Public Health Awareness Project

Phase 4 Submission

During Phase 4 of the project, we successfully completed the loading and preprocessing of the dataset. Subsequently, we commenced the implementation of advanced algorithms, including hyperparameter tuning, for the analysis of the public health awareness campaign using IBM Cognos to achieve effective visualization. Our primary focus shifted towards defining precise analysis objectives, acquiring campaign data from the provided source, and employing robust algorithms such as Random Forest, k Nearest Neighbors, Support Vector Machines, and Decision Trees.

Analysis Objectives:

Algorithmic Analysis with Hyperparameter Tuning:
 a. Implement and fine-tune the Random Forest algorithm to enhance predictive modeling capabilities.
 b. Apply k Nearest Neighbors to identify patterns and relationships within the campaign dataset.
 c. Utilize Support Vector Machines to classify and analyze complex relationships in the campaign data.
 d. Employ Decision Trees to extract valuable insights and decision-making criteria from the dataset.

Audience Reach:
 a. Conduct an in-depth analysis of the campaign's reach using the implemented algorithms.
 b. Evaluate temporal patterns in audience engagement and reach over the campaign duration.

Geographical and Demographic Coverage:
 a. Leverage algorithmic capabilities to extract demographic insights, including age, gender, education level, and income.
 b. Explore the geographical distribution of the audience reached, utilizing algorithmic tools for spatial analysis.

Awareness Levels:
 a. Employ algorithms to assess changes in awareness levels before and after

the campaign.
b. Identify the most effective messages, slogans, or content through algorithmic analysis.

Campaign Impact:
a. Quantify the overall impact on public health behavior and knowledge using advanced algorithms.
b. Investigate correlations between campaign engagement metrics and behavioral changes.

By integrating these advanced algorithms and techniques, our analysis aims to provide a comprehensive and nuanced understanding of the public health awareness campaign's effectiveness.

DATA PROCESSING AND CLEANING

Code is uploaded in the github repository

(The following have been done in google collab using Python3)

In this process, the following have been performed:- 1) Importing the required python libraries such as pandas and numpy.

2) Loading the dataset into a dataframe. The dataset has been provided in the following link : https://www.kaggle.com/datasets/osmi/mental-healthin-tech-survey
3) Adressing missing values.
4) Replacing null values when necesarry.
5) Normalising data which are inconsistent. For eg: male, Male ,M all refer to the same types. Making all of them as male has been done.

Google collab link for entire code :
https://colab.research.google.com/drive/1TZwHowM1ktUcpnUmxIhXg37K3rVk1tdo?usp=sharing

Visualization Using IBM Cognos

Visualization of the processed and cleaned data has been done using IBM Cognos.

IBM Cognos Link :

https://us3.ca.analytics.ibm.com/bi/?perspective=dashboard&pathRef=.my_folders%2Fdashboard&action=view&mode=dashboard

In [1]:
```python
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt


print('Successfully imported')
```

```
Successfully imported
```

In [3]:
```python
data = pd.read_csv('survey (2).csv')
data.head()
```

Out[3]:

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfere	no_emplo
0	27-08-2014 11:29	37	male	United States	IL	No	No	Yes	Often	Ju
1	27-08-2014 11:29	44	male	United States	IN	No	No	No	Rarely	More
2	27-08-2014 11:29	32	male	Canada	No	No	No	No	Rarely	Ju
3	27-08-2014 11:29	31	male	United Kingdom	No	No	Yes	Yes	Often	26
4	27-08-2014 11:30	31	male	United States	TX	No	No	No	Never	100

5 rows × 27 columns

In [4]:
```python
if data.isnull().sum().sum() == 0 :
    print ('There is no missing data in our dataset')
else:
    print('There is {} missing data in our dataset '.format(data.isnull().sum().sum()))
```

```
There is no missing data in our dataset
```

In [5]:
```python
frame = pd.concat([data.isnull().sum(), data.nunique(), data.dtypes], axis = 1, sort= False)
frame
```

Out[5]:

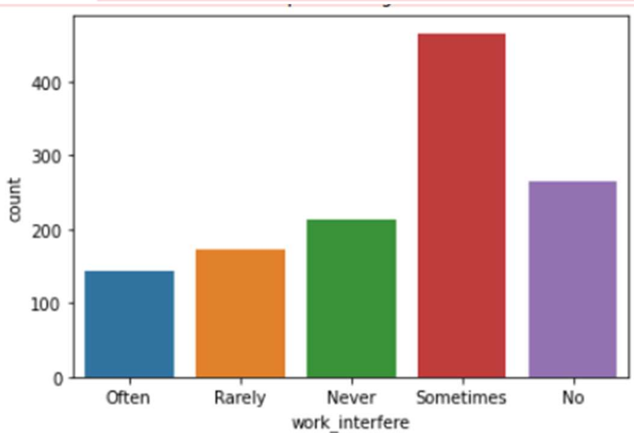
	0	1	2
Timestamp	0	884	object
Age	0	49	int64
Gender	0	5	object
Country	0	48	object
state	0	46	object
self_employed	0	2	object
family_history	0	2	object
treatment	0	2	object
work_interfere	0	5	object
no_employees	0	6	object
remote_work	0	2	object

	0	1	2
tech_company	0	2	object
benefits	0	3	object
care_options	0	3	object
wellness_program	0	3	object
seek_help	0	3	object
anonymity	0	3	object
leave	0	5	object
mental_health_consequence	0	3	object
phys_health_consequence	0	3	object
coworkers	0	3	object
supervisor	0	3	object
mental_health_interview	0	3	object
phys_health_interview	0	3	object
mental_vs_physical	0	3	object
obs_consequence	0	2	object
comments	0	161	object

In [6]:
```
data['work_interfere'].unique()
```

Out[6]:
```
array(['Often', 'Rarely', 'Never', 'Sometimes', 'No'], dtype=object)
```

In [7]:
```
#Plot **work_interfere**
ax = sns.countplot(data = data , x = 'work_interfere');
#Add the value of each parametr on the Plot
ax.bar_label(ax.containers[0]);
```



In [8]:

```
from sklearn.impute import SimpleImputer
import numpy as np
columns_to_drop = ['state', 'comments', 'Timestamp']
for column in columns_to_drop:
    if column in data.columns:
        data = data.drop(columns=[column])


# Fill in missing values in work_interfere column
data['work_interfere'] = np.ravel(SimpleImputer(strategy = 'most_frequent').fit_transform(data[
data['self_employed'] = np.ravel(SimpleImputer(strategy = 'most_frequent').fit_transform(data['

data.head()
```

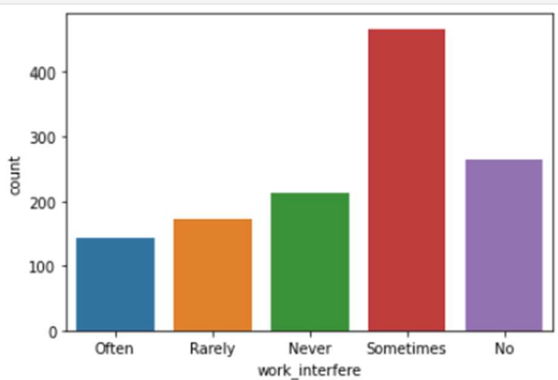
Out[8]:

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_employees	remote_work
0	37	male	United States	No	No	Yes	Often	Jun-25	No
1	44	male	United States	No	No	No	Rarely	More than 1000	No
2	32	male	Canada	No	No	No	Rarely	Jun-25	No
3	31	male	United Kingdom	No	Yes	Yes	Often	26-100	No
4	31	male	United States	No	No	No	Never	100-500	Yes

5 rows × 24 columns

In [9]:

```
ax = sns.countplot(data=data, x='work_interfere');
ax.bar_label(ax.containers[0]);
```



In [10]:

```
#Check unique data in gender columns
print(data['Gender'].unique())
print('')
print('-'*75)
```

```
print('')
#Check number of unique data too.
print('number of unique Gender in our dataset is :', data['Gender'].nunique())
```

```
['male' 'trans' 'cis' 'queer' 'others']

---------------------------------------------------------------------------

number of unique Gender in our dataset is : 5
```

In [11]:

```
#Let's check duplicated data.
if data.duplicated().sum() == 0:
    print('There is no duplicated data:')
else:
    print('Tehre is {} duplicated data:'.format(data.duplicated().sum()))
    #If there is duplicated data drop it.
    data.drop_duplicates(inplace=True)

print('-'*50)
print(data.duplicated().sum())
```

```
Tehre is 4 duplicated data:
--------------------------------------------------
0
```

