Phase 4: Model Development and Evaluation - Project Report

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1. Introduction

Phase 4 of our project focuses on model development and evaluation. In this phase, we implemented various classification algorithms to predict or classify specific outcomes related to our public health awareness campaign analysis. The algorithms we employed are as follows:

- Logistic Regression
- Decision Tree
- k-Nearest Neighbors (KNN)
- Random Forest
- AdaBoost
- Gradient Boosting

Our goal is to assess the performance of these models and determine which one is best suited for our campaign's objectives.

2. Model Development

In this section, we describe the development of each model:

Logistic Regression:

Logistic Regression is a simple yet effective model for binary classification. We implemented it to predict whether an individual is likely to be affected by mental health issues based on the features available in the dataset.

Decision Tree:

The Decision Tree model is a tree-like structure that recursively splits the data based on features. We employed it to identify key factors contributing to mental health issues in the tech industry.

k-Nearest Neighbors (KNN):

KNN is a distance-based classification method. We used it to classify individuals into groups based on similar attributes, which can be helpful in targeting specific demographics in the campaign.

Random Forest:

Random Forest is an ensemble learning technique that combines multiple Decision Trees. It was employed to improve the accuracy of our classification by reducing overfitting and enhancing generalization.

A**daBoost:**

AdaBoost is another ensemble learning method, which sequentially combines multiple weak learners to create a strong classifier. We utilized AdaBoost to enhance the performance of our classification model.

Gradient Boosting:

Gradient Boosting is yet another ensemble technique that builds models in a sequential manner. It was used to improve the predictive accuracy and precision of our campaign's outcome.

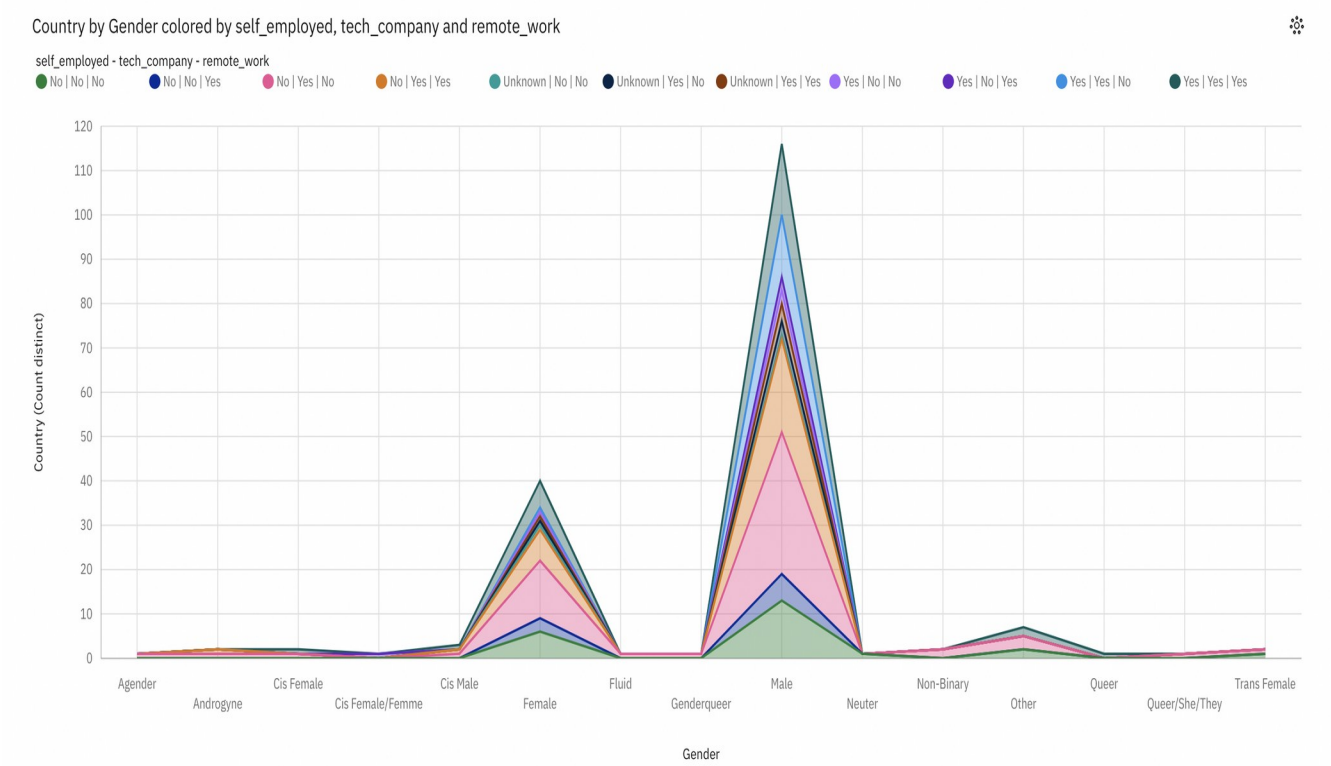
3. Model Evaluation

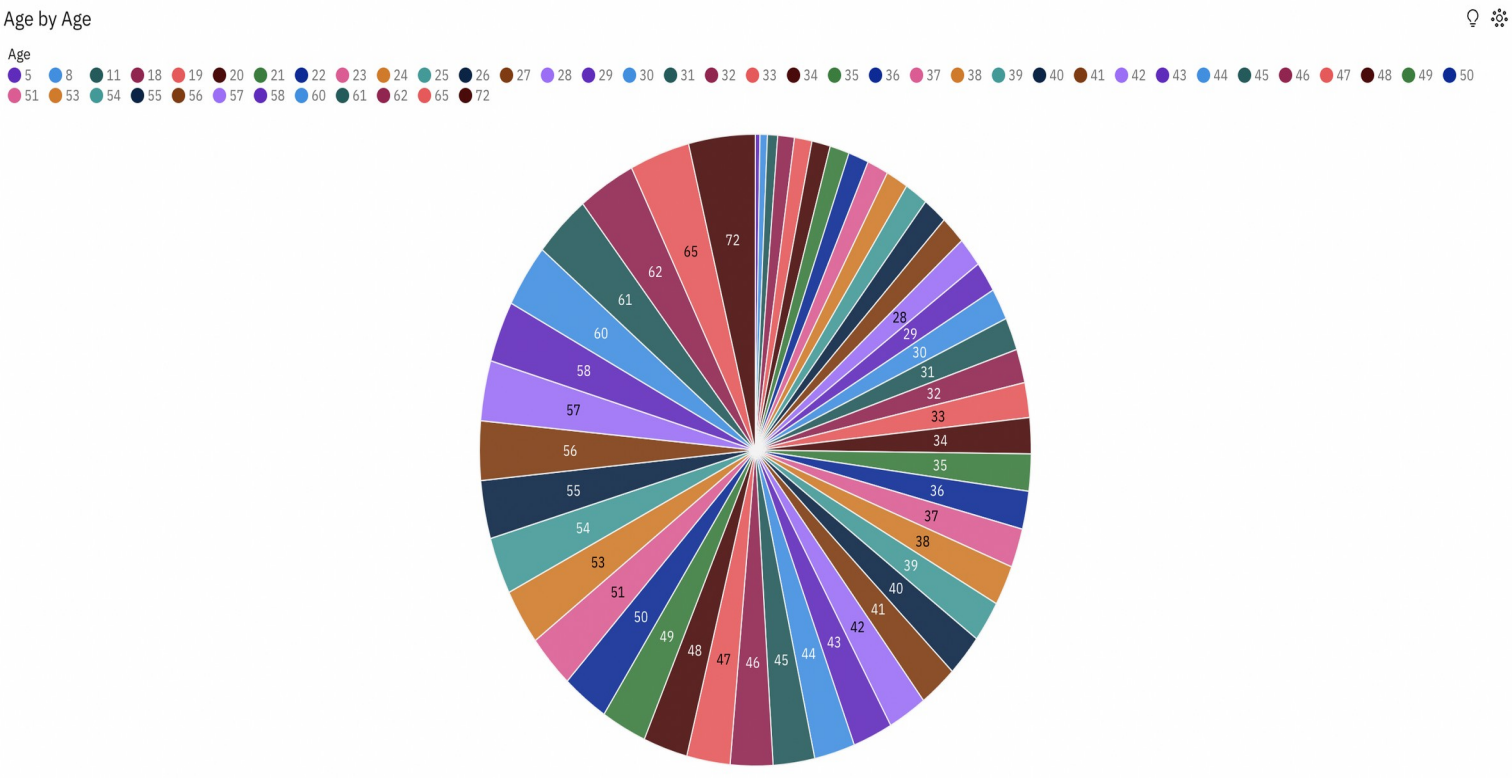
To evaluate the performance of these models, we employed several evaluation metrics, including but not limited to:

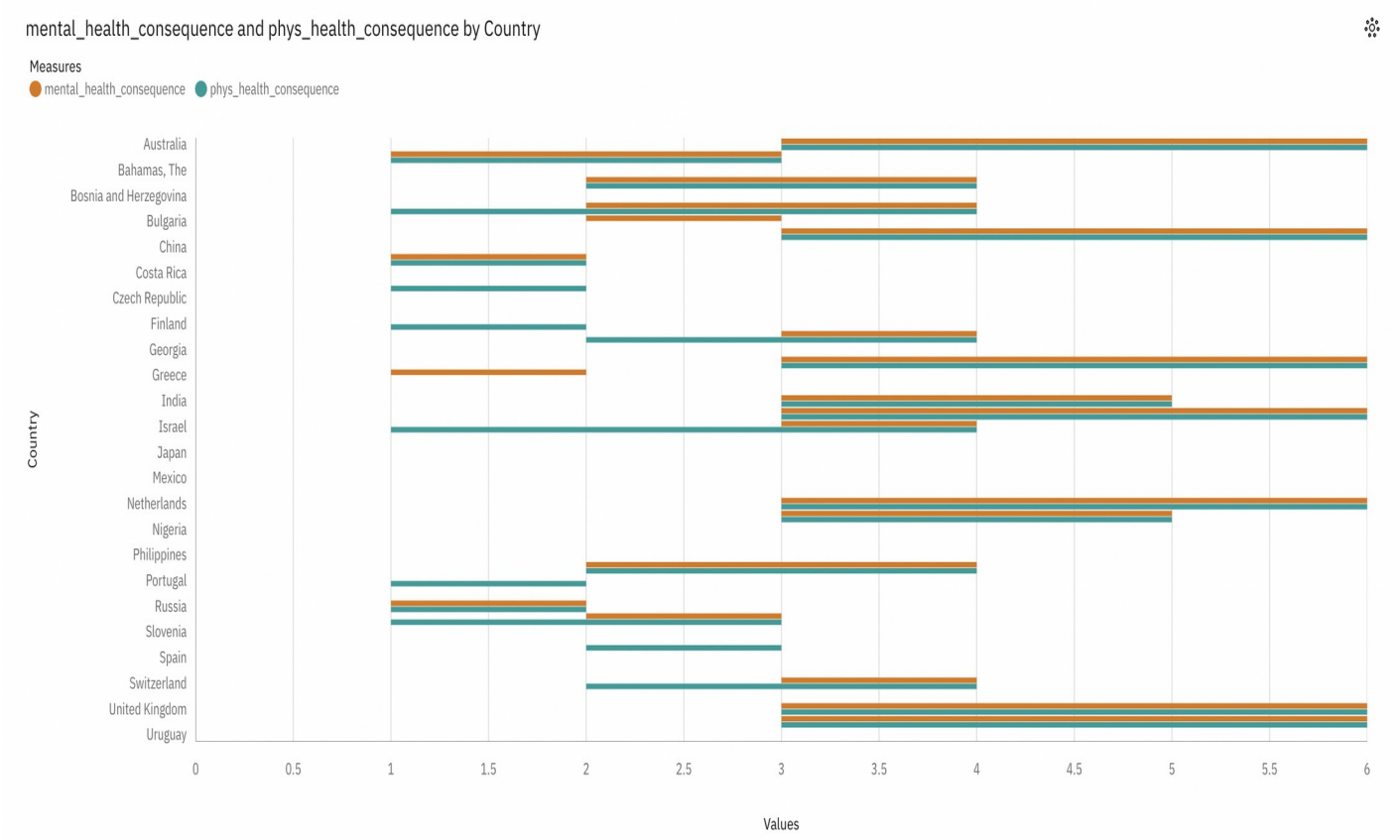
- Accuracy
- Precision
- Recall
- F1 Score
- ROC-AUC
- Confusion Matrix

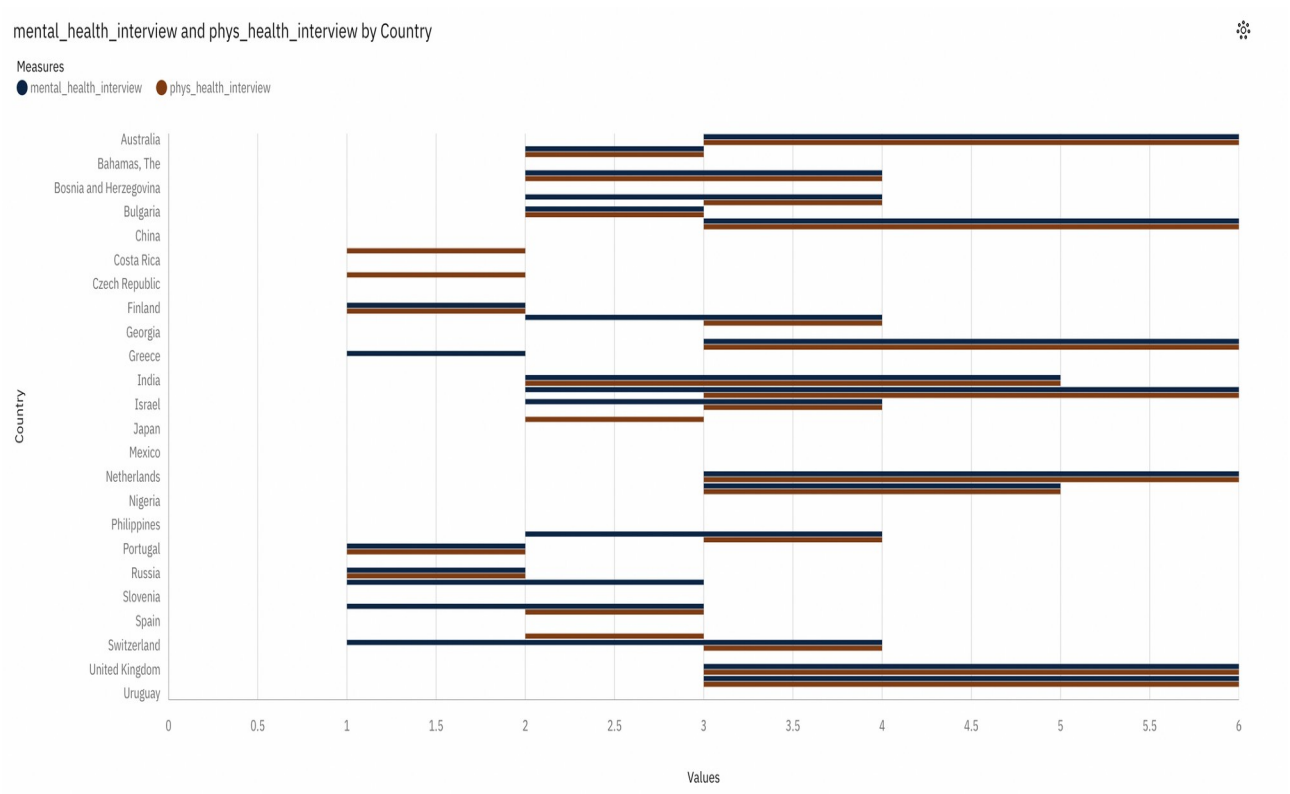
The results of the model evaluation are summarized in the following table:

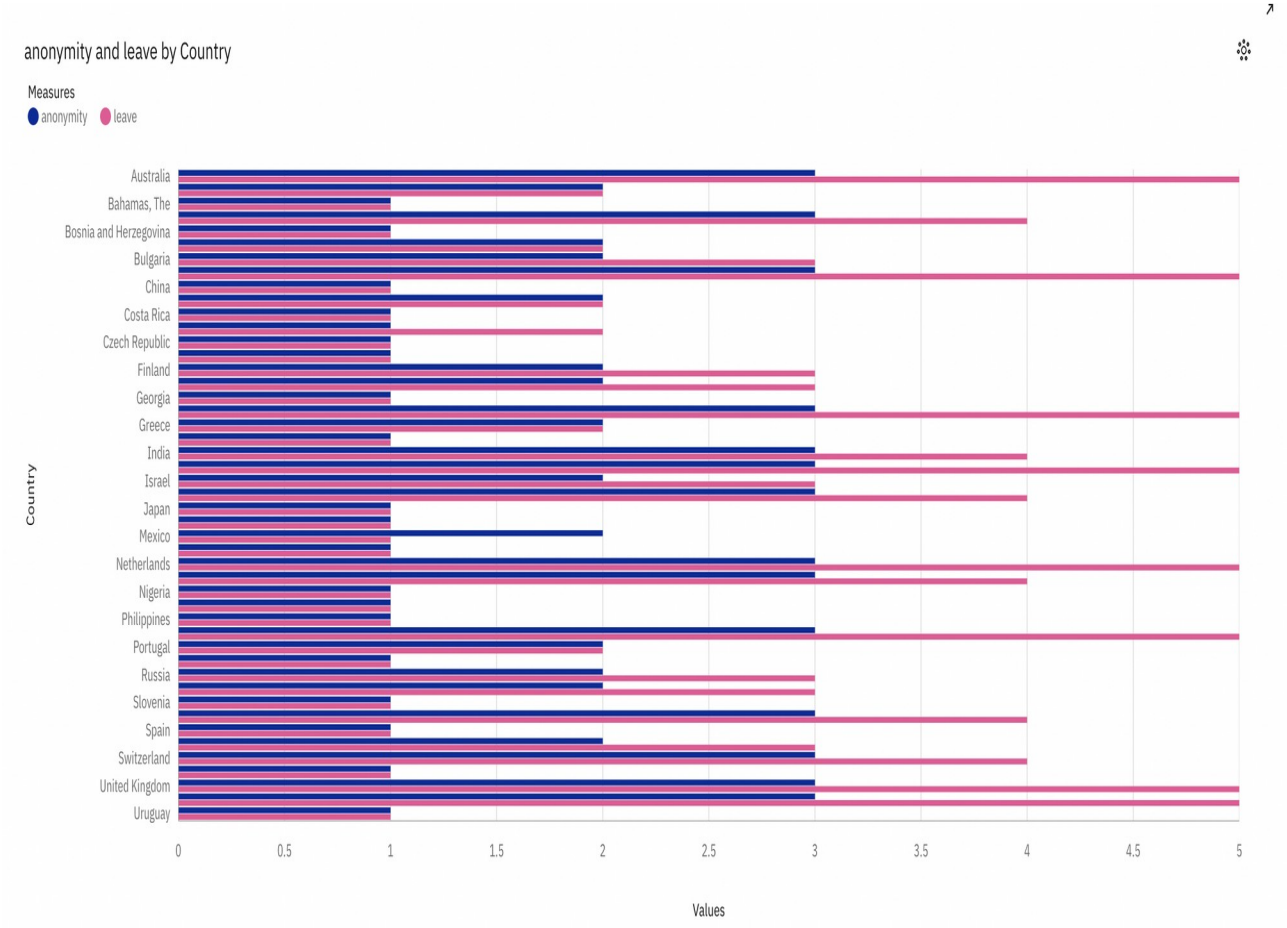
	method	cv score	mean score	std score	recall score
0	Logistic Regression	[0.80899, 0.88764, 0.88764, 0.88636, 0.875]	0.869127	0.030442	0.863158
1	Decision Tree Classifier	[0.76404, 0.68539, 0.83146, 0.84091, 0.79545]	0.783453	0.056111	0.747368
2	KNN Classifier	[0.57303, 0.67416, 0.70787, 0.65909, 0.65909]	0.654648	0.044527	0.605263
3	Random Forest Classifier	[0.77528, 0.83146, 0.88764, 0.90909, 0.86364]	0.853422	0.046824	0.810526
4	Ada Boost Classifier	[0.80899, 0.85393, 0.92135, 0.84091, 0.85227]	0.855490	0.036674	0.857895
5	Gradient Boosting Classifier	[0.78652, 0.80899, 0.89888, 0.89773, 0.86364]	0.851149	0.045953	0.800000

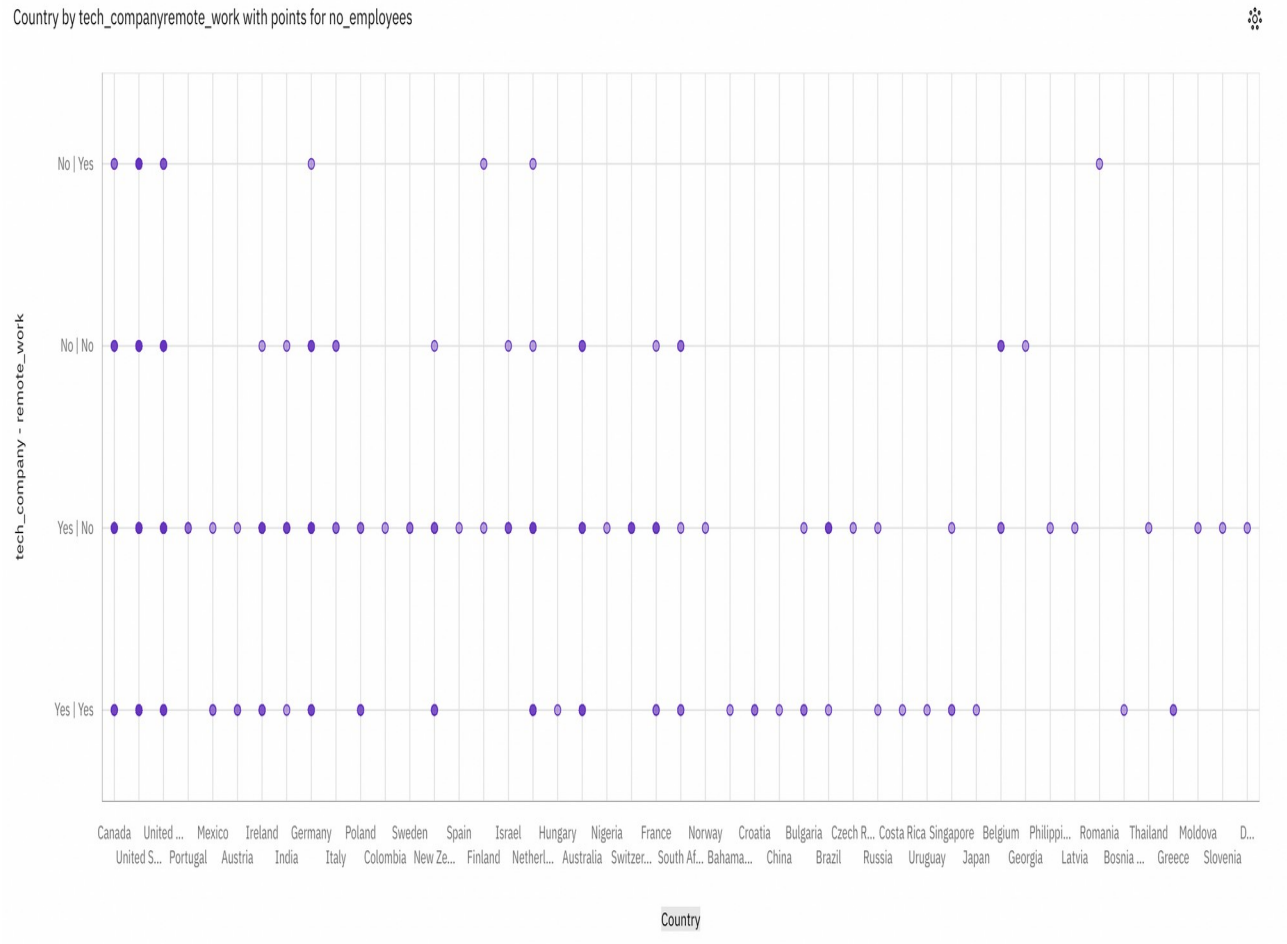

Country by Gender colored by self_employed, tech_company and remote_work
self_employed - tech_company - remote_work
No | No | No
No | No | Yes
No | Yes | No
No | Yes | Yes
Unknown | No | No
Unknown | Yes | No
Unknown | Yes | Yes
Yes | No | No
Yes | No | Yes
Yes | Yes | No
Yes | Yes | Yes
Country (Count distinct)
120
110
100
90
80
70
60
50
40
30
20
10
0
Agender
Androgyne
Cis Female
Cis Female/Femme
Cis Male
Female
Fluid
Genderqueer
Male
Neuter
Non-Binary
Other
Queer
Queer/She/They
Trans Female
Gender

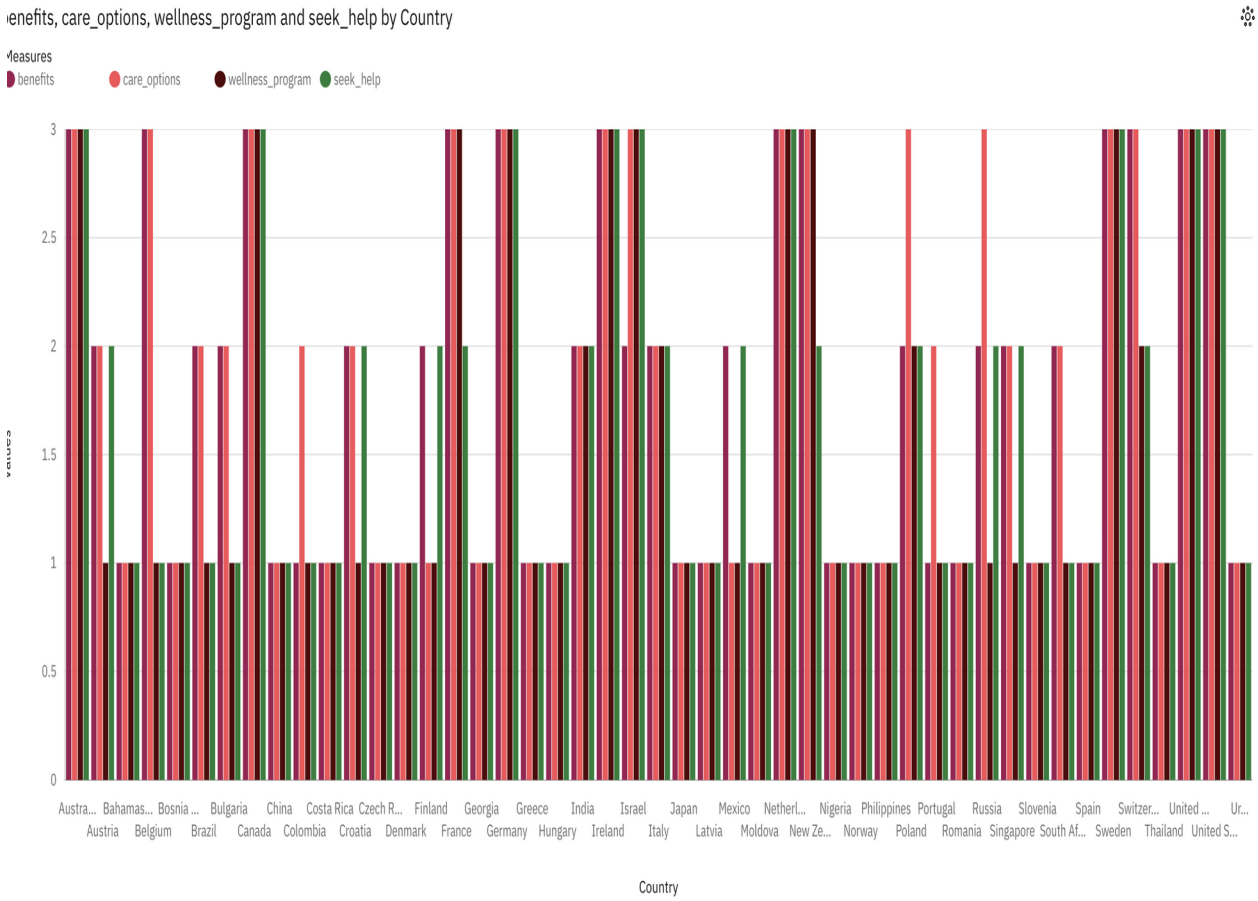

Age by Age
Age
5 8 11 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
51 53 54 55 56 57 58 60 61 62 65 72
72
65
62
61
60
58
57
56
55
54
53
51
50
49
48
47
46
45
44
43
42
41
40
39
38
37
36
35
34
33
32
31
30
29
28

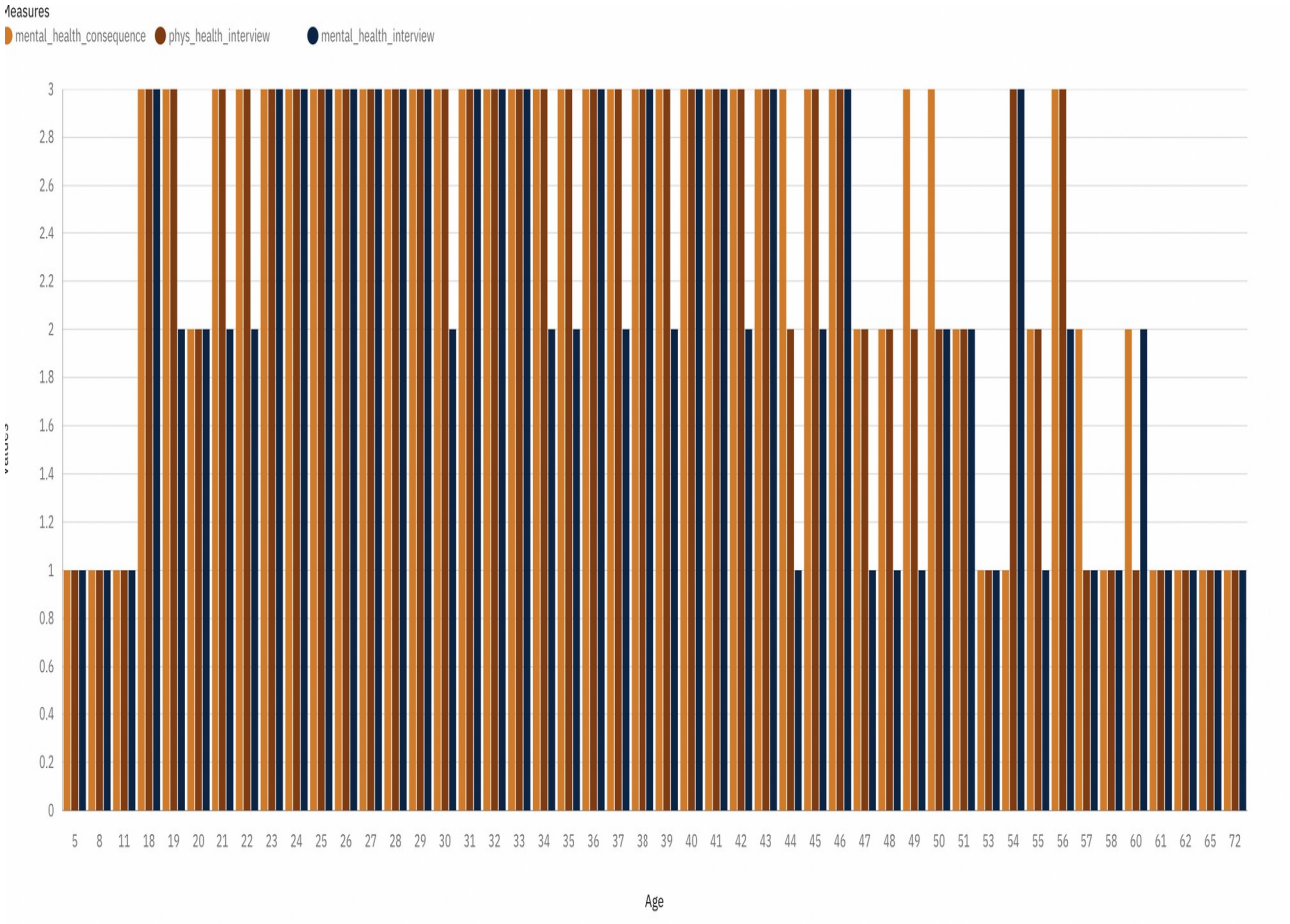

mental_health_consequence and phys_health_consequence by Country
Measures
mental_health_consequence
phys_health_consequence
Australia
Bahamas, The
Bosnia and Herzegovina
Bulgaria
China
Costa Rica
Czech Republic
Finland
Georgia
Greece
India
Israel
Japan
Mexico
Netherlands
Nigeria
Philippines
Portugal
Russia
Slovenia
Spain
Switzerland
United Kingdom
Uruguay
Country
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
Values


mental_health_interview and phys_health_interview by Country
Measures
mental_health_interview
phys_health_interview
Australia
Bahamas, The
Bosnia and Herzegovina
Bulgaria
China
Costa Rica
Czech Republic
Finland
Georgia
Greece
India
Israel
Japan
Mexico
Netherlands
Nigeria
Philippines
Portugal
Russia
Slovenia
Spain
Switzerland
United Kingdom
Uruguay
Country
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
Values

