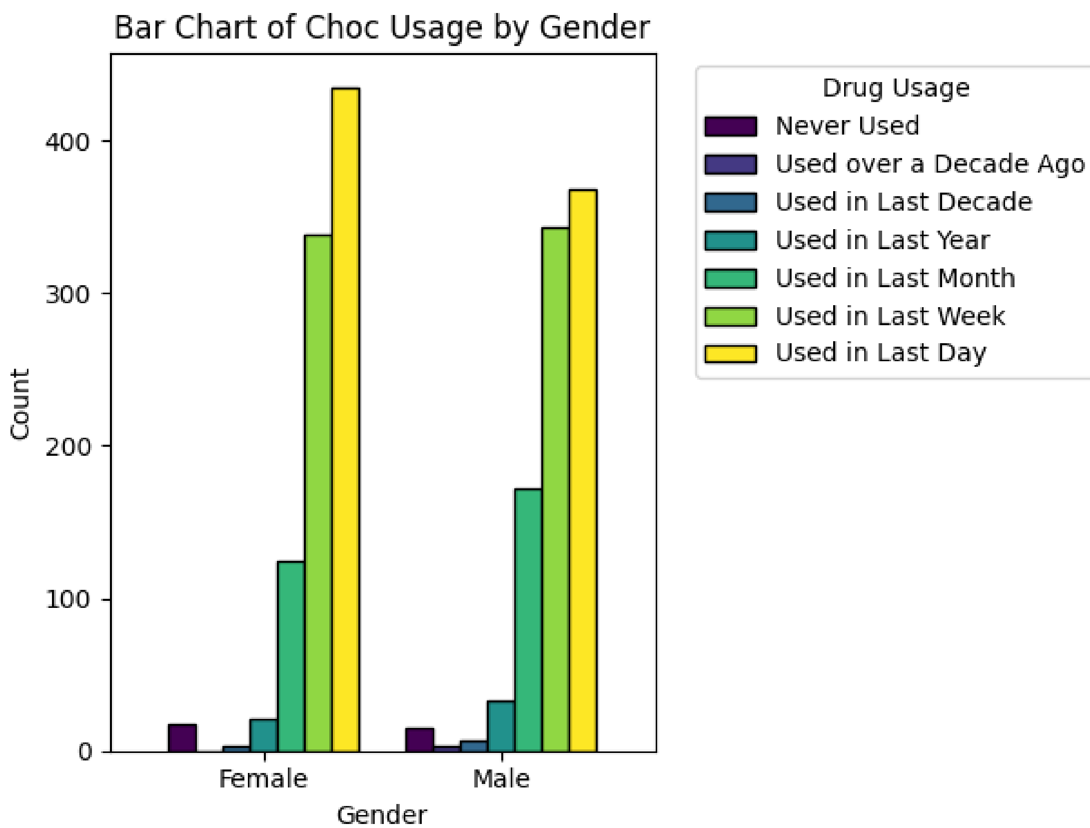



Bar Chart of Amphet Usage by Gender
Count
0
100
200
300
400
500
600
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

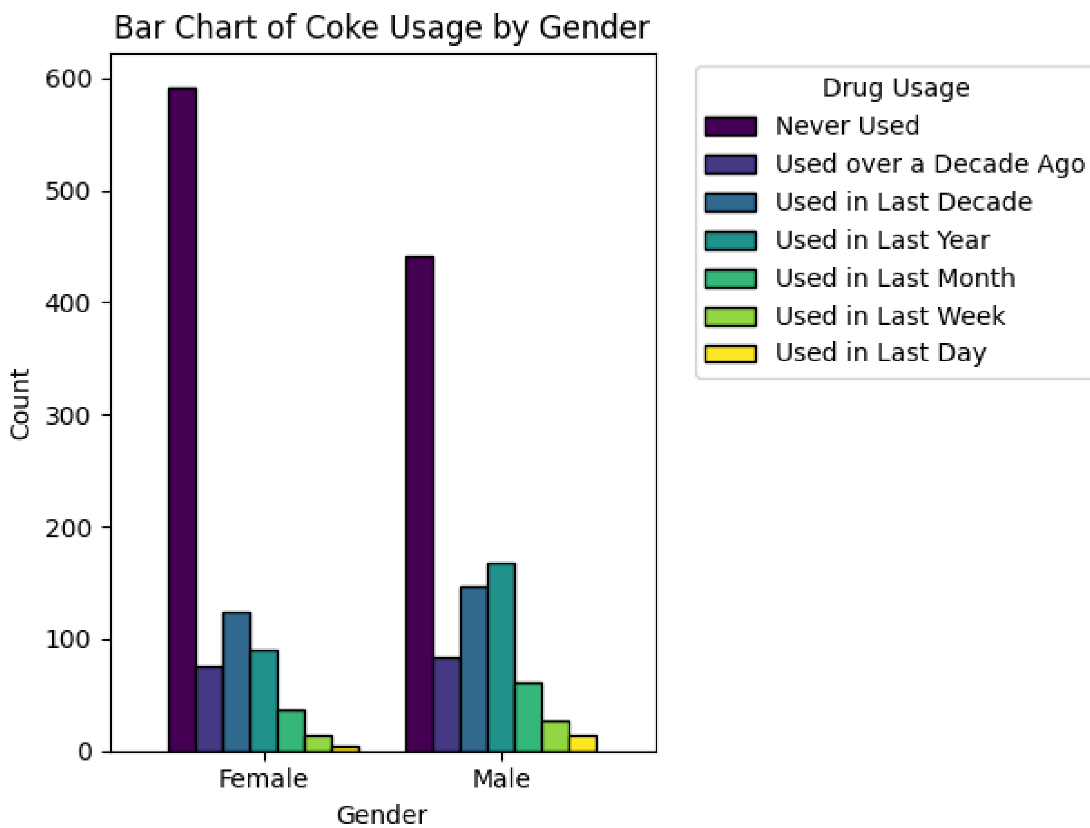

Bar Chart of Amyl Usage by Gender
Count
700
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Bar Chart of Benzos Usage by Gender
Count
Gender
Female
Male
0
100
200
300
400
500
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

