DSC550-T301
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Final Project Milestone-1
Analyze Mental health disorder in Tech Companies
Date: 1/14/2023

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 todetermine 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 project 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 Components:

1. **Data Collection:**
   - Gather a comprehensive dataset from tech companies, including information on employee demographics, work-related factors, and self-reported mental health conditions.
2. **Data understanding and Preprocessing:**
   - Clean and preprocess the dataset to handle missing values, outliers, and ensure data quality. Transform categorical variables and standardize formats for analysis.
3. **Exploratory Data Analysis (EDA):**
   - Utilize Python libraries such as Pandas, Matplotlib, and Seaborn to conduct exploratory data analysis. Visualize distributions, correlations, and trends in mental health-related variables.
4. **Statistical Analysis:**
   - Apply statistical methods to identify significant factors influencing mental health disorders. Conduct hypothesis testing and regression analysis to establish relationships.
5. **Machine Learning Modeling:**
   - Develop machine learning models to predict the likelihood of mental health disorders based on relevant features. Evaluate model performance and interpret results.
6. **Recommendations and Insights:**
   - Provide actionable insights and recommendations for tech companies to improve mental health support for their employees.

Key benefits from the outcome of the project:

By the end of this project, we aim to contribute valuable insights that can inform both employers and employees about mental health in the tech industry. This analysis can serve as a foundation for fostering a healthier and more supportive work environment both from employee and employer perspective. Employers can also offer robust benefit packages to support employees who go through mental health issues. That includes Employee Assistance Programs, Wellness programs that focus on mental and physical health, Health and Disability Insurance or flexible working schedules or time off policies.

Below are the key benefits of this analysis from Employer and Employee perspective :

1. Employee Well-being and Productivity.
2. Reduced Healthcare Costs.
3. Enhanced Employee Morale.
4. Legal Compliance and Corporate Responsibility.
5. Customized Support Programs.
6. Employee Engagement and Satisfaction Surveys.
7. Workplace Culture Improvement.

This topic is relevant to data science as we can analyze and identify the factors/variables that impacts the mental health and justify the relations between variables which is closely related to determine the mental health of employees.We can create a model and feed data into it to identify the employees mental health in the company and provide directions to them to overcome the situation.

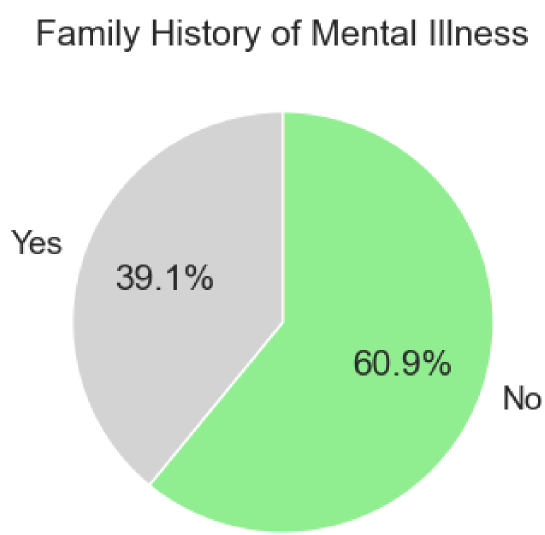
In [89]:

```
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 sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier




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-550\Week-6\\survey.csv")

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

df.columns
```

```
                Timestamp  Age  Gender         Country state self_employed  \
0     2014-08-27 11:29:31   37  Female   United States    IL           NaN   
1     2014-08-27 11:29:37   44       M   United States    IN           NaN   
2     2014-08-27 11:29:44   32    Male          Canada   NaN           NaN   
3     2014-08-27 11:29:46   31    Male  United Kingdom   NaN           NaN   
4     2014-08-27 11:30:22   31    Male   United States    TX           NaN   
...                   ...  ...     ...             ...   ...           ...   
1254  2015-09-12 11:17:21   26    male  United Kingdom   NaN            No   
1255  2015-09-26 01:07:35   32    Male   United States    IL            No   
1256  2015-11-07 12:36:58   34    male   United States    CA            No   
1257  2015-11-30 21:25:06   46       f   United States    NC            No   
1258  2016-02-01 23:04:31   25    Male   United States    IL            No   

     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_consequence  \
0          Somewhat easy                        No                      No   
1             Don't know                     Maybe                      No   
2     Somewhat difficult                        No                      No   
3     Somewhat difficult                       Yes                     Yes   
4             Don't know                        No                      No   
...                  ...                       ...                     ...   
1254       Somewhat easy                        No                      No   
1255  Somewhat difficult                        No                      No   
1256  Somewhat difficult                       Yes                     Yes   
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[89]:
```
Index(['Timestamp', 'Age', 'Gender', 'Country', 'state', 'self_employed',
       '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', 'coworkers',
       'supervisor', 'mental_health_interview', 'phys_health_interview',
       'mental_vs_physical', 'obs_consequence', 'comments'],
      dtype='object')
```

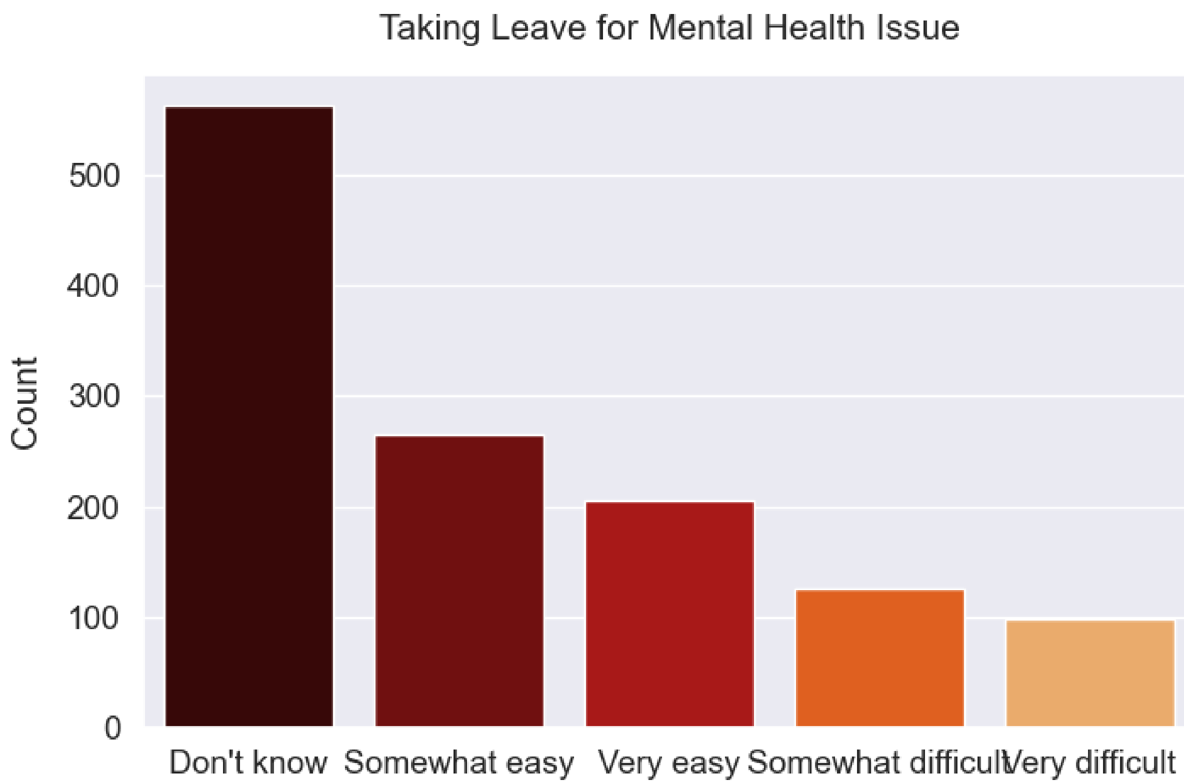
In [91]:
```
# Pie diagram of Family History of Mental illness
yes = len(df[df['family_history'] == 'Yes'])
no = len(df[df['family_history'] == 'No'])

