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#### DSC630-T302
#### Chitramoy Mukherjee
#### Week-1 Assignment
#### Analyze Mental health disorder in Tech Companies
#### Date: 3/12/2024
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Introduction:

In recent years, the tech industry has experienced rapid growth and innovation, bringing about numerous opportunities and challenges. While technological advancements have transformed the way we work, they have also introduced new stressors that can impact the mental health of individuals working in this sector. Recognizing the importance of mental health in the workplace, this project aims to analyze mental health disorders within tech companies using Python. Mental health affects your emotional, psychological and social well-being. Mental health is a key factor to determine the productivity of the employee in any industry and as a whole total performance of the company. If someone is not mentally fit, he can't produce the expected output what he is capable of and it also impacts his co-workers performance and impacts the work environment.

Objective:

The primary objective of this assignment is to gain insights into the prevalence of mental health disorders among employees in the tech industry. By leveraging Python for data analysis, we aim to explore patterns, trends, and potential factors contributing to mental health issues. The analysis will be based on a dataset collected from surveys conducted within tech companies, covering a range of variables related to mental health. This sort of analysis helps the employer to identify and support an individual who may be experiencing a mental health or substance use concern or crisis and connect them with the appropriate employee resources. This allows employer to recognize the signs of someone who maybe struggling and teaches them the skills to know when to reach out and what resources are available. Organizations that incorporate mental health awareness help to create a healthy and productive work environment that reduces the stigma associated with mental illness, increases the organizations mental health literacy and teaches the skills to safely and responsibly respond to a co-workers mental health concern.

Key questions questions to explore visually with survey.csv data:

Below are the questions we will explore visually using the survey.csv data :

1. How easy is it for the employee to take medical leave for a mental health condition?
2. Does the employee sought treatment for a mental health condition?
3. Does family history of mental illness influences employees current mental health?
4. Does the mental health condition interferes respondents work?
5. How the remote work impacts the mental health?
6. Does your employer provide mental health benefits?

7. willingness of the employee to discuss a mental health issue with coworkers?

```
In [1]: import warnings
warnings.filterwarnings('ignore')

# Required python basic Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import string
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk import download
from nltk.stem import PorterStemmer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
import nltk
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.metrics import accuracy_score


from os.path import basename, exists


def download(url):
    filename = basename(url)
    if not exists(filename):
        from urllib.request import urlretrieve

        local, _ = urlretrieve(url, filename)
        print("Downloaded " + local)

### Reading the LabeledTrainData.tsv file into DataFrame
df = pd.read_csv("C:\\Users\\14024\\OneDrive\\Desktop\\MS-DSC\\DSC-630\\Week1\\LabeledTrainData.tsv")

# Display the first few rows of the DataFrame to ensure it's Loaded properly
print(df)

df.columns
```

	Timestamp	Age	Gender	Country	state	self_employ
0	2014-08-27 11:29:31	37	Female	United States	IL	N
1	2014-08-27 11:29:37	44	M	United States	IN	N
2	2014-08-27 11:29:44	32	Male	Canada	NaN	N
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	N
4	2014-08-27 11:30:22	31	Male	United States	TX	N
...
1254	2015-09-12 11:17:21	26	male	United Kingdom	NaN	
1255	2015-09-26 01:07:35	32	Male	United States	IL	
1256	2015-11-07 12:36:58	34	male	United States	CA	
1257	2015-11-30 21:25:06	46	f	United States	NC	
1258	2016-02-01 23:04:31	25	Male	United States	IL	

	family_history	treatment	work_interfere	no_employees	...
0	No	Yes	Often	6-25	...
1	No	No	Rarely	More than 1000	...
2	No	No	Rarely	6-25	...
3	Yes	Yes	Often	26-100	...
4	No	No	Never	100-500	...
...
1254	No	Yes	NaN	26-100	...
1255	Yes	Yes	Often	26-100	...
1256	Yes	Yes	Sometimes	More than 1000	...
1257	No	No	NaN	100-500	...
1258	Yes	Yes	Sometimes	26-100	...

	leave mental_health_consequence	phys_health_consequen
0	Somewhat easy	No
1	Don't know	Maybe
2	Somewhat difficult	No
3	Somewhat difficult	Yes
4	Don't know	No
...
1254	Somewhat easy	No
1255	Somewhat difficult	No
1256	Somewhat difficult	Yes

```

es
1257          Don't know          Yes
No
1258          Don't know          Maybe
No

```

```

      coworkers  supervisor  mental_health_interview  \
0    Some of them      Yes      No
1           No      No      No
2           Yes      Yes      Yes
3    Some of them      No      Maybe
4    Some of them      Yes      Yes
...
1254  Some of them  Some of them      No
1255  Some of them      Yes      No
1256           No      No      No
1257           No      No      No
1258  Some of them      No      No