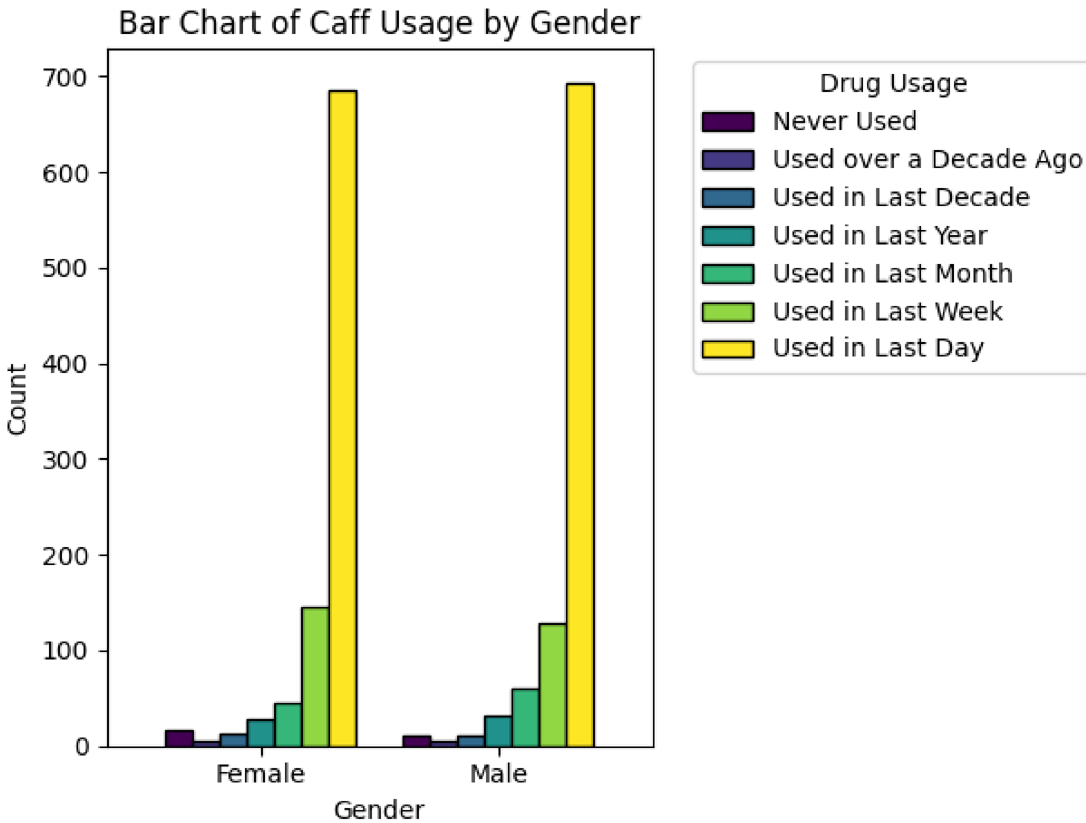

Bar Chart of Cannabis Usage by Gender
Count
300
250
200
150
100
50
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