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, colors=colors)
plt.title('Family History of Mental Illness');
```



From this, we can see that almost 40% of respondents have a family history of mental illness. According to a 2017 study by the Arctic University of Norway, it was discovered that children with parents who had a severe mental illness had up to a 50% chance of developing a mental illness, and a 32% chance of developing a severe mental illness (bipolar disorder, major depressive disorder, schizophrenia, etc). We will look further into this when performing bivariate analysis.

In [92]:

```
# 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 then use .inde
# we later pass into the order parameter of the countplot, sorting the plot in descending orde
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);
```

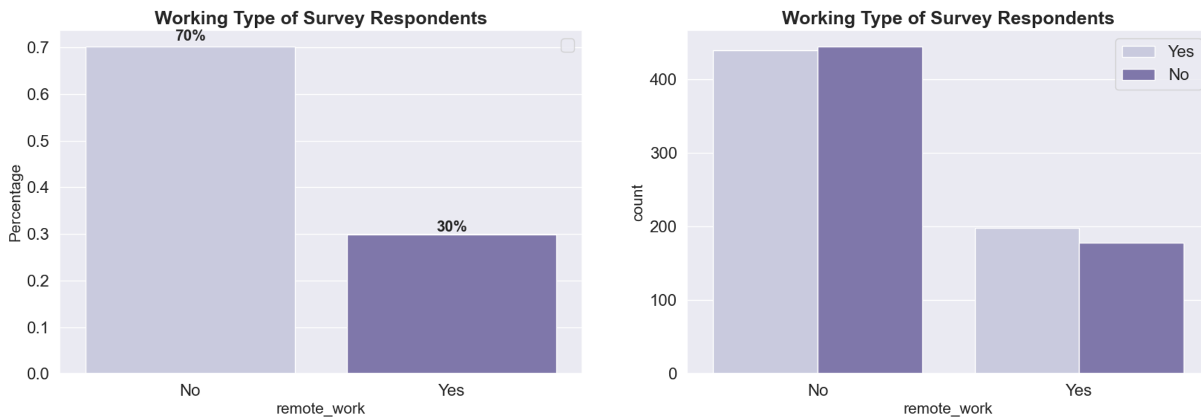


From the above plot, we can see that most respondents do not know whether they are even allowed to take leave for a mental health issue, and there are also quite a number who find it hard to do so, which may be due to the social stigma surrounding mental issues.

In [93]:

```
# Bar diagram plot of Working Type of Survey respondents
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, palette='Purples
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', fontweight='bol

plt.title('Working Type of Survey Respondents', 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['remote_work'], data = eda_percentage,  hue = df['treatment'], palette='Pu
plt.title('Working Type of Survey Respondents', 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.
```

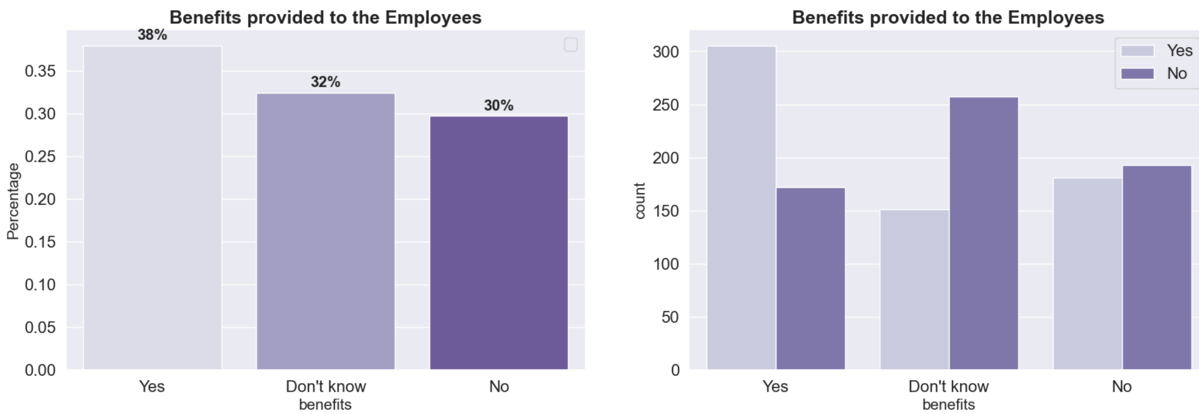


Around 70% of respondents don't work remotely, which means the biggest factor of mental health disorder came up triggered on the workplace. On the other side, it has slightly different between an employee that want to get treatment and don't want to get a treatment. The number of people who seek treatment in both the categories is more or less similar and it does not affect our target variable.

In [94]:

```
# 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('benefits').reset_
ax = sns.barplot(x = 'benefits', y = 'Percentage', data = eda_percentage, palette='Purples')
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', fontweight='bol

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'], palette='Purpl
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.

Final Project Milestone-2
Date: 1/31/2023

Drop any features that are not useful for your model building and explain why they are not useful.

In [95]:

```
# 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
```

In [96]:

```
#missing data
total = df.isnull().sum().sort_values(ascending=False)
percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
print(missing_data)
```

```
                           Total   Percent
comments                    1095  0.869738
state                        515  0.409055
work_interfere               264  0.209690
self_employed                 18  0.014297
seek_help                      0  0.000000
obs_consequence                0  0.000000
mental_vs_physical             0  0.000000
phys_health_interview          0  0.000000
mental_health_interview        0  0.000000
supervisor                     0  0.000000
coworkers                      0  0.000000
phys_health_consequence        0  0.000000
mental_health_consequence      0  0.000000
leave                          0  0.000000
anonymity                      0  0.000000
Timestamp                      0  0.000000
wellness_program               0  0.000000
Age                            0  0.000000
benefits                       0  0.000000
tech_company                   0  0.000000
remote_work                    0  0.000000
no_employees                   0  0.000000
treatment                      0  0.000000
family_history                 0  0.000000
Country                        0  0.000000
Gender                         0  0.000000
care_options                   0  0.000000
```

```
Justification for the features dropped which might not be useful for model building.

Timestamp: This column might not provide useful information for predicting mental health issues.
The timestamp is usually used for tracking when the survey was taken, which is not relevant for
the analysis.

Comments: This column is likely to contain free-form text responses, which can be challenging to
process and analyze. For simplicity and to focus on structured data, it's common to exclude
text-based features. Also as per the data 1095 outof 1258 rows is Null. So this won't be useful
for model.

State: If the dataset is not specifically focused on regional analysis, the state column may not
be relevant for predicting mental health outcomes. It could be dropped unless there's a specific
reason to consider geographical location.Also 515 records are null out of 1258 rows.
```

In [97]:

```
#dealing with missing data
#Let’s get rid of the variables "Timestamp",“comments”, “state” just to make our lives easier
train_df = df.drop(['comments'], axis= 1)
train_df = df.drop(['state'], axis= 1)
train_df = df.drop(['Timestamp'], axis= 1)

train_df.isnull().sum().max() #just checking that there's no missing data missing...
train_df.head(5)
```

Out[97]:

	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfere	no_employees	remote_wo
0	37	Female	United States	IL	NaN	No	Yes	Often	6-25	
1	44	M	United States	IN	NaN	No	No	Rarely	More than 1000	
2	32	Male	Canada	NaN	NaN	No	No	Rarely	6-25	
3	31	Male	United Kingdom	NaN	NaN	Yes	Yes	Often	26-100	
4	31	Male	United States	TX	NaN	No	No	Never	100-500	Y

5 rows × 26 columns

Deal with missing data

In [98]:

```
# Assign default values for each data type
defaultInt = 0
defaultString = 'NaN'
defaultFloat = 0.0

# Create lists by data tpe
intFeatures = ['Age']
stringFeatures = ['Gender', 'Country', 'self_employed', 'family_history', 'treatment', 'work_
                 'no_employees', 'remote_work', 'tech_company', 'anonymity', 'leave', 'mental_
                 'phys_health_consequence', 'coworkers', 'supervisor', 'mental_health_intervi
                 'mental_vs_physical', 'obs_consequence', 'benefits', 'care_options', 'wellne
                 'seek_help']
floatFeatures = []

# Clean the NaN's
for feature in train_df:
    if feature in intFeatures:
        train_df[feature] = train_df[feature].fillna(defaultInt)
    elif feature in stringFeatures:
        train_df[feature] = train_df[feature].fillna(defaultString)
    elif feature in floatFeatures:
        train_df[feature] = train_df[feature].fillna(defaultFloat)
    else:
        print('Error: Feature %s not recognized.' % feature)
train_df.head(5)
```

```
Error: Feature state not recognized.
Error: Feature comments not recognized.
```