```

```

      phys_health_interview  mental_vs_physical  obs_consequence  comments
0           Maybe      Yes      No      NaN
1           No      Don't know      No      NaN
2           Yes      No      No      NaN
3           Maybe      No      Yes      NaN
4           Yes      Don't know      No      NaN
...
1254           No      Don't know      No      NaN
1255           No      Yes      No      NaN
1256           No      No      No      NaN
1257           No      No      No      NaN
1258           No      Don't know      No      NaN

```

```
[1259 rows x 27 columns]
```

```

Out[1]: Index(['Timestamp', 'Age', 'Gender', 'Country', 'state', 'self_employe
d',
      'family_history', 'treatment', 'work_interfere', 'no_employees',
      'remote_work', 'tech_company', 'benefits', 'care_options',
      'wellness_program', 'seek_help', 'anonymity', 'leave',
      'mental_health_consequence', 'phys_health_consequence', 'coworker
s',
      'supervisor', 'mental_health_interview', 'phys_health_interview',
      'mental_vs_physical', 'obs_consequence', 'comments'],
      dtype='object')

```

```
In [2]: # Visualize the data and identify the non-null values
df.info()
```

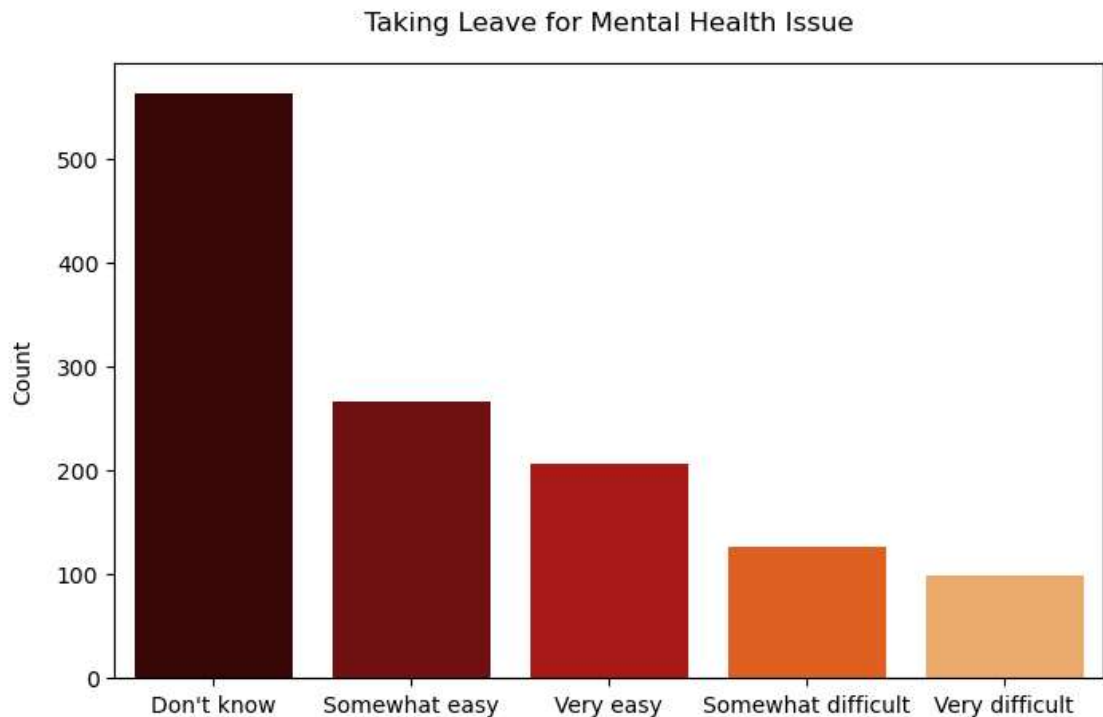
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
 #   Column                                Non-Null Count  Dtype
---  -
 0   Timestamp                            1259 non-null   object
 1   Age                                  1259 non-null   int64
 2   Gender                              1259 non-null   object
 3   Country                             1259 non-null   object
 4   state                               744 non-null    object
 5   self_employed                       1241 non-null   object
 6   family_history                      1259 non-null   object
 7   treatment                           1259 non-null   object
 8   work_interfere                      995 non-null    object
 9   no_employees                        1259 non-null   object
10   remote_work                         1259 non-null   object
11   tech_company                        1259 non-null   object
12   benefits                            1259 non-null   object
13   care_options                       1259 non-null   object
14   wellness_program                   1259 non-null   object
15   seek_help                           1259 non-null   object
16   anonymity                           1259 non-null   object
17   leave                               1259 non-null   object
18   mental_health_consequence          1259 non-null   object
19   phys_health_consequence             1259 non-null   object
20   coworkers                           1259 non-null   object
21   supervisor                          1259 non-null   object
22   mental_health_interview             1259 non-null   object
23   phys_health_interview               1259 non-null   object
24   mental_vs_physical                 1259 non-null   object
25   obs_consequence                    1259 non-null   object
26   comments                            164 non-null    object