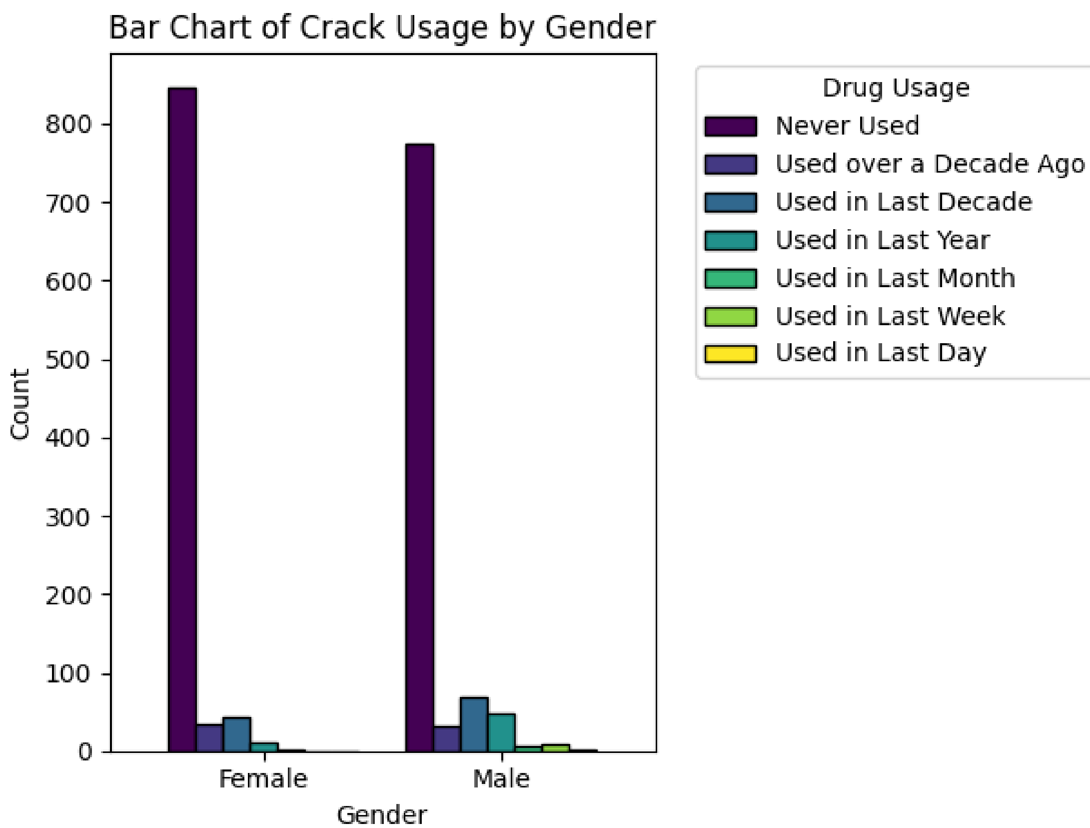


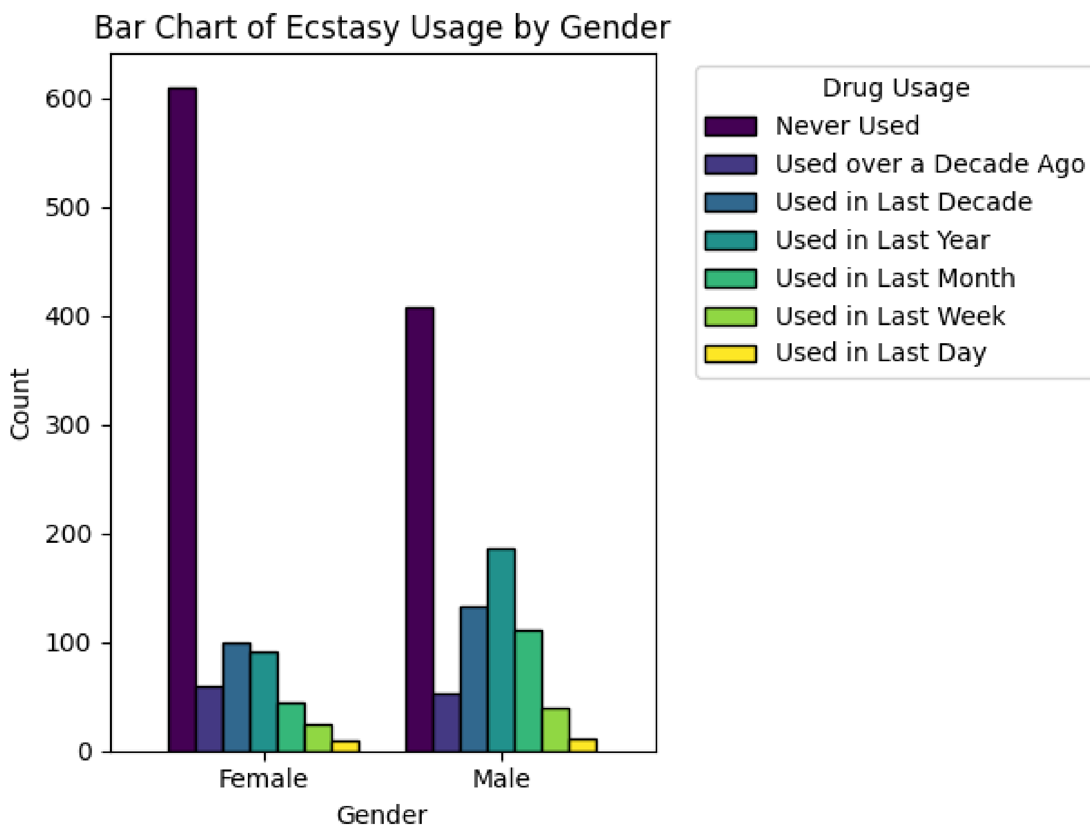
Bar Chart of Choc Usage by Gender
Count
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