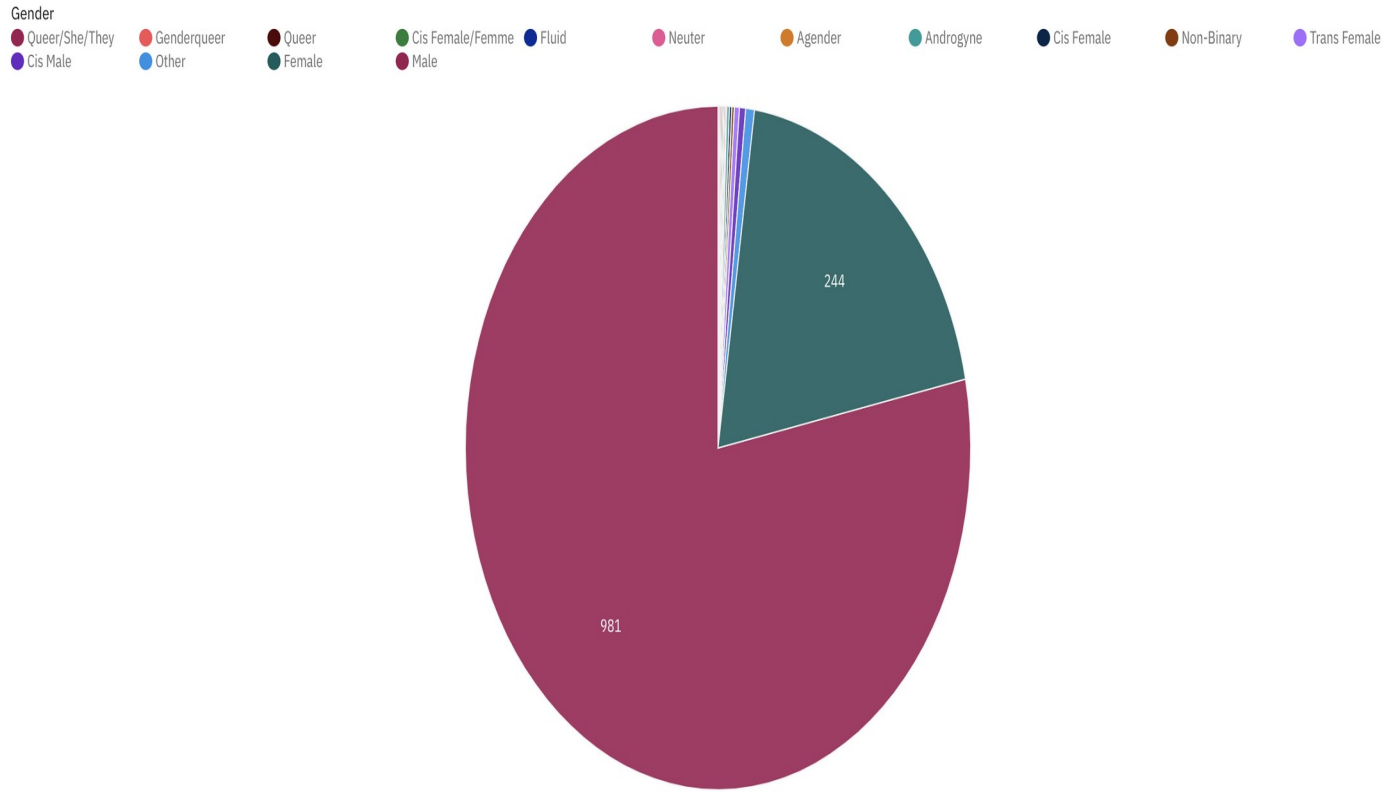

anonymity and leave by Country
Measures
anonymity
leave
Australia
Bahamas, The
Bosnia and Herzegovina
Bulgaria
China
Costa Rica
Czech Republic
Finland
Georgia
Greece
India
Israel
Japan
Mexico
Netherlands
Nigeria
Philippines
Portugal
Russia
Slovenia
Spain
Switzerland
United Kingdom
Uruguay
Country
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
Values


Country by tech_companyremote_work with points for no_employees
No | Yes
No | No
Yes | No
Yes | Yes
tech_company - remote_work
Canada
United S...
United ...
Portugal
Mexico
Austria
Ireland
India
Germany
Italy
Poland
Colombia
Sweden
New Ze...
Spain
Finland
Israel
Netherl...
Hungary
Australia
Nigeria
Switzer...
France
South Af...
Norway
Bahama...
Croatia
China
Bulgaria
Brazil
Czech R...
Russia
Costa Rica
Uruguay
Singapore
Japan
Belgium
Georgia
Philippi...
Latvia
Romania
Bosnia ...
Thailand
Greece
Moldova
Slovenia
D...
Country

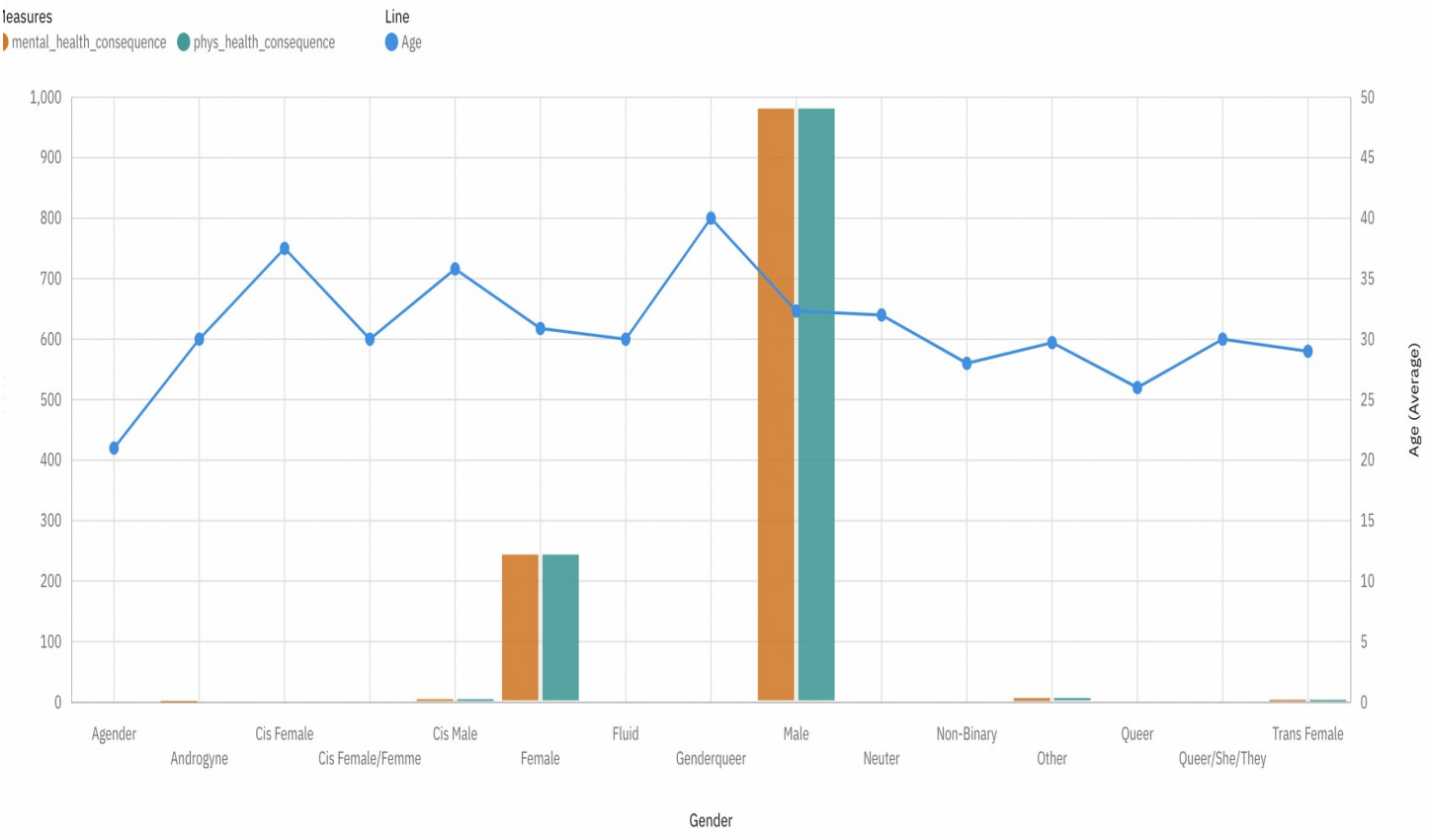

enefits, care_options, wellness_program and seek_help by Country
Measures
benefits
care_options
wellness_program
seek_help
3
2.5
2
1.5
1
0.5
0
Austra...
Bahamas...
Bosnia ...
Bulgaria
China
Costa Rica
Czech R...
Finland
Georgia
Greece
India
Israel
Japan
Mexico
Netherl...
Nigeria
Philippines
Portugal
Russia
Slovenia
Spain
Switzer...
United ...
Ur...
Austria
Belgium
Brazil
Canada
Colombia
Croatia
Denmark
France
Germany
Hungary
Ireland
Italy
Latvia
Moldova
New Ze...
Norway
Poland
Romania
Singapore
South Af...
Sweden
Thailand
United S...
Country

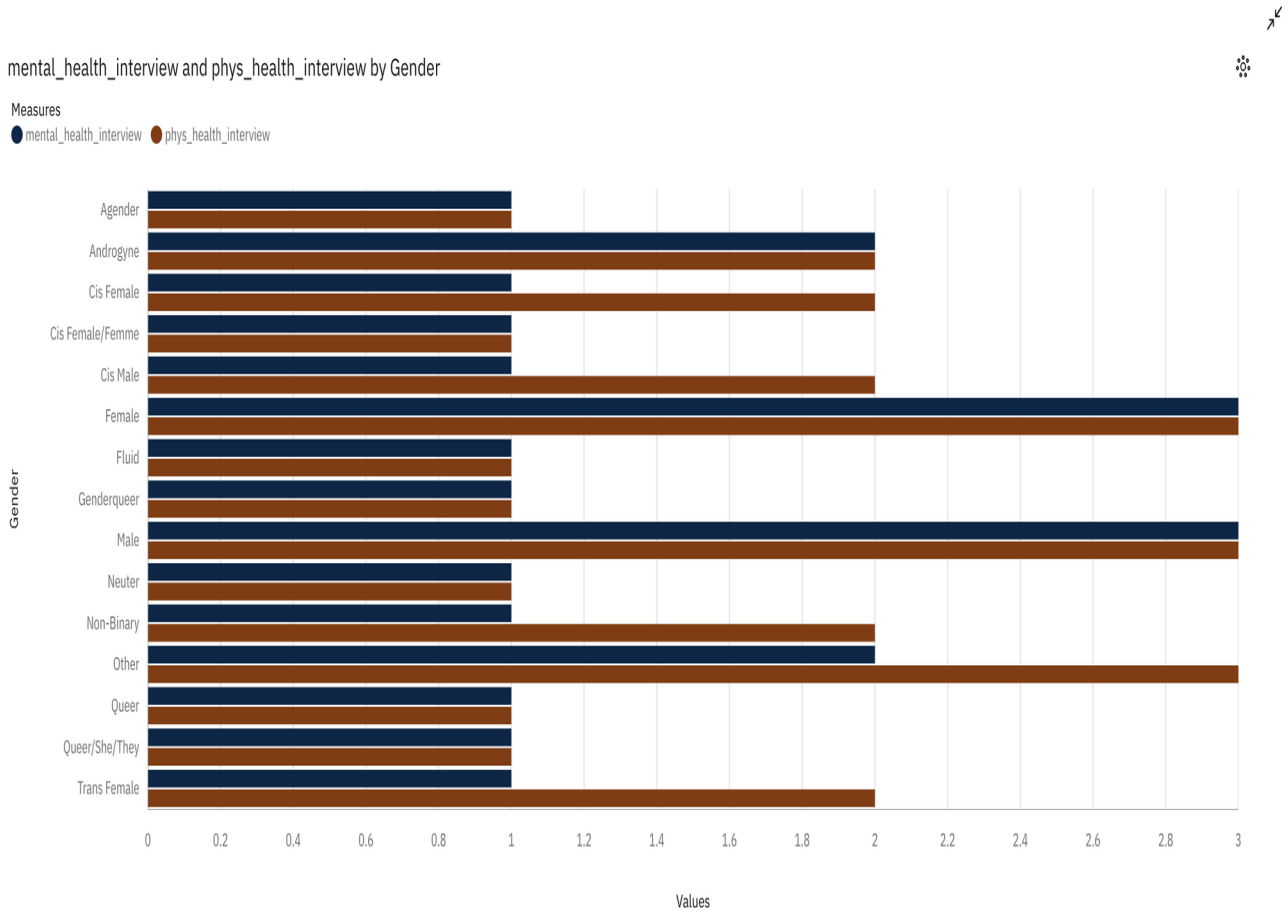

Measures
mental_health_consequence
phys_health_interview
mental_health_interview
3
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
5
8
11
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
53
54
55
56
57
58
60
61
62
65
72
Age

