Rama_Rao_Vydadi_50604256

November 5, 2024

0.0.1 Problem Statement :

0.0.2 This analysis aims to uncover potential causes of mental health disorders by examining the behavioral patterns and histories of affected patients, ### leading to insights for better interventions.

[1]:
```
import pandas as pd
import os
from typing import List, Optional, Dict
import gc
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import GradientBoostingClassifier
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pickle
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪precision_score, recall_score, f1_score, confusion_matrix
```

[2]:
```
def fetch_nsduh_data(year: int) -> Optional[pd.DataFrame]:
    url_placeholder = "https://www.datafiles.samhsa.gov/sites/default/files/
 ↪field-uploads-protected/studies/NSDUH-{year}/NSDUH-{year}-datasets/
 ↪NSDUH-{year}-DS0001/NSDUH-{year}-DS0001-bundles-with-study-info/
 ↪NSDUH-{year}-DS0001-bndl-data-tsv.zip"

    try:
        url = url_placeholder.format(year=year)
        df = pd.read_csv(url, compression='zip', sep='\t', low_memory=False)
        return df
    except Exception as e:
        print(f"An error occurred for year {year}: {e}")
```

```python
        return None
```

[3]:
```python
def check_parquet_exists(years: List[int], output_dir: str) -> Dict[int, bool]:
    existence_check = {}

    for year in years:
        year_path = os.path.join(output_dir, f'year={year}')
        existence_check[year] = os.path.exists(year_path)

    return existence_check
```

[4]:
```python
def write_parquet(df: pd.DataFrame, year: int, output_dir: str, overwrite: bool␣
 ↪= False) -> None:
    try:
        year_dir = os.path.join(output_dir, f'year={year}')
        if overwrite and os.path.exists(year_dir):
            shutil.rmtree(year_dir)  # Remove existing directory to start fresh

        df['year'] = year  # Add the year column for partitioning
        # Write data to Parquet format with partitioning
        df.to_parquet(output_dir, partition_cols=['year'], index=False)

        print(f"Data for year {year} successfully saved to Parquet format in␣
 ↪{output_dir}")
    except Exception as e:
        print(f"Error saving data to Parquet for year {year}: {e}")
```

[5]:
```python
def data_fetch(years_to_fetch: List[int], output_dir: str, overwrite: bool =␣
 ↪False) -> None:
    try:
        for year in years_to_fetch:
            if not overwrite and os.path.exists(os.path.join(output_dir,␣
 ↪f'year={year}')):
                print(f"Data for year {year} already exists. Skipping.")
                continue

            df = fetch_nsduh_data(year)
            if df is not None:
                print(f"Successfully fetched data for year: {year}")
                write_parquet(df, year, output_dir, overwrite)
                del df  # Remove the DataFrame from memory
                gc.collect()  # Force garbage collection

        print("All requested years processed.")
    except Exception as e:
        print(f"An unexpected error occurred in the data_fetch function: {e}")
```

[6]:

```
def read_parquet(input_dir: str, years: Optional[List[int]] = None) -> pd.
↪DataFrame:
    data_frames = []
    available_years = [int(d.split('=')[1]) for d in os.listdir(input_dir) if d.
↪startswith('year=')]
    years_to_read = years if years is not None else available_years

    for year in years_to_read:
        year_path = os.path.join(input_dir, f'year={year}')
        if os.path.exists(year_path):
            df = pd.read_parquet(year_path)

            # Convert data types to reduce memory usage
            for col in df.select_dtypes(include=['float64']).columns:
                df[col] = df[col].astype('float32')

            data_frames.append(df)
        else:
            print(f"Warning: No data found for year {year}")

    if data_frames:
        combined_df = pd.concat(data_frames, ignore_index=True)
        return combined_df
    else:
        print("Warning: No data was loaded.")
        return pd.DataFrame()
```

[7]:

```
if __name__ == "__main__":
    years = [2015, 2016, 2017, 2018, 2019]
    output_directory = "../data/DS/NSDUH"
    data_fetch(years, output_directory, overwrite=False)
    for year in years:
        df = read_parquet(output_directory, [year])
        if year in df:
            print(f"Data for year {year}:")
            print(df[year].head())
        #del df
        gc.collect()
```

```
Data for year 2015 already exists. Skipping.
Data for year 2016 already exists. Skipping.
Data for year 2017 already exists. Skipping.
Data for year 2018 already exists. Skipping.
Data for year 2019 already exists. Skipping.
All requested years processed.
```

0.0.3 Name : Rama Rao Vydadi

0.0.4 Person Number : 50604256

0.0.5 Question 1: How does socioeconomic status (income, education, employment status) influence the likelihood of experiencing mental health disorders?

0.0.6 Hypothesis 1: Individuals with lower income are more likely to experience mental health issues or Unemployment is a significant predictor of mental health disorders

0.0.7 Significance of the question: Understanding the correlation between socio-economic factors and mental health can help identify vulnerable populations and provide support for economically weak population.

0.0.8 Question2: What role does marijuana use play in the aggravation of mental health disorders?

0.0.9 Hypothesis 2: Frequent marijuana use is more common in states where marijuana is legalized, and this is associated with a higher prevalence of depression.

0.0.10 • Understanding the relationship between marijuana use and mental health will help us to answer sensitive questions like should marijuana be banned all over the world

0.0.11 Question 3: What role does hallucinogens play in mental health disorders?

0.0.12 Hypothesis 3: Unregulated use of hallucinogens can cause mental health problems like anxiety and depression.

0.0.13 • Understanding the relationship between use of various hallucinogens and mental health will suggest us to regulate the supply of medical hallucinogens

#We will first perform the basic data cleaning steps and then perform EDA

[8]:
```
df.head()
```

[8]:
```
   QUESTID2    FILEDATE  CIGEVER  CIGOFRSM  CIGWILYR  CIGTRY  CIGYFU  CIGMFU  \
0  43295143  10/09/2020        1        99        99      13    9999      99
1  65095143  10/09/2020        2        99        99     991    9991      91
2  49405143  10/09/2020        1        99        99      22    9999      99
3  51015143  10/09/2020        2        99        99     991    9991      91
4  31825143  10/09/2020        2        99        99     991    9991      91

   CIGREC  CIG30USE  …  POVERTY3  TOOLONG  TROUBUND  PDEN10  COUTYP4  \
0       4        93  …       3.0        2         2       2        2
1      91        91  …       3.0        2         2       2        2
2       4        93  …       3.0        2         2       2        2
3      91        91  …       1.0        2         2       2        2
4      91        91  …       3.0        2         2       2        2

   MAIIN102  AIIND102     ANALWT_C  VESTR  VEREP
0         2         2  6613.865723  40004      2
```

```
1         2         2  6321.580566  40003      1
2         2         2  5045.607422  40008      1
3         2         2  2419.558838  40031      1
4         2         2   575.225464  40010      2

[5 rows x 2741 columns]
```

[9]:
```
df.shape
```

[9]:
```
(56136, 2741)
```

[10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56136 entries, 0 to 56135
Columns: 2741 entries, QUESTID2 to VEREP
dtypes: float32(407), int64(2332), object(2)
memory usage: 1.1+ GB
```

[11]:
```
df.describe()
```

[11]:
```
           QUESTID2       CIGEVER      CIGOFRSM      CIGWILYR        CIGTRY  \
count  5.613600e+04  56136.000000  56136.000000  56136.000000  56136.000000
mean   5.434607e+07      1.542700     78.595554     78.605458    550.575816
std    2.563167e+07      0.498178     39.056828     39.037478    485.236660
min    1.000945e+07      1.000000      1.000000      1.000000      1.000000
25%    3.198245e+07      1.000000     99.000000     99.000000     16.000000
50%    5.403939e+07      2.000000     99.000000     99.000000    991.000000
75%    7.625105e+07      2.000000     99.000000     99.000000    991.000000
max    9.999669e+07      2.000000     99.000000     99.000000    997.000000

             CIGYFU        CIGMFU        CIGREC      CIG30USE       CG30EST  \
count  56136.000000  56136.000000  56136.000000  56136.000000  56136.000000
mean    9840.048846     92.951600     50.651080     80.111248     92.784915
std     1099.156156     12.225758     43.980321     26.734751      4.208800
min     2017.000000      1.000000      1.000000      1.000000      1.000000
25%     9991.000000     91.000000      3.000000     91.000000     91.000000
50%     9991.000000     91.000000     91.000000     91.000000     91.000000
75%     9999.000000     99.000000     91.000000     93.000000     93.000000
max     9999.000000     99.000000     91.000000     98.000000     99.000000

       …      POVERTY3       TOOLONG      TROUBUND        PDEN10  \
count  …  55609.000000  56136.000000  56136.000000  56136.000000
mean   …      2.427179      2.173650      2.199854      1.662997
std    …      0.776759      4.797938      4.794185      0.627146
min    …      1.000000      1.000000      1.000000      1.000000
25%    …      2.000000      2.000000      2.000000      1.000000
50%    …      3.000000      2.000000      2.000000      2.000000
```

```
75%    …      3.000000      2.000000      2.000000      2.000000
max    …      3.000000     98.000000     98.000000      3.000000

            COUTYP4      MAIIN102      AIIND102      ANALWT_C         VESTR  \
count  56136.000000  56136.000000  56136.000000  56136.000000  56136.000000
mean       1.747827      1.982827      1.982560   4902.758301  40025.570899
std        0.762371      0.129915      0.130904   5952.114746     14.388113
min        1.000000      1.000000      1.000000      3.581148  40001.000000
25%        1.000000      2.000000      2.000000   1262.476593  40013.000000
50%        2.000000      2.000000      2.000000   2855.374878  40025.000000
75%        2.000000      2.000000      2.000000   6076.500732  40038.000000
max        3.000000      2.000000      2.000000  77284.484375  40050.000000

              VEREP
count  56136.000000
mean       1.504400
std        0.499985
min        1.000000
25%        1.000000
50%        2.000000
75%        2.000000
max        2.000000

[8 rows x 2739 columns]
```

[12]:
```
df.columns
```

[12]:
```
Index(['QUESTID2', 'FILEDATE', 'CIGEVER', 'CIGOFRSM', 'CIGWILYR', 'CIGTRY',
       'CIGYFU', 'CIGMFU', 'CIGREC', 'CIG30USE',
       …
       'POVERTY3', 'TOOLONG', 'TROUBUND', 'PDEN10', 'COUTYP4', 'MAIIN102',
       'AIIND102', 'ANALWT_C', 'VESTR', 'VEREP'],
      dtype='object', length=2741)
```

[13]:
```
filtered_df=df.copy()
```

Selecting only required columns from the entire dataset (This is an iterative step after performing EDA)

[14]:
```
desired_columns = [
    'QUESTID2', 'IRWRKSTAT', 'IREDUHIGHST2', 'INCOME', 'IRSEX', 'MJEVER',
    'PNRANYLIF', 'COUTYP4', 'MEDMJPA2', 'DSTCHR30', 'ADDPREV', 'LSD', 'PCP',␣
 ↪'PEYOTE', 'MESC', 'PSILCY', 'ECSTMOLLY', 'KETMINESK', 'DMTAMTFXY',␣
 ↪'SALVIADIV', 'HALLUCOTH'
]

filtered_df = df[desired_columns]
```

[15]:
```
#We have various hallucinogens in our dataset we can standardize the mapping␣
↪and remove the unwanted data
#like "Dont know", "Refused" etc with nan values
```

[16]:
```
lsd_mapping = {
    1: 'Yes',  # "Yes"
    2: 'No',   # "No"
    3: 'Yes',  # "Yes logically assigned"
    91: 'No',  # "Never used hallucinogens"
    94: np.nan,  # "Don't know" replaced with NaN
    97: np.nan   # "Refused" replaced with NaN
}