dtypes: int64(1), object(26)
memory usage: 265.7+ KB
```

Defination of each field in the dataset.

1. Timestamp : Time of data entry in YYYY-MM-DD HH:MM:SS format.
2. Age : Age of the respondant.
3. Gender : Gender of the respondant.
4. Country : Country of the respondant.
5. state: If you live in the United States, which state or territory do you live in?
6. self_employed: Are you self-employed?
7. family_history: Do you have a family history of mental illness?
8. treatment: Have you sought treatment for a mental health condition?
9. work_interfere: If you have a mental health condition, do you feel that it interferes with your work?
10. no_employees: How many employees does your company or organization have?
11. remote_work: Do you work remotely (outside of an office) at least 50% of the time?
12. tech_company: Is your employer primarily a tech company/organization?

13. benefits: Does your employer provide mental health benefits?
14. care_options: Do you know the options for mental health care your employer provides?
15. wellness_program: Has your employer ever discussed mental health as part of an employee wellness program?
16. seek_help: Does your employer provide resources to learn more about mental health issues and how to seek help?
17. anonymity: Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?
18. leave: How easy is it for you to take medical leave for a mental health condition?
19. mentalhealthconsequence: Do you think that discussing a mental health issue with your employer would have negative consequences?
20. physhealthconsequence: Do you think that discussing a physical health issue with your employer would have negative consequences?
21. coworkers: Would you be willing to discuss a mental health issue with your coworkers?
22. physhealthinterview: Would you bring up a physical health issue with a potential employer in an interview?
23. mentalvsphysical: Do you feel that your employer takes mental health as seriously as physical health?
24. obs_consequence: Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?
25. comments: Any additional notes or comments

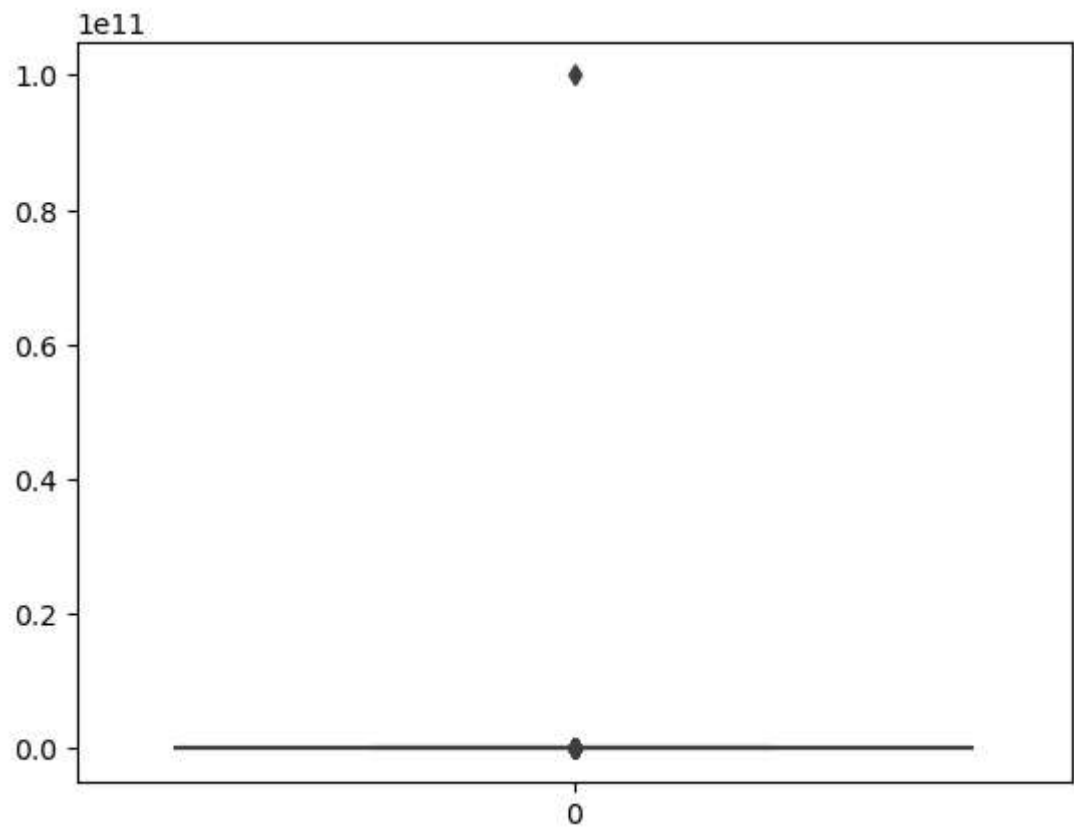
```
In [3]: # Bar diagram plot of how ease to take Leave due to mental health issue  
  
df['leave'].value_counts().index  
plt.figure(figsize=(8,5)) # Size of the figure  
  
# Using value_counts(), we get the count of each answer in descending order  
# we later pass into the order parameter of the countplot, sorting the plot  
order = df['leave'].value_counts().index  
  
plt.title('Taking Leave for Mental Health Issue', pad=15);  
mp = sns.countplot(x='leave', data=df, order=order, palette='gist_heat')  
plt.ylabel('Count', labelpad=10)  
mp.set(xlabel=None);
```



From this we can find that people find it somewhat on a easier side to get a leave sanctioned for mental health reasons because employers feel that mental health demands immense importance than work. The company may sometimes deem to be responsible if its employees health degrades. Hence companies dont take any risks which could be one of the prime reasons.