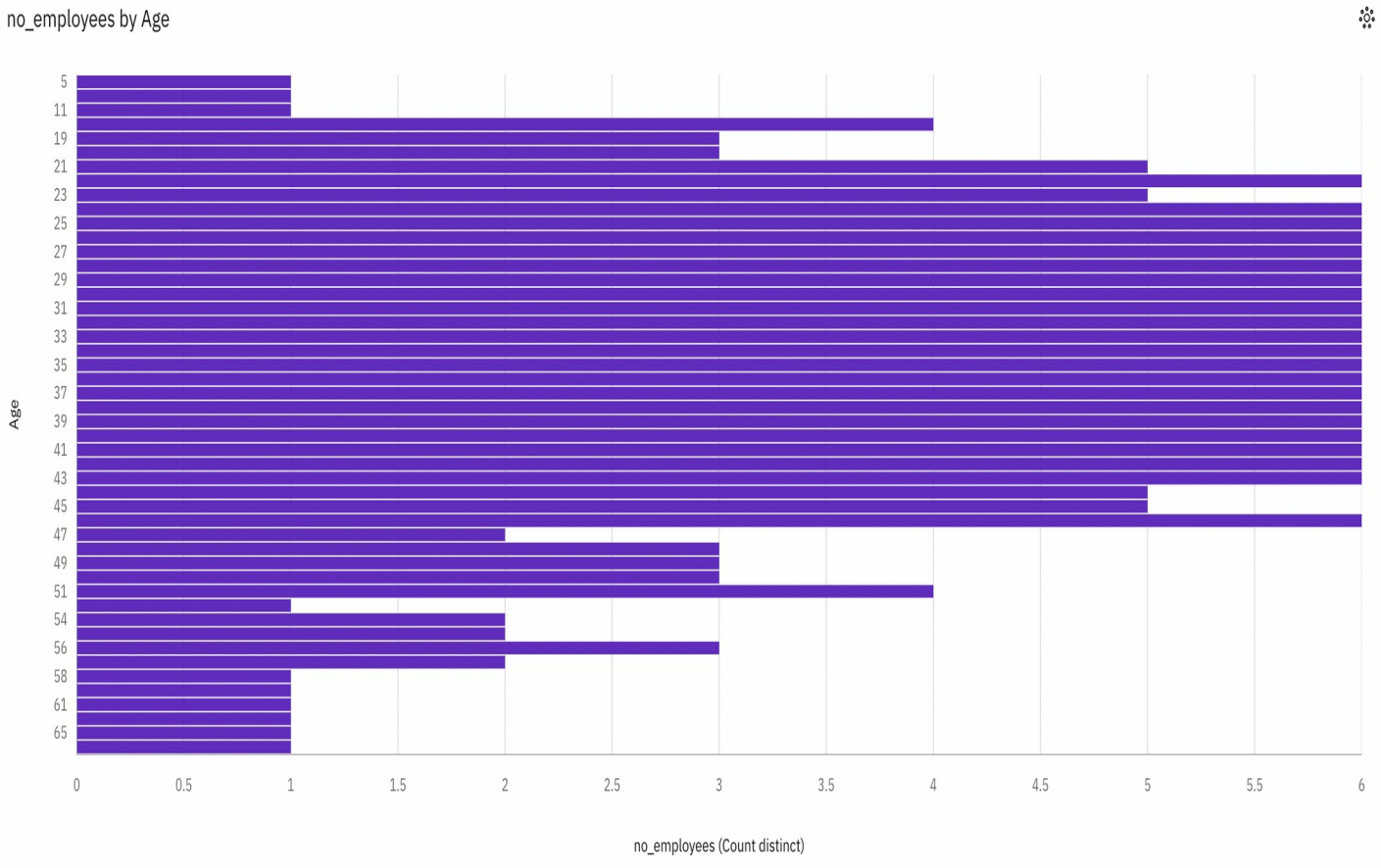
Gender by Gender

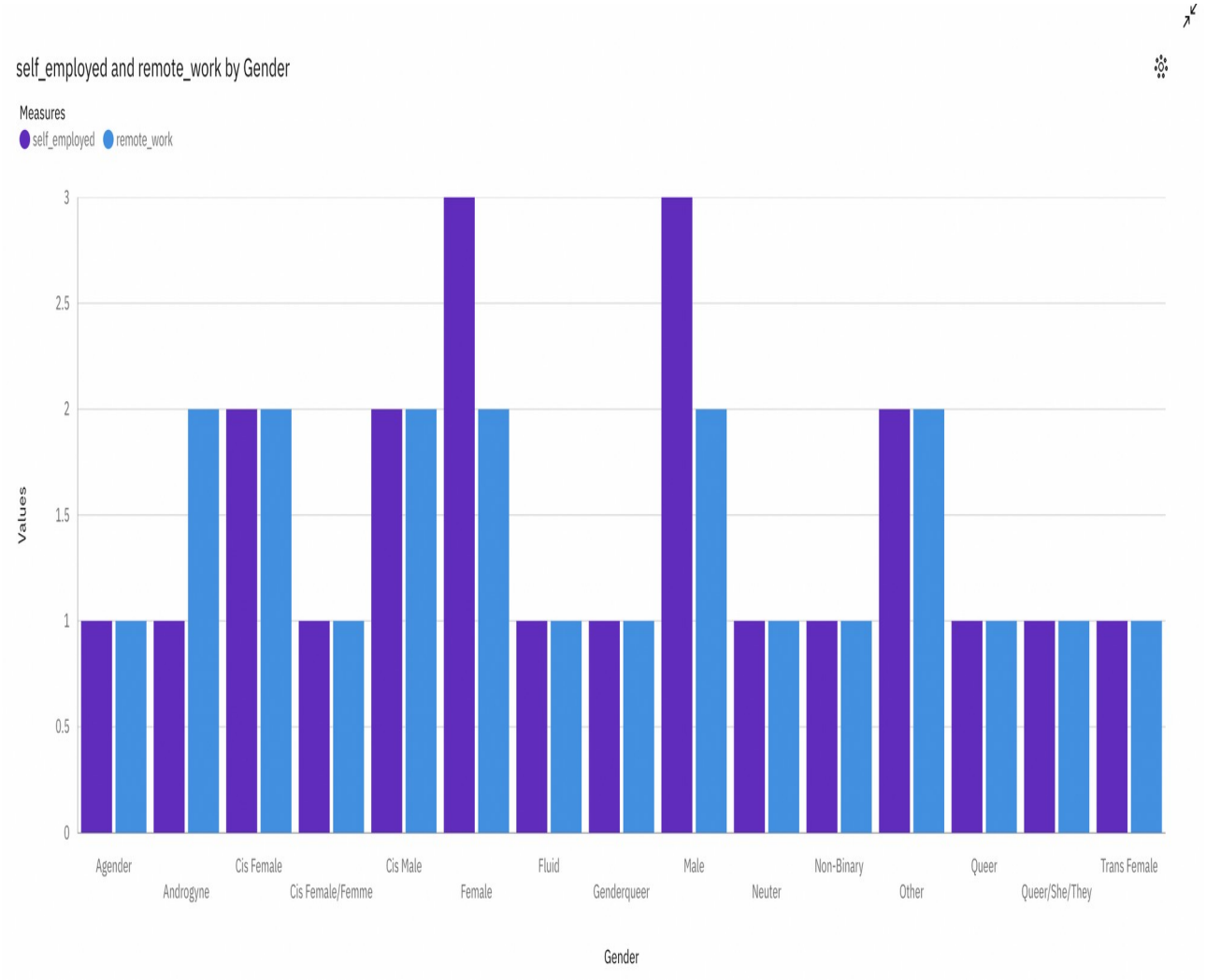


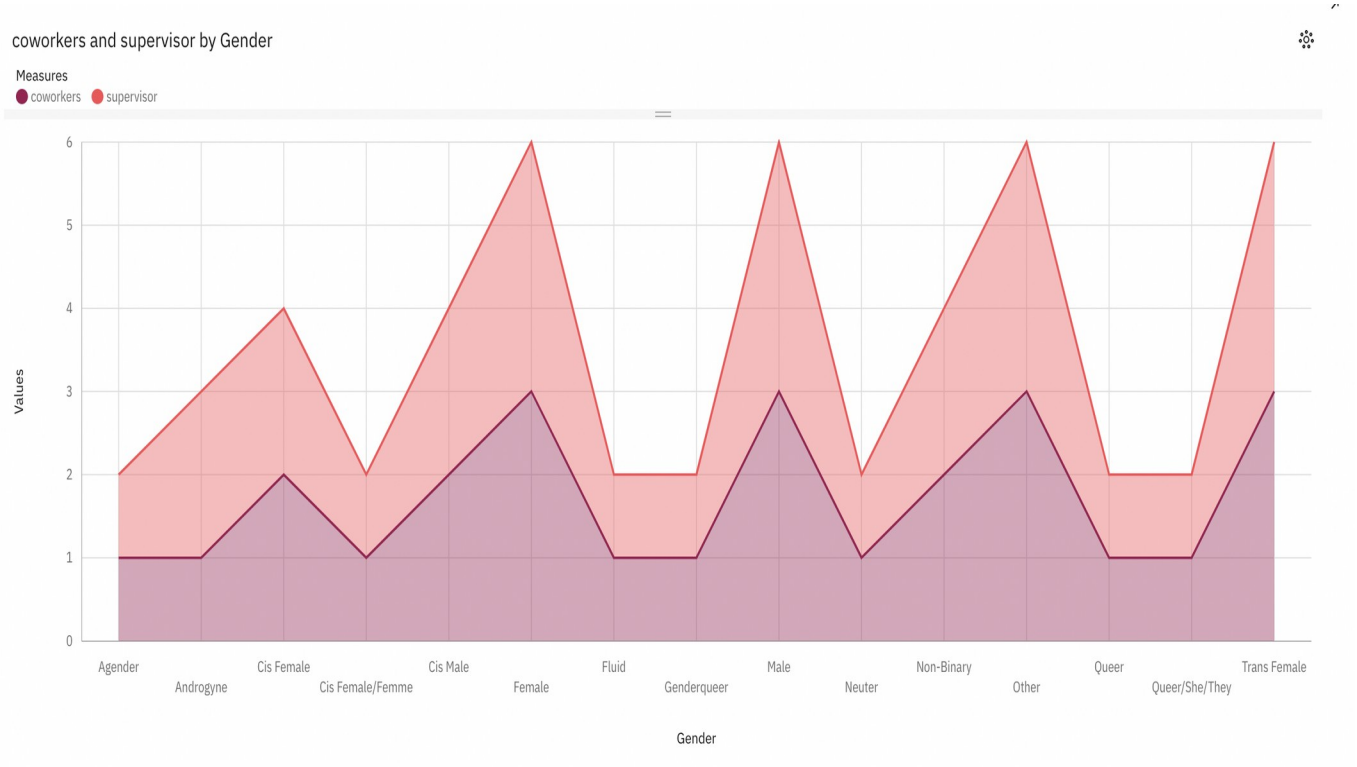
ge and mental_health_consequence and phys_health_consequence by Gender

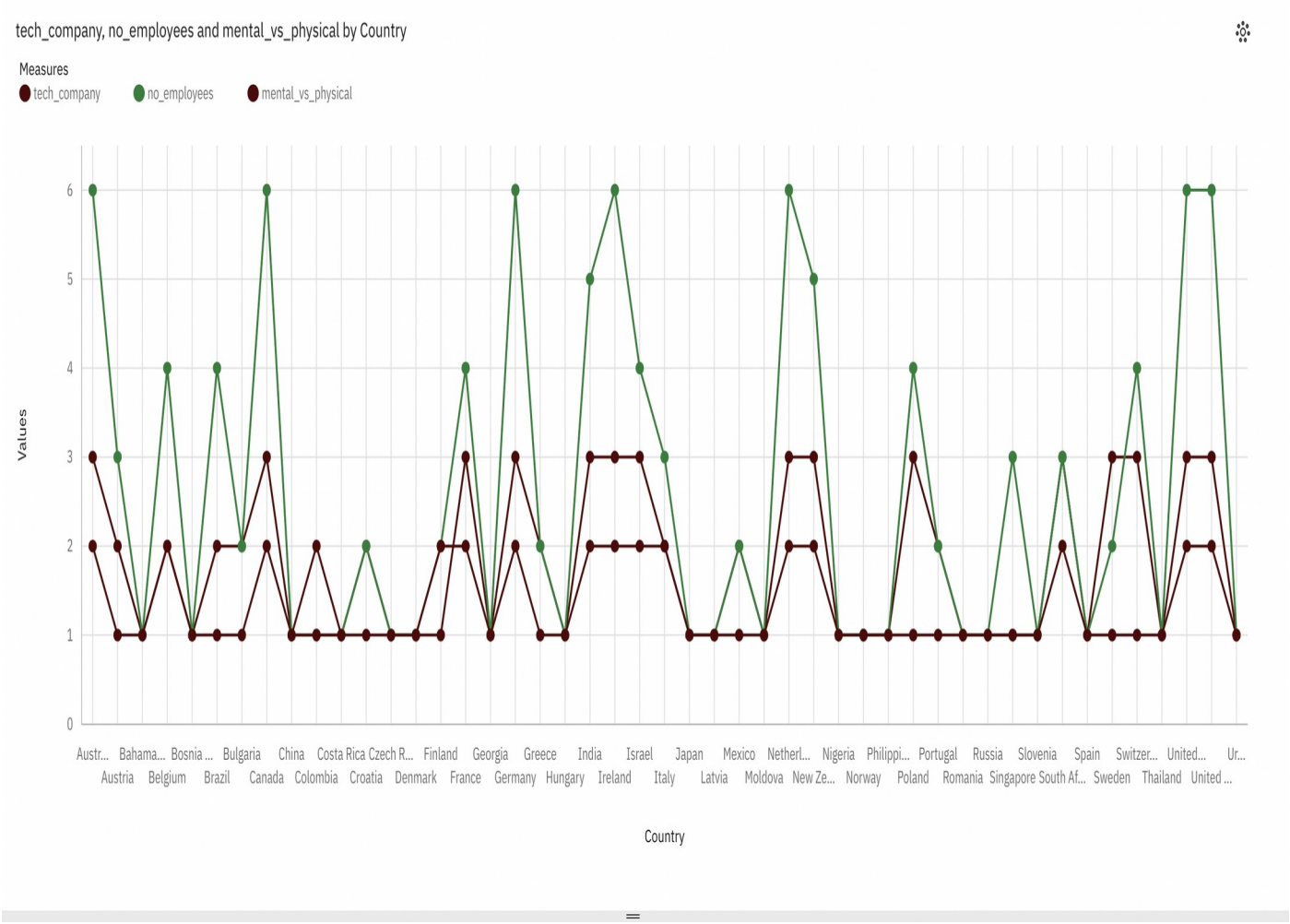


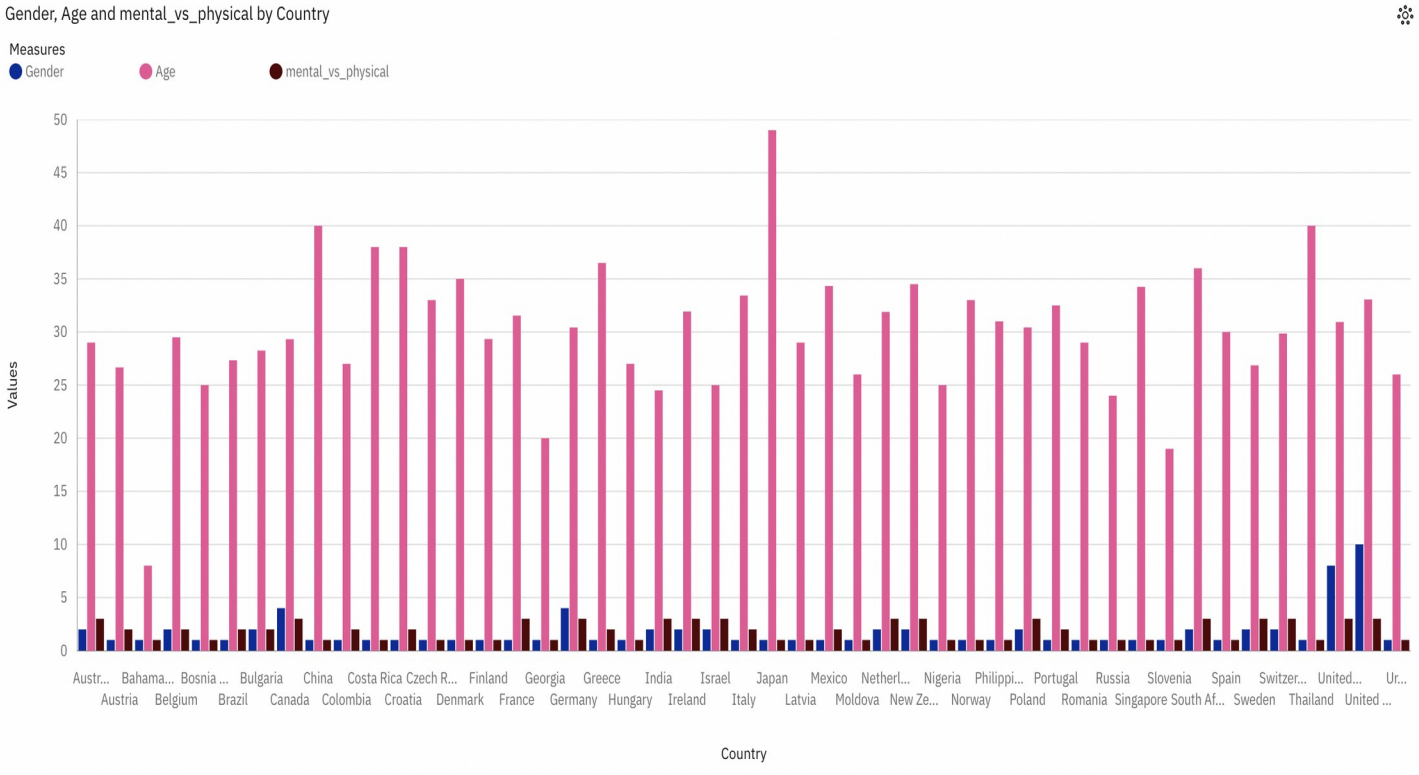

mental_health_interview and phys_health_interview by Gender
Measures
mental_health_interview
phys_health_interview
Agender
Androgyne
Cis Female
Cis Female/Femme
Cis Male
Female
Fluid
Genderqueer
Male
Neuter
Non-Binary
Other
Queer
Queer/She/They
Trans Female
Gender
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3
Values


no_employees by Age
5
11
19
21
23
25
27
29
31
33
35
37
39
41
43
45
47
49
51
54
56
58
61
65
Age
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
no_employees (Count distinct)


self_employed and remote_work by Gender
Measures
self_employed
remote_work
Values
3
2.5
2
1.5
1
0.5
0
Agender
Androgyne
Cis Female
Cis Female/Femme
Cis Male
Female
Fluid
Genderqueer
Male
Neuter
Non-Binary
Other
Queer
Queer/She/They
Trans Female
Gender


coworkers and supervisor by Gender
Measures
coworkers
supervisor
Values
6
5
4
3
2
1
0
Agender
Androgyne
Cis Female
Cis Female/Femme
Cis Male
Female
Fluid
Genderqueer
Male
Neuter
Non-Binary
Other
Queer
Queer/She/They
Trans Female
Gender


tech_company, no_employees and mental_vs_physical by Country
Measures
tech_company
no_employees
mental_vs_physical
Values
0
1
2
3
4
5
6
Austr... Bahama... Bosnia ... Bulgaria China Costa Rica Czech R... Finland Georgia Greece India Israel Japan Mexico Netherl... Nigeria Philippi... Portugal Russia Slovenia Spain Switzer... United... Ur...
Austria Belgium Brazil Canada Colombia Croatia Denmark France Germany Hungary Ireland Italy Latvia Moldova New Ze... Norway Poland Romania Singapore South Af... Sweden Thailand United ...
Country


Gender, Age and mental_vs_physical by Country
Measures
Gender
Age
mental_vs_physical
Values
0
5
10
15
20
25
30
35
40
45
50
Austr... Bahama... Bosnia ... Bulgaria China Costa Rica Czech R... Finland Georgia Greece India Israel Japan Mexico Netherl... Nigeria Philippi... Portugal Russia Slovenia Spain Switzer... United... Ur...
Austria Belgium Brazil Canada Colombia Croatia Denmark France Germany Hungary Ireland Italy Latvia Moldova New Ze... Norway Poland Romania Singapore South Af... Sweden Thailand United ...
Country

In [ ]:

In [ ]:
```
PHASE 4
```

In [ ]:

In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

# PreProcessing
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import SimpleImputer, IterativeImputer
from sklearn.preprocessing import MinMaxScaler


# Splitting Data
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score

# Modeling
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, recall_score, plot_roc_curve
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier


# Tuning
from sklearn.model_selection import GridSearchCV
```

In [ ]:

In [ ]:
```
Data Cleaning
```

In [ ]:

In [67]:
```
mh = pd.read_csv('cleaned_survey.csv')
mh
```

Out[67]:

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfere	no_employees	...	leave	ment
0	2014-08-27 11:29:31	37	Female	United States	IL	Unknown	No	Yes	Often	6-25	...	Somewhat easy	
1	2014-08-27 11:29:37	44	Male	United States	IN	Unknown	No	No	Rarely	More than 1000	...	Don't know	
2	2014-08-27 11:29:44	32	Male	Canada	Unknown	Unknown	No	No	Rarely	6-25	...	Somewhat difficult	
3	2014-08-27 11:29:46	31	Male	United Kingdom	Unknown	Unknown	Yes	Yes	Often	26-100	...	Somewhat difficult	
4	2014-08-27 11:30:22	31	Male	United States	TX	Unknown	No	No	Never	100-500	...	Don't know	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1249	2015-09-12 11:17:21	26	Male	United Kingdom	Unknown	No	No	Yes	Unknown	26-100	...	Somewhat easy	
1250	2015-09-26 01:07:35	32	Male	United States	IL	No	Yes	Yes	Often	26-100	...	Somewhat difficult	
1251	2015-11-07 12:36:58	34	Male	United States	CA	No	Yes	Yes	Sometimes	More than 1000	...	Somewhat difficult	
1252	2015-11-30 21:25:06	46	Female	United States	NC	No	No	No	Unknown	100-500	...	Don't know	
1253	2016-02-01 23:04:31	25	Male	United States	IL	No	Yes	Yes	Sometimes	26-100	...	Don't know	

1254 rows × 27 columns

In [68]:
```
mh.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1254 entries, 0 to 1253
```