In [12]:

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

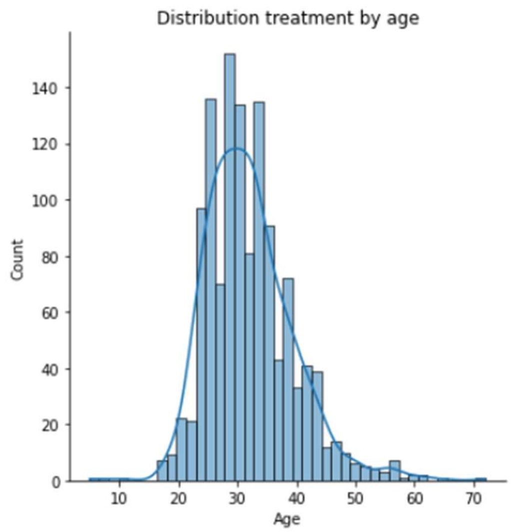
Out[12]:

```
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, 315473,     43,     56,     60,
           54,     55,     48,     20,     57,     58,     47,     62,
           51,     65,     49,      5,     53,     61,      8,     11,
           72])
```

In [13]:

```
#We had a lot of nonsense answers in the Age column too
#This filtering will drop entries exceeding 100 years and those indicating negative values.
data.drop(data[data['Age']<0].index, inplace = True)
data.drop(data[data['Age']>99].index, inplace = True)

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

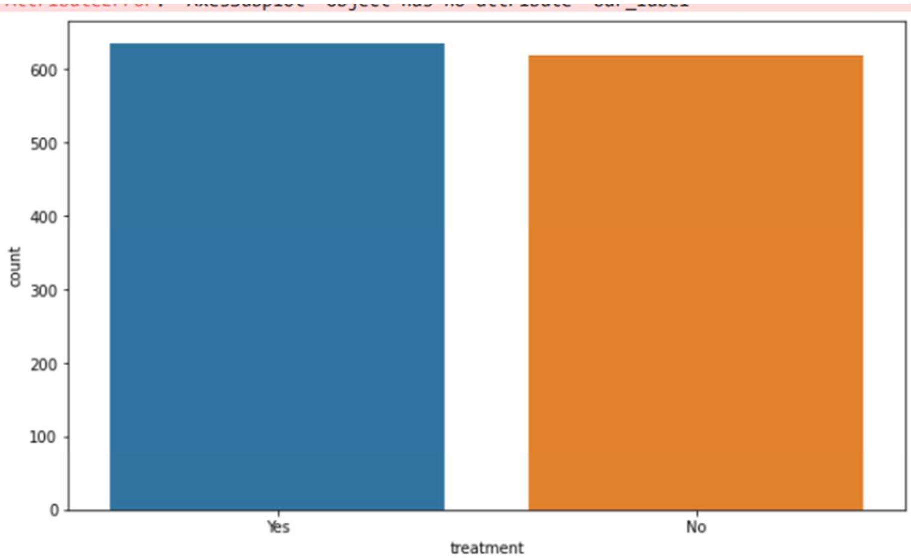
```
[37 44 32 31 33 35 39 42 23 29 36 27 46 41 34 30 40 38 50 24 18 28 26 22
 19 25 45 21 43 56 60 54 55 48 20 57 58 47 62 51 65 49  5 53 61  8 11 72]
```



In [15]:
```python
#In this plot We can see Total number of individuals who received treatment or not.
plt.figure(figsize = (10,6));
treat = sns.countplot(data = data,  x = 'treatment');
treat.bar_label(treat.containers[0]);
plt.title('Total number of individuals who received treatment or not');
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-15-8e3cfe8f45f6> in <module>
      2 plt.figure(figsize = (10,6));
      3 treat = sns.countplot(data = data,  x = 'treatment');
----> 4 treat.bar_label(treat.containers[0]);
      5 plt.title('Total number of individuals who received treatment or not');