Out[98]:

	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfere	no_employees	remote_wo
0	37	Female	United States	IL	NaN	No	Yes	Often	6-25	
1	44	M	United States	IN	NaN	No	No	Rarely	More than 1000	
2	32	Male	Canada	NaN	NaN	No	No	Rarely	6-25	
3	31	Male	United Kingdom	NaN	NaN	Yes	Yes	Often	26-100	
4	31	Male	United States	TX	NaN	No	No	Never	100-500	Y

5 rows × 26 columns

In [99]:
```
#missing data
total = train_df.isnull().sum().sort_values(ascending=False)
percent = (train_df.isnull().sum()/train_df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
print(missing_data)
```

```
                           Total   Percent
comments                    1095  0.869738
state                        515  0.409055
seek_help                      0  0.000000
obs_consequence                0  0.000000
mental_vs_physical             0  0.000000
phys_health_interview          0  0.000000
mental_health_interview        0  0.000000
supervisor                     0  0.000000
coworkers                      0  0.000000
phys_health_consequence        0  0.000000
mental_health_consequence      0  0.000000
leave                          0  0.000000
anonymity                      0  0.000000
Age                            0  0.000000
Gender                         0  0.000000
care_options                   0  0.000000
benefits                       0  0.000000
tech_company                   0  0.000000
remote_work                    0  0.000000
no_employees                   0  0.000000
work_interfere                 0  0.000000
treatment                      0  0.000000
family_history                 0  0.000000
self_employed                  0  0.000000
Country                        0  0.000000
wellness_program               0  0.000000
```

Perform any data extraction/selection steps and Transform features if necessary.

In [100]:

```
# Selecting specific columns of interest
selected_columns = ['Age', 'Gender', 'Country', 'family_history', 'treatment', 'work_interfer

# Creating a new DataFrame with only the selected columns
selected_df = df[selected_columns]

# Filtering data based on a condition (for example, selecting respondents from the United Sta
filtered_df_us = selected_df[selected_df['Country'] == 'United States']

# Filtering data based on another condition (for example, selecting respondents with a family
filtered_df_family_history = selected_df[selected_df['family_history'] == 'Yes']

# Displaying the first few rows of the selected and filtered DataFrames
print("Selected DataFrame:")
print(selected_df.head())

print("\nFiltered DataFrame (United States):")
print(filtered_df_us.head())

print("\nFiltered DataFrame (Family History):")
print(filtered_df_family_history.head())
```

```
Selected DataFrame:
   Age  Gender         Country family_history treatment work_interfere  \
0   37  Female   United States             No       Yes          Often
1   44       M   United States             No        No         Rarely
2   32    Male          Canada             No        No         Rarely
3   31    Male  United Kingdom            Yes       Yes          Often
4   31    Male   United States             No        No          Never

     no_employees
0            6-25
1  More than 1000
2            6-25
3          26-100
4         100-500

Filtered DataFrame (United States):
   Age  Gender        Country family_history treatment work_interfere  \
0   37  Female  United States             No       Yes          Often
1   44       M  United States             No        No         Rarely
4   31    Male  United States             No        No          Never
5   33    Male  United States            Yes        No      Sometimes
6   35  Female  United States            Yes       Yes      Sometimes

     no_employees
0            6-25
1  More than 1000
4         100-500
5            6-25
6             1-5

Filtered DataFrame (Family History):
    Age  Gender         Country family_history treatment work_interfere  \
3    31    Male  United Kingdom            Yes       Yes          Often
5    33    Male   United States            Yes        No      Sometimes
6    35  Female   United States            Yes       Yes      Sometimes
8    42  Female   United States            Yes       Yes      Sometimes
12   42  female   United States            Yes       Yes      Sometimes

   no_employees
3        26-100
5          6-25
6           1-5
8       100-500
12       26-100
```

In [101]:

```
# Example transformations
# 1. Handling Missing Values
df['Age'].fillna(df['Age'].median(), inplace=True)

# 2. Scaling Numerical Features
numerical_columns = df.select_dtypes(include=['number']).columns
scaler = StandardScaler()
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])

# 3. Log Transformation
df['Log_Age'] = df['Age'].apply(lambda x: 0 if x == 0 else np.log(x))

# Display the transformed DataFrame
print(df.head())
```

```
             Timestamp       Age  Gender         Country state self_employed  \
0  2014-08-27 11:29:31 -0.028194  Female   United States    IL           NaN
1  2014-08-27 11:29:37 -0.028194       M   United States    IN           NaN
2  2014-08-27 11:29:44 -0.028194    Male          Canada   NaN           NaN
3  2014-08-27 11:29:46 -0.028194    Male  United Kingdom   NaN           NaN
4  2014-08-27 11:30:22 -0.028194    Male   United States    TX           NaN

  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  ...

  mental_health_consequence phys_health_consequence     coworkers supervisor  \
0                        No                      No  Some of them        Yes
1                     Maybe                      No            No         No
2                        No                      No           Yes        Yes
3                       Yes                     Yes  Some of them         No
4                        No                      No  Some of them        Yes

  mental_health_interview phys_health_interview mental_vs_physical  \
0                      No                 Maybe                Yes
1                      No                    No         Don't know
2                     Yes                   Yes                 No
3                   Maybe                 Maybe                 No
4                     Yes                   Yes         Don't know

  obs_consequence comments Log_Age
0              No      NaN     NaN
1              No      NaN     NaN
2              No      NaN     NaN
3             Yes      NaN     NaN
4              No      NaN     NaN

[5 rows x 28 columns]
```