```
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Timestamp                  1254 non-null   object
 1   Age                        1254 non-null   int64 
 2   Gender                     1254 non-null   object
 3   Country                    1254 non-null   object
 4   state                      1254 non-null   object
 5   self_employed              1254 non-null   object
 6   family_history             1254 non-null   object
 7   treatment                  1254 non-null   object
 8   work_interfere             1254 non-null   object
 9   no_employees               1254 non-null   object
 10  remote_work                1254 non-null   object
 11  tech_company               1254 non-null   object
 12  benefits                   1254 non-null   object
 13  care_options               1254 non-null   object
 14  wellness_program           1254 non-null   object
 15  seek_help                  1254 non-null   object
 16  anonymity                  1254 non-null   object
 17  leave                      1254 non-null   object
 18  mental_health_consequence  1254 non-null   object
 19  phys_health_consequence    1254 non-null   object
 20  coworkers                  1254 non-null   object
 21  supervisor                 1254 non-null   object
 22  mental_health_interview    1254 non-null   object
 23  phys_health_interview      1254 non-null   object
 24  mental_vs_physical         1254 non-null   object
 25  obs_consequence            1254 non-null   object
 26  comments                   1254 non-null   object
dtypes: int64(1), object(26)
memory usage: 264.6+ KB
```

In [69]:
```
mh.isna().sum()/len(mh.index)*100
```

Out[69]:
```
Timestamp                  0.0
Age                        0.0
Gender                     0.0
Country                    0.0
state                      0.0
self_employed              0.0
family_history             0.0
treatment                  0.0
work_interfere             0.0
no_employees               0.0
remote_work                0.0
tech_company               0.0
```

```
benefits                    0.0
care_options                0.0
wellness_program            0.0
seek_help                   0.0
anonymity                   0.0
leave                       0.0
mental_health_consequence   0.0
phys_health_consequence     0.0
coworkers                   0.0
supervisor                  0.0
mental_health_interview     0.0
phys_health_interview       0.0
mental_vs_physical          0.0
obs_consequence             0.0
comments                    0.0
dtype: float64
```

In [70]:
```
mh.drop(columns=['Timestamp', 'Country', 'state', 'comments'], inplace = True)
```

In [71]:
```
mh.rename({'self_employed' : 'Self_Employed', 'family_history' : 'Family_History',
           'treatment' : 'Treatment', 'work_interfere' : 'Work_Interfere',
           'no_employees': 'Employee_Numbers', 'remote_work': 'Remote_Work', 'tech_company': 'Tech_Company',
           'benefits': 'Benefits', 'care_options': 'Care_Options', 'wellness_program': 'Wellness_Program',
           'seek_help': 'Seek_Help', 'anonymity': 'Anonymity', 'leave': 'Medical_Leave',
           'mental_health_consequence': 'Mental_Health_Consequence',
           'phys_health_consequence': 'Physical_Health_Consequence', 'coworkers': 'Coworkers',
           'supervisor': 'Supervisor', 'mental_health_interview': 'Mental_Health_Interview',
           'phys_health_interview': 'Physical_Health_Interview', 'mental_vs_physical': 'Mental_VS_Physical',
           'obs_consequence': 'Observed_Consequence'} , inplace = True , axis = 1)
```

In [72]:
```
mh['Age'].unique()
```

Out[72]:
```
array([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,  5, 53, 61,  8, 11, 72])
```

In [73]:
```
mh['Age'].replace([mh['Age'][mh['Age'] < 15]], np.nan, inplace = True)
mh['Age'].replace([mh['Age'][mh['Age'] > 100]], np.nan, inplace = True)

mh['Age'].unique()
```

Out[73]:
```
array([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., nan, 53., 61., 72.])
```

In [74]:
```
mh['Gender'].unique()
```

Out[74]:
```
array(['Female', 'Male', 'Trans Female', 'Cis Female', 'Cis Male',
       'Queer/She/They', 'Non-Binary', 'Other', 'Fluid', 'Genderqueer',
       'Androgyne', 'Agender', 'Cis Female/Femme', 'Neuter', 'Queer'],
      dtype=object)
```

In [75]:
```
mh['Gender'].replace(['Male ', 'male', 'M', 'm', 'Male', 'Cis Male',
                      'Man', 'cis male', 'Mail', 'Male-ish', 'Male (CIS)',
                       'Cis Man', 'msle', 'Malr', 'Mal', 'maile', 'Make',], 'Male', inplace = True)

mh['Gender'].replace(['Female ', 'female', 'F', 'f', 'Woman', 'Female',
                      'femail', 'Cis Female', 'cis-female/femme', 'Femake', 'Female (cis)',
                      'woman',], 'Female', inplace = True)

mh["Gender"].replace(['Female (trans)', 'queer/she/they', 'non-binary',
                      'fluid', 'queer', 'Androgyne', 'Trans-female', 'male leaning androgynous',
                       'Agender', 'A little about you', 'Nah', 'All',
                       'ostensibly male, unsure what that really means',
                       'Genderqueer', 'Enby', 'p', 'Neuter', 'something kinda male?',
                       'Guy (-ish) ^_^', 'Trans woman',], 'Queer', inplace = True)
```

In [76]:
```
mh['Gender'].value_counts()
```

Out[76]:
```
Male                986
Female              246
Other                 7
Queer                 6
Trans Female          4
Non-Binary            2
Cis Female/Femme      1
Fluid                 1
Queer/She/They        1
Name: Gender, dtype: int64
```

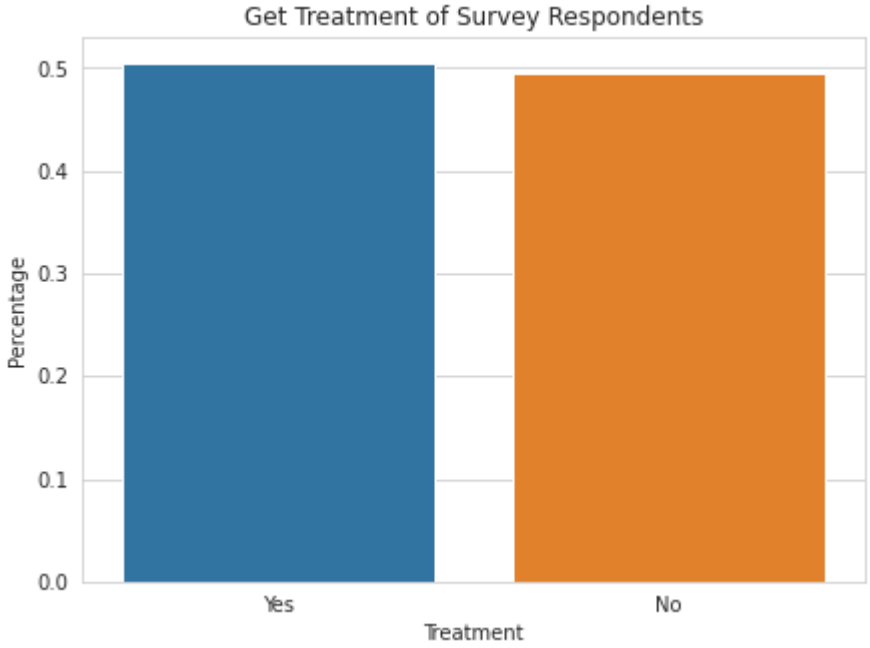
In [ ]:

In [ ]:
```
EDA
```

In [ ]:

In [77]:
```
mh_eda = mh.copy()
```

In [78]:
```
sns.set_style("whitegrid")
plt.figure(figsize = (7,5))
eda_percentage = mh_eda['Treatment'].value_counts(normalize = True).rename_axis('Treatment').reset_index(name = 'Percen
sns.barplot(x = 'Treatment', y = 'Percentage', data = eda_percentage.head(10))
plt.title('Get Treatment of Survey Respondents')
plt.show()
```



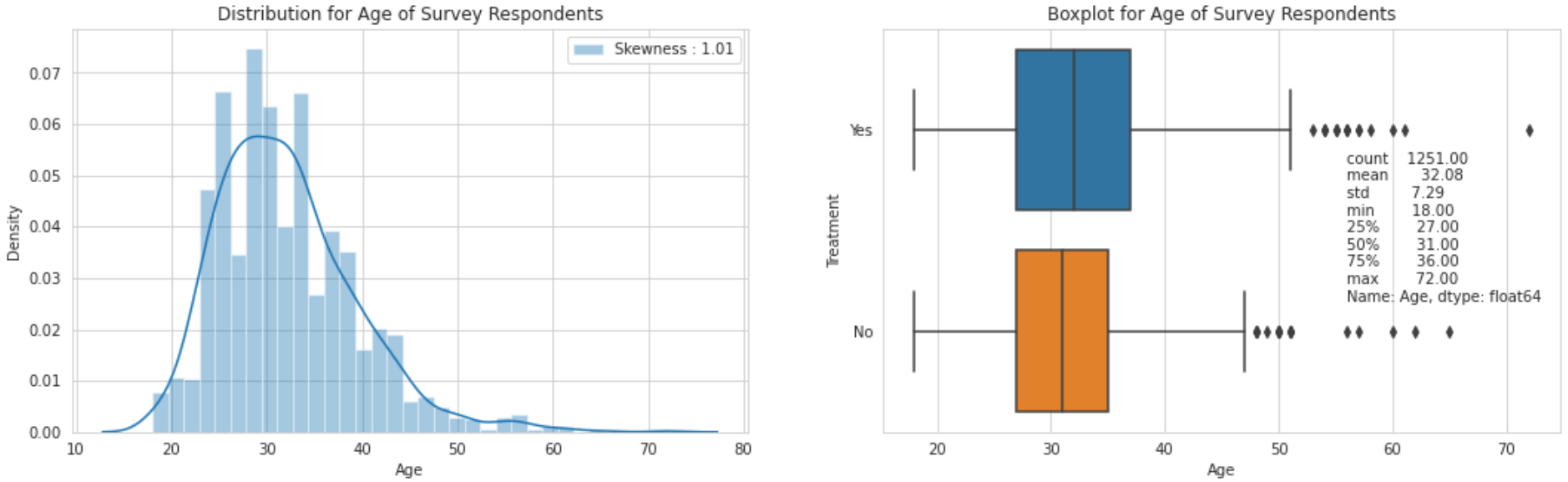
In [ ]:

In [ ]:
```
This is the respondents result of question,
'Have you get treatment for a mental health condition?'.
The percentage of respondents who want to get treatment is 50%. Workplaces
that promote mental health and support people with mental disorders are more
likely to reduce absenteeism, increase productivity and benefit from associated
economic gains. If employees enjoy good mental health, employees can:
make the most of your potential,
```

```
cope with what life throws at you,
play a full part in your relationships, your workplace, and your community.
I decided to separate them into 3 aspects to see what factors that company give
so employees want to get a treatment:
Employee's profiling
Employee's work environtment
Employee's mental health facilities
```

In [ ]:

In [79]:
```
plt.figure(figsize = (18,5))
plt.subplot(1,2,1)
sns.distplot(mh_eda['Age'], label = 'Skewness : %.2f'%(mh_eda['Age'].skew()))
plt.legend(loc = 0, fontsize = 10)
plt.title('Distribution for Age of Survey Respondents')
plt.subplot(1,2,2)
sns.boxplot(x = "Age", y = "Treatment", data = mh_eda)
plt.title('Boxplot for Age of Survey Respondents')
age = str(mh_eda['Age'].describe().round(2))
plt.text(56, 0.85, age)
plt.show()
```

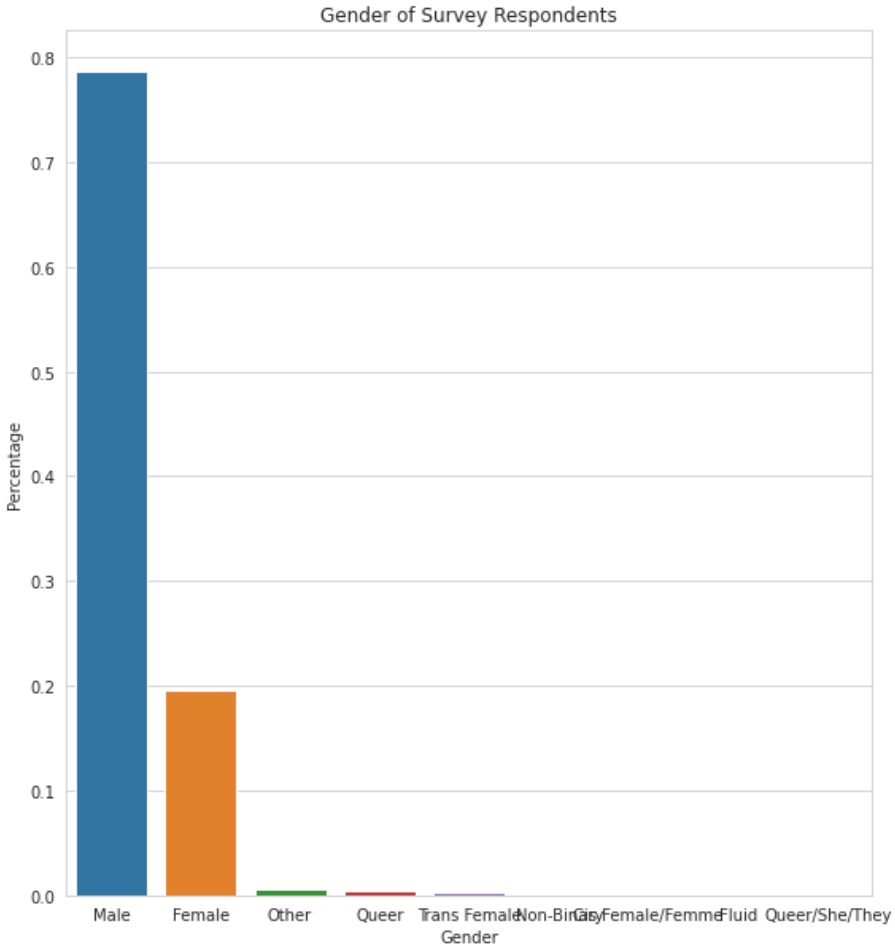


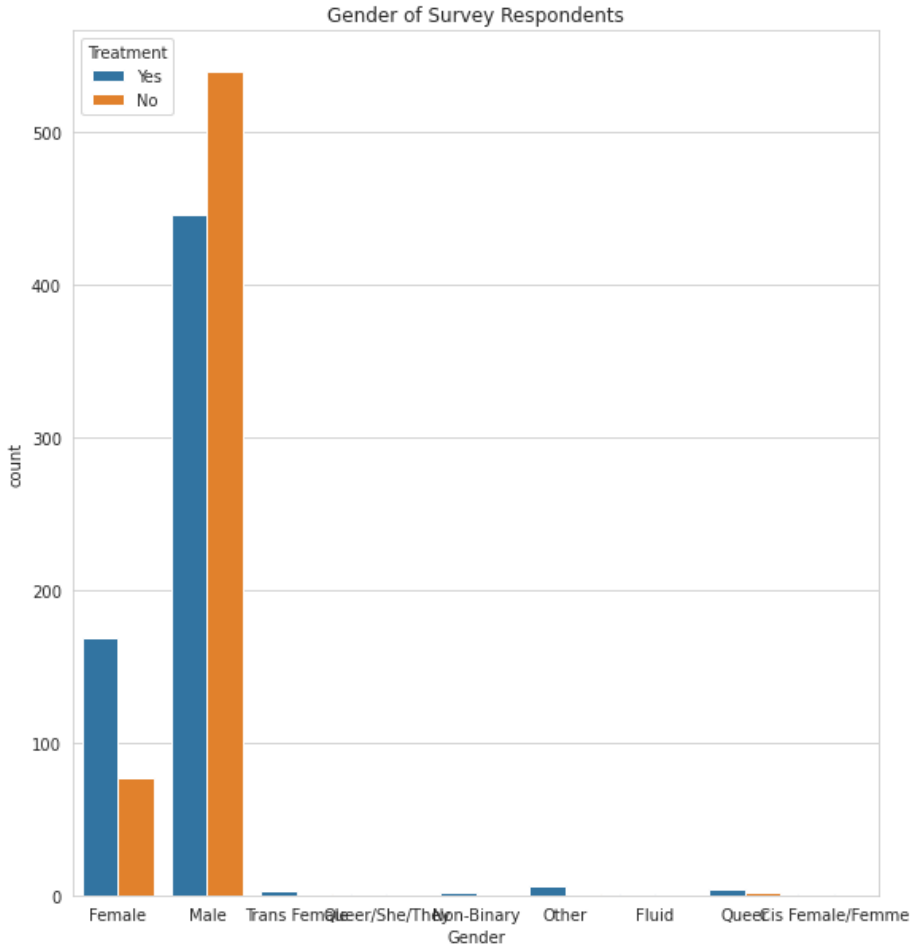
In [ ]:

In [ ]:
```
Skewness
Based on the plot, the skewness score is 1.01, which means the data are highly
skewed and with Positive skewness where the mode is
smaller than mean or median.
It's indicated that most of the employees that fill the survey around the end
20s to early 40s. I assume that they on between
mid to senior-level positions. The distribution of ages is right-skewed which
is expected as the tech industry tends to have younger employees.
From an article that I read, young (usually white, mostly male) faces of start-up
founders like Mark
Zuckerberg and other “tech bros” have become the symbol and stereotypical image that tends
to represent the tech industry.
Boxplot
From the boxplot, there is no statistically significant difference of ages between respondents
that get treatment and no treatment.
```

In [ ]:
```
```

In [81]:
```
plt.figure(figsize = (20,10))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Gender'].value_counts(normalize = True).rename_axis('Gender').reset_index(name = 'Percentage')
sns.barplot(x = 'Gender', y = 'Percentage', data = eda_percentage.head(10))
plt.title('Gender of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Gender'], hue = mh_eda['Treatment'])
plt.title('Gender of Survey Respondents')
plt.show()
```





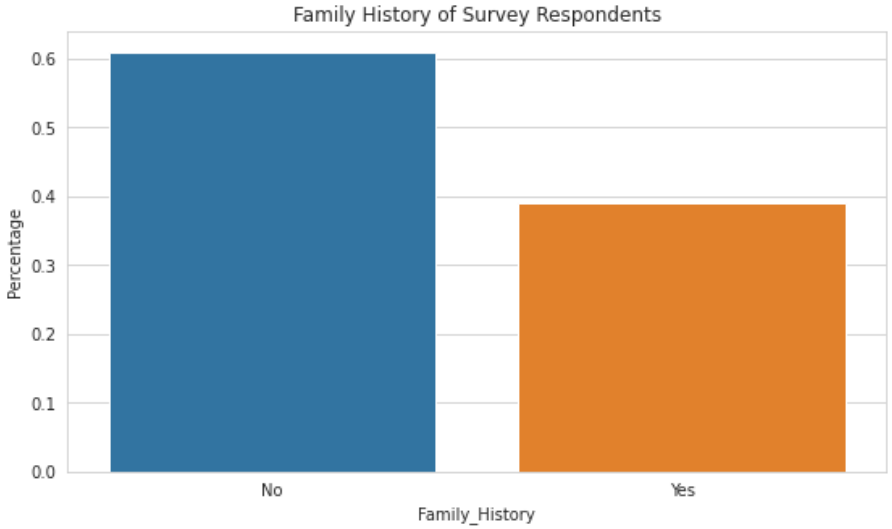
In [ ]:

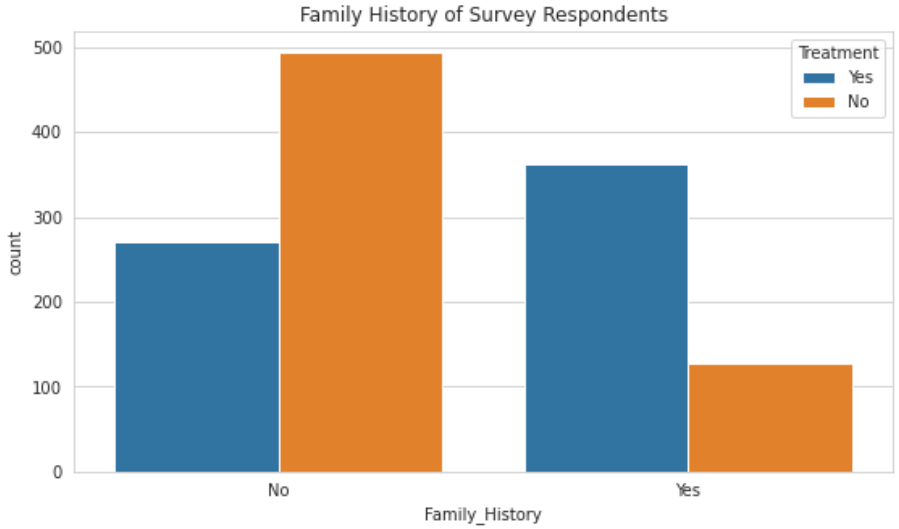
In [ ]:
```
This is the respondents result of question, 'What is your gender identities?'.
Almost 79% of respondents are male, not surprisingly, especially in the tech field.
The very large gap between men and women causes
higher competitive pressure for women than men. Based on the plot, female that want
to get treatment is high around 70%. Maybe some
of them get sexual harrassment or racism at work because female are scarce in the tech industry.
There is a Queer entry of less than 2%. Although the percentage of queer is very low,
it still deserves to dig out some new
insights. For example, such a small proportion can show a significant difference in
the count of who wants the treatments,
indicating that for the queer, mental health problems are serious too.
```

