California State University - Los Angeles

Mental Health Analysis in Tech

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Instructor Balan

Introduction

In modern society, the discourse surrounding mental health has undergone a remarkable evolution, going beyond its historical mark to become a crucial point of public attention and concern. This transformation is particularly remarkable within the workplace, where organizations are increasingly recognizing the importance of prioritizing employee well-being as a base of sustainable success. Within the dynamic landscape of the tech industry, renowned for its innovative spirit and relentless pursuit of progress, the topic of mental health has emerged as a critical concern. The "Mental Health in Tech Survey" dataset serves as a growth of insights into the intersection of technology and mental well-being. In recent years, this dataset has gathered attention as a valuable resource for researchers and the strongest matches seeking to understand the frequency, determinants, and consequences of mental health issues among tech professionals. Collected through a survey administered to individuals working in various tech-related roles, the dataset offers a rich tapestry of responses encompassing a wide range of demographic, occupational, and psychosocial variables. Within the tech sector, individuals often find themselves navigating a myriad of challenges, ranging from tight deadlines and high-stakes projects to intense competition and demanding work cultures. These pressures can take a toll on one's mental health, manifesting in various forms such as stress, anxiety, and burnout. Moreover, the common stigma surrounding mental illness in many workplace environments often worsens these issues, creating barriers to seeking help and support. By analyzing the huge lineup of responses collected through this survey, we can uncover insights into the factors influencing mental health outcomes among tech professionals. In an article (2022), the authors share their analysis with the help of a pie chart. In that chart, question 1 (seeking therapy) is represented by the inside pie, whereas question 2 is represented by the outer rim (degree of work interfere).

Although 49% of participants (blue section, n=436/883) sought therapy, signaling that they have or had a mental illness, the majority of them still suffer at work on a regular basis, ranging from rarely to frequently. There is still a group of people (14 percent, n=127/883) who suffer at work to varying degrees despite never seeking treatment (the red part). From statistics and job roles to organizational policies and access to resources, the dataset provides a holistic view of the multifaceted nature of mental health in the tech sector. Our project seeks to leverage the power of data analysis to extract meaningful insights from the "Mental Health in Tech Survey" dataset. Through a combination of statistical methods and machine learning techniques, we aim to identify patterns, trends, and associations that shed light on the frequency and determinants of mental health issues within the tech community. By uncovering actionable insights, we hope to inform strategies and involvement aimed at promoting mental well-being and creating a supportive work environment for tech professionals.

Dataset URL and Dataset Description

Dataset URL: [Mental Health in Tech Survey (kaggle.com)]

Dataset Description:

Field Name	Data Description	Example Value
Timestamp	The time in which the survey was taken	2014-08-27 11:29:31
Age	The age of the participant	37
Gender	The gender of the participant	Female

Country	The country of where the survey was done	United States
state	The state of the participant if they live in the United States	IL
self_employed	If the participant is self- employed	N/A
family_history	If the participant has a history of mental illness in the family	No
treatment	If the participant has sought out treatment for a mental health condition	Yes
work_interfere	If the participant had any interferences at work because of their mental health	Often
no_employees	How many employees the company has	6-25
remote_work	Does the company allows at least 50% of remote work	No
tech_company	Is the company primarily a tech company	Yes
benefits	If the employer provide mental health benefits	Yes
care_options	If the participant is aware of the mental health options provided by the employer	Not sure
wellness_program	If the participant has ever discussed mental health as part of the employee wellness program they offer	No
seek_help	If there are resources for mental health being provided by the employer	Yes
anonymity	If the participant's anonymity is protected if they choose to take advantage of any resources	Yes

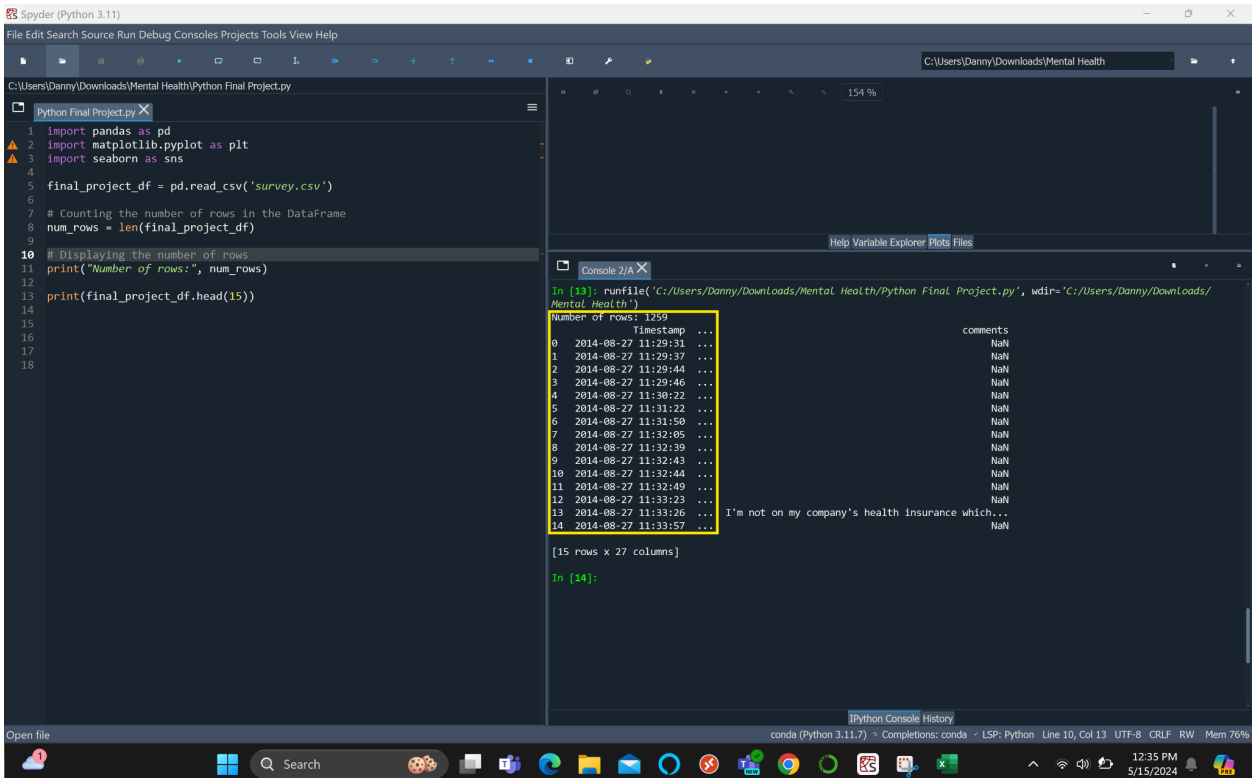
leave	How easy it is to take medical leave for a mental health condition	Somewhat easy
mental_health_consequences	If the participant thinks that discussing a mental health issue would result in a negative consequence	No
phys_health_consequence	If the participant thinks that discussing a physical health issue would result in a negative consequence	No
coworkers	If the participant is willing to discuss a mental health issue with their coworkers	Some of them
supervisor	If the participant is willing to discuss a mental health issue with their direct supervisor	Yes
mental_health_interview	If the participant is willing to discuss a mental health issue with a potential employer at a future interview	No
phys_health_interview	If the participant is willing to discuss a physical health issue with their coworkers	Maybe
mental_vs_physical	If the participant feels that mental health is taken as seriously as physical health	Yes
obs_consequences	If the participant has heard of observed negative consequences for coworkers with mental health conditions in your workplace	No
comments	Any additional notes that were made by the participant	N/A

Data Cleaning

1) Convert Data Type

We began by changing the "Timestamp" column's name to "Date." Given that this is a survey, analyzing the dataset by year provides a more comprehensive perspective than by specific timestamps. We chose to retain only the month and year since the precise time and day of survey completion were not necessary. To achieve this, we first renamed the "Timestamp" column to "Date" in our dataframe, making it simpler to understand when the survey responses were collected. Next, we converted the column's data type to "datetime" and extracted just the month and year from the entries. This step is crucial because it simplifies the data, allowing for easier analysis and interpretation of trends over time. Benefits to making it this way ensures consistency across the dataset, facilitating easier comparison and summarization.