In [102]:

```
#clean 'Gender'
#Slower case all columm's elements
gender = train_df['Gender'].str.lower()
#print(gender)

#Select unique elements
gender = train_df['Gender'].unique()

#Made gender groups
male_str = ["male", "m", "male-ish", "maile", "mal", "male (cis)", "make", "male ", "man","ms
trans_str = ["trans-female", "something kinda male?", "queer/she/they", "non-binary","nah", "
female_str = ["cis female", "f", "female", "woman",  "femake", "female ","cis-female/femme",

for (row, col) in train_df.iterrows():

    if str.lower(col.Gender) in male_str:
        train_df['Gender'].replace(to_replace=col.Gender, value='male', inplace=True)

    if str.lower(col.Gender) in female_str:
        train_df['Gender'].replace(to_replace=col.Gender, value='female', inplace=True)

    if str.lower(col.Gender) in trans_str:
        train_df['Gender'].replace(to_replace=col.Gender, value='trans', inplace=True)

#Get rid of unwanted values
stk_list = ['A little about you', 'p']
train_df = train_df[~train_df['Gender'].isin(stk_list)]

print(train_df['Gender'].unique())
```

```
['female' 'male' 'trans']
```

In [103]:

```
#complete missing age with mean
train_df['Age'].fillna(train_df['Age'].median(), inplace = True)

# Fill with media() values < 18 and > 120
s = pd.Series(train_df['Age'])
s[s<18] = train_df['Age'].median()
train_df['Age'] = s
s = pd.Series(train_df['Age'])
s[s>120] = train_df['Age'].median()
train_df['Age'] = s

#Ranges of Age
train_df['age_range'] = pd.cut(train_df['Age'], [0,20,30,65,100], labels=["0-20", "21-30", "3
```

In [104]:

```
#There are only 0.014% of self employed so let's change NaN to NOT self_employed
#Replace "NaN" string from defaultString
train_df['self_employed'] = train_df['self_employed'].replace([defaultString], 'No')
print(train_df['self_employed'].unique())
```

```
['No' 'Yes']
```

In [105]:

```
#There are only 0.20% of self work_interfere so let's change NaN to "Don't know
#Replace "NaN" string from defaultString

train_df['work_interfere'] = train_df['work_interfere'].replace([defaultString], 'Don\'t know
print(train_df['work_interfere'].unique())
```

```
['Often' 'Rarely' 'Never' 'Sometimes' "Don't know"]
```

In [106]:

```
#Encoding data
labelDict = {}
for feature in train_df:
    le = preprocessing.LabelEncoder()
    le.fit(train_df[feature])
    le_name_mapping = dict(zip(le.classes_, le.transform(le.classes_)))
    train_df[feature] = le.transform(train_df[feature])
    # Get labels
    labelKey = 'label_' + feature
    labelValue = [*le_name_mapping]
    labelDict[labelKey] =labelValue

for key, value in labelDict.items():
    print(key, value)

#Get rid of 'Country'
train_df = train_df.drop(['Country'], axis= 1)
train_df.head()
```

```
alth issue. Additionally I have contributed to this by staying in the same job with the s
ame employer for 10+ years.', 'I found it difficult to answer all of the questions effect
ively as many of them would depend on the nature of the mental health issues as some seem
more socially accepted than others. For some people telling your current supervisor that
you have a history of bi-polar disorder might be easier than telling a potential employer
that you have a history of compulsive gambling. They might both be bits of irrelevant inf
ormation (past behavior and not indicators of future behavior). However western culture p
ushes us to appear as capable as possible to our supervisors in pursuit of excellence in
our work. Providing information that could create a negative bias seems like a more genui
ne and yet more risky approach to the discussion.', 'I have Narcolepsy and have been fire
d from a job before for falling asleep standing up during a meeting. I was standing up in
the back of the room so that i could pace and try to prevent myself from falling asleep.
I still managed to fall asleep while standing and fell over against the wall. I was fired
the next day. The worst part is this is a condition i had given months of notice about to
my boss and i reminded her of it before the meeting. I worked at a hospital at the time.
I would have thought that they would be more accommodating.', "I have an exceptional empl
oyer. I haven't run into problems with any employer I've had but consider myself lucky.",
"I have been incredibly public about my own struggle in my own conversations and in socia
```

Engineer new useful features.

In [107]:

```
# Engineering a new feature: Age Group
bins = [0, 18, 35, 50, 100]
labels = ['0-18', '19-35', '36-50', '51+']
df['Age_Group'] = pd.cut(df['Age'], bins=bins, labels=labels, right=False)

# Engineering a binary feature: Has_Treatment
df['Has_Treatment'] = df['treatment'].map({'Yes': 1, 'No': 0})

# Engineering a feature based on work interference level
df['Work_Interference_Level'] = df['work_interfere'].map({'Never': 0, 'Rarely': 1, 'Sometimes

# Display the new DataFrame with engineered features
print(df.head())

#### Age Group: A new categorical feature is created to represent different age groups based o
####  Has Treatment: A binary feature is created indicating whether the respondent has receive
#### Work Interference Level: A numerical feature is created to represent the level of work in
```

```
             Timestamp       Age  Gender         Country state self_employed  \
0  2014-08-27 11:29:31 -0.028194  Female   United States    IL           NaN
1  2014-08-27 11:29:37 -0.028194       M   United States    IN           NaN
2  2014-08-27 11:29:44 -0.028194    Male          Canada   NaN           NaN
3  2014-08-27 11:29:46 -0.028194    Male  United Kingdom   NaN           NaN
4  2014-08-27 11:30:22 -0.028194    Male   United States    TX           NaN

  family_history treatment work_interfere    no_employees  ... supervisor  \
0             No       Yes          Often            6-25  ...        Yes
1             No        No         Rarely  More than 1000  ...         No
2             No        No         Rarely            6-25  ...        Yes
3            Yes       Yes          Often          26-100  ...         No
4             No        No          Never         100-500  ...        Yes

  mental_health_interview phys_health_interview mental_vs_physical  \
0                      No                 Maybe                Yes
1                      No                    No         Don't know
2                     Yes                   Yes                 No
3                   Maybe                 Maybe                 No
4                     Yes                   Yes         Don't know

  obs_consequence comments Log_Age Age_Group Has_Treatment  \
0              No      NaN     NaN       NaN             1
1              No      NaN     NaN       NaN             0
2              No      NaN     NaN       NaN             0
3             Yes      NaN     NaN       NaN             1
4              No      NaN     NaN       NaN             0

  Work_Interference_Level
0                     3.0
1                     1.0
2                     1.0
3                     3.0
4                     0.0

[5 rows x 31 columns]
```