```
In [15]: ▶ # Create a boxplot from survey.csv data against Age column.
```

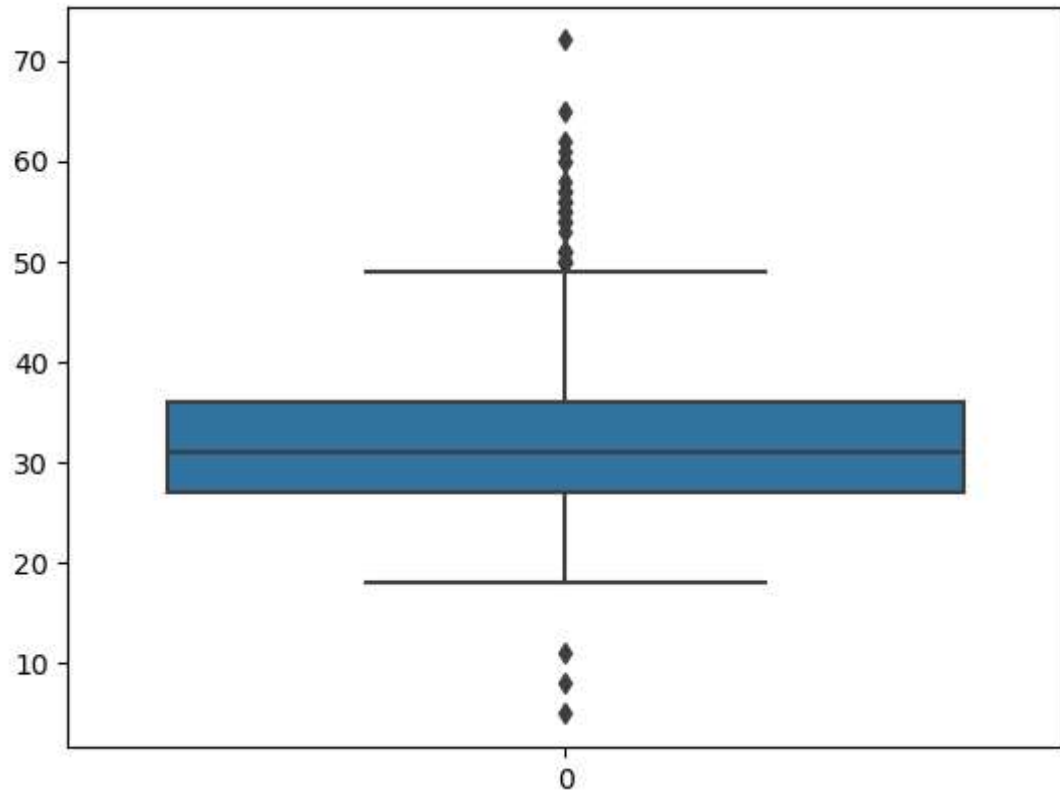
```
sns.boxplot(df['Age'])
```



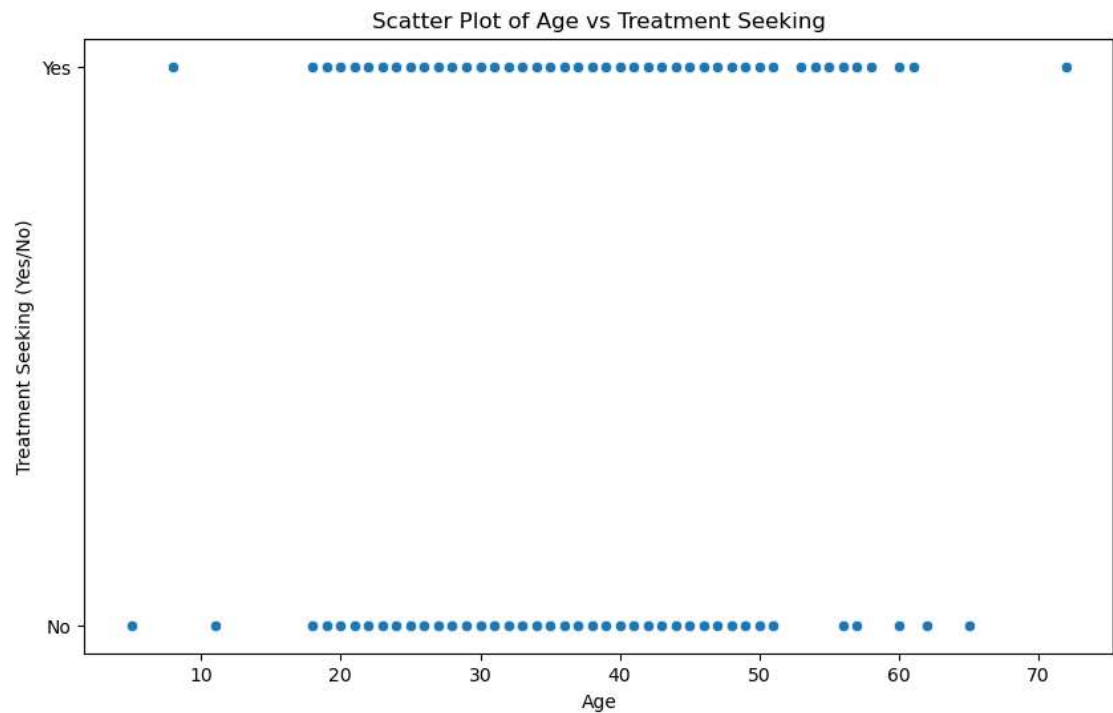
From this we can clearly see that 'Age' column has many outliers.