# Apply the mapping to the 'LSD' column
filtered_df['LSD'] = filtered_df['LSD'].map(lsd_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\1422645912.py:11:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df['LSD'] = filtered_df['LSD'].map(lsd_mapping)
```

[17]:
```
#we can create similar mapping for all hallucinogens
```

[18]:
```
substance_mapping = {
    1: 'Yes',  # "Yes"
    2: 'No',   # "No"
    91: 'No',  # "Never used hallucinogens"
    94: np.nan,  # "Don't know" replaced with NaN
    97: np.nan   # "Refused" replaced with NaN
}

substance_columns = ['PCP', 'PEYOTE', 'MESC', 'PSILCY', 'ECSTMOLLY',␣
↪'KETMINESK', 'DMTAMTFXY', 'SALVIADIV', 'HALLUCOTH']

for col in substance_columns:
    filtered_df[col] = filtered_df[col].map(substance_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\497884309.py:12:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
  filtered_df[col] = filtered_df[col].map(substance_mapping)
```

[19]:
```
# Since we have a lot of hallucinogens we can generalize the use of them by␣
↪creating a new column which will have yes if any one of the
#hallucinogens in dataset is used
```

[20]:
```
hallucinogen_columns = ['LSD', 'PCP', 'PEYOTE', 'MESC', 'PSILCY', 'ECSTMOLLY',␣
↪'KETMINESK', 'DMTAMTFXY', 'SALVIADIV', 'HALLUCOTH']

filtered_df['hallucinogens'] = filtered_df[hallucinogen_columns].apply(
    lambda row: 'Yes' if 'Yes' in row.values else ('No' if all(val == 'No' for␣
↪val in row.values) else np.nan), axis=1
)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\3382138147.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df['hallucinogens'] = filtered_df[hallucinogen_columns].apply(
```

[21]:
```
# Now only considering hallucination column created in filtered_df
desired_columns = [
    'QUESTID2', 'IRWRKSTAT', 'IREDUHIGHST2', 'INCOME', 'IRSEX', 'MJEVER',
    'PNRANYLIF', 'COUTYP4', 'MEDMJPA2', 'DSTCHR30', 'ADDPREV', 'hallucinogens' ]

filtered_df = filtered_df[desired_columns]
```

0.0.14 Data Cleaning

[22]:
```
filtered_df.head()
```

[22]:

	QUESTID2	IRWRKSTAT	IREDUHIGHST2	INCOME	IRSEX	MJEVER	PNRANYLIF	\
0	43295143	1	11	4	1	1	1	
1	65095143	1	11	4	2	2	1	
2	49405143	1	11	4	1	1	1	
3	51015143	4	6	1	2	2	1	
4	31825143	4	7	4	1	2	2	

	COUTYP4	MEDMJPA2	DSTCHR30	ADDPREV	hallucinogens
0	2	2	3	1	No
1	2	1	5	1	No
2	2	1	5	2	No
3	2	1	4	2	No
4	2	1	4	1	No

0.0.15 Handling Special codes like Bad Data, Legitimate Skip etc in depression column which does not add value to the analysis

Replace special codes which does not add value with NaN values 85: 'Bad Data', 97: 'Refused', 98: 'Blank', 99: 'Legitimate Skip'

[23]:
```python
filtered_df['ADDPREV'].replace([85, 97, 98, 99], np.nan, inplace=True)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\2321724339.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  filtered_df['ADDPREV'].replace([85, 97, 98, 99], np.nan, inplace=True)
```

[24]:
```python
filtered_df['ADDPREV'].unique()
```

[24]:
```
array([ 1.,  2., nan, 94.])
```

In the IRWRKSTAT (EMPLOYMENT STATUS) column - 99 indicates 12-14 year olds, this data might not be useful for analysis hence we can remove this data as these people might also be having some income, since we cannot say the exact income level it is better to drop these values

[25]:
```python
filtered_df['IRWRKSTAT'].replace([99], np.nan, inplace=True)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\753615126.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  filtered_df['IRWRKSTAT'].replace([99], np.nan, inplace=True)
```

Since we have more than 11 levels of education in the dataset, we can categorize the education levels into 3 different levels which make more sense i.e Primary, Secondary and Higher education based on the grade studying

[26]:
```python
# Define a function to categorize the education levels
def categorize_education(value):
    if value < 7:
        return 'primary education'
    elif value in [8, 9]:
        return 'intermediate education'
    else:
        return 'higher education'

filtered_df['IREDUHIGHST2'] = filtered_df['IREDUHIGHST2'].
 ↪apply(categorize_education)
```

[27]:
```python
filtered_df.head()
```

[27]:

	QUESTID2	IRWRKSTAT	IREDUHIGHST2	INCOME	IRSEX	MJEVER	PNRANYLIF	\
0	43295143	1.0	higher education	4	1	1	1	
1	65095143	1.0	higher education	4	2	2	1	
2	49405143	1.0	higher education	4	1	1	1	
3	51015143	4.0	primary education	1	2	2	1	
4	31825143	4.0	higher education	4	1	2	2	

	COUTYP4	MEDMJPA2	DSTCHR30	ADDPREV	hallucinogens
0	2	2	3	1.0	No
1	2	1	5	1.0	No
2	2	1	5	2.0	No
3	2	1	4	2.0	No
4	2	1	4	1.0	No

MJEVER contains 94 and 97 which are dont know and refused to answer, these rows are not useful in our analysis hence we can exclude this data

[28]:
```python
filtered_df['MJEVER'].replace([94, 97], np.nan, inplace=True)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\3512628858.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  filtered_df['MJEVER'].replace([94, 97], np.nan, inplace=True)
```

[29]:
```
#Pain releiver use in lifetime 5 indicates logically assigned yes which means␣
↪this value is logically made as yes, so we can replace this
#with 1 in the final data
```

[30]:
```
filtered_df['PNRANYLIF'].replace(5, 1, inplace=True)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\422161004.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  filtered_df['PNRANYLIF'].replace(5, 1, inplace=True)
```

[31]:
```
#replcaing values which are not useful with NA
filtered_df['PNRANYLIF'].replace([94, 97, 98], np.nan, inplace=True)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\3256104701.py:2:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  filtered_df['PNRANYLIF'].replace([94, 97, 98], np.nan, inplace=True)
```

In the column How often do you feel sad, there are many columns which cannot be used for analysis we can replace them with NaN

[32]:
```
#replcaing values which are not useful with NA
filtered_df['DSTCHR30'].replace([85, 94, 97, 98, 99], np.nan, inplace=True)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\1097070963.py:2:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.
```

```
For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  filtered_df['DSTCHR30'].replace([85, 94, 97, 98, 99], np.nan, inplace=True)
```

[33]:
```python
filtered_df.head()
```

[33]:
```
   QUESTID2  IRWRKSTAT        IREDUHIGHST2  INCOME  IRSEX  MJEVER  PNRANYLIF  \
0  43295143        1.0    higher education       4      1     1.0        1.0
1  65095143        1.0    higher education       4      2     2.0        1.0
2  49405143        1.0    higher education       4      1     1.0        1.0
3  51015143        4.0   primary education       1      2     2.0        1.0
4  31825143        4.0    higher education       4      1     2.0        2.0

   COUTYP4  MEDMJPA2  DSTCHR30  ADDPREV hallucinogens
0        2         2       3.0      1.0            No
1        2         1       5.0      1.0            No
2        2         1       5.0      2.0            No
3        2         1       4.0      2.0            No
4        2         1       4.0      1.0            No
```

[34]:
```python
#Removal of duplicates from the data frame
filtered_df.drop_duplicates(inplace=True)
```

[35]:
```python
#Set display options to have 2 decimals to have proper scale for future␣
 ↪operations
pd.options.display.float_format = '{:.2f}'.format
```

[36]:
```python
filtered_df.describe()
```

[36]:
```
         QUESTID2  IRWRKSTAT   INCOME    IRSEX   MJEVER  PNRANYLIF  COUTYP4  \
count    56136.00   49581.00 56136.00 56136.00 56097.00   55670.00 56136.00
mean  54346070.01       2.22     2.72     1.52     1.56       1.49     1.75
std   25631667.47       1.30     1.14     0.50     0.50       0.50     0.76
min   10009454.00       1.00     1.00     1.00     1.00       1.00     1.00
25%   31982452.50       1.00     2.00     1.00     1.00       1.00     1.00
50%   54039390.00       2.00     3.00     2.00     2.00       1.00     2.00
75%   76251052.50       4.00     4.00     2.00     2.00       2.00     2.00
max   99996688.00       4.00     4.00     2.00     2.00       2.00     3.00

       MEDMJPA2  DSTCHR30  ADDPREV
count  56136.00  42411.00 42508.00
mean       1.30      4.37     1.89
std        0.46      0.98     4.59
min        1.00      1.00     1.00
```

```
25%         1.00      4.00     1.00
50%         1.00      5.00     2.00
75%         2.00      5.00     2.00
max         2.00      5.00    94.00
```

[37]:
```
education_mapping = {
    'higher education': 3,
    'primary education': 1,
    'intermediate education': 2
}
filtered_df['IREDUHIGHST2'] = filtered_df['IREDUHIGHST2'].
  ↪replace(education_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\4283032743.py:6:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  filtered_df['IREDUHIGHST2'] =
filtered_df['IREDUHIGHST2'].replace(education_mapping)
```

[38]:
```
filtered_df.head()
```

[38]:
```
   QUESTID2  IRWRKSTAT  IREDUHIGHST2  INCOME  IRSEX  MJEVER  PNRANYLIF  \
0  43295143       1.00             3       4      1    1.00       1.00
1  65095143       1.00             3       4      2    2.00       1.00
2  49405143       1.00             3       4      1    1.00       1.00
3  51015143       4.00             1       1      2    2.00       1.00
4  31825143       4.00             3       4      1    2.00       2.00

   COUTYP4  MEDMJPA2  DSTCHR30  ADDPREV hallucinogens
0        2         2      3.00     1.00            No
1        2         1      5.00     1.00            No
2        2         1      5.00     2.00            No
3        2         1      4.00     2.00            No
4        2         1      4.00     1.00            No
```

[39]:
```
filtered_df.shape
```

[39]: (56136, 12)

[40]:
```
#Since we have already replaced unnecessary values with NaN we can drop these␣
  ↪values as they are no longer useful
```

[41]:
```
null_values = filtered_df.isnull().sum()

print(null_values)
```

```
QUESTID2              0
IRWRKSTAT          6555
IREDUHIGHST2          0
INCOME                0
IRSEX                 0
MJEVER               39
PNRANYLIF           466
COUTYP4               0
MEDMJPA2              0
DSTCHR30          13725
ADDPREV           13628
hallucinogens       245
dtype: int64
```

[42]:
```
filtered_df_cleaned = filtered_df.dropna(subset=['IRWRKSTAT', 'DSTCHR30',␣
↪'ADDPREV', 'PNRANYLIF','MJEVER' ])
```

[43]:
```
filtered_df_cleaned.shape
```

[43]:
```
(42166, 12)
```

[44]:
```
filtered_df_cleaned['IRWRKSTAT'].unique()
```

[44]:
```
array([1., 4., 3., 2.])
```

[45]:
```
irwrkstat_mapping = {
    1: 'Employed full time',
    2: 'Employed part time',
    3: 'Unemployed',
    4: 'Other (incl. not in labor force)',
    99: '12-14 year olds'
}

filtered_df_cleaned['IRWRKSTAT'] = filtered_df_cleaned['IRWRKSTAT'].
↪map(irwrkstat_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\2354628446.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['IRWRKSTAT'] =
filtered_df_cleaned['IRWRKSTAT'].map(irwrkstat_mapping)
```

[46]:
```
filtered_df_cleaned[['IRWRKSTAT']].head()
```

```
[46]:                    IRWRKSTAT
0                Employed full time
1                Employed full time
2                Employed full time
3   Other (incl. not in labor force)
4   Other (incl. not in labor force)
```

```
[47]: income_mapping = {
          1: 'Less than $20,000',
          2: '$20,000 - $49,999',
          3: '$50,000 - $74,999',
          4: '$75,000 or more'
      }

      filtered_df_cleaned['INCOME'] = filtered_df_cleaned['INCOME'].
       ↪map(income_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\4064115886.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['INCOME'] =
filtered_df_cleaned['INCOME'].map(income_mapping)
```

```
[48]: filtered_df_cleaned[['INCOME']].head()
```

```
[48]:             INCOME
0    $75,000 or more
1    $75,000 or more
2    $75,000 or more
3  Less than $20,000
4    $75,000 or more
```

```
[49]: gender_mapping = {
          1: 'Male',
          2: 'Female'
      }

      filtered_df_cleaned['IRSEX'] = filtered_df_cleaned['IRSEX'].map(gender_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\4015784729.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['IRSEX'] =
filtered_df_cleaned['IRSEX'].map(gender_mapping)
```

[50]:
```
filtered_df_cleaned.head()
```

[50]:
```
   QUESTID2                        IRWRKSTAT  IREDUHIGHST2  \
0  43295143               Employed full time             3
1  65095143               Employed full time             3
2  49405143               Employed full time             3
3  51015143  Other (incl. not in labor force)             1
4  31825143  Other (incl. not in labor force)             3

              INCOME   IRSEX  MJEVER  PNRANYLIF  COUTYP4  MEDMJPA2  DSTCHR30  \
0    $75,000 or more    Male    1.00       1.00        2         2      3.00
1    $75,000 or more  Female    2.00       1.00        2         1      5.00
2    $75,000 or more    Male    1.00       1.00        2         1      5.00
3  Less than $20,000  Female    2.00       1.00        2         1      4.00
4    $75,000 or more    Male    2.00       2.00        2         1      4.00