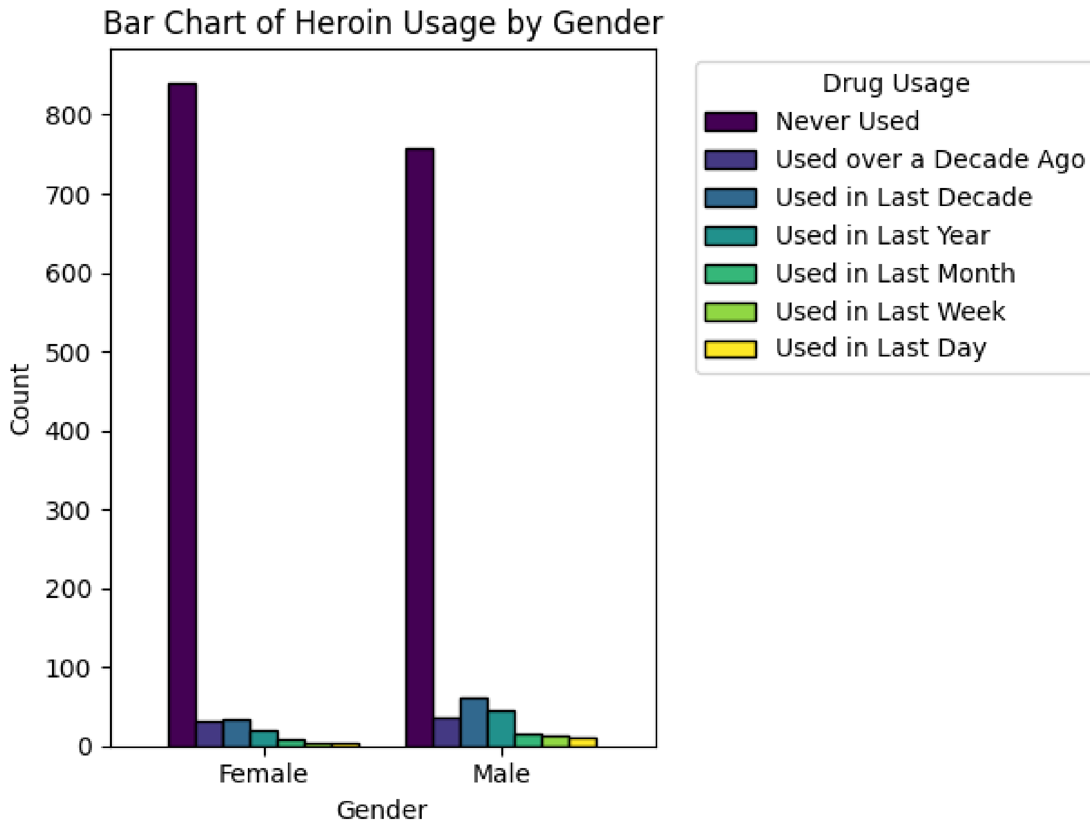


Bar Chart of Coke Usage by Gender
Count
0
100
200
300
400
500
600
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

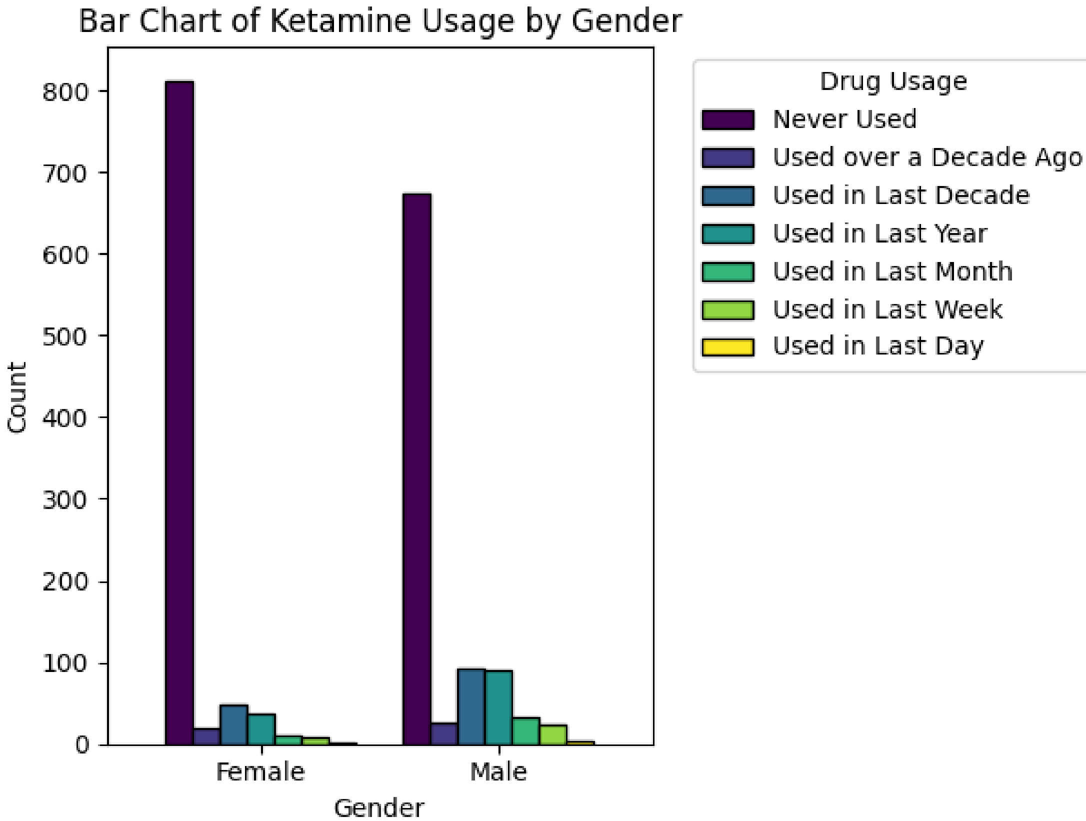

Bar Chart of Caff Usage by Gender
Count
700
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Bar Chart of Crack Usage by Gender
Count
800
700
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