```
In [20]: # Removing outliers  
df.drop(df[df['Age'] < 0].index, inplace = True)  
df.drop(df[df['Age'] > 100].index, inplace = True)  
  
sns.boxplot(df['Age'])  
  
# This shows us that the median age is around 30 which we have to consider
```

Out[20]: <Axes: >

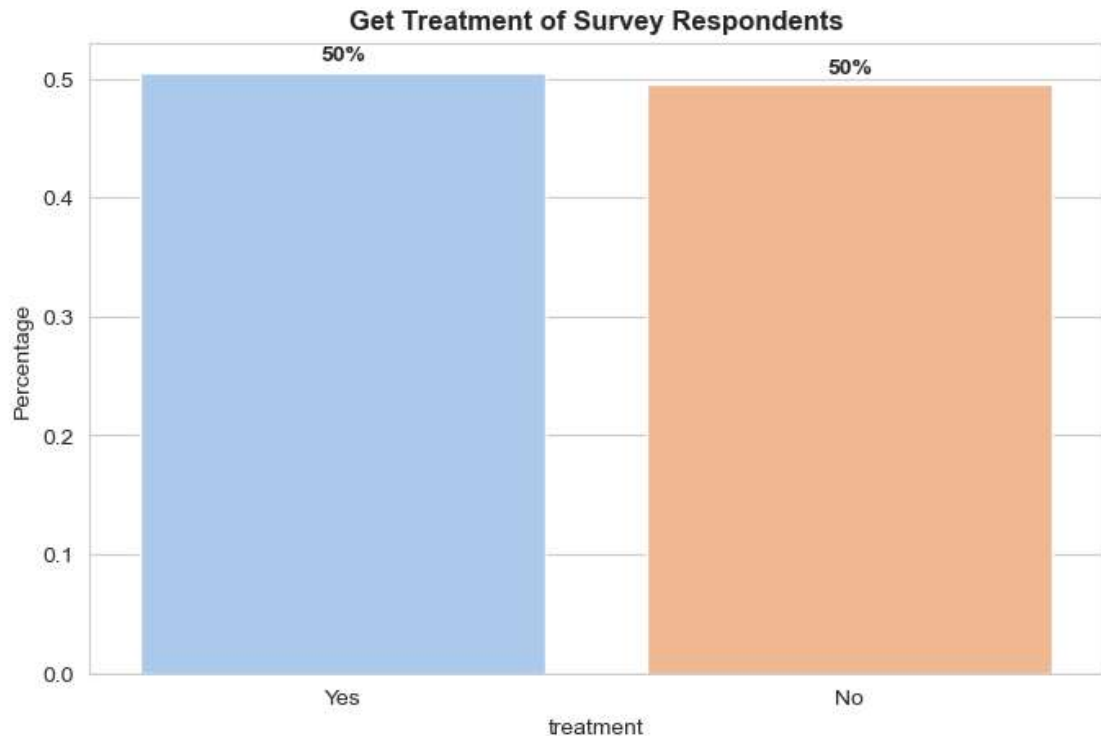


```
In [21]: # create a bivariate plot using Age and tretement column from survey.csv  
# Selecting relevant columns  
relevant_columns = ['Age', 'treatment']  
subset_data = df[relevant_columns]  
  
# Removing any rows with missing values in selected columns  
subset_data = subset_data.dropna()  
  
# Plotting  
plt.figure(figsize=(10, 6))  
sns.scatterplot(x='Age', y='treatment', data=subset_data)  
plt.title('Scatter Plot of Age vs Treatment Seeking')  
plt.xlabel('Age')  
plt.ylabel('Treatment Seeking (Yes/No)')  
plt.show()  
  
# This code creates a scatter plot with age on the x-axis and treatment se  
# Each point in the plot represents a respondent's age and whether they so
```