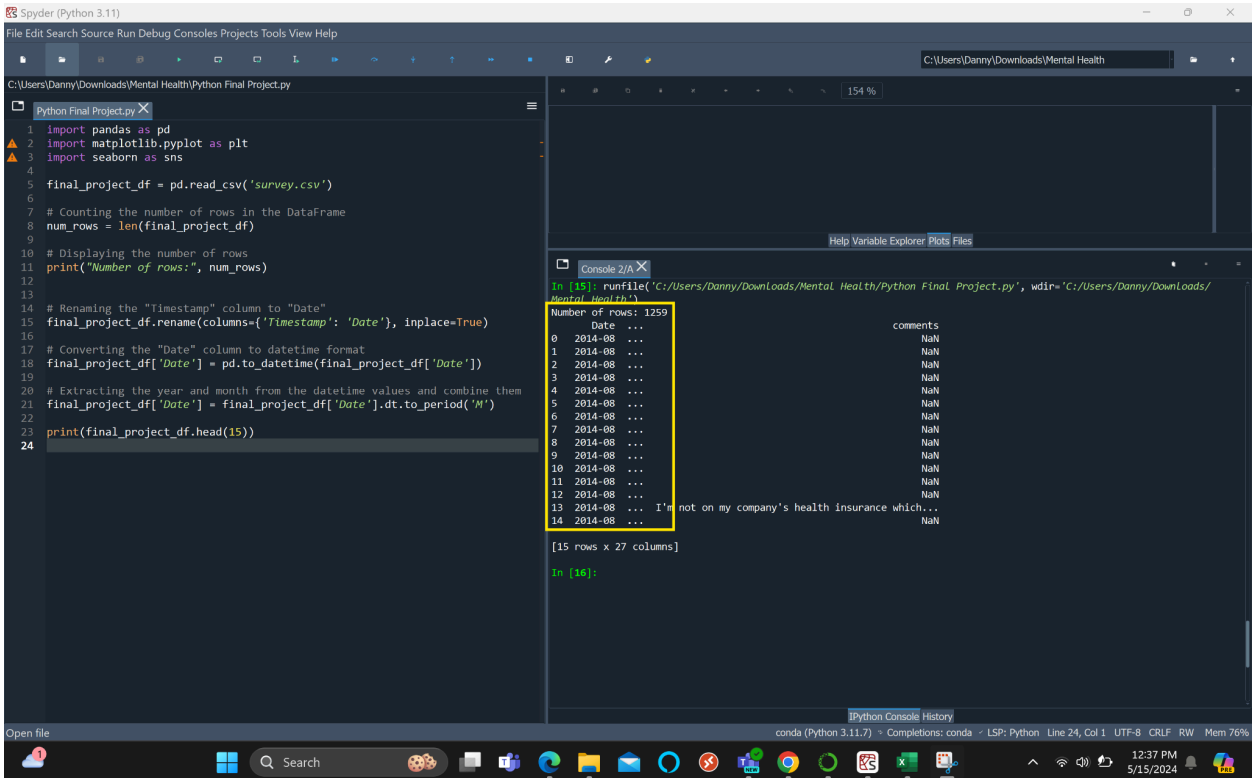
Pre-Data Cleaning




```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

final_project_df = pd.read_csv('survey.csv')

# Counting the number of rows in the DataFrame
num_rows = len(final_project_df)

# Displaying the number of rows
print("Number of rows:", num_rows)

print(final_project_df.head(15))
```

```
Number of rows: 1259
             Timestamp  ...                                           comments
0    2014-08-27 11:29:31  ...                                                NaN
1    2014-08-27 11:29:37  ...                                                NaN
2    2014-08-27 11:29:44  ...                                                NaN
3    2014-08-27 11:29:46  ...                                                NaN
4    2014-08-27 11:30:22  ...                                                NaN
5    2014-08-27 11:31:22  ...                                                NaN
6    2014-08-27 11:31:50  ...                                                NaN
7    2014-08-27 11:32:05  ...                                                NaN
8    2014-08-27 11:32:39  ...                                                NaN
9    2014-08-27 11:32:43  ...                                                NaN
10   2014-08-27 11:32:44  ...                                                NaN
11   2014-08-27 11:32:49  ...                                                NaN
12   2014-08-27 11:33:23  ...                                                NaN
13   2014-08-27 11:33:26  ...  I'm not on my company's health insurance which...
14   2014-08-27 11:33:57  ...                                                NaN
```

Post-Data Cleaning:



```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

final_project_df = pd.read_csv('survey.csv')

# Counting the number of rows in the DataFrame
num_rows = len(final_project_df)

# Displaying the number of rows
#print("Number of rows:", num_rows)

#print(final_project_df.head(15))

# Renaming the "Timestamp" column to "Date"
final_project_df.rename(columns={'Timestamp': 'Date'}, inplace=True)

# Converting the "Date" column to datetime format
final_project_df['Date'] = pd.to_datetime(final_project_df['Date'])

# Extracting the year and month from the datetime values and combine them
final_project_df['Date'] = final_project_df['Date'].dt.to_period('M')

print(final_project_df.head(15))
```

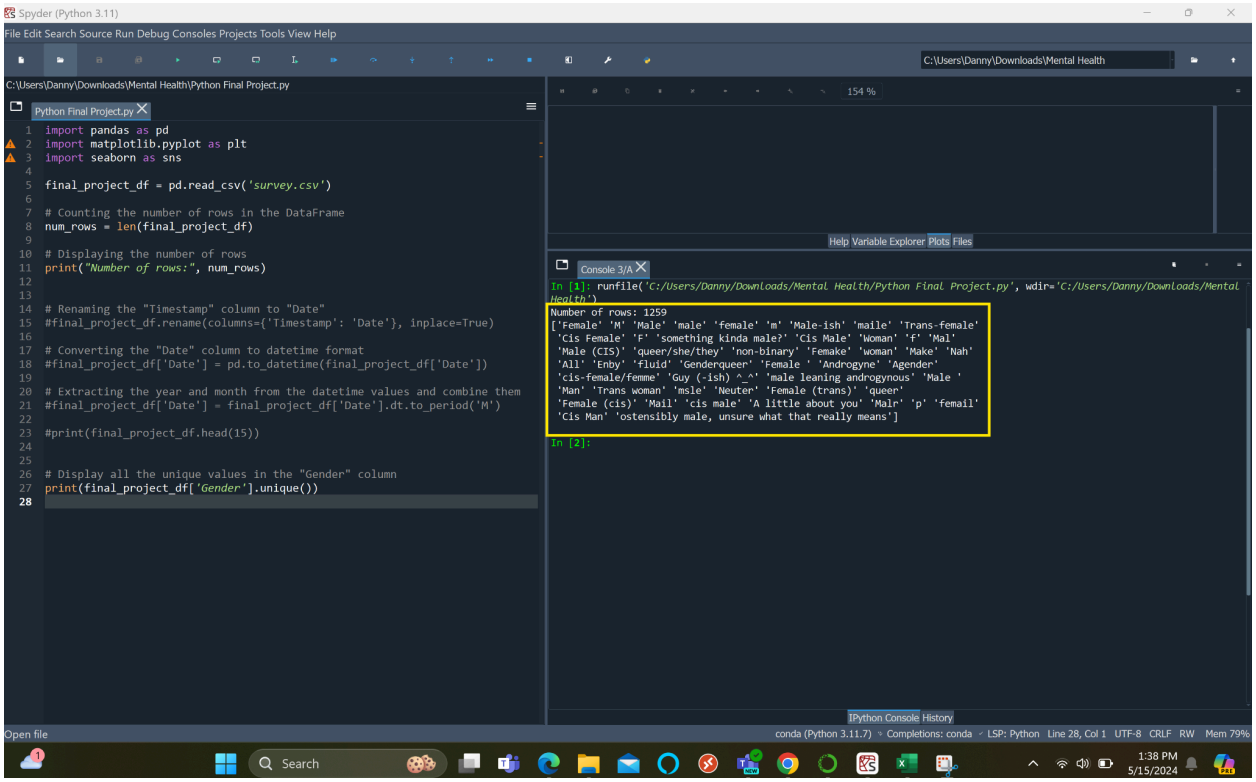
```
Number of rows: 1259
       Date  ...                                           comments
0   2014-08  ...                                                NaN
1   2014-08  ...                                                NaN
2   2014-08  ...                                                NaN
3   2014-08  ...                                                NaN
4   2014-08  ...                                                NaN
5   2014-08  ...                                                NaN
6   2014-08  ...                                                NaN
7   2014-08  ...                                                NaN
8   2014-08  ...                                                NaN
9   2014-08  ...                                                NaN
10  2014-08  ...                                                NaN
11  2014-08  ...                                                NaN
12  2014-08  ...                                                NaN
13  2014-08  ...  I'm not on my company's health insurance which...
14  2014-08  ...                                                NaN
```

2) Data Imputation

The survey received a wide range of responses to the question about gender. To simplify the data, we categorized gender into three groups: Male, Female, and Other. This approach ensures that all participants are represented. We included any response that was not explicitly "Male" or "Female" under the "Other" category. We accomplished this by identifying all unique values in the gender column and mapping them to our standardized categories.