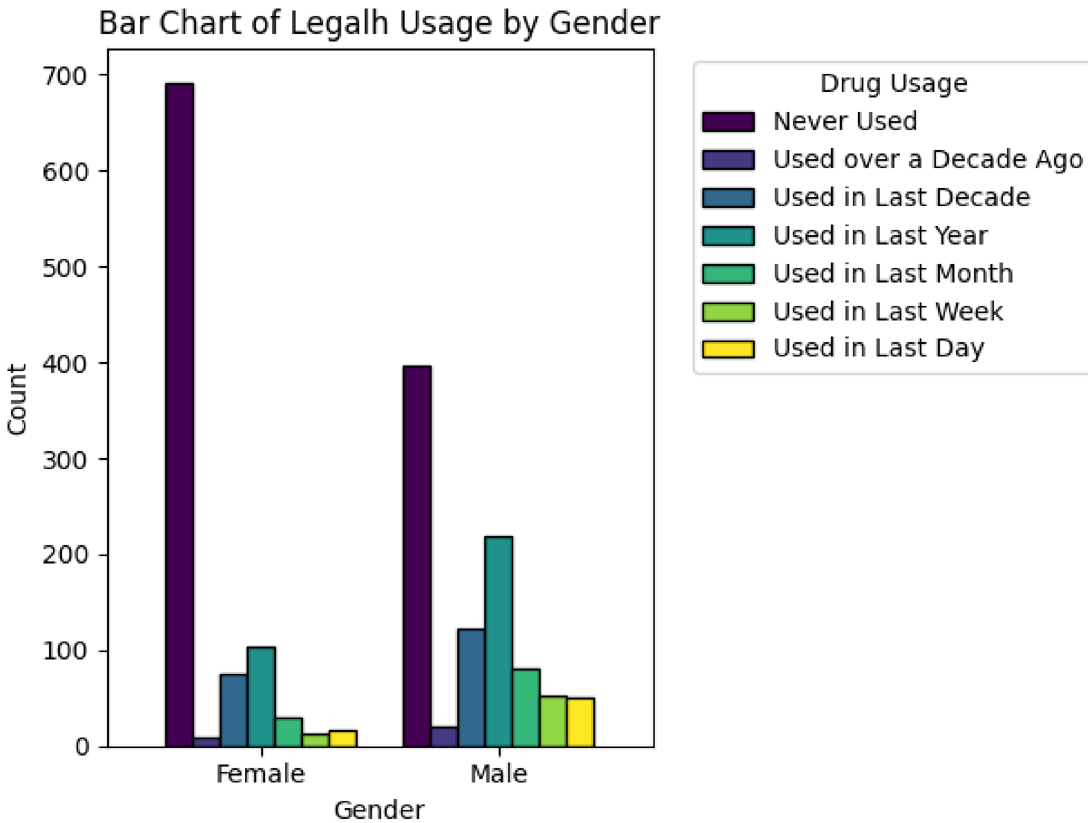

Bar Chart of Ecstasy Usage by Gender
Count
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

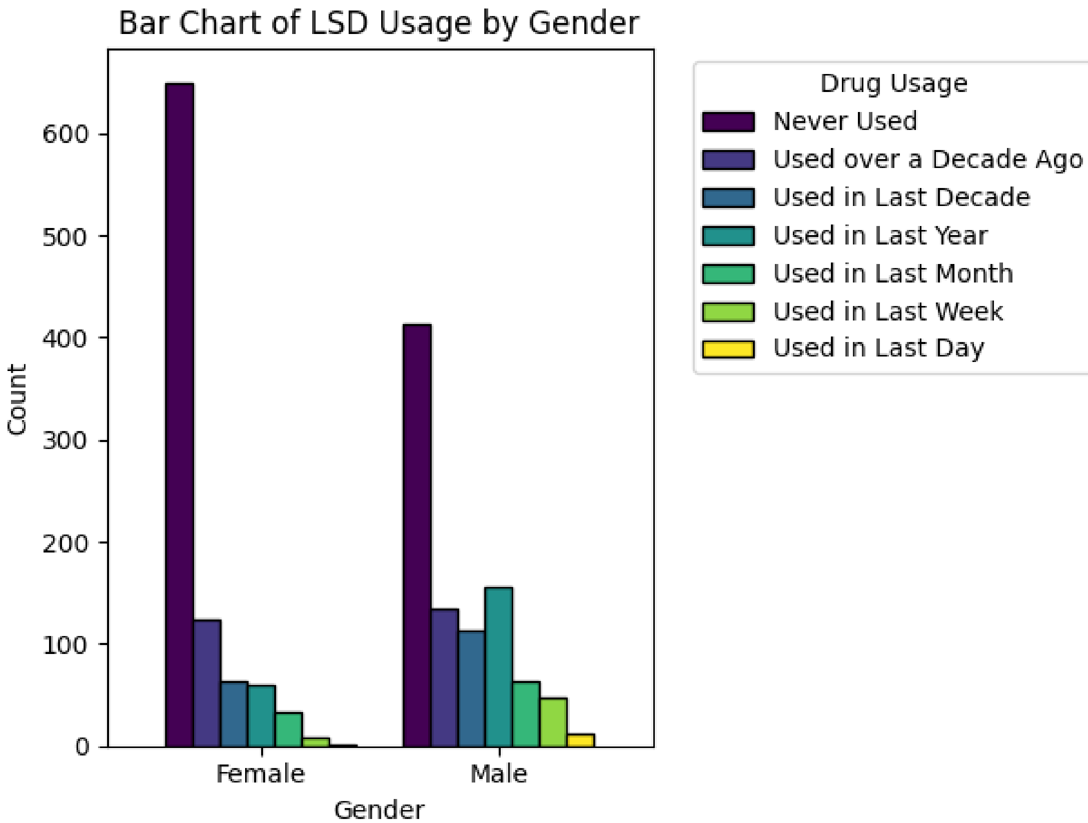


Bar Chart of Heroin Usage by Gender
Count
800
700
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