```
In my opinion, maybe they received hate speech or
discrimination in the workplace.
```

In [ ]:

In [82]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Family_History'].value_counts(normalize = True).rename_axis('Family_History').reset_index(name
sns.barplot(x = 'Family_History', y = 'Percentage', data = eda_percentage)
plt.title('Family History of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Family_History'], hue = mh_eda['Treatment'])
plt.title('Family History of Survey Respondents')
plt.show()
```





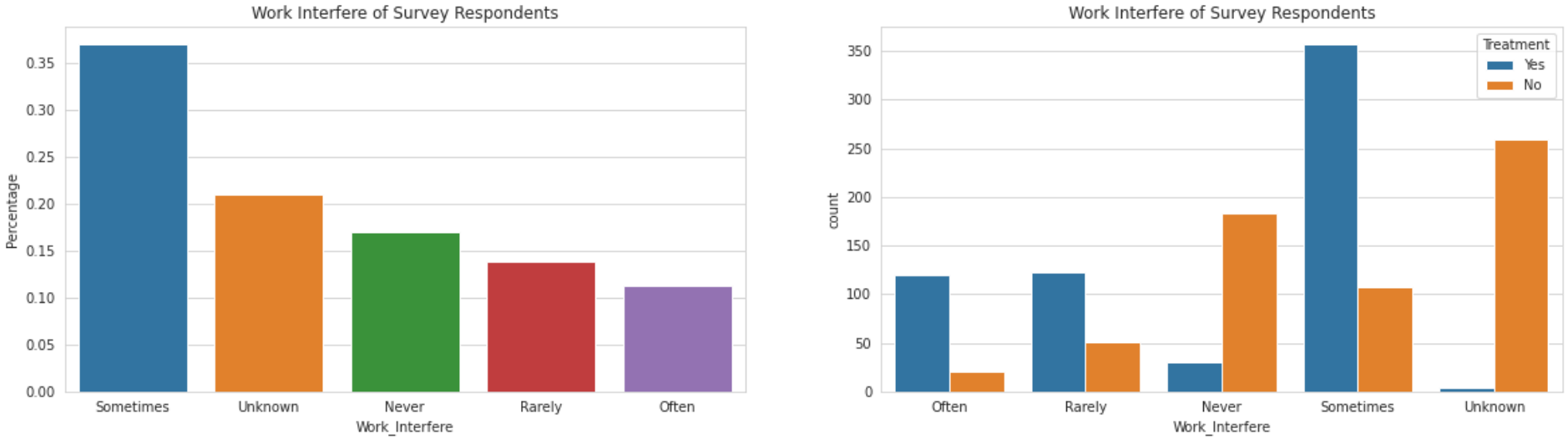
In [ ]:

In [ ]:
```
This is the respondents result of question,
'Do you have a family history of mental illness?'.
From 40% of respondents who say that they have a family history
of mental illness, the plot shows that they significantly
want to get treatment rather than without a family history. This
is acceptable, remember the fact that people with a family
history pay more attention to mental illness. Family history is a
significant risk factor for many mental health disorders.
```

```
The apple does not fall far from the tree, as it is relatively
common for families with mental illness symptoms to have one
or more relatives with histories of similar difficulties.
```

In [ ]:

In [83]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Work_Interfere'].value_counts(normalize = True).rename_axis('Work_Interfere').reset_index(name
sns.barplot(x = 'Work_Interfere', y = 'Percentage', data = eda_percentage)
plt.title('Work Interfere of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Work_Interfere'], hue = mh_eda['Treatment'])
plt.title('Work Interfere of Survey Respondents')
plt.show()
```



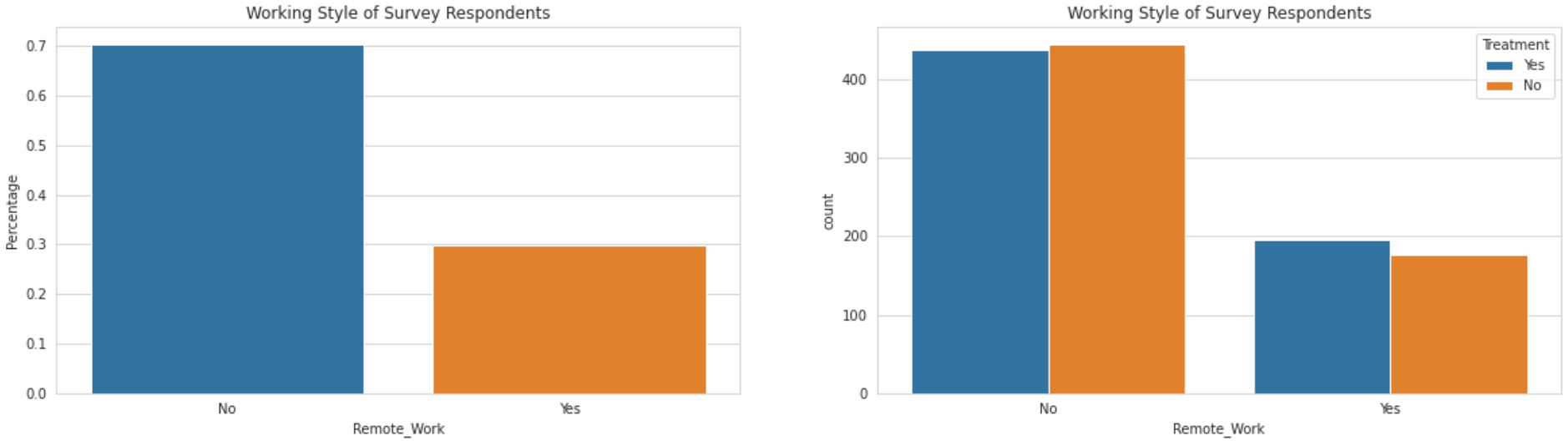
In [ ]:

In [ ]:
```
This is the respondents result of question, 'If you have a mental
health condition, do you feel that it interferes with your work?'.
About 78% of respondents have experienced interference at work with
a ratio of rarely, sometimes, and frequently.
Mental health conditions sometimes become an interfere while working
about 45%. The plots prove that almost 80%
want to get treatment. But it's surprising to know even mental health
```

```
never has interfered at work, there is a little
group that still want to get treatment before it become a job stress.
It can be triggered by the requirements of the
job do not match the capabilities, resources or needs of the worker.
```

In [ ]:

In [84]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Remote_Work'].value_counts(normalize = True).rename_axis('Remote_Work').reset_index(name = 'Pe
sns.barplot(x = 'Remote_Work', y = 'Percentage', data = eda_percentage)
plt.title('Working Style of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Remote_Work'], hue = mh_eda['Treatment'])
plt.title('Working Style of Survey Respondents')
plt.show()
```



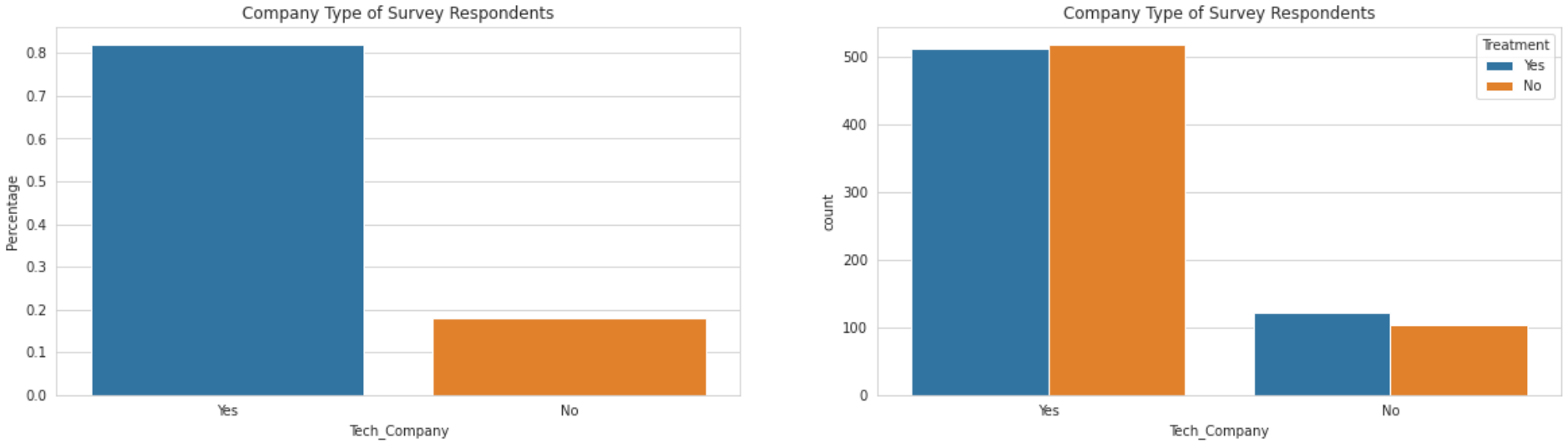
In [ ]:

In [ ]:
```
This is the respondents result of question, Do you work remotely
(outside of an office) at least 50% of the time?.
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. But it's getting interesting when we see a
respondent who works 50% of the workday remotely. The employee
who want to get treatment is a little bit higher. I have no idea
why those employees work remotely to analyze more because the data
doesn't provide that information.
```

In [ ]:

In [85]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Tech_Company'].value_counts(normalize = True).rename_axis('Tech_Company').reset_index(name = '
sns.barplot(x = 'Tech_Company', y = 'Percentage', data = eda_percentage)
plt.title('Company Type of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Tech_Company'], hue = mh_eda['Treatment'])
plt.title('Company Type of Survey Respondents')
plt.show()
```



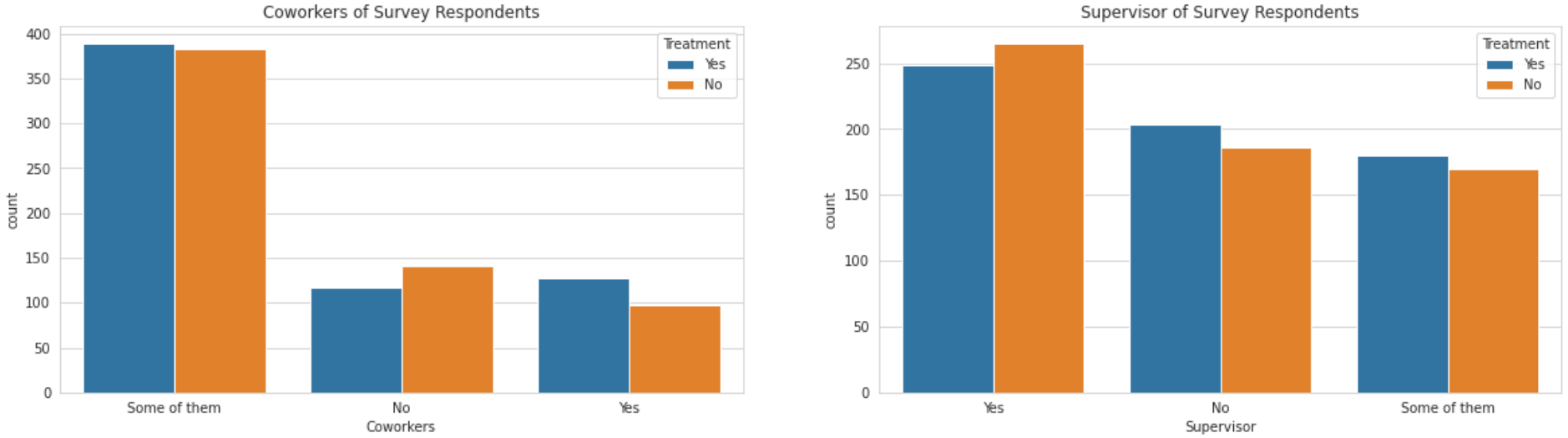
In [ ]:

In [ ]:
```
This is the respondents result of question, 'Is your employer
primarily a tech company/organization?'.
Even the main target of the survey is the tech field, there are
18% of companies belong to the non-tech field. But it
can be seen from the plot whether the company belongs to the
```

```
tech field or not, mental health still becomes a big problem.
I think the environment affects a lot of employees and some of
them can't take it for granted like abuse at the workplace.
However, I found that the number of employees in the technology
field that want to get treatment is slightly lower than no
treatment. But the non-technical field is the opposite. Maybe
the non-tech company give more support for employee to get treatment?
```

In [ ]:

In [86]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
sns.countplot(mh_eda['Coworkers'], hue = mh_eda['Treatment'])
plt.title('Coworkers of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Supervisor'], hue = mh_eda['Treatment'])
plt.title('Supervisor of Survey Respondents')
plt.show()
```