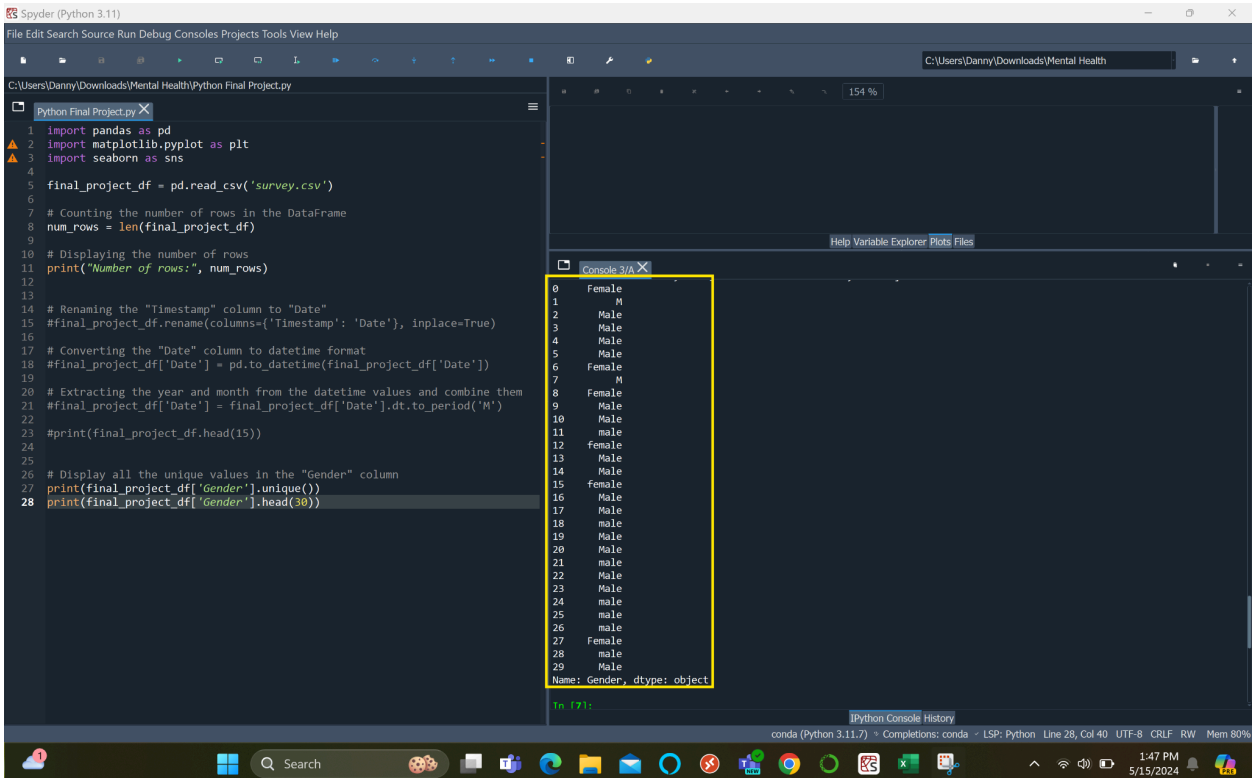
This proved beneficial as it provided a standard category that was able to easily identify the variety of applicants when it came down to Gender. Furthermore, all the data was kept as accurate as possible as it was free from spelling errors and differences in punctuation.

Pre-Data Cleaning:



```
# Display all the unique values in the "Gender" column
print(final_project_df['Gender'].unique())
```

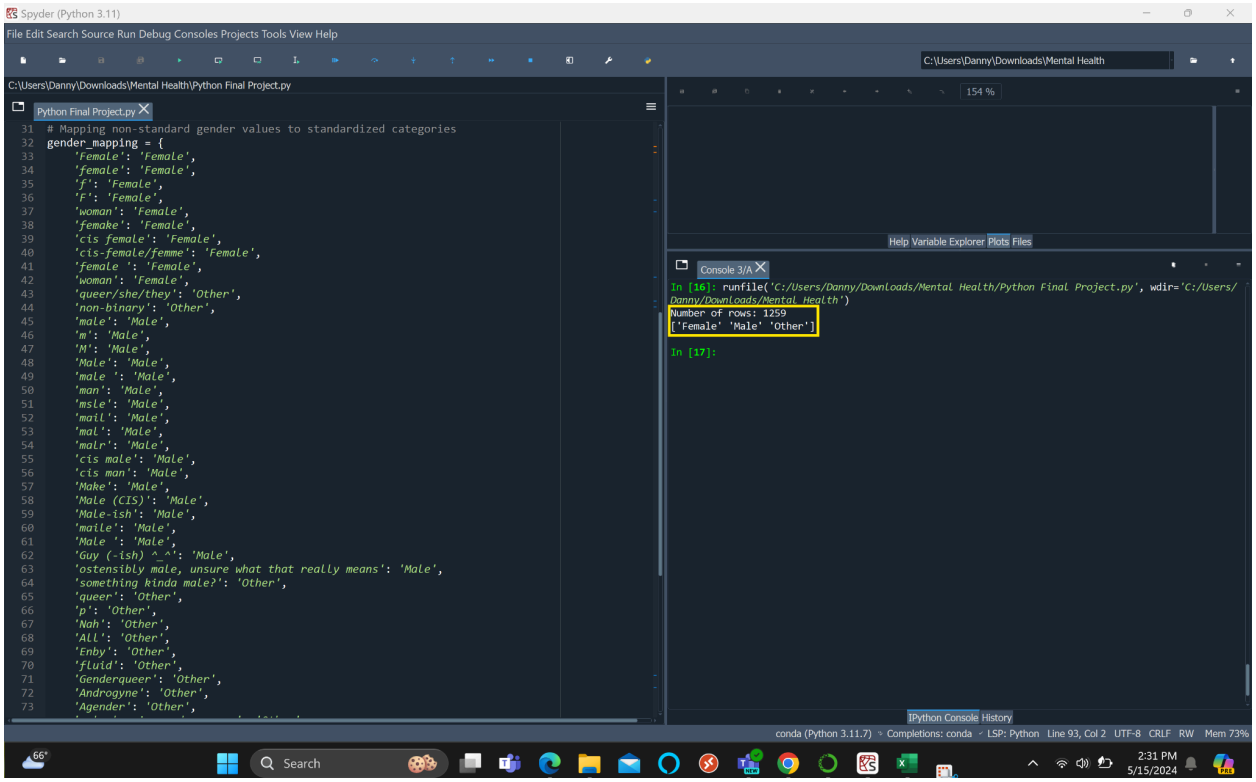
```
Number of rows: 1259
['Female' 'M' 'Male' 'male' 'female' 'm' 'Male-ish' 'maile' 'Trans-female'
 'Cis Female' 'F' 'something kinda male?' 'Cis Male' 'Woman' 'f' 'Mal'
 'Male (CIS)' 'queer/she/they' 'non-binary' 'Femake' 'woman' 'Make' 'Nah'
 'All' 'Enby' 'fluid' 'Genderqueer' 'Female ' 'Androgyne' 'Agender'
 'cis-female/femme' 'Guy (-ish) ^_^' 'male leaning androgynous' 'Male '
 'Man' 'Trans woman' 'msle' 'Neuter' 'Female (trans)' 'queer'
 'Female (cis)' 'Mail' 'cis male' 'A little about you' 'Malr' 'p' 'femail'
 'Cis Man' 'ostensibly male, unsure what that really means']
```




```
# Display all the unique values in the "Gender" column
print(final_project_df['Gender'].unique())
print(final_project_df['Gender'].head(30))
```

```
0      Female
1           M
2        Male
3        Male
4        Male
5        Male
6      Female
7           M
8      Female
9        Male
10       Male
11       male
12     female
13       Male
14       Male
15     female
16       Male
17       Male
18       male
19       Male
20       Male
21       male
22       Male
23       Male
24       male
25       male
26       male
27     Female
28       male
29       Male
Name: Gender, dtype: object
```