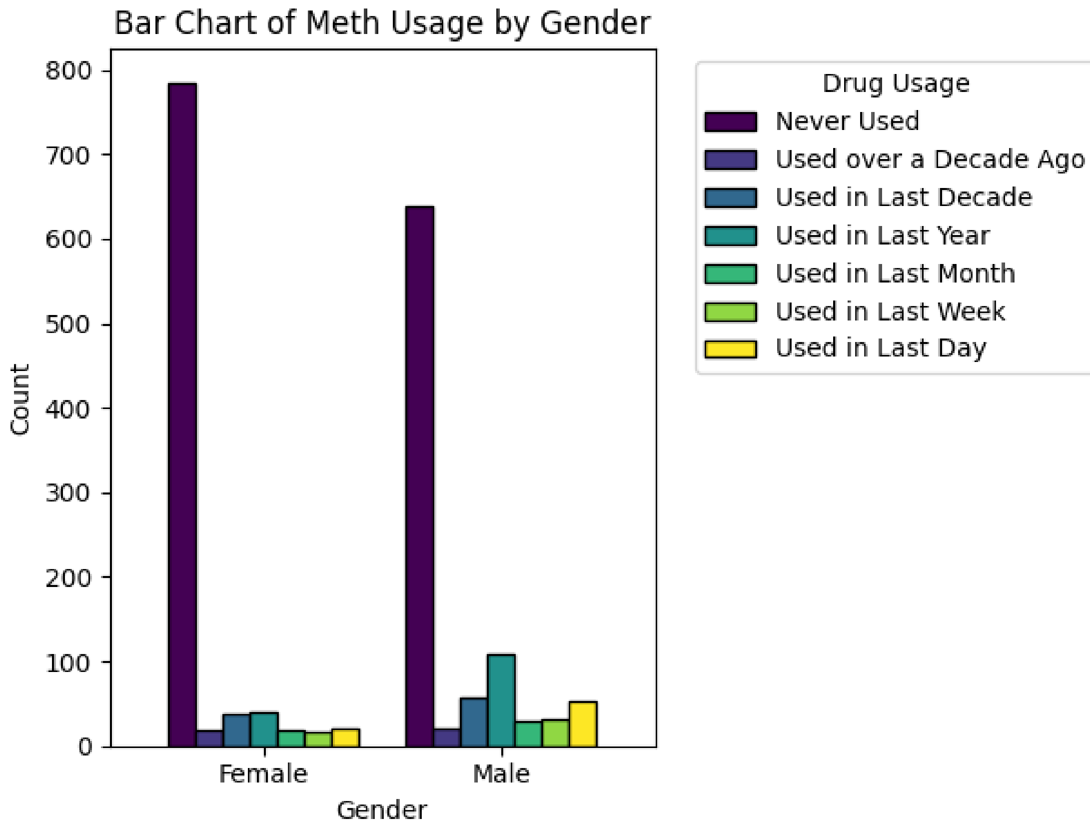


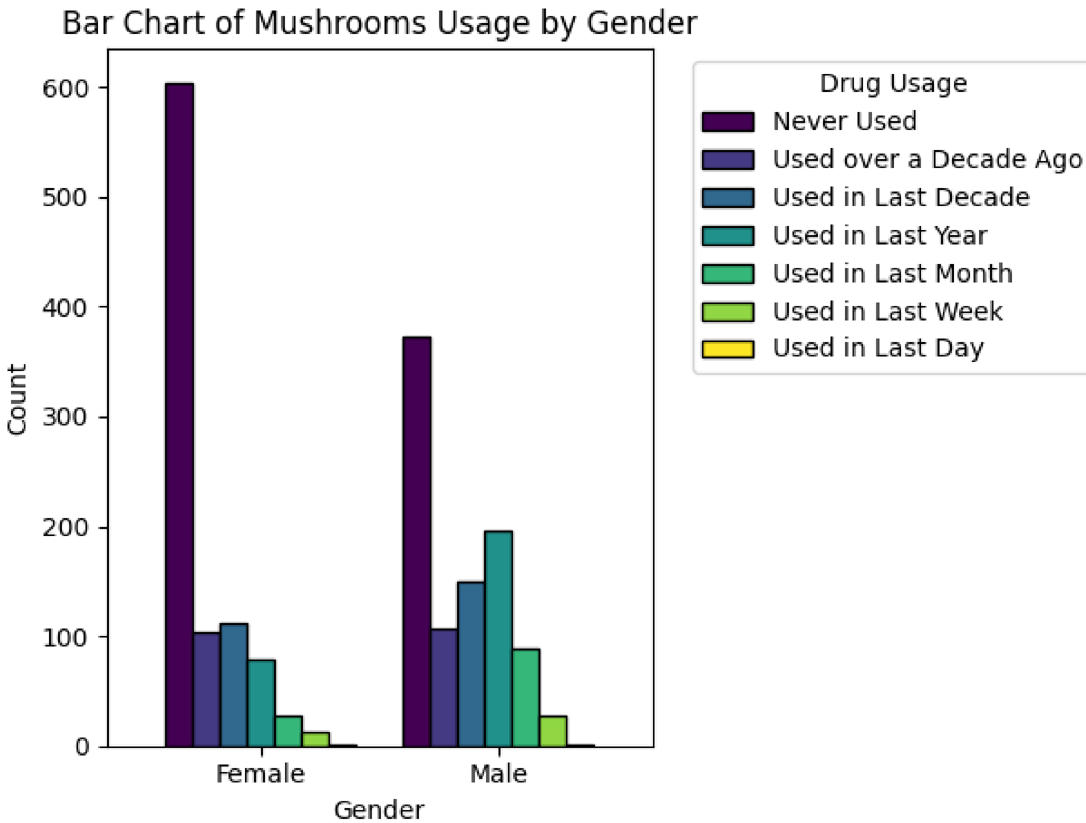
Bar Chart of Ketamine Usage by Gender
Count
800
700
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