   ADDPREV hallucinogens
0     1.00            No
1     1.00            No
2     2.00            No
3     2.00            No
4     1.00            No
```

[51]:
```
filtered_df_cleaned['IREDUHIGHST2'].unique()
```

[51]:
```
array([3, 1, 2])
```

[52]:
```
# Define a function to categorize the education levels
def categorize_education(value):
    if value==1:
        return 'primary education'
    elif value==2:
        return 'High School education'
    else:
        return 'College Degree'

filtered_df_cleaned['IREDUHIGHST2'] = filtered_df_cleaned['IREDUHIGHST2'].
  ↪apply(categorize_education)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\809615653.py:10:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['IREDUHIGHST2'] =
filtered_df_cleaned['IREDUHIGHST2'].apply(categorize_education)
```

[53]:
```python
filtered_df_cleaned['IREDUHIGHST2'].unique()
```

[53]:
```
array(['College Degree', 'primary education', 'High School education'],
      dtype=object)
```

[54]:
```python
mj_mapping = {
    1: 'Yes',
    2: 'No'
}

filtered_df_cleaned['MJEVER'] = filtered_df_cleaned['MJEVER'].map(mj_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\3622425528.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['MJEVER'] = filtered_df_cleaned['MJEVER'].map(mj_mapping)
```

[55]:
```python
mj_mapping = {
    1.00: 'Yes',
    2.00: 'No'
}



filtered_df_cleaned['PNRANYLIF'] = filtered_df_cleaned['PNRANYLIF'].
 ↪map(mj_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\2351626243.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['PNRANYLIF'] =
filtered_df_cleaned['PNRANYLIF'].map(mj_mapping)
```

[56]:
```python
metro_mapping = {
    1: 'Large Metro',
    2: 'Small Metro',
    3: 'Non Metro'
```

```
}


filtered_df_cleaned['COUTYP4'] = filtered_df_cleaned['COUTYP4'].
↪map(metro_mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\1158216921.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['COUTYP4'] =
filtered_df_cleaned['COUTYP4'].map(metro_mapping)
```

[57]:
```
mapping = {
    1: 'All of the time',
    2: 'Most of the time',
    3: 'Some of the time',
    4: 'A little of the time',
    5: 'None of the time',
    99: 'Legitimate skip'
}
filtered_df_cleaned['DSTCHR30'] = filtered_df_cleaned['DSTCHR30'].map(mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\2251930963.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['DSTCHR30'] = filtered_df_cleaned['DSTCHR30'].map(mapping)
```

[58]:
```
filtered_df_cleaned['ADDPREV'].unique()
```

[58]:
```
array([ 1.,  2., 94.])
```

[59]:
```
mapping = {
    1.00: 'Yes',
    2.00: 'No',
    94.00: 'No'
}
filtered_df_cleaned['ADDPREV'] = filtered_df_cleaned['ADDPREV'].map(mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\3008980501.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['ADDPREV'] = filtered_df_cleaned['ADDPREV'].map(mapping)
```

[60]:
```
mapping = {
    1: 'Yes',
    2: 'No',
}
filtered_df_cleaned['MEDMJPA2'] = filtered_df_cleaned['MEDMJPA2'].map(mapping)
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\88440773.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned['MEDMJPA2'] = filtered_df_cleaned['MEDMJPA2'].map(mapping)
```

Renaming columns for better readability

[61]:
```
column_mapping = {
    'IRWRKSTAT': 'Employment',
    'IREDUHIGHST2': 'education',
    'INCOME': 'income',
    'IRSEX': 'sexual orientation',
    'MJEVER': 'Ever used marijuana',
    'PNRANYLIF': 'ANY PAIN RELIEVER USE IN LIFETIME',
    'COUTYP4': 'COUNTY METRO/NONMETRO STATUS',
    'MEDMJPA2': 'STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW',
    'DSTCHR30': 'HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP',
    'ADDPREV': 'SEVERAL DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD'
}

filtered_df_cleaned.rename(columns=column_mapping, inplace=True)
filtered_df__cleaned = filtered_df_cleaned.copy()
filtered_df__cleaned['Mental_Health_Disorder'] = filtered_df__cleaned['SEVERAL␣
↪DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD'].apply(lambda x: 1 if x == 'Yes'␣
↪else 0)
filtered_df__cleaned = filtered_df__cleaned.drop(columns=['SEVERAL DAYS OR LNGR␣
↪WHEN FELT SAD/EMPTY/DPRSD'])
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\48733474.py:14:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  filtered_df_cleaned.rename(columns=column_mapping, inplace=True)
```

[62]:
```
e_df = pd.get_dummies(filtered_df__cleaned, columns=['sexual␣
↪orientation','STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW', 'Ever used␣
↪marijuana','COUNTY METRO/NONMETRO STATUS', 'ANY PAIN RELIEVER USE IN␣
↪LIFETIME', 'hallucinogens', 'Employment','education','income'],␣
↪drop_first=True)
e_df = e_df.replace({True: 1, False: 0})
target_order = {"None of the time": 0, "A little of the time": 1, "Some of the␣
↪time": 2, "Most of the time": 3, "All of the time": 4}
e_df['HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP'] = e_df['HOW OFTEN FELT␣
↪SAD NOTHING COULD CHEER YOU UP'].map(target_order)
df = e_df.copy()
req_X_cols = [w for w in df.columns if w not in ['Mental_Health_Disorder',␣
↪'QUESTID2']]
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\1325856201.py:2:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  e_df = e_df.replace({True: 1, False: 0})
```

[63]:
```
X = df[req_X_cols]
X = df.drop(columns=['Mental_Health_Disorder'])
y = df['Mental_Health_Disorder']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.86,␣
↪random_state=42)
```

[64]:
```
model = GradientBoostingClassifier()
model.fit(X_train.drop(columns=['QUESTID2']), y_train)
y_pred = model.predict(X_test.drop(columns=['QUESTID2']))
mmi = [i for i, (actual, predicted) in enumerate(zip(y_test, y_pred)) if actual␣
↪!= predicted]
mmr = X_test.iloc[mmi].copy()
mmr['True Label'] = y_test.iloc[mmi].values
mmr['Predicted Label'] = y_pred[mmi]

print("\nRecords where predictions do not match actual values:")
mmr.shape
```

```
Records where predictions do not match actual values:
```

[64]:
```
(8918, 19)
```

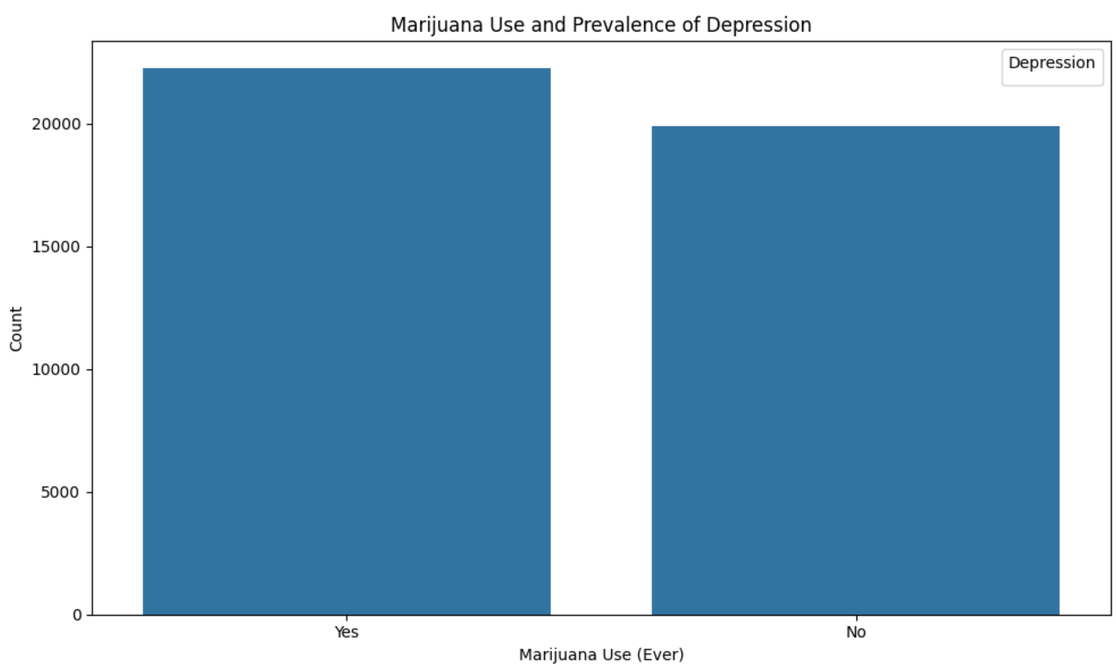
[65]:
```
filtered_df_cleaned.shape
```

[65]: (42166, 12)

[66]:
```
matching_ids = mmr['QUESTID2'].values
filtered_df_cleaned.loc[filtered_df_cleaned['QUESTID2'].isin(matching_ids),␣
↪'QUESTID2'] = np.nan
```

[67]:
```
# Relationship between marijuana use and depression
plt.figure(figsize=(10, 6))
sns.countplot(data=filtered_df__cleaned, x='Ever used marijuana')
plt.title('Marijuana Use and Prevalence of Depression')
plt.xlabel('Marijuana Use (Ever)')
plt.ylabel('Count')
plt.legend(title='Depression')
plt.tight_layout()
plt.show()
```

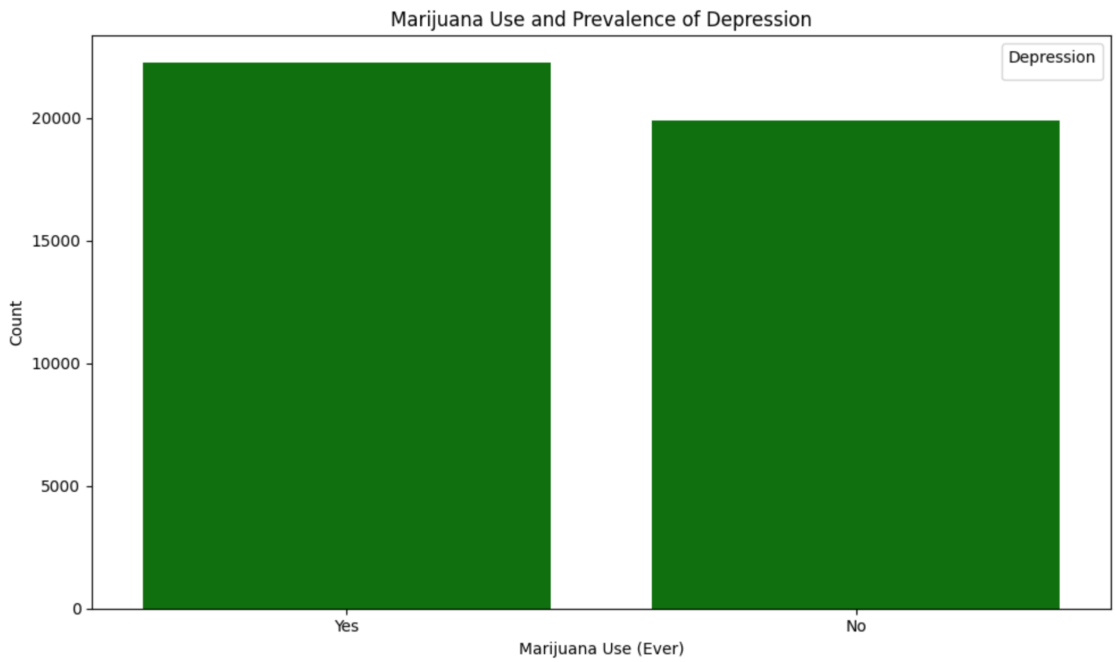
```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\907183047.py:7:
UserWarning: No artists with labels found to put in legend.  Note that artists
whose label start with an underscore are ignored when legend() is called with no
argument.
  plt.legend(title='Depression')
```



[68]:
```
plt.figure(figsize=(10, 6))
sns.countplot(data=filtered_df__cleaned, x='Ever used marijuana', color='green')
plt.title('Marijuana Use and Prevalence of Depression')
plt.xlabel('Marijuana Use (Ever)')
```

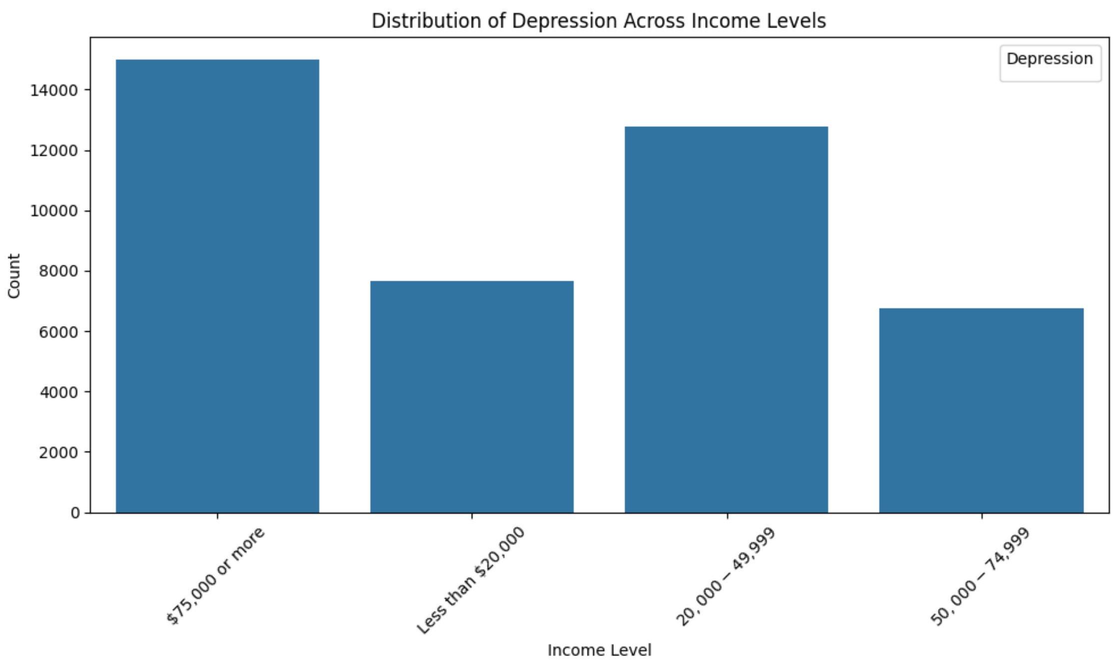
```
plt.ylabel('Count')
plt.legend(title='Depression')
plt.tight_layout()
plt.show()
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\1524618430.py:6:
UserWarning: No artists with labels found to put in legend.  Note that artists
whose label start with an underscore are ignored when legend() is called with no
argument.
  plt.legend(title='Depression')
```

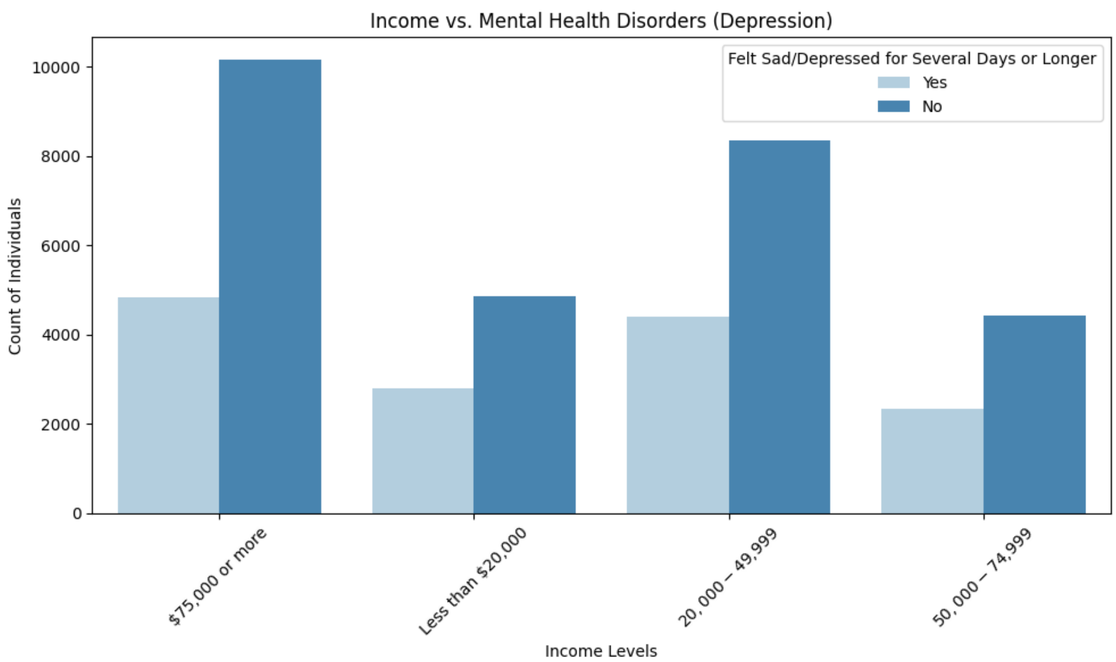


[69]:
```
plt.figure(figsize=(10, 6))
sns.countplot(data=filtered_df_cleaned, x='income')
plt.title('Distribution of Depression Across Income Levels')
plt.xlabel('Income Level')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Depression')
plt.tight_layout()
plt.show()
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\1276217604.py:7:
UserWarning: No artists with labels found to put in legend.  Note that artists
whose label start with an underscore are ignored when legend() is called with no
argument.
  plt.legend(title='Depression')
```



[70]:
```python
# Question 1: How does socioeconomic status (income, education, employment status) influence mental health?
# Bar plot to show the distribution of depression (Sadness) across different income levels.