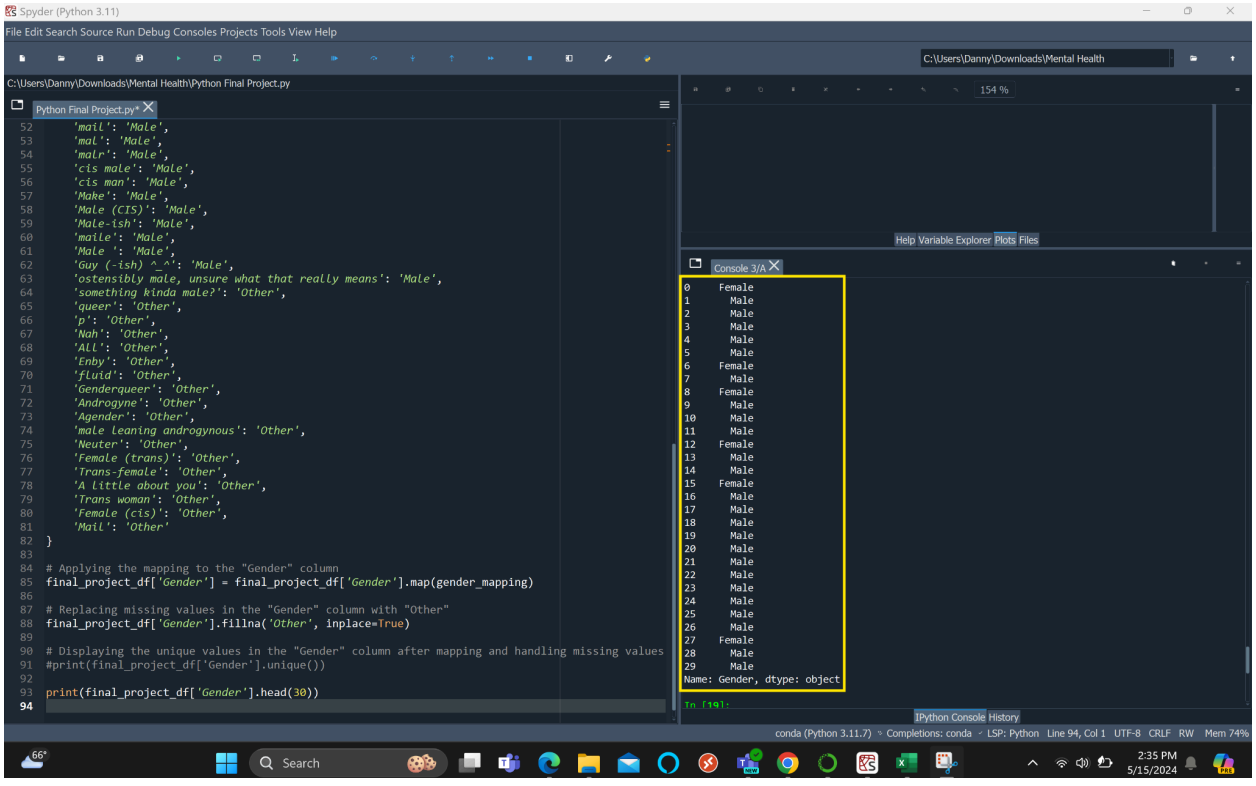
Post-Data Cleaning:



```python
# Mapping non-standard gender values to standardized categories
gender_mapping = {
    'Female': 'Female',
    'female': 'Female',
    'f': 'Female',
    'F': 'Female',
    'woman': 'Female',
    'femake': 'Female',
    'cis female': 'Female',
    'cis-female/femme': 'Female',
    'female ': 'Female',
    'woman': 'Female',
    'queer/she/they': 'Other',
    'non-binary': 'Other',
    'male': 'Male',
    'm': 'Male',
    'M': 'Male',
    'Male': 'Male',
    'male ': 'Male',
    'man': 'Male',
    'msle': 'Male',
    'mail': 'Male',
    'mal': 'Male',
    'malr': 'Male',
    'cis male': 'Male',
    'cis man': 'Male',
    'Make': 'Male',
    'Male (CIS)': 'Male',
    'Male-ish': 'Male',
    'maile': 'Male',
    'Male ': 'Male',
    'Guy (-ish) ^_^': 'Male',
    'ostensibly male, unsure what that really means': 'Male',
    'something kinda male?': 'Other',
    'queer': 'Other',
    'p': 'Other',
    'Nah': 'Other',
    'All': 'Other',
    'Enby': 'Other',
    'fluid': 'Other',
    'Genderqueer': 'Other',
    'Androgyne': 'Other',
    'Agender': 'Other',
```

```
    'male leaning androgynous': 'Other',
    'Neuter': 'Other',
    'Female (trans)': 'Other',
    'Trans-female': 'Other',
    'A little about you': 'Other',
    'Trans woman': 'Other',
    'Female (cis)': 'Other',
    'Mail': 'Other'
}

# Applying the mapping to the "Gender" column
final_project_df['Gender'] = final_project_df['Gender'].map(gender_mapping)

# Replacing missing values in the "Gender" column with "Other"
final_project_df['Gender'].fillna('Other', inplace=True)

# Displaying the unique values in the "Gender" column after mapping and handling missing values
print(final_project_df['Gender'].unique())
```

```
Number of rows: 1259
['Female' 'Other' 'Male']
```




```
print(final_project_df['Gender'].head(30))
```

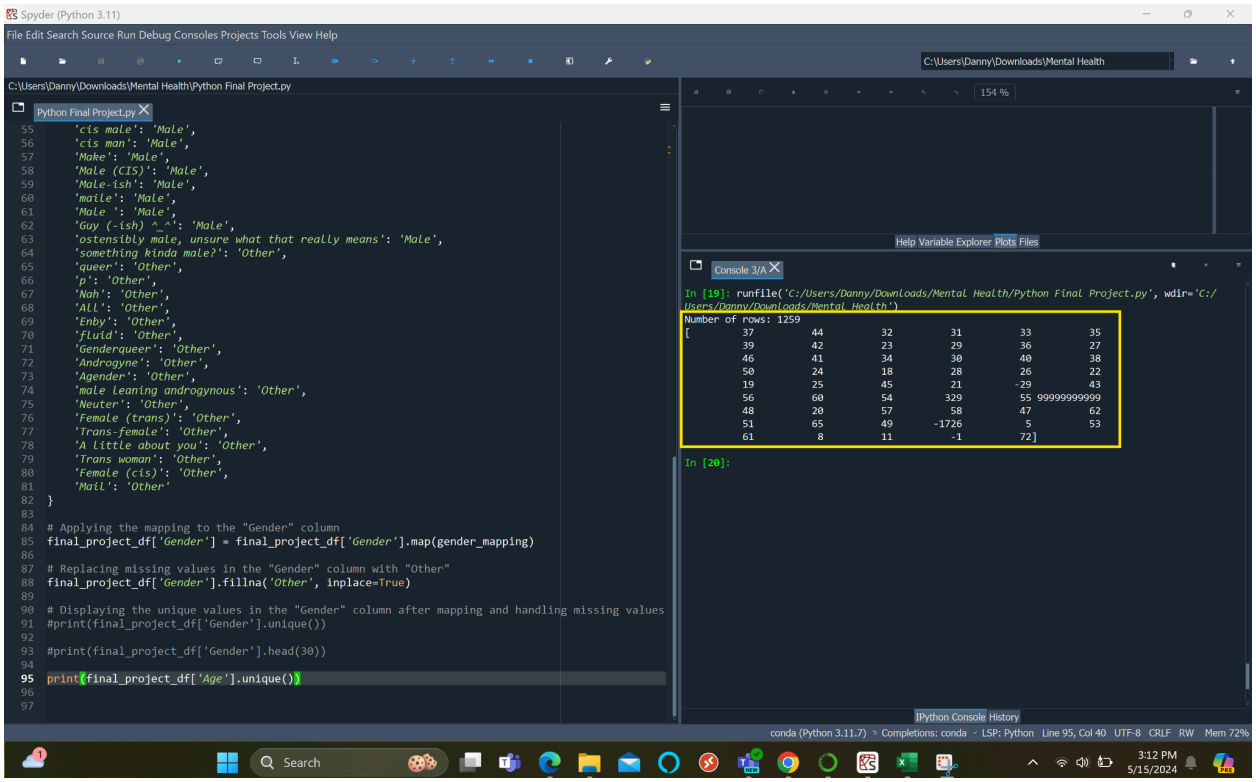
```
0     Female
1       Male
2       Male
3       Male
4       Male
5       Male
6     Female
7       Male
8     Female
9       Male
10      Male
11      Male
12    Female
13      Male
14      Male
15    Female
16      Male
17      Male
18      Male
19      Male
20      Male
21      Male
22      Male
23      Male
24      Male
25      Male
26      Male
27    Female
28      Male
29      Male
Name: Gender, dtype: object
```

3) Removing Missing Values

We are updating the "Age" column to replace any blank entries or implausible numbers. We set the minimum age to 18, as this is the age at which young adults can work without a permit, and the maximum age to 80, since it is unlikely for individuals in their 80s to be employed at a tech firm. Guessing the survey respondent's age introduces a lot of uncertainty. Adding arbitrary numbers would distort the column's descriptive statistics. Therefore, we opted to replace any such values with the average age to maintain the accuracy of the column's statistical representation.

This proved to be beneficial as that maintains as much data integrity as possible. Any other number outside the range we decided upon would not make sense.