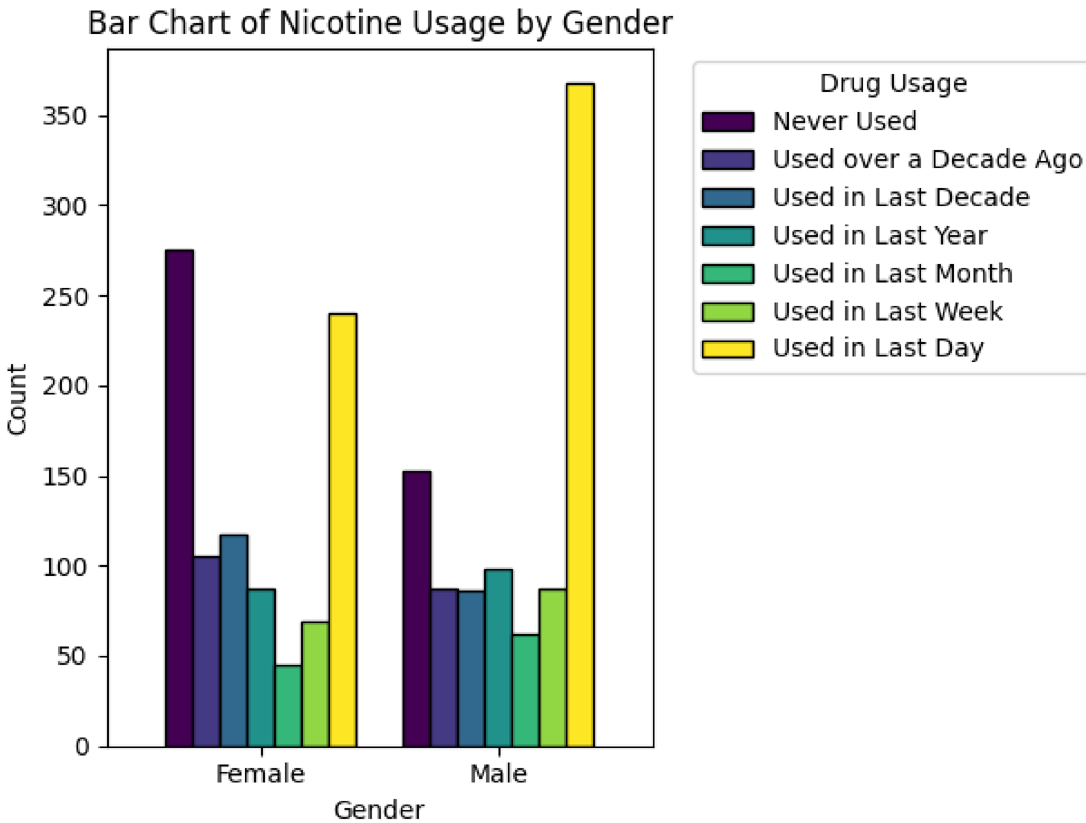

Bar Chart of Legalh Usage by Gender
700
600
500
400
300
200
100
0
Count
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day