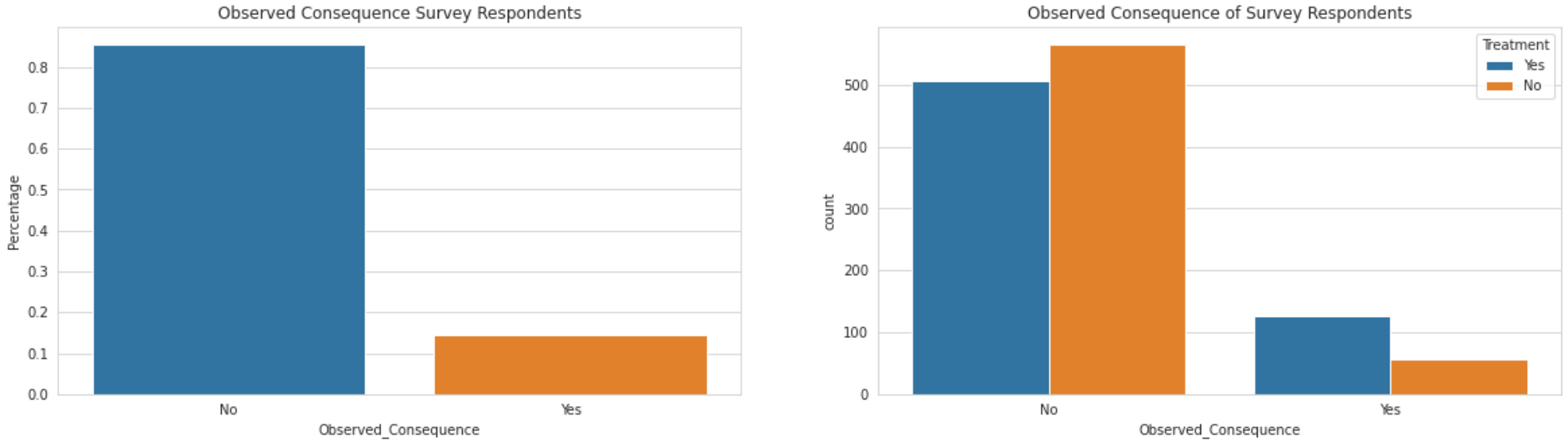
In [ ]:

In [ ]:
```
This is the respondents result of question, 'Would you be willing to
discuss a mental health issue with your coworkers?'.
From 18% of respondents who say yes to discuss it with coworkers,
60% of them want to get treatment.
```

```
About 60% of respondents decide to discuss some of them with coworkers.
Employees who do that and want to get treatment are half
of them. Let's see if the respondent will discuss it with a supervisor or not.
This is the respondents result of question, 'Would you be willing to
discuss a mental health issue with your direct supervisor(s)?'.
From 40% of respondents who say yes to discuss with supervisor, only
55% of them that want to get treatment. I think maybe talking
to someone in a higher position could help the relief.
It's the opposite while employees discuss with coworkers.
```

In [ ]:

In [87]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Observed_Consequence'].value_counts(normalize = True).rename_axis('Observed_Consequence').rese
sns.barplot(x = 'Observed_Consequence', y = 'Percentage', data = eda_percentage)
plt.title('Observed Consequence Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Observed_Consequence'], hue = mh_eda['Treatment'])
plt.title('Observed Consequence of Survey Respondents')
plt.show()
```

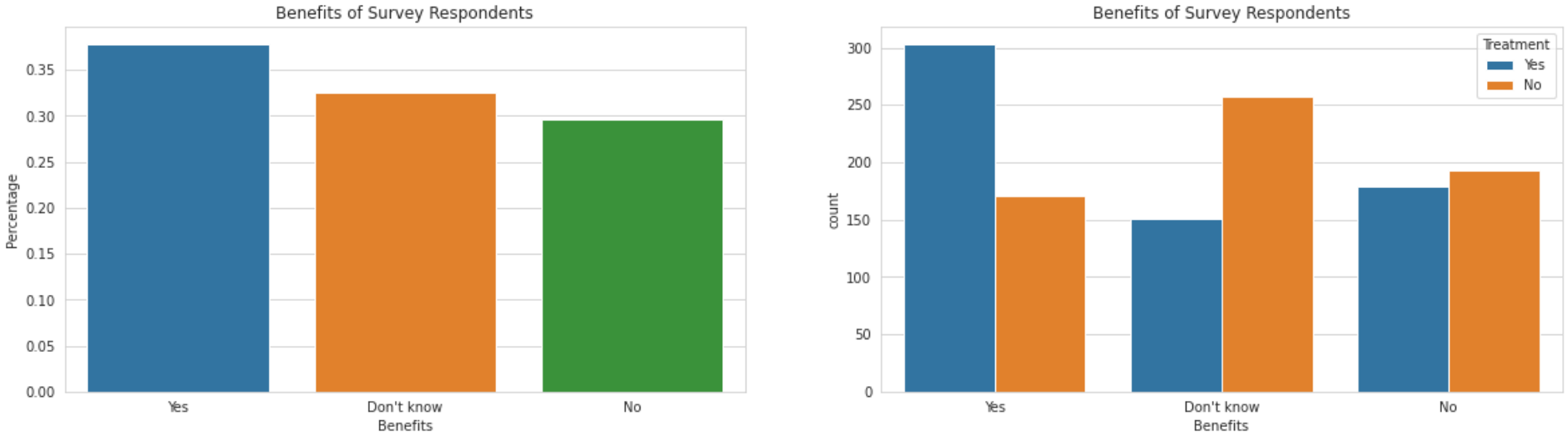


In [ ]:

In [ ]:
```
This is the respondents result of question,
'Have you heard of or observed negative consequences for coworkers with mental health
conditions in your workplace?'.
From 15% of respondents who say yes about knowing the
negative consequences for coworkers with mental heatlh condition,
almost 70% of them that want to get treatment. After the employee
knows about the negative consequences, it becomes a good
trigger for someone to get treatment to prevent mental health conditions.
```

In [ ]:
```
```

In [88]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Benefits'].value_counts(normalize = True).rename_axis('Benefits').reset_index(name = 'Percenta
sns.barplot(x = 'Benefits', y = 'Percentage', data = eda_percentage)
plt.title('Benefits of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Benefits'], hue = mh_eda['Treatment'])
plt.title('Benefits of Survey Respondents')
plt.show()
```

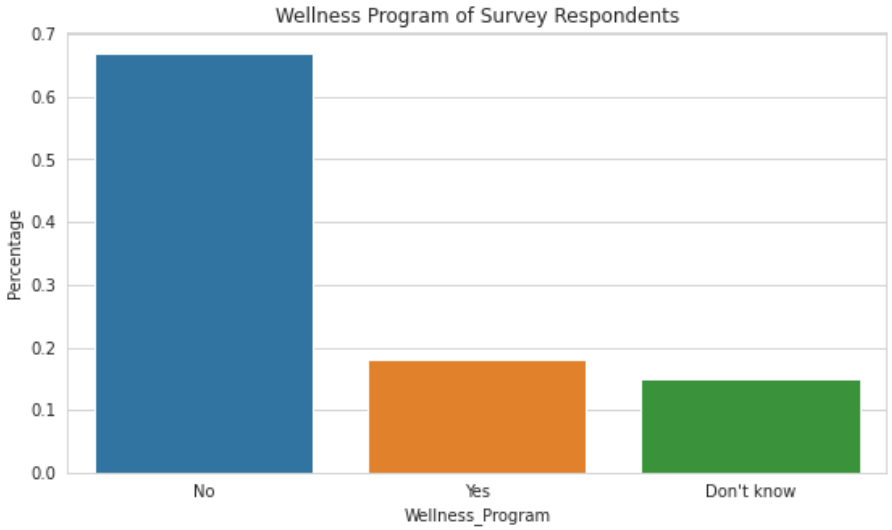


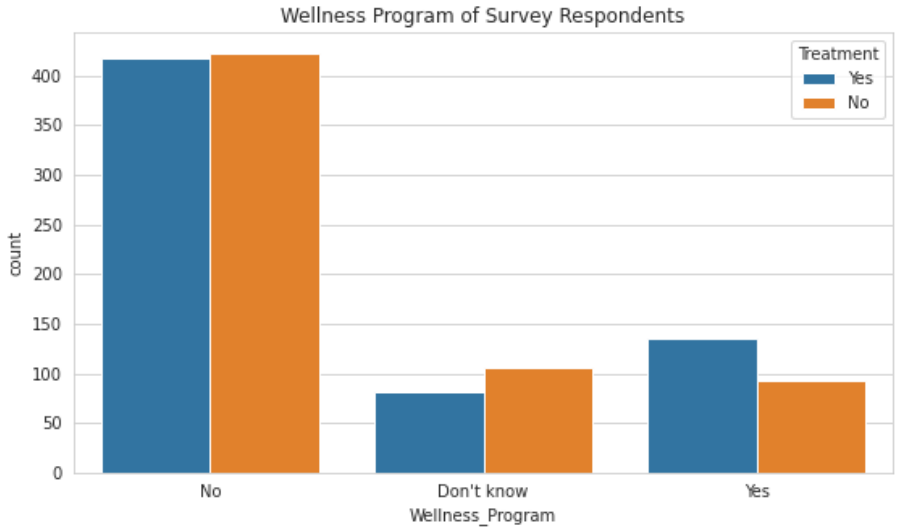
In [ ]:
```
```

In [ ]:
```
This is the respondents result of question, 'Does your employer
mental health benefits?'.
Only 35% of respondents know about mental health benefits that the
company provides for them.
For employees who know the benefits, almost 60% of the employees want to get treatment.
Surprisingly, there is an employee who
doesn't know and says that the company doesn't provide still want to get treatment.
I assume that maybe the company can't
provide it properly because of budgeting or financial struggling.
```

In [ ]:
```
```

In [89]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Wellness_Program'].value_counts(normalize = True).rename_axis('Wellness_Program').reset_index(
sns.barplot(x = 'Wellness_Program', y = 'Percentage', data = eda_percentage)
plt.title('Wellness Program of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Wellness_Program'], hue = mh_eda['Treatment'])
plt.title('Wellness Program of Survey Respondents')
plt.show()
```



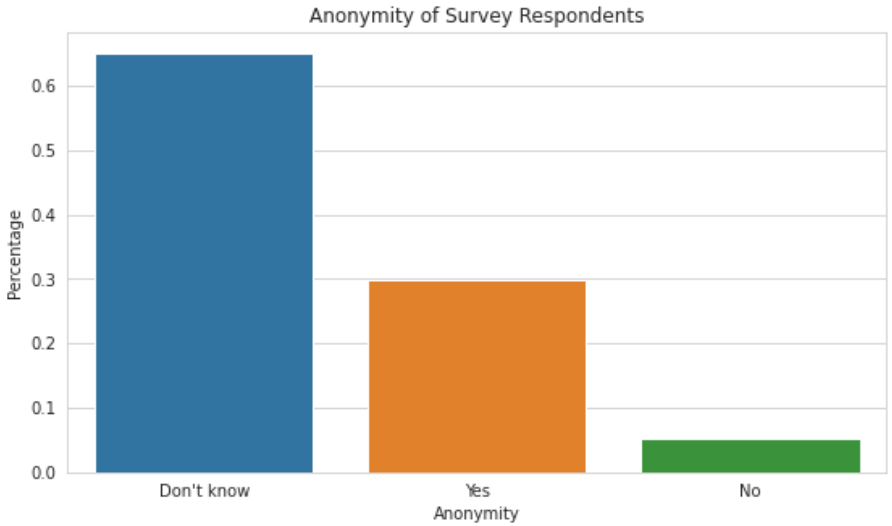


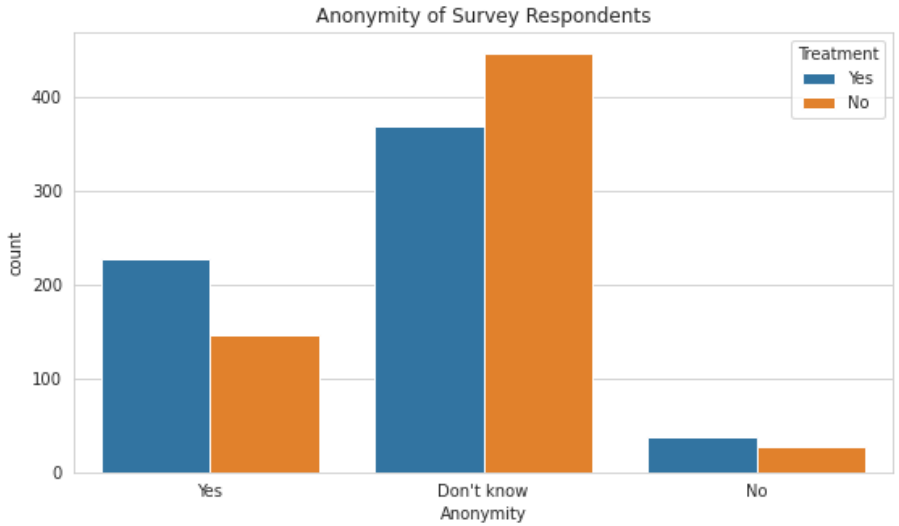
In [ ]:
```
```

In [ ]:
```
This is the respondents result of question,
'Has your employer ever discussed mental health as part of an employee wellness program?'.
About 19% of the repondents say yes about become a part of employee wellness program
and 60% of employee want to get treatment. After
become a part of wellness program, i assume that employee feels a good vibe about it.
More than 65% of respondents say that there aren't any wellness programs that provide
by their company. But half of the respondents want to get treatment, which means the company need to provide it soon.
Based on my curiosity about company's benefit before, I think it makes sense if
it's about company budgeting. I know it will spend a lot of money, moreover, the
company has a lot of employees to taking care of. My second thought, it's still about
budgeting but for a small company, it will be a lot of struggle.
```

In [ ]:
```
```

In [90]:
```
plt.figure(figsize = (20,5))
plt.subplot(1,2,1)
eda_percentage = mh_eda['Anonymity'].value_counts(normalize = True).rename_axis('Anonymity').reset_index(name = 'Percen
sns.barplot(x = 'Anonymity', y = 'Percentage', data = eda_percentage)
plt.title('Anonymity of Survey Respondents')
plt.subplot(1,2,2)
sns.countplot(mh_eda['Anonymity'], hue = mh_eda['Treatment'])
plt.title('Anonymity of Survey Respondents')
plt.show()
```





In [ ]:

In [ ]:
```
This is the respondents result of question,
'Is your anonymity protected if you choose to take advantage of mental health or
substance abuse treatment resources?'.
About 30% of respondents say yes if their anonymity is protected while taking advantage
of mental health or substance abuse treatment resources and almost 65% of employees want
to get treatment. The employee feels that the company protected their privacy and it's a
good move for the company to build trust with their employees. Because of that, the employee wants to get
treatment to be better.
```

In [ ]:

In [ ]:

In [ ]:
```
Conclusion

Nearly 86% of employees report improved work performance and
lower rates of absenteeism after receiving treatment for depression,
according to an April 2018 article in the Journal of Occupational
and Environmental Medicine. This means big gains in retention
and productivity for employers. By providing employees access to mental
health benefits, the company can begin to create a culture of
understanding and compassion at the tech company. And having employees
```

```
who feel cared for and happy isn't just good, it's good business.

Based on profiling the respondents
Companies must know that gender and family history greatly influence the
decision to get treatment for employees. So if the company wants
to provide more support, the company must make an assessment of the
employee's personality because different characters can determine
different needs. Age can also be a trigger, considering that most of
them are young so there is a high chance that they will be
open-minded to get treatment.

Based on the work environment of respondents
Work interference is the most influential of employees who want to get
treatment. This means the company should consider
providing facilities to anticipate job stress on employees. Some of
the companies decide to make a private room or silent room in
case employees suddenly feel stress and need a private moment to relieve.