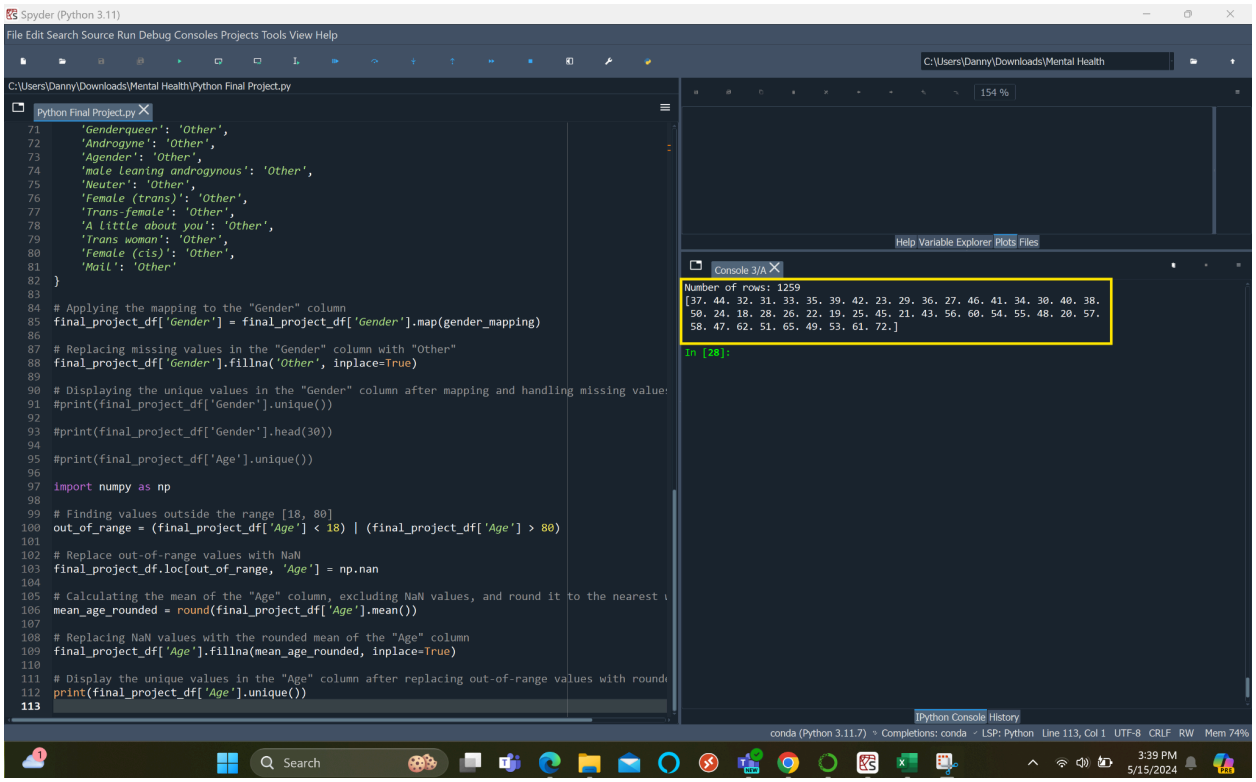
Pre-Data Cleaning:




```
print(final_project_df['Age'].unique())
```

```
Number of rows: 1259
[          37          44          32          31          33          35
           39          42          23          29          36          27
           46          41          34          30          40          38
           50          24          18          28          26          22
           19          25          45          21         -29          43
           56          60          54         329          55 99999999999
           48          20          57          58          47          62
           51          65          49       -1726           5          53
           61           8          11          -1          72]
```

Post-Data Cleaning:




```python
import numpy as np

# Finding values outside the range [18, 80]
out_of_range = (final_project_df['Age'] < 18) | (final_project_df['Age'] > 80)

# Replace out-of-range values with NaN
final_project_df.loc[out_of_range, 'Age'] = np.nan

# Calculating the mean of the "Age" column, excluding NaN values, and round it to the nearest whole number
mean_age_rounded = round(final_project_df['Age'].mean())

# Replacing NaN values with the rounded mean of the "Age" column
final_project_df['Age'].fillna(mean_age_rounded, inplace=True)

# Display the unique values in the "Age" column after replacing out-of-range values with rounded mean
print(final_project_df['Age'].unique())
```

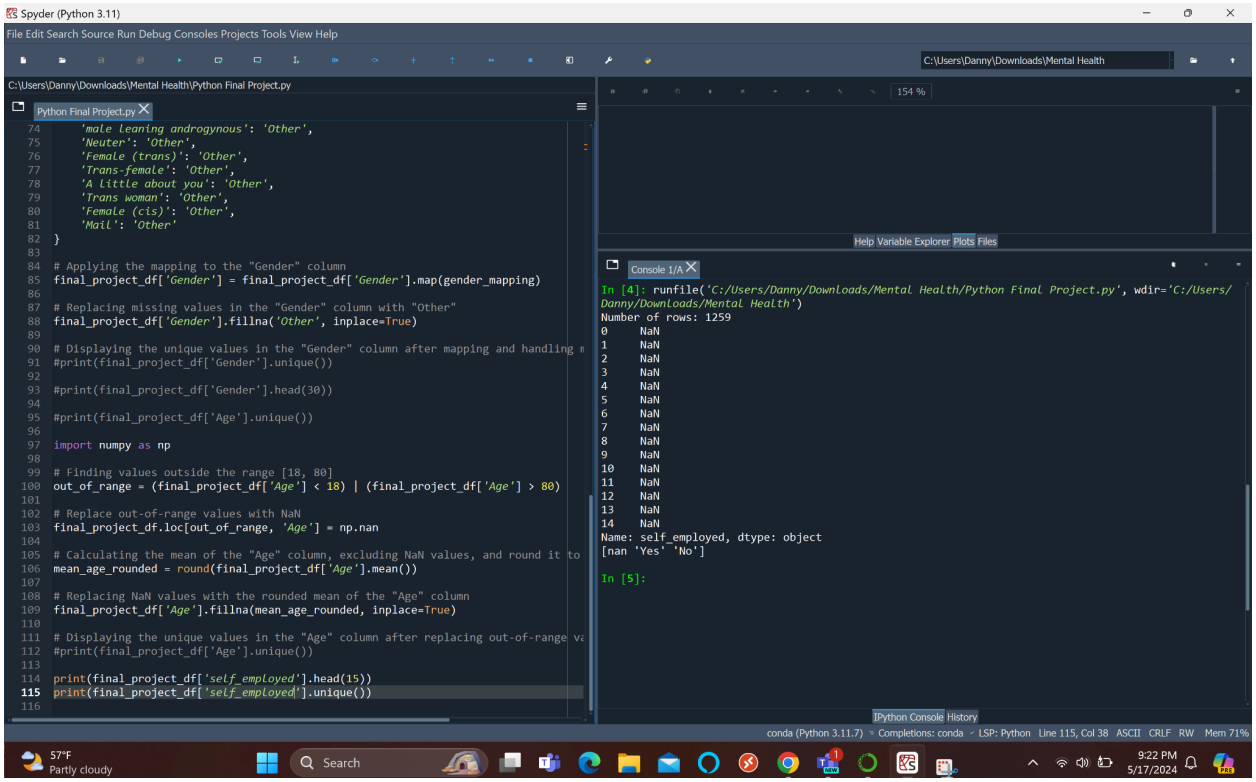
```
Number of rows: 1259
[37. 44. 32. 31. 33. 35. 39. 42. 23. 29. 36. 27. 46. 41. 34. 30. 40. 38.
 50. 24. 18. 28. 26. 22. 19. 25. 45. 21. 43. 56. 60. 54. 55. 48. 20. 57.
 58. 47. 62. 51. 65. 49. 53. 61. 72.]
```

4) Data Transformation

We decided to transform the data for the “self_employed” column so that we could standardize any response that was given for this question into a Yes or No. Responses included N/A in which we reasoned that if the person was self-employed, then they would simply say

“yes” instead of putting N/A. By this logic, we made any N/A to equal no. This is beneficial because we are able to gain more insights and get more counts out of the values we currently have.

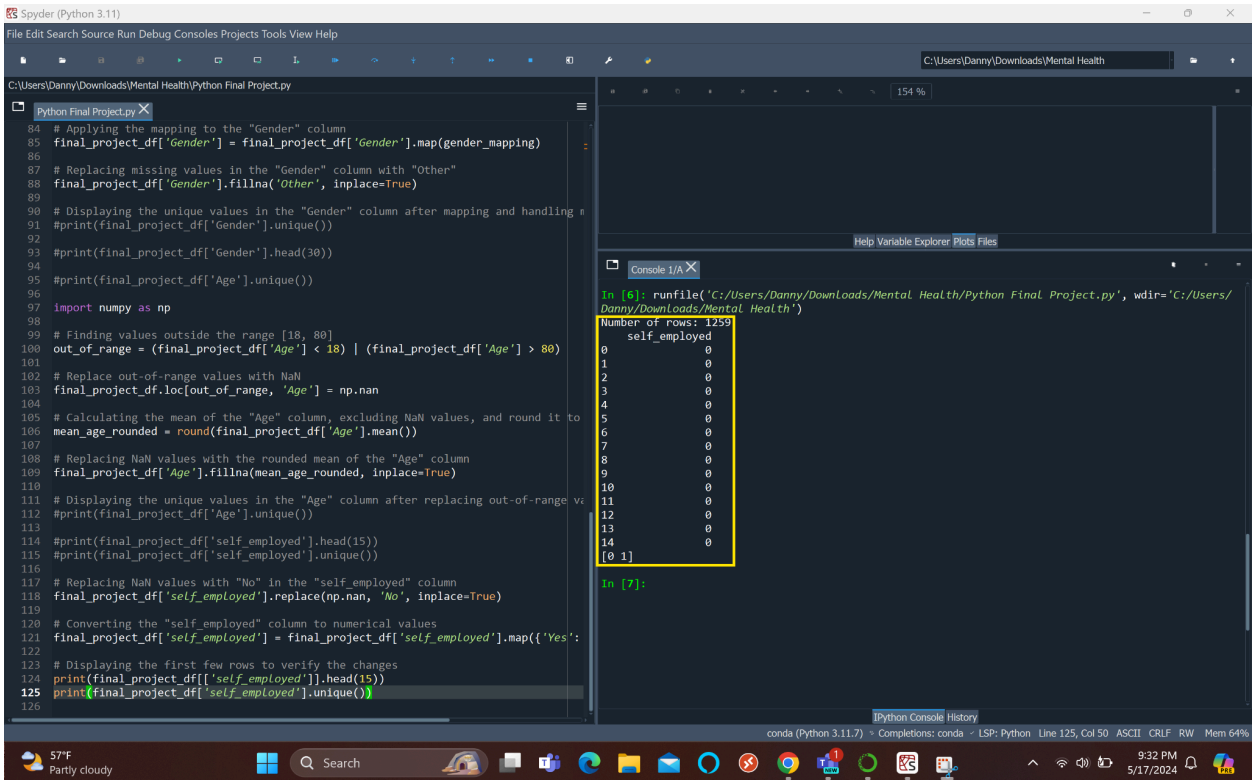
Pre-Data Cleaning:




```
print(final_project_df['self_employed'].head(15))
print(final_project_df['self_employed'].unique())
```

```
Number of rows: 1259
0     NaN
1     NaN
2     NaN
3     NaN
4     NaN
5     NaN
6     NaN
7     NaN
8     NaN
9     NaN
10    NaN
11    NaN
12    NaN
13    NaN
14    NaN
Name: self_employed, dtype: object
[nan 'Yes' 'No']
```