```
In [43]: ▶ # Bar diagram to analyze how easy for employee sought treatment for a ment
sns.set_style("whitegrid")
plt.figure(figsize = (8,5))
plt.title('Get Treatment of Survey Respondents', fontsize=12, fontweight='
eda_percentage = df['treatment'].value_counts(normalize = True).rename_axi

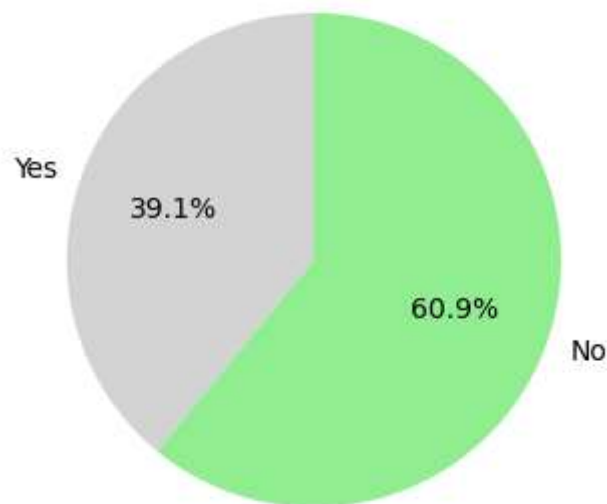
ax = sns.barplot(x = 'treatment', y = 'Percentage', data = eda_percentage.
for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='cente
```



Above plotting shows that the percentage of respondents who want to get treatment is exactly 50%. Workplaces that promote mental health and support people with mental disorders are more likely to have increased productivity, reduce absenteeism, and benefit from associated economic gains.

```
In [12]: ▶ # Pie diagram to analyze family history of mental illness influences empl  
yes = len(df[df['family_history'] == 'Yes'])  
no = len(df[df['family_history'] == 'No'])  
  
count = [yes, no]  
labels = ['Yes', 'No']  
colors = ['lightgrey', 'lightgreen']  
  
# Customizing the pie chart  
plt.figure(figsize=(8,4))  
explode = (0, 1, 1) # Only the second slice will explode  
pc = plt.pie(count, labels=labels, autopct='%1.1f%%', startangle=90, color  
plt.title('Family History of Mental Illness');
```

Family History of Mental Illness



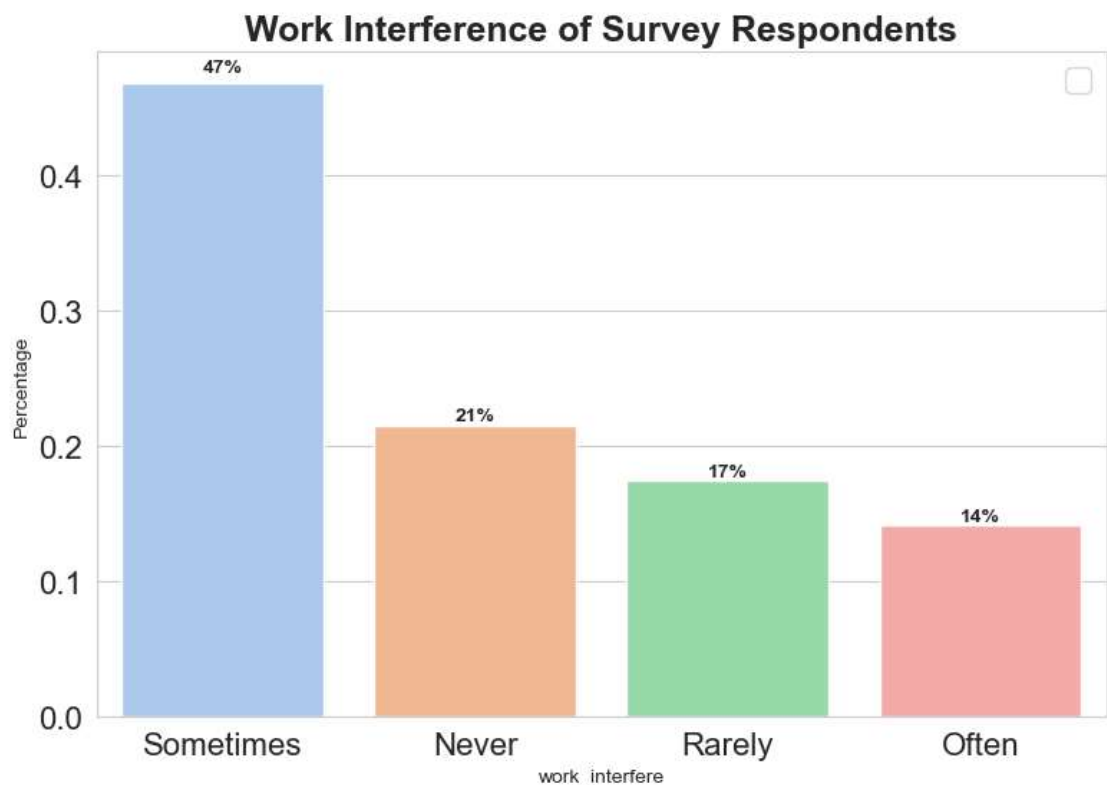
From the above plot, we can see that most respondents do not know whether they are even allowed to take leave for a mental health issue, and there are also quite a number who find it hard to do so, which may be due to the social stigma surrounding mental issues.