In [108]:

```
# Separate numeric and categorical features
numeric_features = df.select_dtypes(include=['number']).columns.tolist()
categorical_features = df.select_dtypes(include=['object']).columns.tolist()

# Display the lists of numeric and categorical features
print("Numeric Features:")
print(numeric_features)

print("\nCategorical Features:")
print(categorical_features)
```

```
Numeric Features:
['Age', 'Log_Age', 'Has_Treatment', 'Work_Interference_Level']

Categorical Features:
['Timestamp', 'Gender', 'Country', 'state', 'self_employed', 'family_history', 'treatment',
'work_interfere', 'no_employees', 'remote_work', 'tech_company', 'benefits', 'care_options',
'wellness_program', 'seek_help', 'anonymity', 'leave', 'mental_health_consequence', 'phys_he
alth_consequence', 'coworkers', 'supervisor', 'mental_health_interview', 'phys_health_interv
iew', 'mental_vs_physical', 'obs_consequence', 'comments']
```

In [109]:

```
# Apply one-hot encoding to categorical columns
df_encoded = pd.get_dummies(df, columns=categorical_features, drop_first=True)

# Display the first few rows of the encoded DataFrame
print(df_encoded.head())
```

```
        Age  Log_Age Age_Group  Has_Treatment  Work_Interference_Level  \
0 -0.028194      NaN       NaN              1                      3.0   
1 -0.028194      NaN       NaN              0                      1.0   
2 -0.028194      NaN       NaN              0                      1.0   
3 -0.028194      NaN       NaN              1                      3.0   
4 -0.028194      NaN       NaN              0                      0.0   

   Timestamp_2014-08-27 11:29:37  Timestamp_2014-08-27 11:29:44  \
0                          False                          False   
1                           True                          False   
2                          False                           True   
3                          False                          False   
4                          False                          False   

   Timestamp_2014-08-27 11:29:46  Timestamp_2014-08-27 11:30:22  \
0                          False                          False   
1                          False                          False   
2                          False                          False   
3                           True                          False   
4                          False                           True   

   Timestamp_2014-08-27 11:31:22  ...  \
0                          False  ...   
1                          False  ...   
2                          False  ...   
3                          False  ...   
4                          False  ...   

   comments_Would you bring up a mental health issue with a potential employer in an intervi
ew?Poignant.  \
0                                              False   
1                                              False   
2                                              False   
3                                              False   
4                                              False   

   comments_YOU MAY WANT TO THROW OUT MY ENTRY.I answered all of these questions with the as
sumption that Attention Deficit Disorder is considered a mental illness and with ADD in min
d.  \
0                                              False   
1                                              False   
2                                              False   
3                                              False   
4                                              False   

   comments_as a UK-based company we don't have any medical provisions as it's all provided 
on the National Health Service (for now!) However if we do need to take days off for any kin
d of health problems everyone is understanding :)  \
0                                              False   
1                                              False   
2                                              False   
3                                              False   
4                                              False   

   comments_fwiw I am a co founder of this company and the would you X in an interview quest
ions shouldn't reflect how I would treat anyone addressing their own phys/mental health issu
e to me in such a situation.   \
0                                              False   
1                                              False   
2                                              False   
3                                              False   
4                                              False   

   comments_i'm in a country with social health care so my options are not dependant on my e
mployer. this makes a few of the early questions less relevant than they would be for a resi
dent of the US.  \
0                                              False   
```

```
1                                               False
2                                               False
3                                               False
4                                               False

   comments_it is my opinion that bad mental health is a red flag for employers and i would
never bring it up.  \
0                                               False
1                                               False
2                                               False
3                                               False
4                                               False

   comments_password: testered  \
0                        False
1                        False
2                        False
3                        False
4                        False

   comments_suffer from CR-PTSD so all answered based on that  \
0                                               False
1                                               False
2                                               False
3                                               False
4                                               False

   comments_thanks for what you're doing. FYI these questions dont quite work for entreprene
urs where employer == cofounders / sr mgmt / me  \
0                                               False
1                                               False
2                                               False
3                                               False
4                                               False

   comments_you rock for doing this!
0                              False
1                              False
2                              False
3                              False
4                              False

[5 rows x 1590 columns]
```

In [110]:

```
# Create dummy variables for categorical columns
df_dummies = pd.get_dummies(df, columns=categorical_columns, drop_first=True)

# Display the first few rows of the DataFrame with dummy variables
print(df_dummies.head())
```