Based on the mental health facilities of respondents
The company needs to provide a good benefit for employees so they can
maintain their mental health. If the company can don't
have resources for it, there are so many third parties who can be
hired to maintain a wellness program for the company.
Building trust like keep private about whom employee that gets treatment
also can also give a trigger for employee want to get treatment.
```

In [ ]:

In [ ]:
```
PreProcessing

Preprocessing Scheme

OneHotEncoding: Gender, Family History, Employee Numbers, Remote
    Work, Tech Company, Benefits, Care Options, Wellness Program,
    Seek Help, Anonymity, Medical Leave, Mental Health Consequence,
    Physical Health Consequence, Coworkers, Supervisor,
    Mental Health Interview, Physical Health Interview,
    Mental VS Physical, Observed Consequence
Simple Imputer Most Frequent: Self Employed, Work Interfere
Iterative Impute: Age
Target: Treatment
```

In [ ]:

In [91]:
```
mode_onehot_pipe = Pipeline([
    ('encoder', SimpleImputer(strategy = 'most_frequent')),
    ('one hot encoder', OneHotEncoder(handle_unknown = 'ignore'))])

transformer = ColumnTransformer([
    ('one hot', OneHotEncoder(handle_unknown = 'ignore'), ['Gender', 'Family_History', 'Employee_Numbers',
                                                           'Remote_Work', 'Tech_Company', 'Benefits', 'Care_Options',
                                                           'Wellness_Program', 'Seek_Help', 'Anonymity',
                                                           'Medical_Leave', 'Mental_Health_Consequence',
                                                           'Physical_Health_Consequence', 'Coworkers', 'Supervisor',
                                                           'Mental_Health_Interview', 'Physical_Health_Interview',
                                                           'Mental_VS_Physical', 'Observed_Consequence']),
    ('mode_onehot_pipe', mode_onehot_pipe, ['Self_Employed', 'Work_Interfere']),
    ('iterative', IterativeImputer(max_iter = 10, random_state = 0), ['Age'])])
```

In [92]:
```
mh['Treatment'].value_counts()/mh.shape[0]*100
```

Out[92]:
```
Yes    50.478469
No     49.521531
Name: Treatment, dtype: float64
```

In [93]:
```
mh['Treatment'] = np.where(mh['Treatment'] == 'Yes', 1, 0)
```

In [94]:
```
X = mh.drop('Treatment', axis = 1)
y = mh['Treatment']
```

In [95]:
```
X.shape
```

Out[95]:
```
(1254, 22)
```

In [96]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,
                                                    stratify = y,
                                                     test_size = 0.3,
                                                    random_state = 2222)
```

In [ ]:

In [ ]:

In [ ]:
```
Modeling
Define Model

In supervised learning, algorithms learn from labeled data.
In this case, I use Classification technique for determining which
class is yes and no.
I use 3 basic models and 4 ensemble models to predict.
Basic models:
Logistic Regression (logreg)
Decision Tree Classifier (tree)
K-Nearest Neighbor (knn)
Ensemble models:
Random Forest Classifier (rf)
Ada Boost Classifier (ada)
Gradient Boosting Classifier (grad)
```

In [ ]:

In [ ]:

In [97]:
```
logreg = LogisticRegression()
tree = DecisionTreeClassifier(random_state = 2222)
knn = KNeighborsClassifier()
rf = RandomForestClassifier(random_state = 2222)
ada = AdaBoostClassifier(random_state = 2222)
grad = GradientBoostingClassifier(random_state = 2222)
```

In [ ]:

In [ ]:
```
Cross Validation:
```

In [ ]:

In [98]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

```
# PreProcessing
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import SimpleImputer, IterativeImputer
from sklearn.preprocessing import MinMaxScaler

# Splitting Data
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score

# Modeling
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, recall_score, plot_roc_curve
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier

logreg_pipe = Pipeline([('transformer', transformer), ('logreg', logreg)])
tree_pipe = Pipeline([('transformer', transformer), ('tree', tree)])
knn_pipe = Pipeline([('transformer', transformer), ('knn', knn)])
rf_pipe = Pipeline([('transformer', transformer), ('rf', rf)])
ada_pipe = Pipeline([('transformer', transformer), ('ada', ada)])
grad_pipe = Pipeline([('transformer', transformer), ('grad', grad)])

def model_evaluation(model, metric):
    model_cv = cross_val_score(model, X_train, y_train, cv=StratifiedKFold(n_splits=5), scoring=metric)
    return model_cv

logreg_pipe_cv = model_evaluation(logreg_pipe, 'recall')
tree_pipe_cv = model_evaluation(tree_pipe, 'recall')
knn_pipe_cv = model_evaluation(knn_pipe, 'recall')
rf_pipe_cv = model_evaluation(rf_pipe, 'recall')
ada_pipe_cv = model_evaluation(ada_pipe, 'recall')
grad_pipe_cv = model_evaluation(grad_pipe, 'recall')

for model in [logreg_pipe, tree_pipe, knn_pipe, rf_pipe, ada_pipe, grad_pipe]:
    model.fit(X_train, y_train)

score_cv = [logreg_pipe_cv.round(5), tree_pipe_cv.round(5), knn_pipe_cv.round(5),
            rf_pipe_cv.round(5), ada_pipe_cv.round(5), grad_pipe_cv.round(5)]
score_mean = [logreg_pipe_cv.mean(), tree_pipe_cv.mean(), knn_pipe_cv.mean(), rf_pipe_cv.mean(),
              ada_pipe_cv.mean(), grad_pipe_cv.mean()]
```

```
score_std = [logreg_pipe_cv.std(), tree_pipe_cv.std(), knn_pipe_cv.std(), rf_pipe_cv.std(),
             ada_pipe_cv.std(), grad_pipe_cv.std()]
score_recall_score = [recall_score(y_test, logreg_pipe.predict(X_test)),
            recall_score(y_test, tree_pipe.predict(X_test)),
            recall_score(y_test, knn_pipe.predict(X_test)),
            recall_score(y_test, rf_pipe.predict(X_test)),
            recall_score(y_test, ada_pipe.predict(X_test)),
            recall_score(y_test, grad_pipe.predict(X_test))
           ]

method_name = ['Logistic Regression', 'Decision Tree Classifier', 'KNN Classifier', 'Random Forest Classifier',
               'Ada Boost Classifier', 'Gradient Boosting Classifier']

cv_summary = pd.DataFrame({
    'method': method_name,
    'cv score': score_cv,
    'mean score': score_mean,
    'std score': score_std,
    'recall score': score_recall_score
})

cv_summary
```

Out[98]:

	method	cv score	mean score	std score	recall score
0	Logistic Regression	[0.80899, 0.88764, 0.88764, 0.88636, 0.875]	0.869127	0.030442	0.863158
1	Decision Tree Classifier	[0.76404, 0.68539, 0.83146, 0.84091, 0.79545]	0.783453	0.056111	0.747368
2	KNN Classifier	[0.57303, 0.67416, 0.70787, 0.65909, 0.65909]	0.654648	0.044527	0.605263
3	Random Forest Classifier	[0.77528, 0.83146, 0.88764, 0.90909, 0.86364]	0.853422	0.046824	0.810526
4	Ada Boost Classifier	[0.80899, 0.85393, 0.92135, 0.84091, 0.85227]	0.855490	0.036674	0.857895
5	Gradient Boosting Classifier	[0.78652, 0.80899, 0.89888, 0.89773, 0.86364]	0.851149	0.045953	0.800000

In [ ]:

In [ ]: HyperParam Tuning:

In [ ]:

In [99]:
```
lr_estimator = Pipeline([
    ('transformer', transformer),
    ('model', logreg)])

hyperparam_space = {
    'model__C': [ 1, 0.5, 0.1, 0.05, 0.01],
    'model__solver': ['newton-cg', 'lbfgs', 'liblinear'],
    'model__class_weight': ['balanced', 'dict'],
    'model__max_iter': [100, 200, 300],
    'model__multi_class': ['auto', 'ovr', 'multinomial'],
    'model__random_state': [2222]
}

grid_lr = GridSearchCV(
                lr_estimator,
                param_grid = hyperparam_space,
                cv = StratifiedKFold(n_splits = 5),
                scoring = 'recall',
                n_jobs = -1)

grid_lr.fit(X_train, y_train)

print('best score', grid_lr.best_score_)
print('best param', grid_lr.best_params_)
```

```
best score 0.8781664964249234
best param {'model__C': 0.1, 'model__class_weight': 'balanced', 'model__max_iter': 100, 'model__multi_class': 'multinom
ial', 'model__random_state': 2222, 'model__solver': 'newton-cg'}
```

In [100…
```
logreg_pipe.fit(X_train, y_train)
recall_logreg = (recall_score(y_test, logreg_pipe.predict(X_test)))

grid_lr.best_estimator_.fit(X_train, y_train)
recall_grid = (recall_score(y_test, grid_lr.predict(X_test)))

score_list = [recall_logreg, recall_grid]
method_name = ['Logistic Regression Before Tuning', 'Logistic Regression After Tuning']
best_summary = pd.DataFrame({
    'method': method_name,
    'score': score_list
})
best_summary
```

Out[100…

	method	score
0	Logistic Regression Before Tuning	0.863158
1	Logistic Regression After Tuning	0.826316

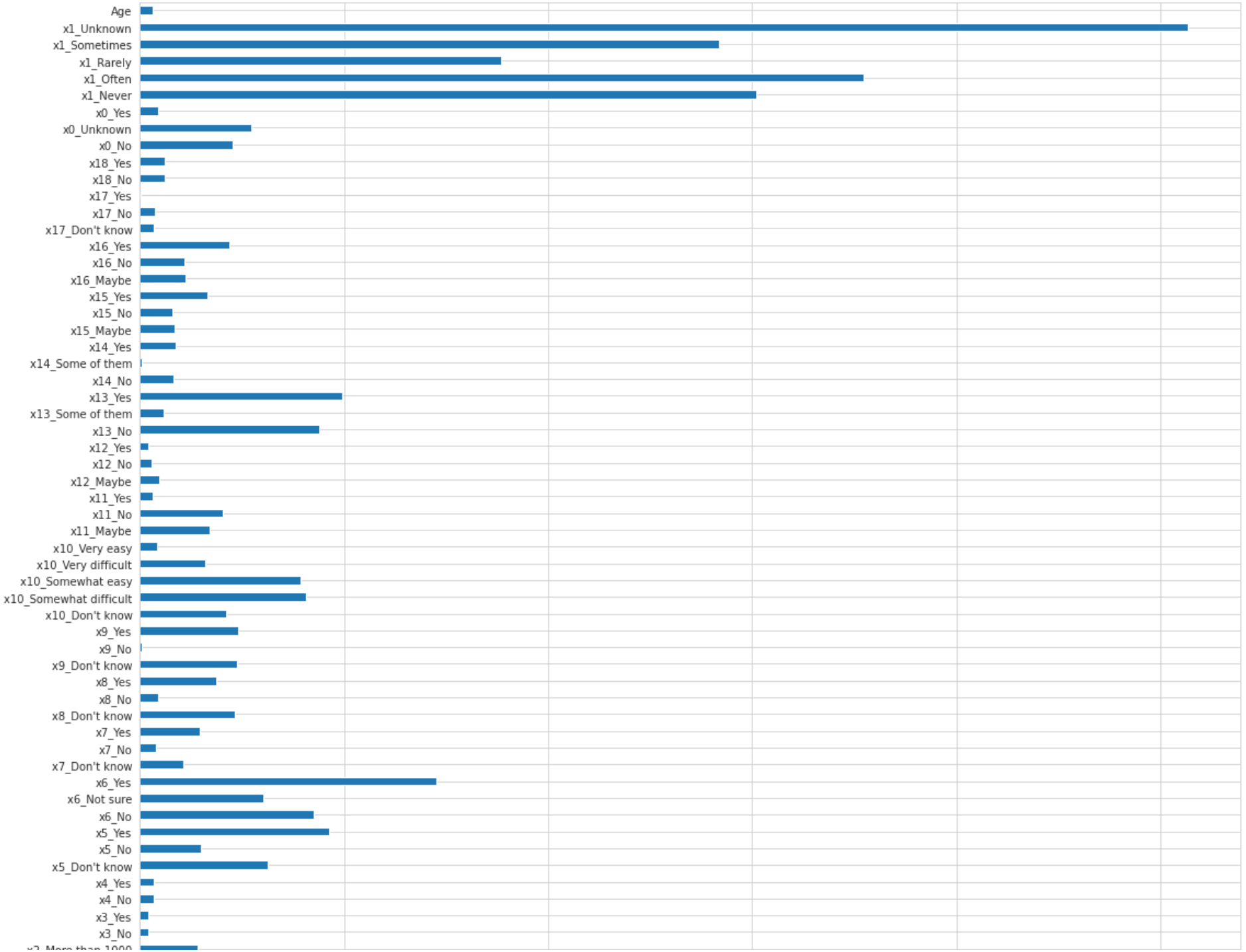
In [ ]:

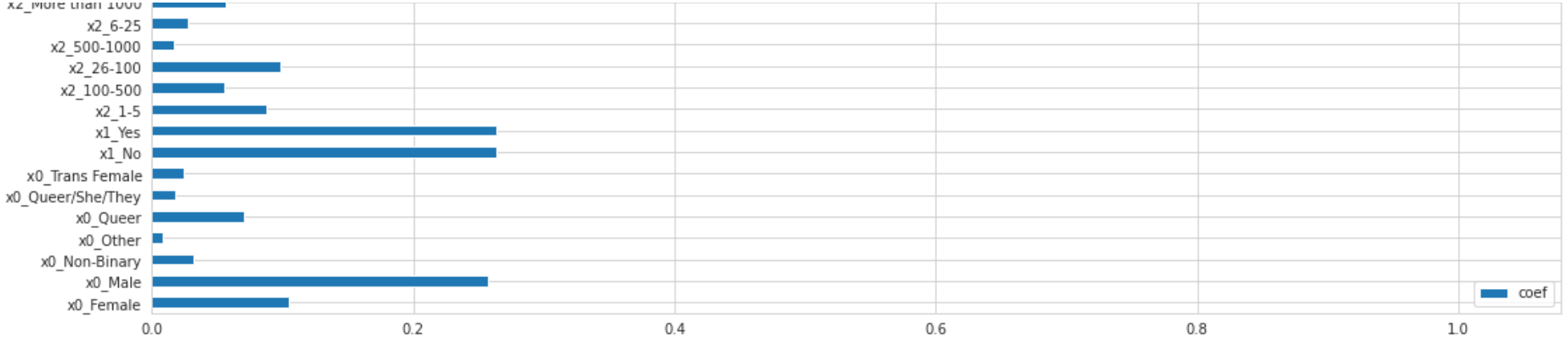
In [ ]:
```
Feature Selection using Tuning Result:
```

In [ ]:

In [101…
```
features = list(transformer.transformers_[0][1].get_feature_names())+list(transformer.transformers_[1][1][1].get_featur
coef_table = pd.DataFrame({'coef': grid_lr.best_estimator_[1].coef_.flatten()}, index = features)
abs(coef_table).plot(kind = 'barh', figsize = (18,20))
```

Out[101…
```
<AxesSubplot:>
```


Age
x1_Unknown
x1_Sometimes
x1_Rarely
x1_Often
x1_Never
x0_Yes
x0_Unknown
x0_No
x18_Yes
x18_No
x17_Yes
x17_No
x17_Don't know
x16_Yes
x16_No
x16_Maybe
x15_Yes
x15_No
x15_Maybe
x14_Yes
x14_Some of them
x14_No
x13_Yes
x13_Some of them
x13_No
x12_Yes
x12_No
x12_Maybe
x11_Yes
x11_No
x11_Maybe
x10_Very easy
x10_Very difficult
x10_Somewhat easy
x10_Somewhat difficult
x10_Don't know
x9_Yes
x9_No
x9_Don't know
x8_Yes
x8_No
x8_Don't know
x7_Yes
x7_No
x7_Don't know
x6_Yes
x6_Not sure
x6_No
x5_Yes
x5_No
x5_Don't know
x4_Yes
x4_No
x3_Yes
x3_No



In [ ]:

In [ ]:
```
Based on selecting features based on coefficient score,
I decided to drop 4 features manually who gets a score under 0.05 for
all answer choices for every feature. There are Age, x3(Remote_work),
x7(Wellness_Program), x12(Physical_Health_Consequence).
```

In [ ]:

In [ ]:

In [ ]:
```
Re-run Using Feature Selection
linkcode
Preprocessing Scheme

OneHotEncoding: Gender, Family History, Employee Numbers, Tech Company,
    Benefits, Care Options, Seek Help, Anonymity, Medical Leave, Mental Health
    Consequence, Coworkers, Supervisor, Mental Health Interview, Physical Health Interview, Mental_VS_Physical,
Observed_Consequence
Mode: Self Employed, Work Interfere
Target: Treatment
```

In [ ]:

In [102…
```
mh_tuning = mh.copy()
mh_tuning.drop(columns = ['Age', 'Remote_Work', 'Wellness_Program', 'Physical_Health_Consequence'], inplace = True)
mh_tuning.head()
```

Out[102…

	Gender	Self_Employed	Family_History	Treatment	Work_Interfere	Employee_Numbers	Tech_Company	Benefits	Care_Options	Seek_Help	A
0	Female	Unknown	No	1	Often	6-25	Yes	Yes	Not sure	Yes	
1	Male	Unknown	No	0	Rarely	More than 1000	No	Don't know	No	Don't know	D
2	Male	Unknown	No	0	Rarely	6-25	Yes	No	No	No	D
3	Male	Unknown	Yes	1	Often	26-100	Yes	No	Yes	No	
4	Male	Unknown	No	0	Never	100-500	Yes	Yes	No	Don't know	D

In [103…

```
mode_onehot_pipe_second = Pipeline([
    ('encoder', SimpleImputer(strategy = 'most_frequent')),
    ('one hot encoder', OneHotEncoder(handle_unknown = 'ignore'))])

transformer_second = ColumnTransformer([
    ('one hot', OneHotEncoder(handle_unknown = 'ignore'), ['Gender', 'Family_History', 'Employee_Numbers',
                                                           'Tech_Company', 'Benefits', 'Care_Options',
                                                           'Seek_Help', 'Anonymity', 'Medical_Leave',
                                                           'Mental_Health_Consequence', 'Coworkers',
                                                           'Supervisor','Mental_Health_Interview',
                                                           'Physical_Health_Interview', 'Mental_VS_Physical',
                                                           'Observed_Consequence',]),
    ('mode_onehot_pipe', mode_onehot_pipe_second, ['Self_Employed', 'Work_Interfere']),])
```

In [104…

```
X_select = mh_tuning.drop('Treatment', axis = 1)
y_select = mh_tuning['Treatment']
```

In [105…

```
X_select_train, X_select_test, y_select_train, y_select_test = train_test_split(X_select,y_select,
                                                    stratify = y_select,
                                                     test_size = 0.3,
                                                    random_state = 2222)
```

In [107…

```
logreg_second = LogisticRegression(C = 0.5, class_weight = 'dict', max_iter = 100,
                                   multi_class = 'auto', random_state = 2222, solver = 'newton-cg')
logreg_second_pipe = Pipeline([('transformer', transformer_second), ('model', logreg_second)])
```

```
logreg_second_pipe.fit(X_select_train, y_select_train)
print('After Feature Selection Process, the score is ', recall_score(y_select_test, logreg_second_pipe.predict(X_select
```

```
After Feature Selection Process, the score is  0.868421052631579
```

In [ ]:

4. Conclusion

In conclusion, the model development and evaluation phase provided us with valuable insights into the performance of different classification algorithms for our public health awareness campaign analysis. Based on the evaluation metrics, we can determine the most suitable model for our specific objectives.