Post-Data Cleaning:

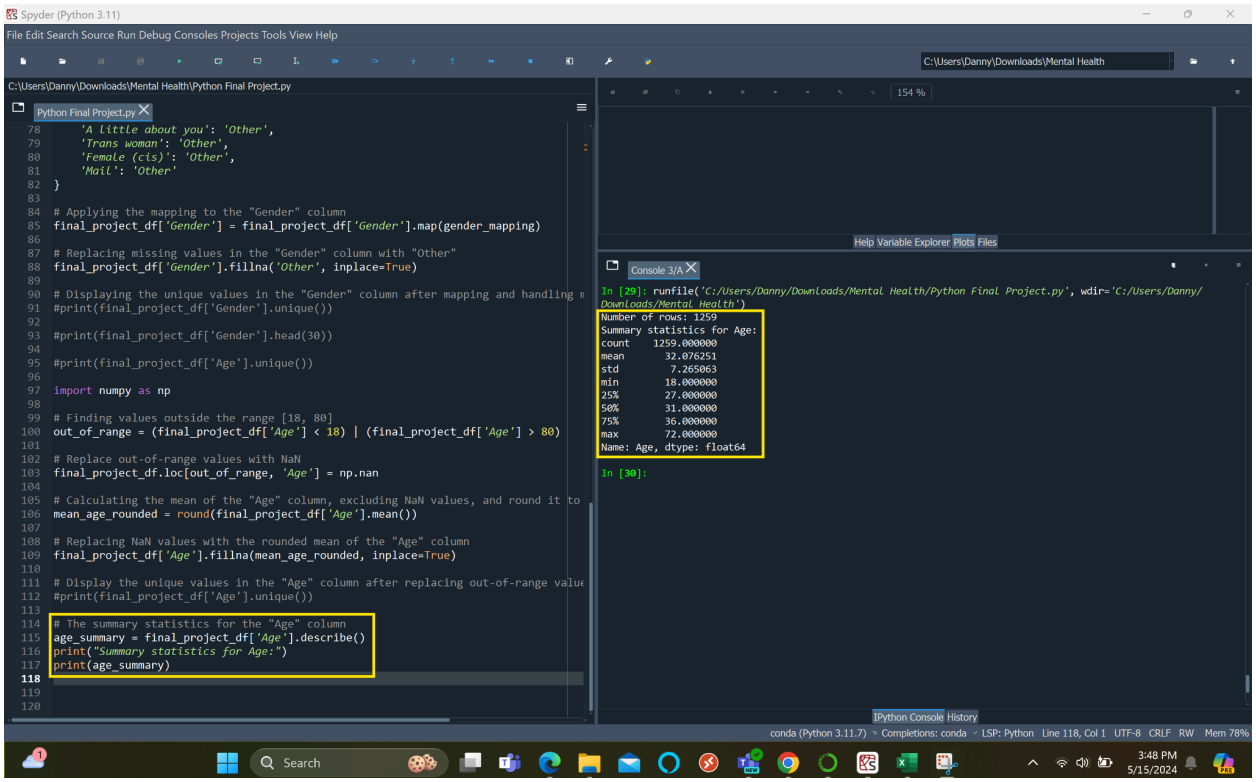



```
# Replacing NaN values with "No" in the "self_employed" column
final_project_df['self_employed'].replace(np.nan, 'No', inplace=True)

# Converting the "self_employed" column to numerical values
final_project_df['self_employed'] = final_project_df['self_employed'].map({'Yes': 1, 'No': 0})

# Displaying the first few rows to verify the changes
print(final_project_df[['self_employed']].head(15))
print(final_project_df['self_employed'].unique())
```

```
Number of rows: 1259
    self_employed
0                0
1                0
2                0
3                0
4                0
5                0
6                0
7                0
8                0
9                0
10               0
11               0
12               0
13               0
14               0
[0 1]
```

Summary Statistics

Statistical Analysis for Age:



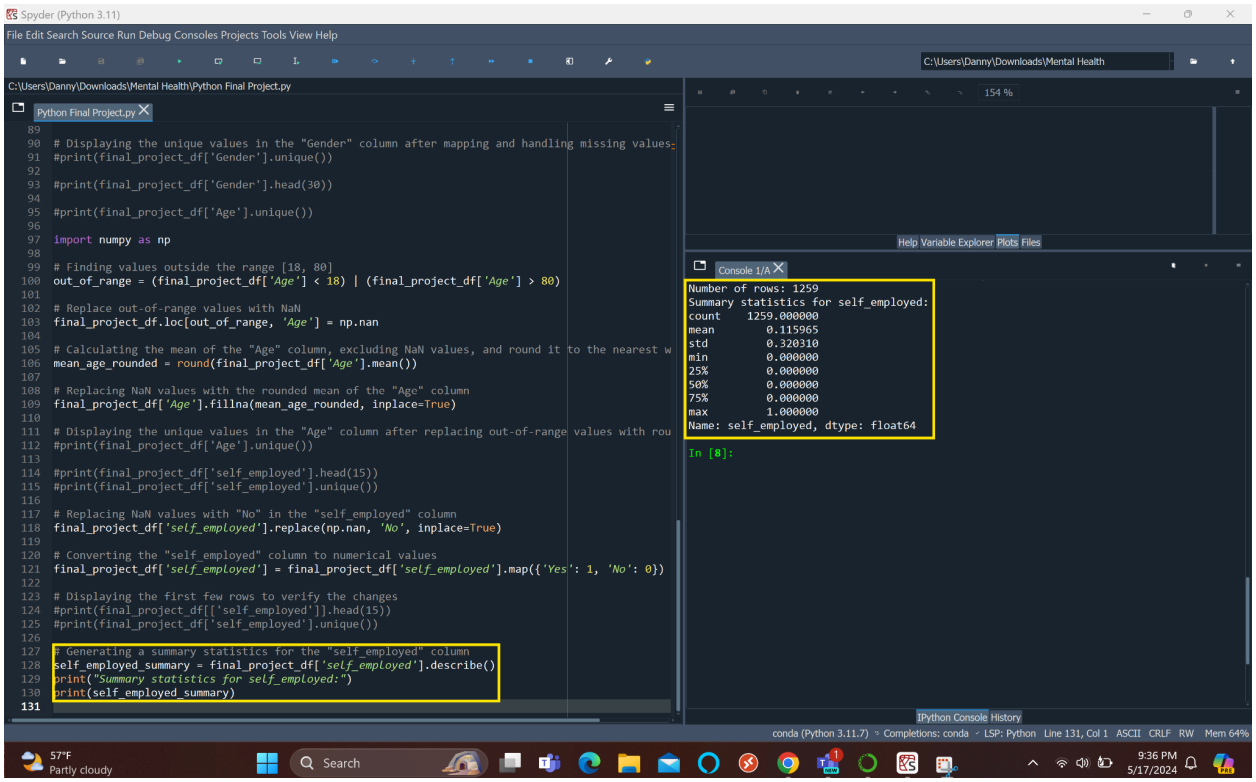

```python
# The summary statistics for the "Age" column
age_summary = final_project_df['Age'].describe()
print("Summary statistics for Age:")
print(age_summary)
```

```
Number of rows: 1259
Summary statistics for Age:
count    1259.000000
mean       32.076251
std         7.265063
min        18.000000
25%        27.000000
50%        31.000000
75%        36.000000
max        72.000000
Name: Age, dtype: float64
```

The summary statistics for the "Age" column show data from 1,259 entries. The statistics that are revealed are the number of observations, minimum, maximum, mode, medium, mean, and standard deviation. The average age is approximately 32.08 years, with a standard deviation of 7.27 years. The ages range from 18 to 72 years, with the 25th percentile at 27 years, the median (50th percentile) at 31 years, and the 75th percentile at 36 years.