```
In [44]: ▶ plt.figure(figsize = (20,6))
plt.subplot(1,2,1)
eda_percentage = df['work_interfere'].value_counts(normalize = True).rename
ax = sns.barplot(x = 'work_interfere', y = 'Percentage', data = eda_perce
for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='center

plt.title('Work Interference of Survey Respondents', fontsize=18, fontweig
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)
```

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.

Out[44]: <matplotlib.legend.Legend at 0x232b887da50>



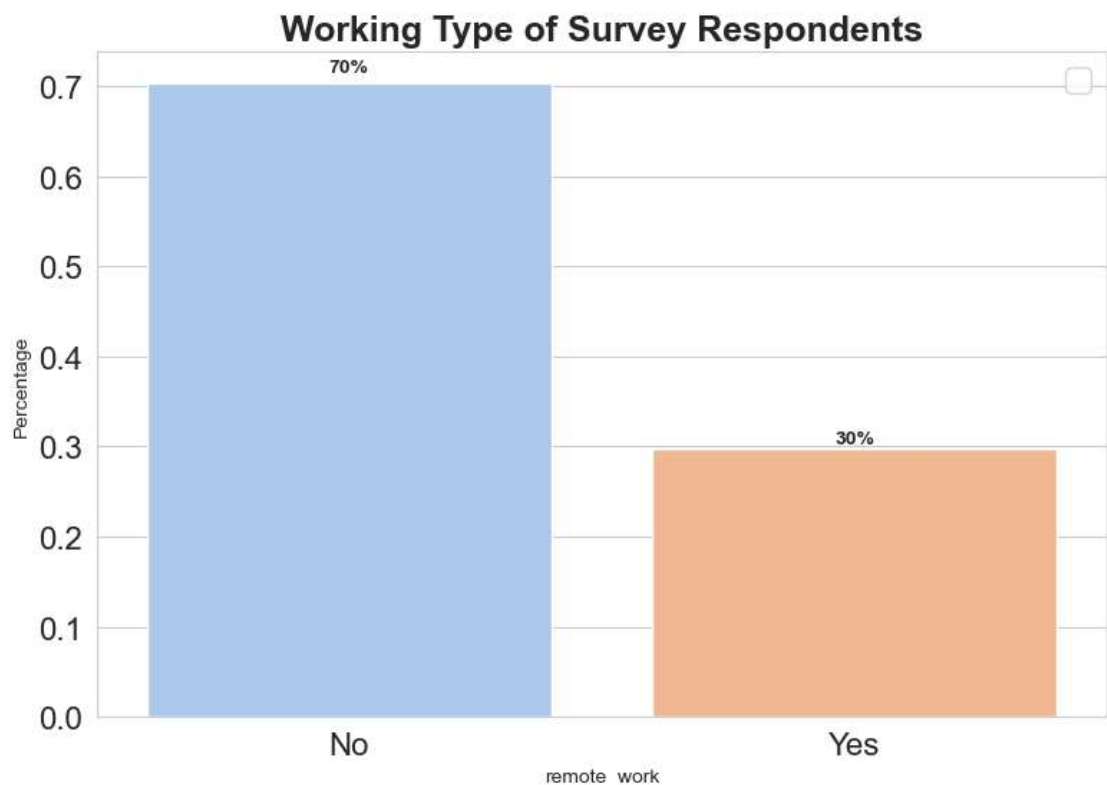
On seeing the graph we can conclude that around 47% of people say that sometimes work interferes with their mental health. Now 'Sometimes' is a really vague response to a question, and more often than not these are the people who actually face a condition but are too shy/reluctant to choose the extreme category.

```
In [45]: ▶ plt.figure(figsize = (20,6))
plt.subplot(1,2,1)
eda_percentage = df['remote_work'].value_counts(normalize = True).rename_axis('remote_work')
ax = sns.barplot(x = 'remote_work', y = 'Percentage', data = eda_percentage)
for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='center')