# Create a plot for the influence of income on experiencing mental health disorders (depression)
plt.figure(figsize=(10, 6))
sns.countplot(data=filtered_df_cleaned, x='income', hue='SEVERAL DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD', palette="Blues")
plt.title('Income vs. Mental Health Disorders (Depression)')
plt.xlabel('Income Levels')
plt.ylabel('Count of Individuals')
plt.xticks(rotation=45)
plt.legend(title='Felt Sad/Depressed for Several Days or Longer')
plt.tight_layout()
plt.show()
```

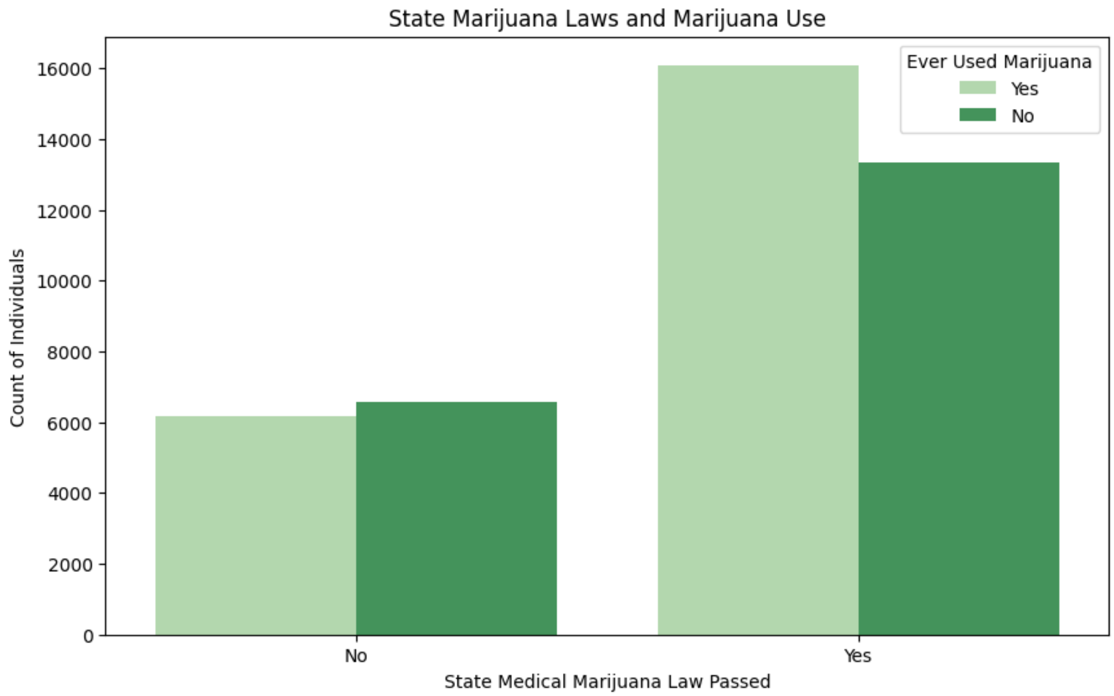


0.0.16 Observations:

1 From the above graphs we might conclude that people whose income is less than $20,000 (which is the least among the others) are more likely to

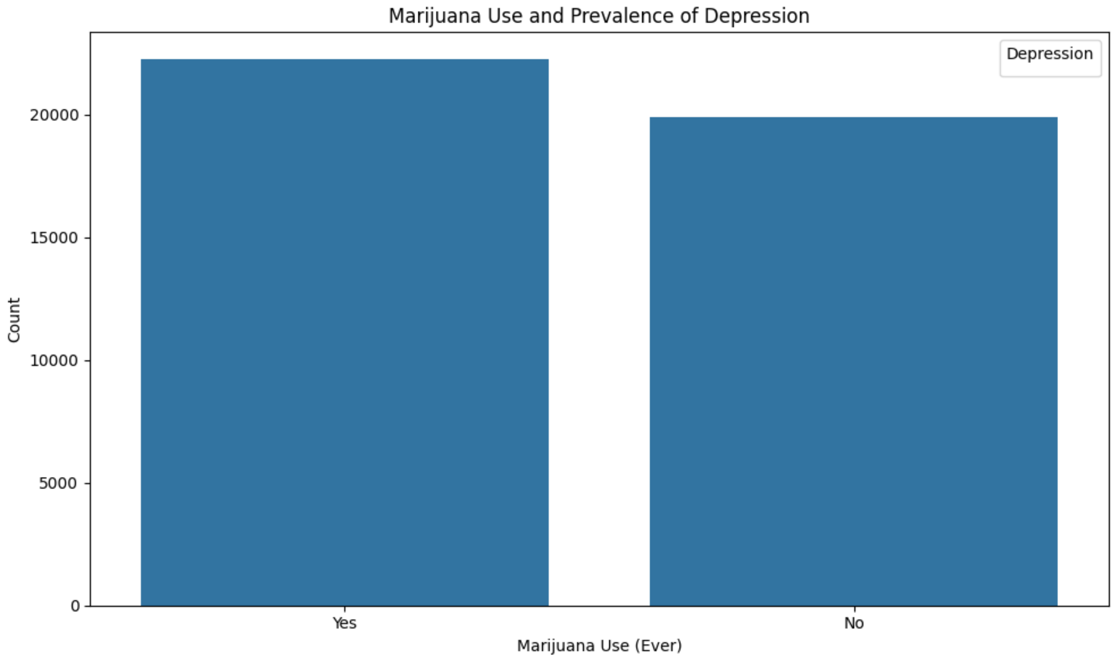
2 feel depressed.

[71]:
```
# Question 2: The role of marijuana use in mental health
# We will create a bar plot to see the relation between marijuana use, state␣
↪marijuana laws, and depression

plt.figure(figsize=(10, 6))
sns.countplot(data=filtered_df__cleaned, x='STATE MEDICAL MJ LAW PASSED AT TIME␣
↪OF INTERVIEW', hue='Ever used marijuana', palette="Greens")
plt.title('State Marijuana Laws and Marijuana Use')
plt.xlabel('State Medical Marijuana Law Passed')
plt.ylabel('Count of Individuals')
plt.legend(title='Ever Used Marijuana')
#plt.tight_layout()
plt.show()
```



[72]:
```
# Relationship between marijuana use and depression
plt.figure(figsize=(10, 6))
sns.countplot(data=filtered_df__cleaned, x='Ever used marijuana')
plt.title('Marijuana Use and Prevalence of Depression')
plt.xlabel('Marijuana Use (Ever)')
plt.ylabel('Count')
plt.legend(title='Depression')
plt.tight_layout()
plt.show()
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\907183047.py:7:
UserWarning: No artists with labels found to put in legend.  Note that artists
whose label start with an underscore are ignored when legend() is called with no
argument.
  plt.legend(title='Depression')
```



2.0.1 -x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-x-

2.0.2 Phase 2 starts here:

2.0.3 Question1: What role does marijuana use play in the aggravation of mental health disorders?

2.0.4 Hypothesis 1: Frequent marijuana use is more common in states where marijuana is legalized, and this is associated with a higher prevalence of depression.

2.0.5 • Understanding the relationship between marijuana use and mental health will help us to answer sensitive questions like should marijuana be banned all over the world

2.0.6 Question 2: What role does hallucinogens play in mental health disorders?

2.0.7 Hypothesis 2: Unregulated use of hallucinogens can cause mental health problems like anxiety and depression.

2.0.8 • Understanding the relationship between use of various hallucinogens and mental health will suggest us to regulate the supply of medical hallucinogens

[73]:
```
#making a copy of original dataset for analysis for another question
filtered_df_cleaned_org=filtered_df_cleaned.copy()
```

[74]:
```
# Excluding the features which are not relevant to above analysis
```

```
columns_to_exclude = ['Employment', 'education', 'income', 'sexual␣
↪orientation', 'COUNTY METRO/NONMETRO STATUS']

# Select columns that are not in the exclusion list
filtered_df_cleaned = filtered_df_cleaned[[col for col in filtered_df_cleaned.
↪columns if col not in columns_to_exclude]]
```

[75]:
```
filtered_df_cleaned=filtered_df_cleaned.rename(columns={'ANY PAIN RELIEVER USE␣
↪IN LIFETIME':'PAIN RELIEVER USE', 'hallucinogens':'Hallucinogens usage'})
```

[76]:
```
filtered_df_cleaned = filtered_df_cleaned.dropna()
```

[77]:
```
# We will use the column "SEVERAL DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD" as␣
↪the output column which will be the final outcome column, we will assume
# "Yes" as experiencing mental health issues and "No" as not experiencing them
```

[78]:
```
filtered_df_cleaned['Mental_Health_Disorder'] = filtered_df_cleaned['SEVERAL␣
↪DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD'].apply(lambda x: 1 if x == 'Yes'␣
↪else 0)

# we will drop the original target column as it is already used in above column
filtered_df_cleaned = filtered_df_cleaned.drop(columns=['SEVERAL DAYS OR LNGR␣
↪WHEN FELT SAD/EMPTY/DPRSD'])
```

[79]:
```
# converting categorical variables into binary columns using One-hot encoding␣
↪to make the data suitable for ML algorithms
```

[80]:
```
encoded_df = pd.get_dummies(filtered_df_cleaned, columns=[ 'STATE MEDICAL MJ␣
↪LAW PASSED AT TIME OF INTERVIEW', 'Ever used marijuana', 'PAIN RELIEVER␣
↪USE','Hallucinogens usage'], drop_first=True)

encoded_df.head()
```

[80]:
```
     QUESTID2 HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0 43295143.00                                 Some of the time
2 49405143.00                                 None of the time
3 51015143.00                               A little of the time
6 65565143.00                                 None of the time
7 45375143.00                                 None of the time