Some insights that we were able to discover were that most of the people that the average age of people that are working in tech are about 31 years old.

Statistical Analysis for Self_Employed:

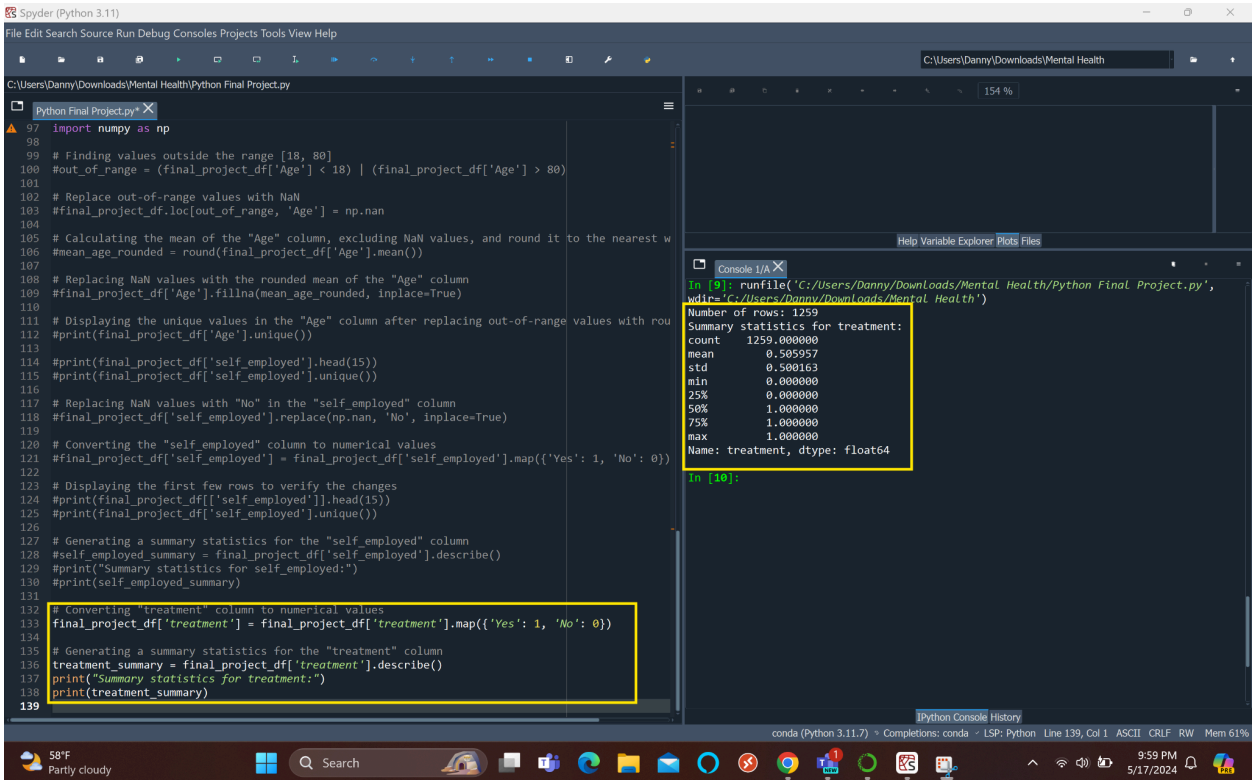



```python
# Generating a summary statistics for the "self_employed" column
self_employed_summary = final_project_df['self_employed'].describe()
print("Summary statistics for self_employed:")
print(self_employed_summary)
```

```
Number of rows: 1259
Summary statistics for self_employed
count    1259.000000
mean        0.115965
std         0.320310
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000
Name: self_employed, dtype: float64
```

The summary statistics for the `self_employed` column reveal that out of 1,259 respondents, the vast majority are not self-employed. This is indicated by the mean value of 0.116, where 1 represents "Yes" for self-employed and 0 represents "No." The data shows a significant skew towards respondents not being self-employed, as reflected by the median (50th percentile) being 0, and the same for the 25th and 75th percentiles. The standard deviation of 0.32 suggests some variation, but the predominant value is 0. The minimum and maximum values are 0 and 1 respectively, reinforcing the nature of this data. Overall, the majority of respondents are not self-employed, with a small proportion indicating self-employment.

Statistical Analysis for Treatment:



```python
# Converting "treatment" column to numerical values
final_project_df['treatment'] = final_project_df['treatment'].map({'Yes': 1, 'No': 0})

# Generating a summary statistics for the "treatment" column
treatment_summary = final_project_df['treatment'].describe()
print("Summary statistics for treatment:")
print(treatment_summary)
```

```
Number of rows: 1259
Summary statistics for treatment:
count    1259.000000
mean        0.505957
std         0.500163
min         0.000000
25%         0.000000
50%         1.000000
75%         1.000000
max         1.000000
Name: treatment, dtype: float64
```

The summary statistics for the treatment column indicate that out of 1,259 respondents, approximately 50.6% have sought treatment for mental health issues, as reflected by the mean value of 0.506. The distribution of responses is fairly balanced, with the standard deviation of 0.500 showing typical variability for the data. The minimum value is 0 (representing "No"), while the maximum value is 1 (representing "Yes"). Notably, the median and the 75th percentile are both 1, suggesting that more than half of the respondents have sought treatment. This indicates a slight skew towards respondents being more likely to seek treatment, highlighting significant mental health treatment engagement within the dataset.

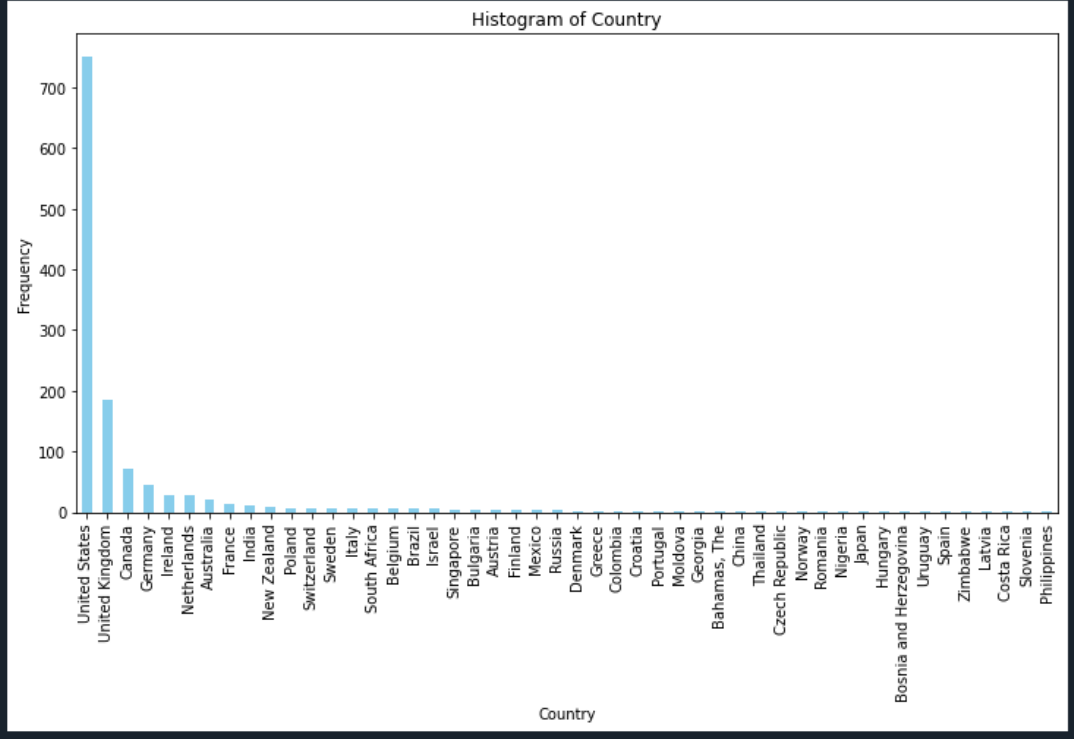
Analysis & Visualizations

Visualization 1:

Which country has the highest frequency in mental health identification all over the world?

```
128
129  # Plot the histogram using Matplotlib
130  plt.figure(figsize=(12, 6))
131  country_counts.plot(kind='bar', color='skyblue')
132  plt.title('Histogram of Country')
133  plt.xlabel('Country')
134  plt.ylabel('Frequency')
135  plt.show()
136
137
```

```
Console 1/A
Name: Age, dtype: float64
```