plt.title('Working Type of Survey Respondents', fontsize=18, fontweight='bold')
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)
```

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.

Out[45]: <matplotlib.legend.Legend at 0x232ba59da10>



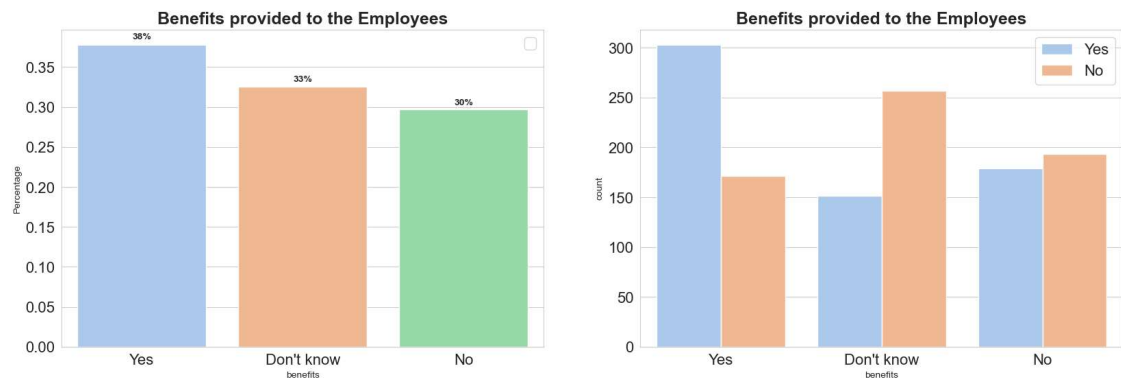
Around 70% of respondents don't work remotely, which means the biggest factor of mental health disorder came up triggered on the workplace.

```
In [46]: ▶ # Bar plot of benefits provided to the employees
plt.figure(figsize = (20,6))
plt.subplot(1,2,1)
eda_percentage = df['benefits'].value_counts(normalize = True).rename_axis
ax = sns.barplot(x = 'benefits', y = 'Percentage', data = eda_percentage,
for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='center')

plt.title('Benefits provided to the Employees', fontsize=18, fontweight='bold')
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)

plt.subplot(1,2,2)
sns.countplot(x=df['benefits'], data = eda_percentage, hue = df['treatment'])
plt.title('Benefits provided to the Employees', fontsize=18, fontweight='bold')
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)
plt.show()
```

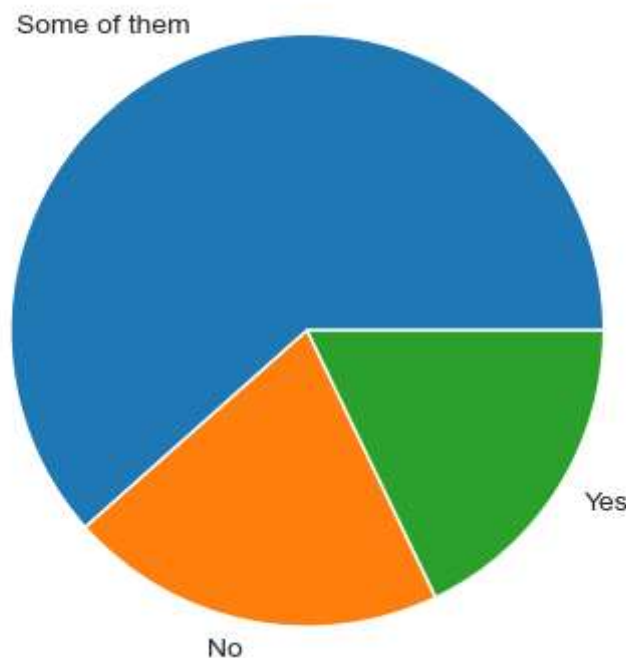
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



We see that around 38% of the respondents said that their employer provided them mental health benefits, whereas a significant number (32%) of them didn't even know whether they were provided this benefit. Coming to the second graph, we see that for the people who YES said to mental health benefits, around 63% of them said that they were seeking medical help. Surprisingly, the people who said NO for the mental health benefits provided by the company, close to 45% of them who want to seek mental health treatment.


```
In [39]: ▶ #pie plot tow show the willingness to discuss a mental health issue with c
plt.pie(df['coworkers'].value_counts(),labels=df['coworkers'].unique())
df['coworkers'].value_counts()
```

```
Out[39]: coworkers
Some of them    772
No              258
Yes            224
Name: count, dtype: int64
```



So people prefer to share about their mental health with only some of their coworkers or sometimes dont even want to share sometimes because there may be coworkers who would just empathize and demotivate even more.

Conclusion :

From the above plotting we can conclude the below observations.

1. Cases show that more than 50% of people surveyed in countries like US,Australia and Canada undergo treatment for mental ailments.
2. People who are in the early 30's usually undergo treatment but there are extreme cases like 8 years and 72 years people recieving the same treatment.
3. It is interesting to find that people face mental trauma regardless of whether they are self employed or not.
4. People feel that sharing about their mental or physical health with employers would help them a bit but they are reluctant to share the same with their coworkers.They would prefer to share with only some of the coworkers.
5. The surveyed people agree that their mental health somewhat affects their productivity at work.

6. People feel that their employers somewhat easily sanction leave for mental health issues. The reason maybe that the employer does not want to take any risk of overloading the patient with work.
7. People dont know whether the employer considers mental health issues as seriously as the physical ones. The ambiguity still remains about people's reaction towards mental health.

References :

1. Kaggle : For source dataset.
2. matplotlib.org : For python plot basics understanding.