   Mental_Health_Disorder  \
0                       1
2                       0
3                       0
6                       0
7                       0
```

```
   STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW_Yes  \
0                                              False
2                                               True
3                                               True
6                                               True
7                                               True

   Ever used marijuana_Yes  PAIN RELIEVER USE_Yes  Hallucinogens usage_Yes
0                     True                   True                    False
2                     True                   True                    False
3                    False                   True                    False
6                     True                  False                    False
7                    False                   True                    False
```

[81]:

```
# Converting boolean  values to 1 and 0
encoded_df = encoded_df.replace({True: 1, False: 0})
encoded_df.head()
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\3547169791.py:2:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  encoded_df = encoded_df.replace({True: 1, False: 0})
```

[81]:

```
      QUESTID2 HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0 43295143.00                                  Some of the time
2 49405143.00                                  None of the time
3 51015143.00                              A little of the time
6 65565143.00                                  None of the time
7 45375143.00                                  None of the time

   Mental_Health_Disorder  \
0                       1
2                       0
3                       0
6                       0
7                       0

   STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW_Yes  \
0                                                  0
2                                                  1
3                                                  1
6                                                  1
7                                                  1

   Ever used marijuana_Yes  PAIN RELIEVER USE_Yes  Hallucinogens usage_Yes
0                        1                      1                        0
```

```
2                        1                       1                         0
3                        0                       1                         0
6                        1                       0                         0
7                        0                       1                         0
```

[82]:
```
encoded_df['HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP'].unique()
```

[82]:
```
array(['Some of the time', 'None of the time', 'A little of the time',
       'Most of the time', 'All of the time'], dtype=object)
```

[83]:
```
target_order = {
    "None of the time": 0,
    "A little of the time": 1,
    "Some of the time": 2,
    "Most of the time": 3,
    "All of the time": 4
}


encoded_df['HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP'] = encoded_df['HOW␣
 ↪OFTEN FELT SAD NOTHING COULD CHEER YOU UP'].map(target_order)

encoded_df['HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP'].unique()
```

[83]:
```
array([2, 0, 1, 3, 4])
```

[84]:
```
encoded_df.head()
```

[84]:
```
     QUESTID2  HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0 43295143.00                                              2
2 49405143.00                                              0
3 51015143.00                                              1
6 65565143.00                                              0
7 45375143.00                                              0

   Mental_Health_Disorder  \
0                       1
2                       0
3                       0
6                       0
7                       0

   STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW_Yes  \
0                                                  0
2                                                  1
3                                                  1
6                                                  1
```

```
7                                               1

   Ever used marijuana_Yes  PAIN RELIEVER USE_Yes  Hallucinogens usage_Yes
0                        1                      1                        0
2                        1                      1                        0
3                        0                      1                        0
6                        1                      0                        0
7                        0                      1                        0
```

[85]:
```python
df=encoded_df.copy()
df.head()
```

[85]:
```
     QUESTID2  HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0 43295143.00                                              2
2 49405143.00                                              0
3 51015143.00                                              1
6 65565143.00                                              0
7 45375143.00                                              0

   Mental_Health_Disorder  \
0                       1
2                       0
3                       0
6                       0
7                       0

   STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW_Yes  \
0                                                  0
2                                                  1
3                                                  1
6                                                  1
7                                                  1

   Ever used marijuana_Yes  PAIN RELIEVER USE_Yes  Hallucinogens usage_Yes
0                        1                      1                        0
2                        1                      1                        0
3                        0                      1                        0
6                        1                      0                        0
7                        0                      1                        0
```

[86]:
```python
#Excluding the columns to predict and the ID which is unique for each row
req_X_cols = [w for w in df.columns if w not in␣
 ↪['Mental_Health_Disorder','QUESTID2']]
```

[87]:
```python
X = df[req_X_cols]
y = df['Mental_Health_Disorder'] #Outcome
```

[88]:

```
data=df.copy()
```

2.0.9 We will calculate Variance Inflation Factor to detect multicollinearity among features

High VIF indicates high multicollinearity, which can negatively impact model performance and interpretation. Hence, we

[89]:

```
vif_data = pd.DataFrame()
vif_data["Feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]

print(vif_data)
```

```
                                           Feature  VIF
0      HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP 1.38
1   STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVI… 1.90
2                            Ever used marijuana_Yes 2.41
3                              PAIN RELIEVER USE_Yes 2.04
4                            Hallucinogens usage_Yes 1.50
```

A VIF value greater than 10 indicates high collinearity and this should be removed. However, we can observe that all the features have VIF less than 5 this indicates that multicollinearity is not an issue in our case

2.1 Model Selection

2.1.1 Logistic Regression:

Mental health data has complex, non-linear relationships between features and the target variable. Since Logistic Regression has a linear decision boundary in the feature space, this model might fail to capture these non-linear interactions adequately. ### Random Forest: In this method multiple decision trees are built and merged finally to get accurate and stable predictions. This model is better than logistic regression as it can handle both linear and non-linear relationships well. This model can also reduce overfitting by averaging, but it is computationally expensive. ### Gradient Boosting: This is another ensemble technique that builds trees sequentially, with each tree correcting the errors of the previous one. It is known for its high predictive performance but may require careful tuning to avoid overfitting. ### XGBoost This model is suitable for our case because it can effectively handle complex and non-linear relationships between features. This can also handle class imbalance, making it suitable for real-world datasets. Additionally, it has built-in regularization which prevents overfitting.

[90]:

```
X = data.drop(columns=['QUESTID2', 'Mental_Health_Disorder'])
y = data['Mental_Health_Disorder']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

models = {
```

```
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'Random Forest': RandomForestClassifier(),
    'Gradient Boosting': GradientBoostingClassifier(),
    'XGBoost': XGBClassifier(use_label_encoder=False, eval_metric='logloss'),
}

model_performance = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    test_accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    model_performance[name] = {'Test Accuracy': test_accuracy, 'F1 Score': f1}

performance_df = pd.DataFrame(model_performance).T
performance_df
```

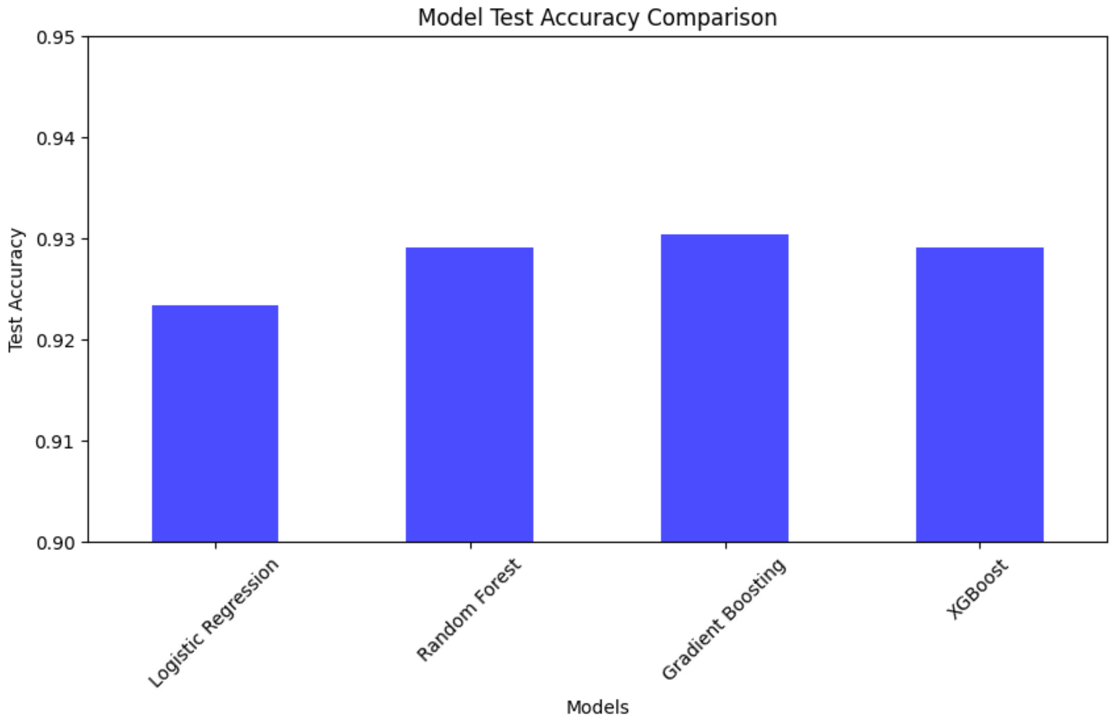
```
C:\Users\Rama Rao\AppData\Local\Programs\Python\Python312\Lib\site-
packages\xgboost\core.py:158: UserWarning: [22:41:21] WARNING: C:\buildkite-
agent\builds\buildkite-windows-cpu-autoscaling-
group-i-0ed59c031377d09b8-1\xgboost\xgboost-ci-windows\src\learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

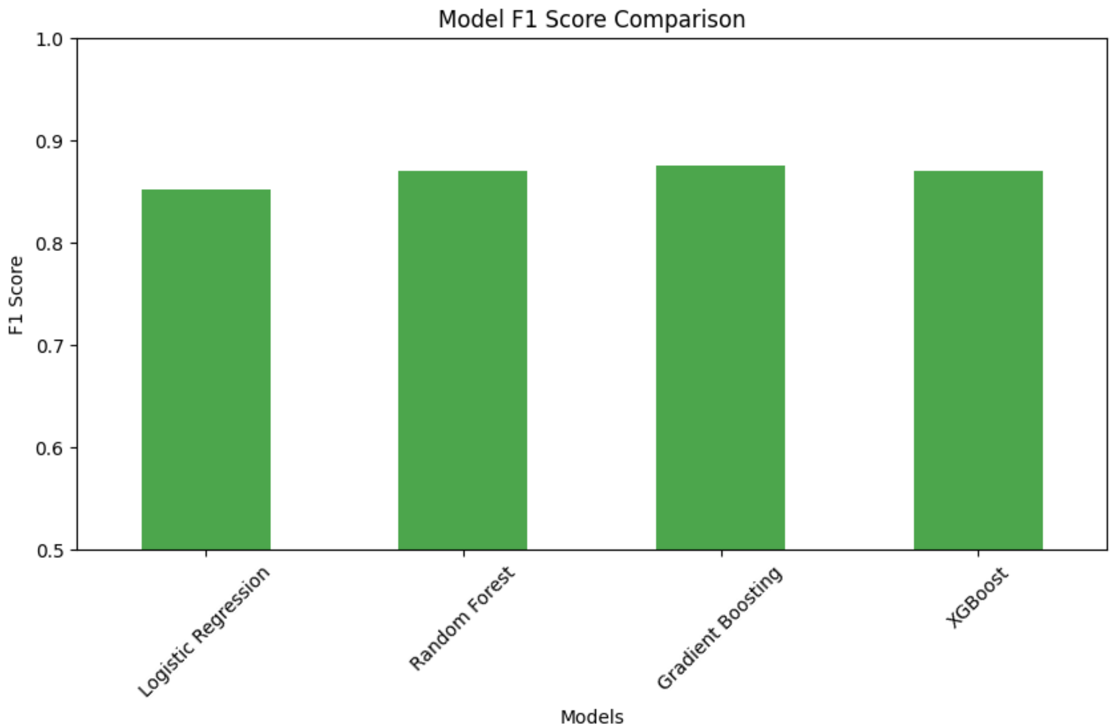
[90]:

	Test Accuracy	F1 Score
Logistic Regression	0.92	0.85
Random Forest	0.93	0.87
Gradient Boosting	0.93	0.87
XGBoost	0.93	0.87

[91]:
```
plt.figure(figsize=(10, 5))
performance_df['Test Accuracy'].plot(kind='bar', color='blue', alpha=0.7)
plt.title('Model Test Accuracy Comparison')
plt.ylabel('Test Accuracy')
plt.xlabel('Models')
plt.ylim(0.90, 0.95)  # Adjusting the y-axis range to highlight variations
plt.xticks(rotation=45)
plt.show()

# Plotting F1 Score with adjusted y-axis range to highlight differences
plt.figure(figsize=(10, 5))
performance_df['F1 Score'].plot(kind='bar', color='green', alpha=0.7)
plt.title('Model F1 Score Comparison')
plt.ylabel('F1 Score')
plt.xlabel('Models')
```

```
plt.ylim(0.5, 1.0)  # Adjusting the y-axis range to highlight variations
plt.xticks(rotation=45)
plt.show()
```





2.2 Finalizing the model to be used

2.2.1 Test Accuracy:

This metric measures overall correctness of the predictions. This will help us to understand how well the model performs on the entire test set. ### F1 Score: This metric is the harmonic mean of precision and recall, this is useful while dealing with cases having class imbalance issue. This gives a measure of how well the model identifies the positive class.