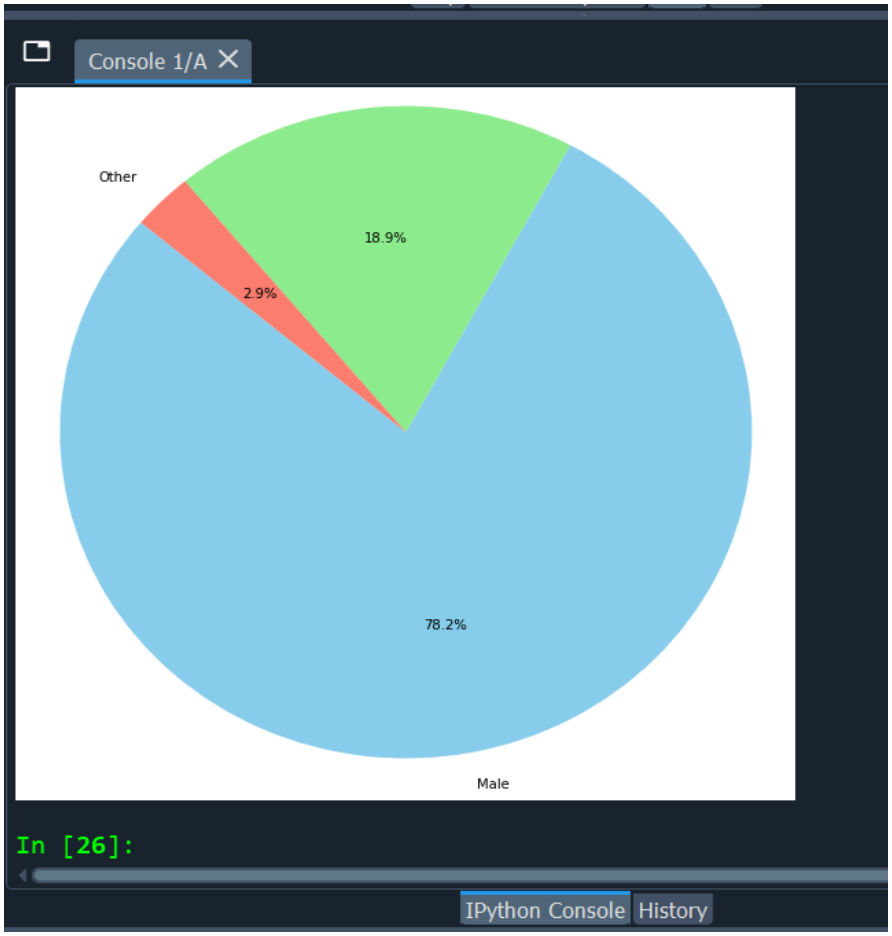

```
In [21]:
```

IPython Console History

The bar chart above represents the distribution of survey respondents across different countries. Each bar in the chart corresponds to a specific country, with the length of the bar indicating the number of respondents from that country. The x-axis displays the countries included in the dataset, while the y-axis represents the count of respondents. The color choice of sky blue provides a visually appealing and easily distinguishable representation of the data. By examining the heights of the bars, we can quickly identify which countries have the highest and lowest numbers of respondents in the survey. The USA is at the top of the list followed by the United Kingdom and Canada. The difference between the responders from the USA and UK is remarkable as the USA is more than 700 and the UK is close to 200.

Visualization 2:
Comparison of mental health issues among genders in Tech.

```
136
137  # Count the occurrences of each gender in the "Gender" column
138  gender_counts = final_project_df['Gender'].value_counts()
139
140  # Plot the pie chart using Matplotlib
141  #plt.figure(figsize=(8, 8))
142  gender_counts.plot(kind='pie', autopct='%1.1f%%', startangle=140, colors=['skyblue', 'lightgreen', 'salmon'])
143  plt.title('Pie Chart of Gender Distribution')
144  plt.ylabel('')  # Remove y-label
145  plt.axis('equal')  # Ensure the pie is drawn as a circle
146  plt.tight_layout()  # Adjust layout
147  #plt.show()
148
```

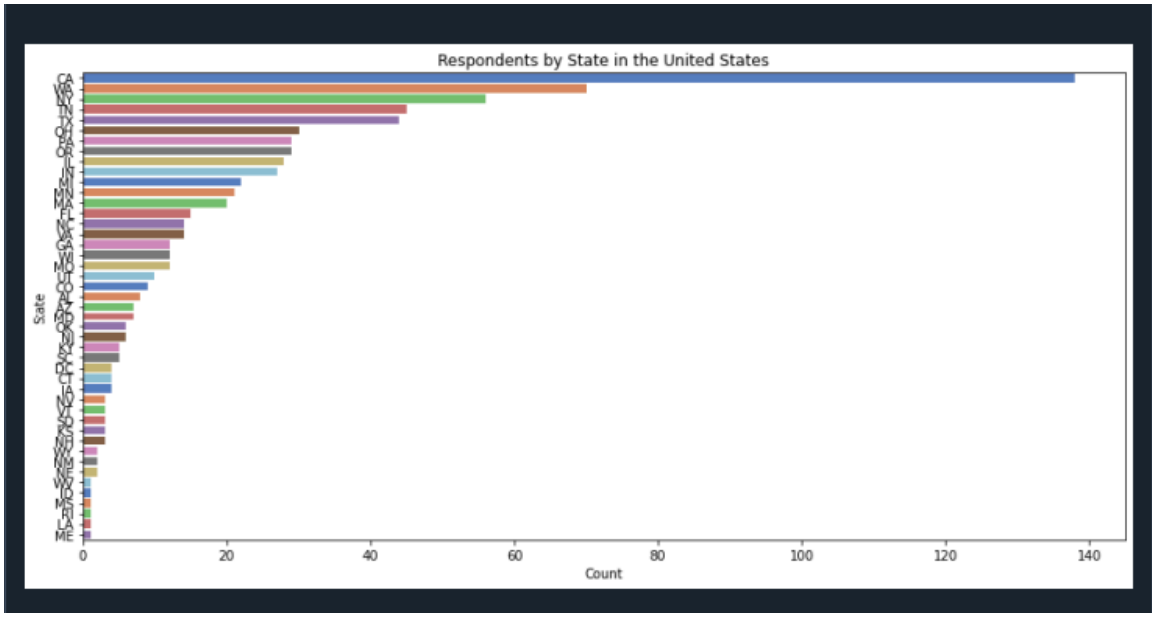


The pie chart illustrates the gender distribution among respondents in our dataset. The majority of respondents were male represented in color blue, comprising 78.2% of the total, followed by female in color green respondents at 18.9%. Additionally, a smaller proportion of respondents identify as non-binary, genderqueer, or other gender identities, making up 2.9%. The predominance of male respondents suggests potential gender biases in survey participation or broader population tally trends, highlighting the importance of inclusive data collection practices. Recognizing and understanding the diversity of gender identities represented in our dataset is essential for promoting inclusivity and ensuring that our analyses and decision-making processes are representative of all voices.

Visualization 3

What are the stats of respondents among states in the dominant country in question 1?

```
149
150  # Filter the data for respondents from the United States
151  us_data = final_project_df[final_project_df['Country'] == 'United States']
152
153  # Count the occurrences of each state in the filtered data
154  state_counts = us_data['state'].value_counts()
155
156  # Plot the bar plot using Seaborn
157  plt.figure(figsize=(12, 6))
158  sns.barplot(x=state_counts.values, y=state_counts.index, palette='muted')
159  plt.title('Respondents by State in the United States')
160  plt.xlabel('Count')
161  plt.ylabel('State')
162  plt.tight_layout()
163  plt.show()
164
```



The bar plot illustrates the distribution of survey respondents across various states in the United States. Each bar represents a specific state, with the length of the bar corresponding to the count of respondents from that state. The most dominant state is California followed by Washington and New York. This visualization provides a clear comparison of respondent distribution across states, allowing for easy identification of states with the highest and lowest

participation rates in the survey. By examining the heights of the bars, we can discern which states contributed the most to the dataset and which states had comparatively lower representation. Additionally, the bar plot enables us to identify any outliers or anomalies in the data, such as states with exceptionally high or low respondent counts, which may warrant further investigation or analysis. Overall, the bar plot offers valuable insights into the geographic distribution of survey respondents, aiding in understanding the regional representation and statistical composition of the dataset.

References

1) *Mental Health Analysis in Tech Workplace - IEOM*, ieomsociety.org/proceedings/2022orlando/495.pdf.
2) Rawal, Jahnvi. "Mental Health in Tech Survey." *Medium*, Medium, 1 Sept. 2022, medium.com/@jahnvirawal/mental-health-in-tech-survey-c059e4db87a2.
3) Uddin, Md Milon, et al. "Mental Health Analysis in Tech Workplace." *IEOM Society*, IEOM Society, 11 June 2022, index.ieomsociety.org/index.cfm/article/view/ID/3684.