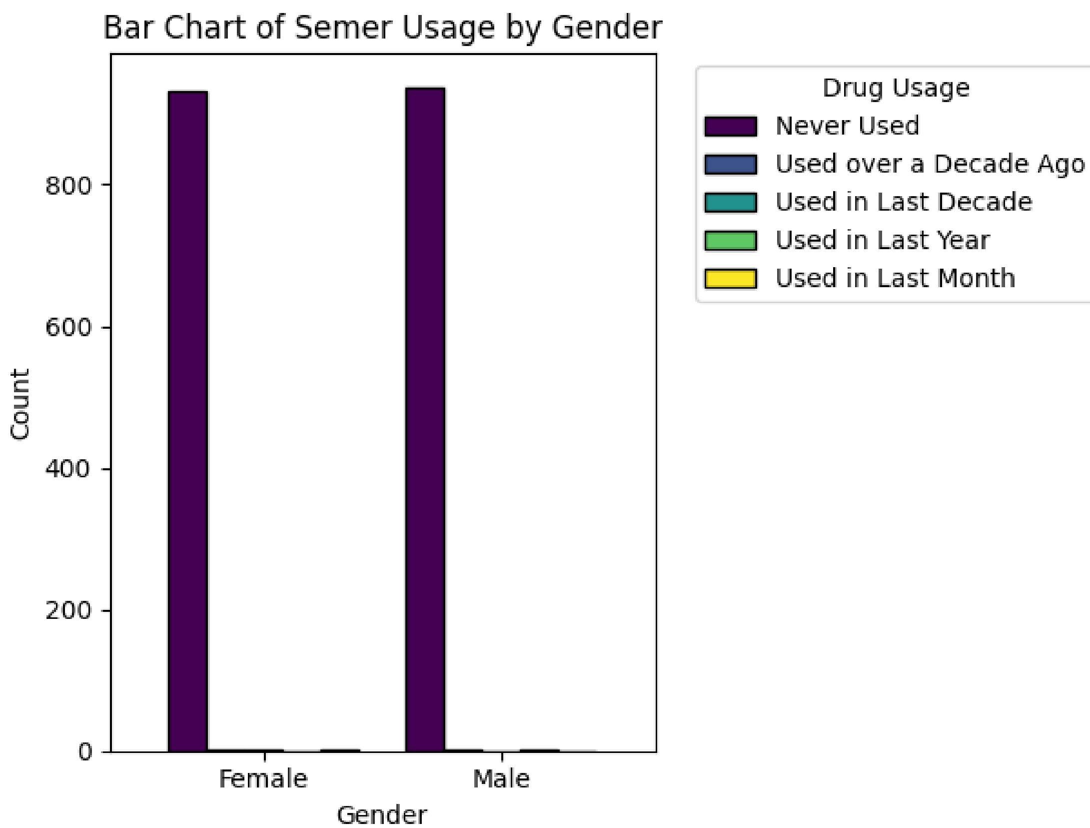


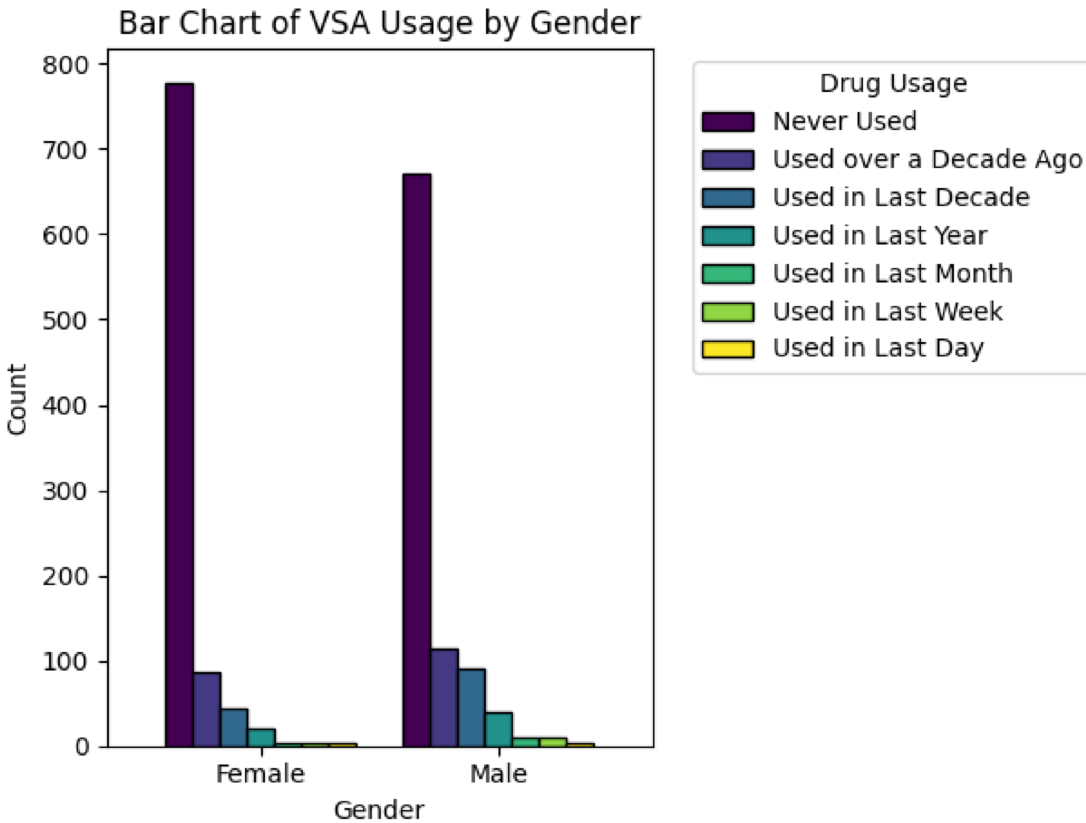
Bar Chart of LSD Usage by Gender
Count
0
100
200
300
400
500
600
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Bar Chart of Meth Usage by Gender
Count
800
700
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Bar Chart of Mushrooms Usage by Gender
Count
600
500
400
300
200
100
0
Female
Male
Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Bar Chart of Nicotine Usage by Gender
Count
Gender
Female
Male
0
50
100
150
200
250
300
350
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Used in Last Week
Used in Last Day


Bar Chart of Semer Usage by Gender
Drug Usage
Never Used
Used over a Decade Ago
Used in Last Decade
Used in Last Year
Used in Last Month
Count
800
600
400
200
0
Female
Male
Gender



5.4.1 Analysis:

The stacked bar charts highlight the following gender-specific trends: - **Alcohol and Cannabis**: Males report slightly higher recent usage compared to females. - **Cocaine and Ecstasy**: Males also show higher recent usage, suggesting a gender-based preference or higher accessibility. - **Benzodiazepines and Amphetamines**: The usage patterns are relatively similar across genders, with only slight variations in recent usage frequencies.

Understanding these differences can help in designing more effective gender-specific prevention and treatment programs.

6 Export notebook as PDF

[105]:
```
!ls
```

```
assignment3.ipynb                 data
assignment3.pdf                   drug_consumption_preprocessed.csv
```

[106]:
```
!jupyter nbconvert assignment3.ipynb --to pdf --out script.pdf
```

```
[NbConvertApp] WARNING | Unrecognized alias: 'out', it will have no effect.
```

```
[NbConvertApp] Converting notebook assignment3.ipynb to pdf
/usr/local/anaconda3/envs/uts-
pdpp/share/jupyter/nbconvert/templates/latex/display_priority.j2:32:
UserWarning: Your element with mimetype(s)
dict_keys(['application/vnd.plotly.v1+json']) is not able to be represented.
  ((*- endblock -*))
[NbConvertApp] Support files will be in assignment3_files/
[NbConvertApp] Making directory ./assignment3_files
[NbConvertApp] Writing 259119 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 21538919 bytes to assignment3.pdf
```

[107]:
```
!ls
```

```
assignment3.ipynb                  data
assignment3.pdf                    drug_consumption_preprocessed.csv
```