In case of Logistic Regression, the F1 Score is the lowest among all models evaluated. This indicates that logistic regression might not be useful for balancing precision and recall, which is very important for our case.

Random Forest has slighlty high accuracy and F1 Score compared to Logistic Regression. It can capture non-linear relationships and is more robust. However, this model does not perform as good as Gradient Boosting.

Gradient Boosting achieves the highest Test Accuracy and F1 Score among all the models which we have evaluated. Hence, this is the most effective at correctly predicting both classes and balancing precision and recall.

XGBoost performs similarly to Random Forest, with the same Test Accuracy and F1 Score. Although it is known for its efficiency and performance, it does not outperform Gradient Boosting in this case.

Conclusion: Hence we will choose Gradient Boosting as the final model as it provides the best balance between accuracy and the F1 Score. This is the most suitable option in our case as

both performance and the handling of imbalanced classes are important to us.

[92]:
```python
model = GradientBoostingClassifier()

model.fit(X_train, y_train)

with open('gradient_boosting_model.pkl', 'wb') as f:
    pickle.dump(model, f)

with open('gradient_boosting_model.pkl', 'rb') as f:
    loaded_model = pickle.load(f)
```

[93]:
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, confusion_matrix

y_pred = loaded_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
print("Model Evaluation Metrics:")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Model Evaluation Metrics:
Accuracy: 0.930421686746988
Precision: 0.860502405130946
Recall: 0.8890115958034235
F1 Score: 0.8745247148288974
```

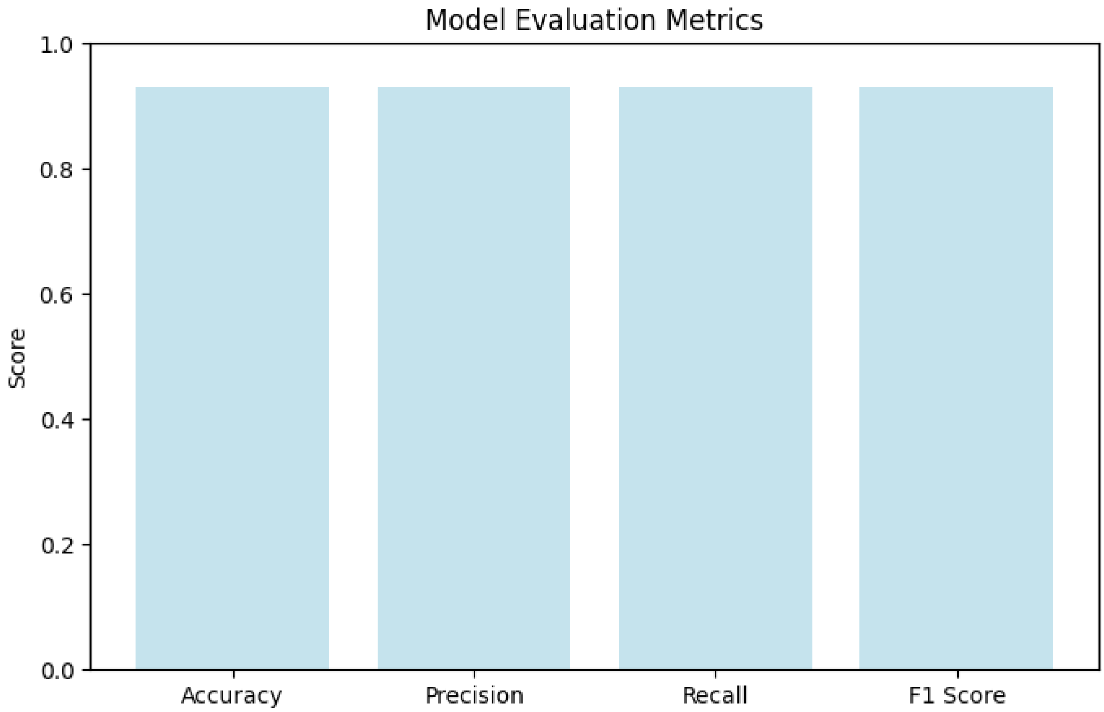
[94]:
```python
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪precision_score, recall_score, f1_score, confusion_matrix

y_pred = loaded_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')  # Use␣
 ↪'weighted' for multiclass if applicable
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
conf_matrix = confusion_matrix(y_test, y_pred)

print("Model Evaluation Metrics:")
print("Accuracy:", accuracy)
```

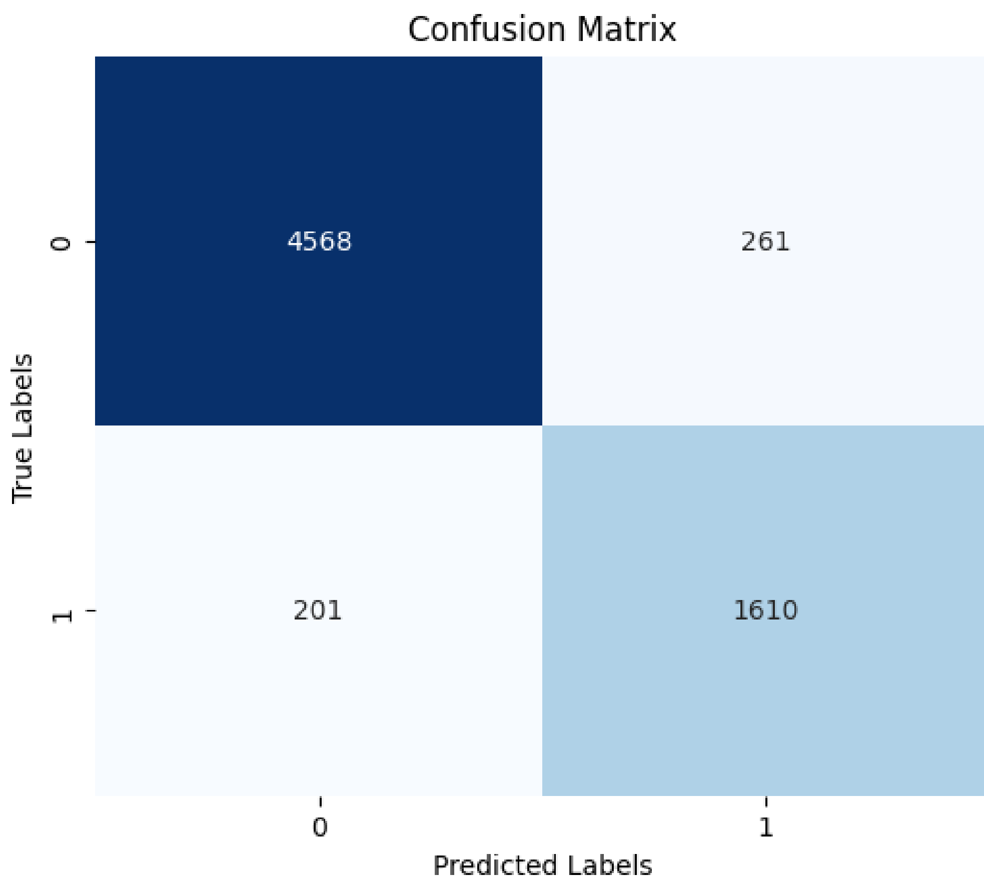
```python
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print("Confusion Matrix:\n", conf_matrix)
print(classification_report(y_test, y_pred))
```

```
Model Evaluation Metrics:
Accuracy: 0.930421686746988
Precision: 0.9313013589837174
Recall: 0.930421686746988
F1 Score: 0.9307711156191577
Confusion Matrix:
 [[4568  261]
 [ 201 1610]]
              precision    recall  f1-score   support

           0       0.96      0.95      0.95      4829
           1       0.86      0.89      0.87      1811

    accuracy                           0.93      6640
   macro avg       0.91      0.92      0.91      6640
weighted avg       0.93      0.93      0.93      6640
```

[95]:

```python
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
scores = [accuracy, precision, recall, f1]

plt.figure(figsize=(8, 5))
plt.bar(metrics, scores, color='lightblue', alpha=0.7)
plt.title("Model Evaluation Metrics")
plt.ylim(0, 1)
plt.ylabel("Score")
plt.show()

plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```


Model Evaluation Metrics
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score



2.3 Checking the most important features which led to the predictions to evaluate our initial hypothesis

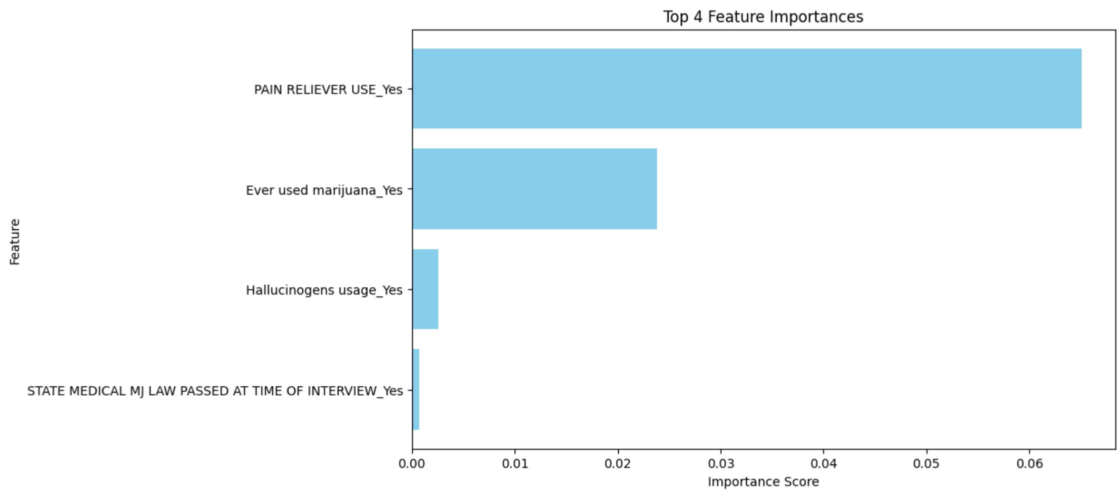
[96]:
```
feature_names = X_train.columns

feature_importances = loaded_model.feature_importances_
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
})
feature_importance = feature_importance_df[feature_importance_df['Feature'] !=␣
↪'HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP']

top_features = feature_importance.sort_values(by='Importance', ascending=False)

top_feature_names = top_features.head(5)['Feature']
print("Top Features:")
print(top_feature_names)
```

```
Top Features:
3                                PAIN RELIEVER USE_Yes
2                              Ever used marijuana_Yes
4                              Hallucinogens usage_Yes
1     STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVI…
Name: Feature, dtype: object
```

[97]:

```python
feature_names = X_train.columns
feature_importances = loaded_model.feature_importances_
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
})
feature_importance = feature_importance_df[feature_importance_df['Feature'] != 'HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP']
top_features = feature_importance.sort_values(by='Importance', ascending=False).head()
top_feature_names = top_features['Feature']
top_importance_values = top_features['Importance']
print("Top Features:")
print(top_feature_names)
plt.figure(figsize=(10, 6))
plt.barh(top_feature_names, top_importance_values, color='skyblue')
plt.gca().invert_yaxis()
plt.title("Top 4 Feature Importances")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.show()
```

```
Top Features:
3                                PAIN RELIEVER USE_Yes
2                              Ever used marijuana_Yes
4                              Hallucinogens usage_Yes
1     STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVI…
Name: Feature, dtype: object
```



2.4 From the above data we can conclude the following -

- Frequent marijuana use which is more common in states where marijuana is legalized, and this is associated with a higher prevalence of bad mental health conditions
- Usage of hallucinogens is also associated with bad mental health conditions
- We have observed that pain reliever use is a significant feature in predicting mental health disorders. This suggests that the unregulated use of pain relievers, often for recreational purposes, may contribute to bad mental health. Hence, it is essential to ensure that pain relievers are only accessible through proper prescriptions from authorized medical professionals.

2.4.1 Question 3: How does socioeconomic status (income, education, employment status) influence the likelihood of experiencing mental health disorders?

2.4.2 Hypothesis 1: Individuals with lower income are more likely to experience mental health issues or Unemployment is a significant predictor of mental health disorders

2.4.3 Significance of the question: Understanding the correlation between socio-economic factors and mental health can help identify vulnerable populations and provide support for economically weak population.