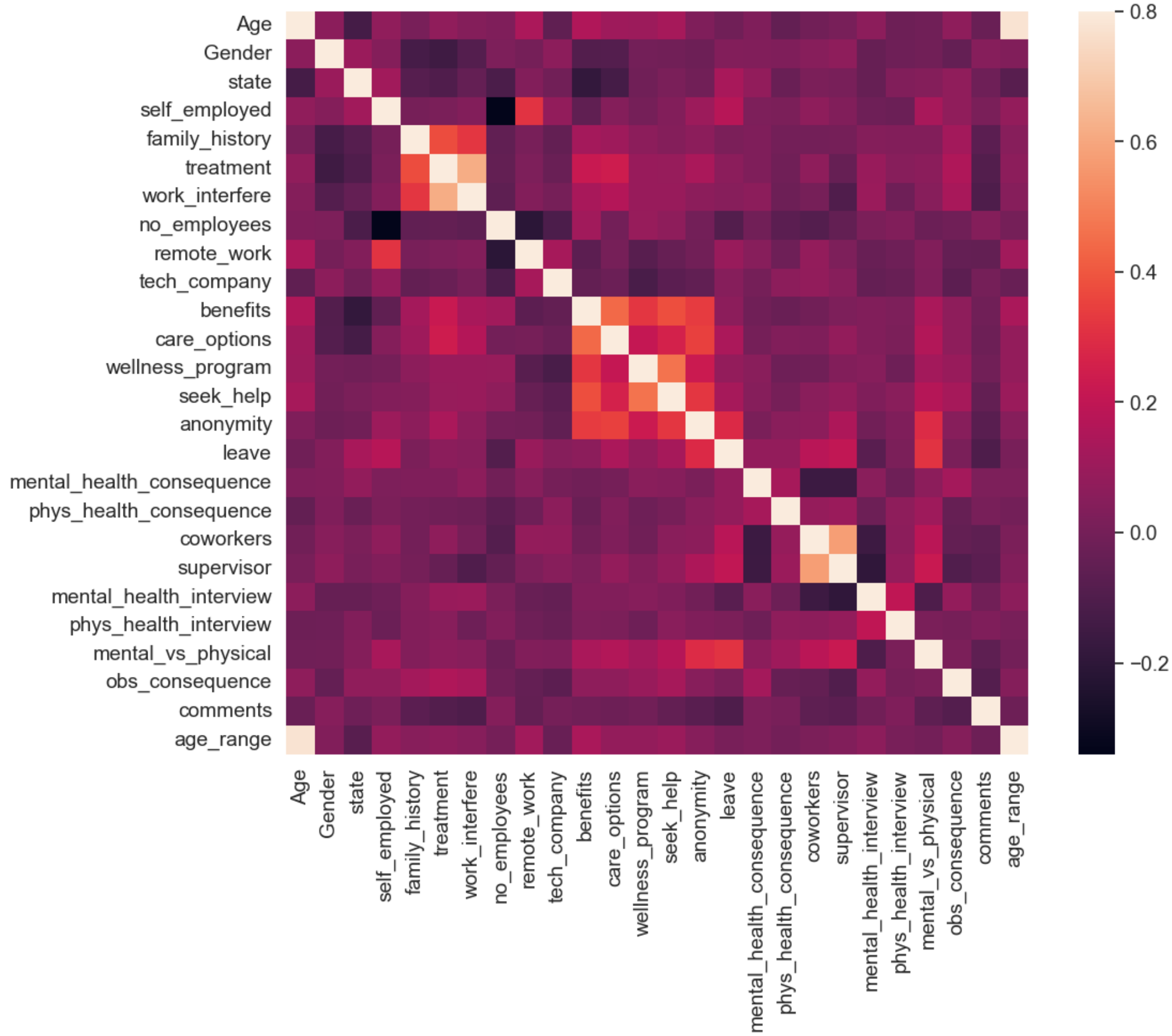
```
        Age  Log_Age Age_Group  Has_Treatment  Work_Interference_Level  \
0 -0.028194      NaN       NaN              1                      3.0
1 -0.028194      NaN       NaN              0                      1.0
2 -0.028194      NaN       NaN              0                      1.0
3 -0.028194      NaN       NaN              1                      3.0
4 -0.028194      NaN       NaN              0                      0.0

   Timestamp_2014-08-27 11:29:37  Timestamp_2014-08-27 11:29:44  \
0                          False                          False
1                           True                          False
2                          False                           True
3                          False                          False
4                          False                          False

   Timestamp_2014-08-27 11:29:46  Timestamp_2014-08-27 11:30:22  \
0                          False                          False
1                          False                          False
2                          False                          False
3                           True                          False
4                          False                           True

   Timestamp_2014-08-27 11:31:22  ...  \
0                          False  ...
1                          False  ...
2                          False  ...
3                          False  ...
4                          False  ...

   comments_Would you bring up a mental health issue with a potential employer in an intervi
ew?Poignant.  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_YOU MAY WANT TO THROW OUT MY ENTRY.I answered all of these questions with the as
sumption that Attention Deficit Disorder is considered a mental illness and with ADD in min
d.  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_as a UK-based company we don't have any medical provisions as it's all provided
on the National Health Service (for now!) However if we do need to take days off for any kin
d of health problems everyone is understanding :)  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_fwiw I am a co founder of this company and the would you X in an interview quest
ions shouldn't reflect how I would treat anyone addressing their own phys/mental health issu
e to me in such a situation.   \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_i'm in a country with social health care so my options are not dependant on my e
mployer. this makes a few of the early questions less relevant than they would be for a resi
dent of the US.  \
0                                              False
```

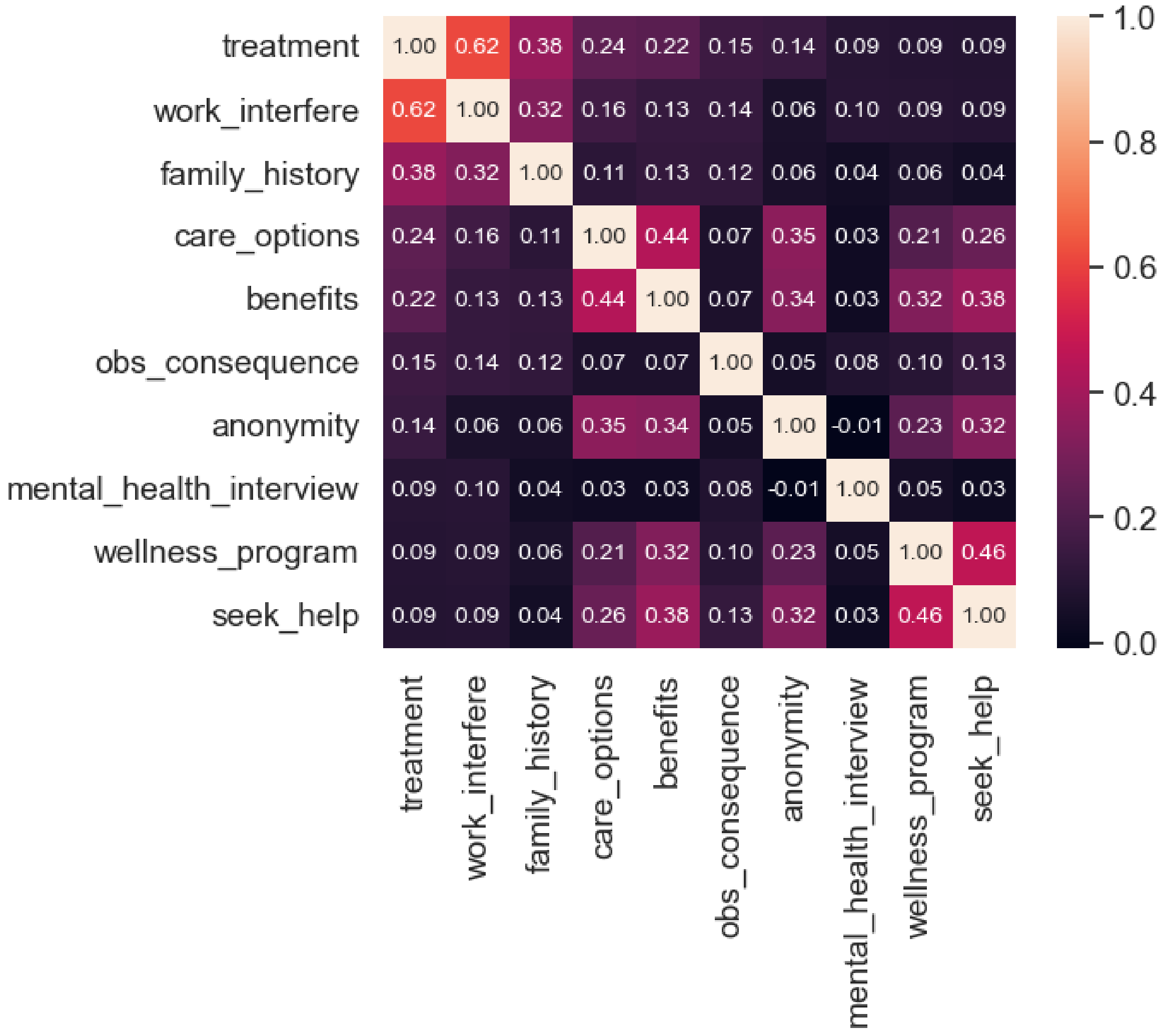
```
1                                              False
2                                              False
3                                              False
4                                              False

   comments_it is my opinion that bad mental health is a red flag for employers and i would
never bring it up.  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_password: testered  \
0                        False
1                        False
2                        False
3                        False
4                        False

   comments_suffer from CR-PTSD so all answered based on that  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_thanks for what you're doing. FYI these questions dont quite work for entreprene
urs where employer == cofounders / sr mgmt / me  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   comments_you rock for doing this!
0                              False
1                              False
2                              False
3                              False
4                              False

[5 rows x 1590 columns]
```

Covariance Matrix. Variability comparison between categories of variables

In [111]:

```
#correlation matrix
corrmat = train_df.corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
plt.show()

#treatment correlation matrix
k = 10 #number of variables for heatmap
cols = corrmat.nlargest(k, 'treatment')['treatment'].index
cm = np.corrcoef(train_df[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size': 10}, y
plt.show()
```





In [112]:

```python
# define X and y
feature_cols = ['Age', 'Gender', 'family_history', 'benefits', 'care_options', 'anonymity', '
X = train_df[feature_cols]
y = train_df.treatment

# split X and y into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=0)

# Create dictionaries for final graph
# Use: methodDict['Stacking'] = accuracy_score
methodDict = {}
rmseDict = ()
```

In [113]:

```
# Build a forest and compute the feature importances
forest = ExtraTreesClassifier(n_estimators=250,
                              random_state=0)

forest.fit(X, y)
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

labels = []
for f in range(X.shape[1]):
    labels.append(feature_cols[f])

# Plot the feature importances of the forest
plt.figure(figsize=(12,8))
plt.title("Feature importances")
plt.bar(range(X.shape[1]), importances[indices],
       color="r", yerr=std[indices], align="center")
plt.xticks(range(X.shape[1]), labels, rotation='vertical')
plt.xlim([-1, X.shape[1]])
plt.show()
```