[98]:
```
filtered_df_cleaned=filtered_df_cleaned_org.copy()
filtered_df_cleaned.dropna()
```

[98]:
```
        QUESTID2                          Employment              education  \
0    43295143.00                  Employed full time         College Degree
2    49405143.00                  Employed full time         College Degree
3    51015143.00  Other (incl. not in labor force)      primary education
6    65565143.00                          Unemployed  High School education
7    45375143.00  Other (incl. not in labor force)  High School education
…            …                                 …                      …
```

```
56125 23883730.00                Employed full time        College Degree
56126 55494730.00  Other (incl. not in labor force)        College Degree
56127 21894730.00  Other (incl. not in labor force)  High School education
56129 61414730.00                Employed full time        College Degree
56130 49614730.00  Other (incl. not in labor force)      primary education

                  income sexual orientation Ever used marijuana  \
0         $75,000 or more              Male                 Yes
2         $75,000 or more              Male                 Yes
3       Less than $20,000            Female                  No
6         $75,000 or more            Female                 Yes
7       $20,000 - $49,999              Male                  No
…                     …                …                 …
56125     $75,000 or more              Male                 Yes
56126   $20,000 - $49,999            Female                  No
56127   $20,000 - $49,999            Female                  No
56129     $75,000 or more            Female                 Yes
56130   $20,000 - $49,999              Male                  No

      ANY PAIN RELIEVER USE IN LIFETIME COUNTY METRO/NONMETRO STATUS  \
0                                   Yes                  Small Metro
2                                   Yes                  Small Metro
3                                   Yes                  Small Metro
6                                    No                  Large Metro
7                                   Yes                    Non Metro
…                                 …                          …
56125                               Yes                  Small Metro
56126                               Yes                  Small Metro
56127                                No                  Large Metro
56129                               Yes                  Small Metro
56130                                No                  Large Metro

      STATE MEDICAL MJ LAW PASSED AT TIME OF INTERVIEW  \
0                                                   No
2                                                  Yes
3                                                  Yes
6                                                  Yes
7                                                  Yes
…                                                …
56125                                              Yes
56126                                              Yes
56127                                              Yes
56129                                               No
56130                                              Yes

      HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0                                  Some of the time
```

```
2                              None of the time
3                          A little of the time
6                              None of the time
7                              None of the time
…                                           …
56125                          None of the time
56126                          None of the time
56127                          Some of the time
56129                      A little of the time
56130                          None of the time

      SEVERAL DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD hallucinogens
0                                                Yes            No
2                                                 No            No
3                                                 No            No
6                                                 No            No
7                                                 No            No
…                                                  …             …
56125                                             No           Yes
56126                                             No            No
56127                                            Yes            No
56129                                            Yes            No
56130                                             No            No

[33199 rows x 12 columns]
```

[99]:

```
# Excluding the features which are not relevant to our analysis
columns_to_exclude = ['sexual orientation', 'Ever used marijuana', 'ANY PAIN␣
↪RELIEVER USE IN LIFETIME', 'STATE MEDICAL MJ LAW PASSED AT TIME OF␣
↪INTERVIEW', 'hallucinogens']
filtered_df_cleaned = filtered_df_cleaned[[col for col in filtered_df_cleaned.
↪columns if col not in columns_to_exclude]]
```

[100]:

```
filtered_df_cleaned['Mental_Health_Disorder'] = filtered_df_cleaned['SEVERAL␣
↪DAYS OR LNGR WHEN FELT SAD/EMPTY/DPRSD'].apply(lambda x: 1 if x == 'Yes'␣
↪else 0)

filtered_df_cleaned = filtered_df_cleaned.drop(columns=['SEVERAL DAYS OR LNGR␣
↪WHEN FELT SAD/EMPTY/DPRSD'])
```

[101]:

```
encoded_df = pd.get_dummies(filtered_df_cleaned, columns=[ 'Employment',␣
↪'education', 'income','COUNTY METRO/NONMETRO STATUS'], drop_first=True)

encoded_df=encoded_df.dropna()
```

[102]:

```
encoded_df = encoded_df.replace({True: 1, False: 0})
encoded_df.head()
```

```
C:\Users\Rama Rao\AppData\Local\Temp\ipykernel_17120\794848686.py:1:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  encoded_df = encoded_df.replace({True: 1, False: 0})
```

[102]:

```
      QUESTID2 HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0 43295143.00                                 Some of the time
2 49405143.00                                 None of the time
3 51015143.00                             A little of the time
6 65565143.00                                 None of the time
7 45375143.00                                 None of the time

   Mental_Health_Disorder  Employment_Employed part time  \
0                       1                              0
2                       0                              0
3                       0                              0
6                       0                              0
7                       0                              0

   Employment_Other (incl. not in labor force)  Employment_Unemployed  \
0                                            0                      0
2                                            0                      0
3                                            1                      0
6                                            0                      1
7                                            1                      0

   education_High School education  education_primary education  \
0                                0                             0
2                                0                             0
3                                0                             1
6                                1                             0
7                                1                             0

   income_$50,000 - $74,999  income_$75,000 or more  income_Less than $20,000  \
0                         0                       1                         0
2                         0                       1                         0
3                         0                       0                         1
6                         0                       1                         0
7                         0                       0                         0

   COUNTY METRO/NONMETRO STATUS_Non Metro  \
0                                       0
2                                       0
3                                       0
6                                       0
```

```
7                                       1

   COUNTY METRO/NONMETRO STATUS_Small Metro
0                                         1
2                                         1
3                                         1
6                                         0
7                                         0
```

[103]:
```
order = {
    "None of the time": 0,
    "A little of the time": 1,
    "Some of the time": 2,
    "Most of the time": 3,
    "All of the time": 4
}
encoded_df['HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP'] = encoded_df['HOW␣
 ↪OFTEN FELT SAD NOTHING COULD CHEER YOU UP'].map(order)
encoded_df['HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP'].unique()
```

[103]:
```
array([2, 0, 1, 3, 4])
```

[104]:
```
encoded_df=encoded_df.dropna()
```

[105]:
```
df=encoded_df.copy()
req_X_cols = [w for w in df.columns if w not in␣
 ↪['Mental_Health_Disorder','QUESTID2']]
X = df[req_X_cols]
y = df['Mental_Health_Disorder'] #Outcome

data=df.copy()
```

[106]:
```
data
```

[106]:
```
         QUESTID2  HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP  \
0     43295143.00                                              2
2     49405143.00                                              0
3     51015143.00                                              1
6     65565143.00                                              0
7     45375143.00                                              0
…             …                                          …
56125 23883730.00                                              0
56126 55494730.00                                              0
56127 21894730.00                                              2
56129 61414730.00                                              1
56130 49614730.00                                              0
```

```
       Mental_Health_Disorder  Employment_Employed part time  \
0                           1                              0
2                           0                              0
3                           0                              0
6                           0                              0
7                           0                              0
…                         …                              …
56125                       0                              0
56126                       0                              0
56127                       1                              0
56129                       1                              0
56130                       0                              0

       Employment_Other (incl. not in labor force)  Employment_Unemployed  \
0                                                0                      0
2                                                0                      0
3                                                1                      0
6                                                0                      1
7                                                1                      0
…                                              …                      …
56125                                            0                      0
56126                                            1                      0
56127                                            1                      0
56129                                            0                      0
56130                                            1                      0

       education_High School education  education_primary education  \
0                                     0                            0
2                                     0                            0
3                                     0                            1
6                                     1                            0
7                                     1                            0
…                                   …                          …
56125                                 0                            0
56126                                 0                            0
56127                                 1                            0
56129                                 0                            0
56130                                 0                            1

       income_$50,000 - $74,999  income_$75,000 or more  \
0                             0                       1
2                             0                       1
3                             0                       0
6                             0                       1
7                             0                       0
…                           …                     …
56125                         0                       1
```

```
56126                        0                        0
56127                        0                        0
56129                        0                        1
56130                        0                        0

       income_Less than $20,000  COUNTY METRO/NONMETRO STATUS_Non Metro  \
0                             0                                       0
2                             0                                       0
3                             1                                       0
6                             0                                       0
7                             0                                       1
…                           …                                     …
56125                         0                                       0
56126                         0                                       0
56127                         0                                       0
56129                         0                                       0
56130                         0                                       0

       COUNTY METRO/NONMETRO STATUS_Small Metro
0                                             1
2                                             1
3                                             1
6                                             0
7                                             0
…                                           …
56125                                         1
56126                                         1
56127                                         0
56129                                         1
56130                                         0

[33248 rows x 13 columns]
```

2.4.4 We will calculate Variance Inflation Factor to detect multicollinearity among features

[107]:
```
vif_data = pd.DataFrame()
vif_data["Feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]

print(vif_data)
```

```
                                        Feature  VIF
0   HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP 1.34
1                    Employment_Employed part time 1.26
2     Employment_Other (incl. not in labor force) 1.50
3                            Employment_Unemployed 1.12
```

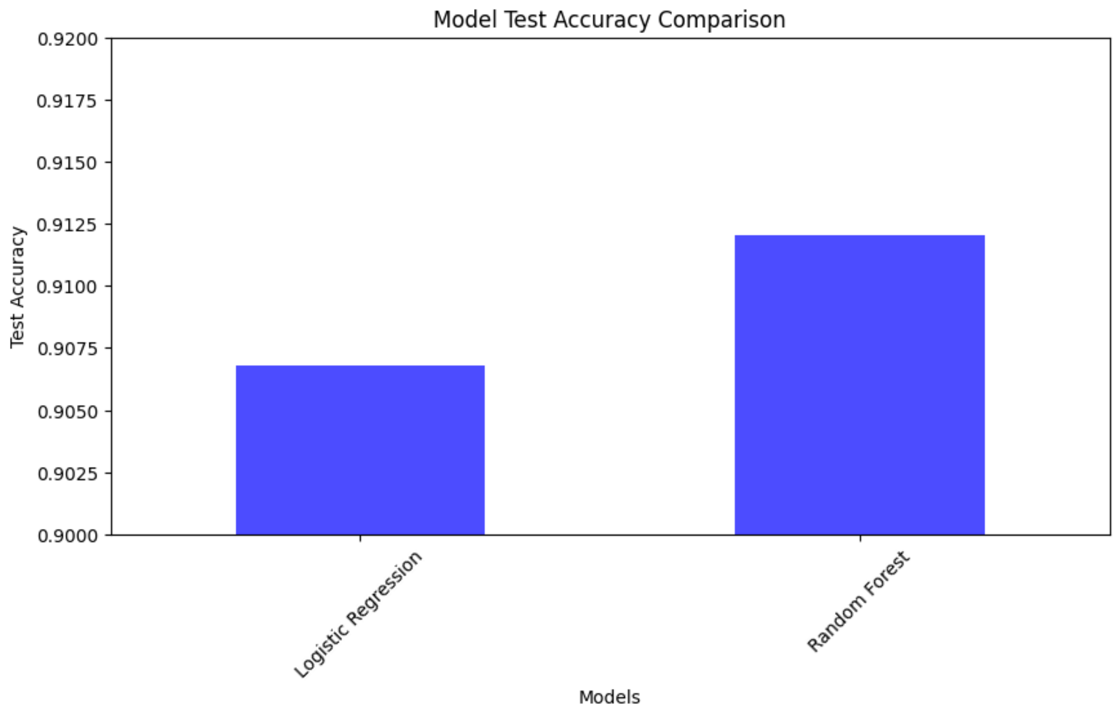
```
4                 education_High School education 1.91
5                     education_primary education 1.15
6                        income_$50,000 - $74,999 1.23
7                          income_$75,000 or more 1.35
8                        income_Less than $20,000 1.52
9          COUNTY METRO/NONMETRO STATUS_Non Metro 1.34
10       COUNTY METRO/NONMETRO STATUS_Small Metro 1.58
```

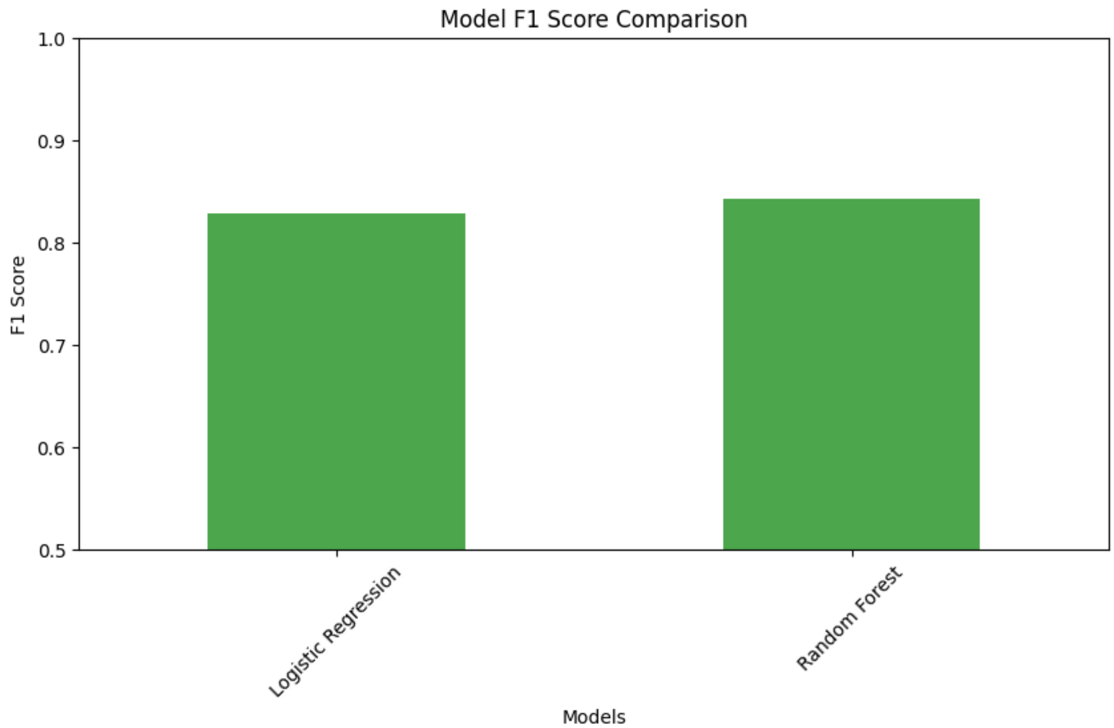
[108]:
```
X = data.drop(columns=['QUESTID2', 'Mental_Health_Disorder'])
y = data['Mental_Health_Disorder']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'Random Forest': RandomForestClassifier()
}
model_performance = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    test_accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    model_performance[name] = {
        'Test Accuracy': round(test_accuracy,5),
        'F1 Score': round(f1,3)
    }
model_performance
```

[108]:
```
{'Logistic Regression': {'Test Accuracy': 0.90677,
  'F1 Score': np.float64(0.828)},
 'Random Forest': {'Test Accuracy': 0.91203, 'F1 Score': np.float64(0.843)}}
```

[109]:
```
performance_df = pd.DataFrame(model_performance).T
performance_df
plt.figure(figsize=(10, 5))
performance_df['Test Accuracy'].plot(kind='bar', color='blue', alpha=0.7)
plt.title('Model Test Accuracy Comparison')
plt.ylabel('Test Accuracy')
plt.xlabel('Models')
plt.ylim(0.90, 0.92)
plt.xticks(rotation=45)
plt.show()
plt.figure(figsize=(10, 5))
performance_df['F1 Score'].plot(kind='bar', color='green', alpha=0.7)
plt.title('Model F1 Score Comparison')
plt.ylabel('F1 Score')
```

```
plt.xlabel('Models')
plt.ylim(0.5, 1.0)
plt.xticks(rotation=45)
plt.show()
```





2.5 Finalizing the model to be used

In case of Logistic Regression, the F1 Score is the lowest among all models evaluated. This indicates that logistic regression might not be useful for balancing precision and recall, which is very important for our case.

Random Forest has slighlty high accuracy and F1 Score compared to Logistic Regression. Additionally, it can capture non-linear relationships and is more robust.

Hence we will be using Random Forest as the final model as it provides the best balance between accuracy and the F1 Score.

[110]:
```
model = RandomForestClassifier()

model.fit(X_train, y_train)

with open('random_forest_model.pkl', 'wb') as f:
    pickle.dump(model, f)

with open('random_forest_model.pkl', 'rb') as f:
    loaded_model = pickle.load(f)

y_pred = loaded_model.predict(X_test)
```

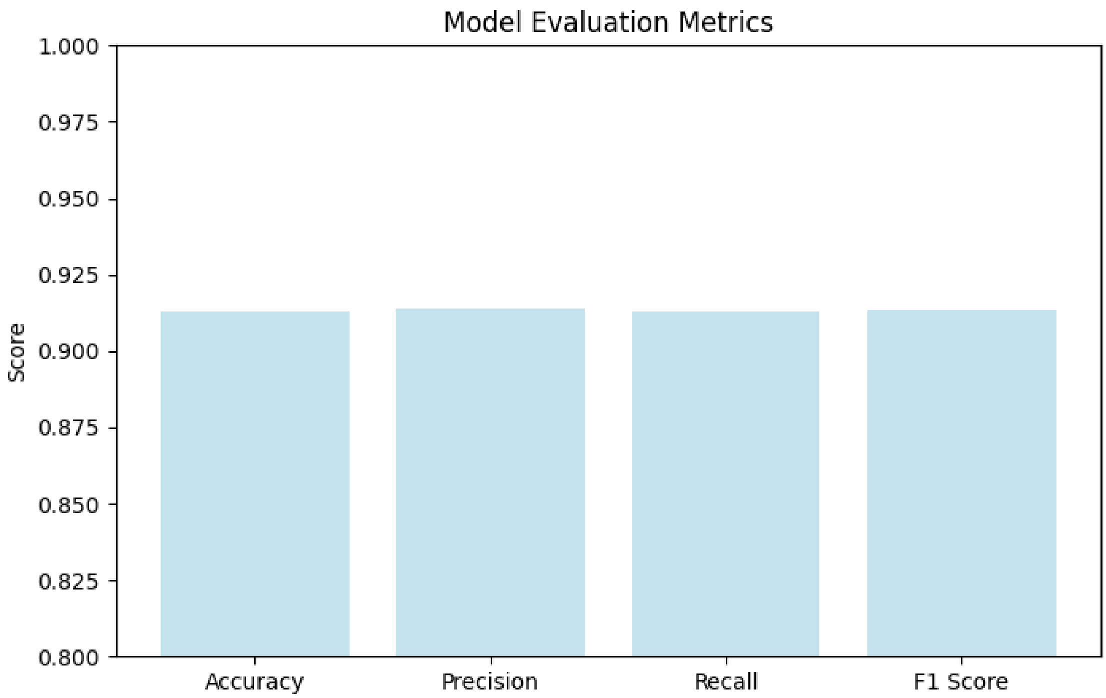
```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
conf_matrix = confusion_matrix(y_test, y_pred)

print("Model Evaluation Metrics:")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print("Confusion Matrix:\n", conf_matrix)
print(classification_report(y_test, y_pred))
```

```
Model Evaluation Metrics:
Accuracy: 0.912781954887218
Precision: 0.9140717339567406
Recall: 0.912781954887218
F1 Score: 0.9133013915713517
Confusion Matrix:
 [[4506  326]
 [ 254 1564]]
              precision    recall  f1-score   support

           0       0.95      0.93      0.94      4832
           1       0.83      0.86      0.84      1818

    accuracy                           0.91      6650
   macro avg       0.89      0.90      0.89      6650
weighted avg       0.91      0.91      0.91      6650
```

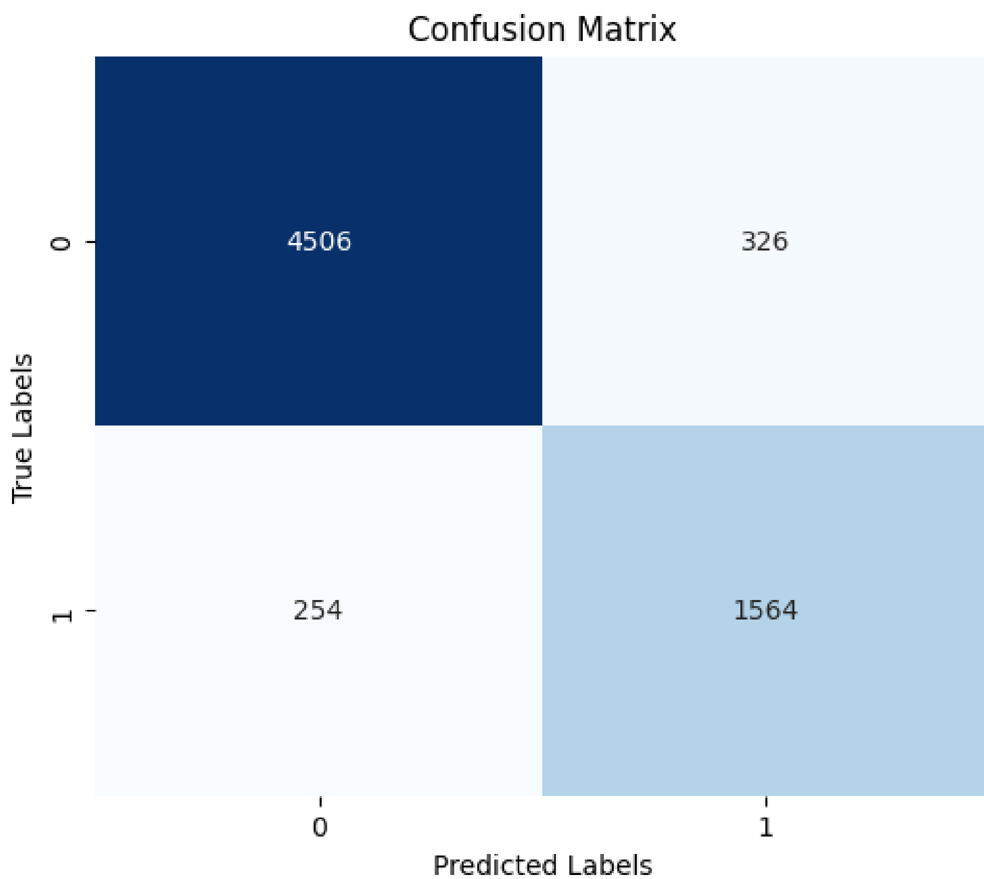
[111]:

```
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
scores = [accuracy, precision, recall, f1]

plt.figure(figsize=(8, 5))
plt.bar(metrics, scores, color='lightblue', alpha=0.7)
plt.title("Model Evaluation Metrics")
plt.ylim(0.8, 1)  # Set y-axis range from 0 to 1 for better visualization
plt.ylabel("Score")
plt.show()

plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
```

```
plt.show()
```



Model Evaluation Metrics
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Score
Accuracy
Precision
Recall
F1 Score



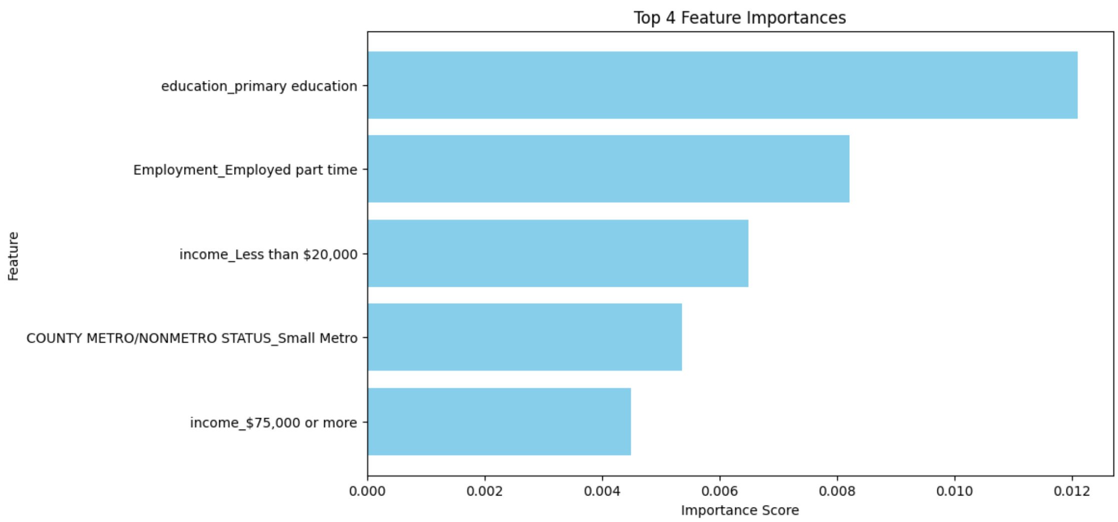
[112]:
```
feature_names = X_train.columns

feature_importances = loaded_model.feature_importances_
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
})
feature_importance = feature_importance_df[feature_importance_df['Feature'] !=␣
↪'HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP']

top_features = feature_importance.sort_values(by='Importance', ascending=False)

top_feature_names = top_features.head(5)['Feature']
print("Top Features:")
print(top_feature_names)
```

```
Top Features:
5                  education_primary education
1                Employment_Employed part time
```

```
8                       income_Less than $20,000
10    COUNTY METRO/NONMETRO STATUS_Small Metro
7                         income_$75,000 or more
Name: Feature, dtype: object
```

[113]:
```
feature_names = X_train.columns
feature_importances = loaded_model.feature_importances_
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
})
feature_importance = feature_importance_df[feature_importance_df['Feature'] !=␣
 ↪'HOW OFTEN FELT SAD NOTHING COULD CHEER YOU UP']
top_features = feature_importance.sort_values(by='Importance', ascending=False).
 ↪head()
top_feature_names = top_features['Feature']
top_importance_values = top_features['Importance']
print("Top Features:")
print(top_feature_names)
plt.figure(figsize=(10, 6))
plt.barh(top_feature_names, top_importance_values, color='skyblue')
plt.gca().invert_yaxis()
plt.title("Top 4 Feature Importances")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.show()
```

```
Top Features:
5                  education_primary education
1                 Employment_Employed part time
8                       income_Less than $20,000
10    COUNTY METRO/NONMETRO STATUS_Small Metro
7                         income_$75,000 or more
Name: Feature, dtype: object
```



2.6 From the above data we can conclude the following -

- Based on above data we can conclude that our initial hypothesis is correct and there is a strong relationship between socioeconomic and educational factors and mental health conditions.
- Education seems to have a strong impact on mental health. People with a high school education or less are more likely to face mental health challenges. This highlights how important education can be in shaping a person's overall well-being.
- The data shows that people earning less than the minimum needed for basic living (around $20,000 a year) or those who are underemployed are more likely to struggle with depression. This indicates the importantance of financial stability and employment for better mental health
- This suggests that there is a need for support for those facing economic challenges

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