AttributeError: 'AxesSubplot' object has no attribute 'bar_label'
```

AttributeError: 'AxesSubplot' object has no attribute 'bar_label'



n [16]:
```python
#Check Dtypes
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1254 entries, 0 to 1258
Data columns (total 24 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Age                        1254 non-null   int64 
 1   Gender                     1254 non-null   object
 2   Country                    1254 non-null   object
 3   self_employed              1254 non-null   object
 4   family_history             1254 non-null   object
 5   treatment                  1254 non-null   object
 6   work_interfere             1254 non-null   object
 7   no_employees               1254 non-null   object
 8   remote_work                1254 non-null   object
 9   tech_company               1254 non-null   object
 10  benefits                   1254 non-null   object
 11  care_options               1254 non-null   object
 12  wellness_program           1254 non-null   object
 13  seek_help                  1254 non-null   object
 14  anonymity                  1254 non-null   object
 15  leave                      1254 non-null   object
 16  mental_health_consequence  1254 non-null   object
 17  phys_health_consequence    1254 non-null   object
 18  coworkers                  1254 non-null   object
 19  supervisor                 1254 non-null   object
 20  mental_health_interview    1254 non-null   object
 21  phys_health_interview      1254 non-null   object
 22  mental_vs_physical         1254 non-null   object
 23  obs_consequence            1254 non-null   object
dtypes: int64(1), object(23)
memory usage: 284.9+ KB
```

In [17]:

```
#Use LabelEncoder to change the Dtypes to 'int'
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
#Make the dataset include all the columns we need to change their dtypes
columns_to_encode = ['Gender', 'Country', 'self_employed','family_history', 'treatment', 'work_
                             'remote_work', 'tech_company','benefits','care_options', 'wellness
                             'seek_help', 'anonymity', 'leave', 'mental_health_consequence', 'p
                             'coworkers', 'supervisor', 'mental_health_interview','phys_health_
                             'mental_vs_physical', 'obs_consequence']
#Write a Loop for fitting LabelEncoder on columns_to_encode
for columns in columns_to_encode:
    data[columns] = le.fit_transform(data[columns])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1254 entries, 0 to 1258
Data columns (total 24 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Age                        1254 non-null   int64
 1   Gender                     1254 non-null   int64
 2   Country                    1254 non-null   int64
 3   self_employed              1254 non-null   int64
 4   family_history             1254 non-null   int64
 5   treatment                  1254 non-null   int64
 6   work_interfere             1254 non-null   int64
 7   no_employees               1254 non-null   int64
 8   remote_work                1254 non-null   int64
 9   tech_company               1254 non-null   int64
 10  benefits                   1254 non-null   int64
 11  care_options               1254 non-null   int64
 12  wellness_program           1254 non-null   int64
 13  seek_help                  1254 non-null   int64
 14  anonymity                  1254 non-null   int64
 15  leave                      1254 non-null   int64
 16  mental_health_consequence  1254 non-null   int64
 17  phys_health_consequence    1254 non-null   int64
```

```
 18  coworkers                 1254 non-null   int64
 19  supervisor                1254 non-null   int64
 20  mental_health_interview   1254 non-null   int64
 21  phys_health_interview     1254 non-null   int64
 22  mental_vs_physical        1254 non-null   int64
 23  obs_consequence           1254 non-null   int64
dtypes: int64(24)
memory usage: 284.9 KB
```

In [18]:
```
#Let's check Standard deviation
data.describe()
```

Out[18]:

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_emp
count	1254.000000	1254.000000	1254.000000	1254.000000	1254.000000	1254.000000	1254.000000	1254.
mean	32.020734	1.012759	37.816587	0.115630	0.390750	0.506380	2.329346	2.
std	7.372511	0.191178	13.320466	0.319908	0.488113	0.500159	1.549652	1.
min	5.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.
25%	27.000000	1.000000	42.000000	0.000000	0.000000	0.000000	1.000000	1.
50%	31.000000	1.000000	45.000000	0.000000	0.000000	1.000000	3.000000	3.
75%	36.000000	1.000000	45.000000	0.000000	1.000000	1.000000	4.000000	4.
max	72.000000	4.000000	47.000000	1.000000	1.000000	1.000000	4.000000	5.

8 rows × 24 columns

In [ ]:
```
Split data to train and test
```

In [19]:
```
from sklearn.model_selection import train_test_split

#I wanna work on 'treatment' column.
X = data.drop(columns = ['treatment'])
y = data['treatment']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)

print(X_train.shape, y_train.shape)
print('-'*30)
print(X_test.shape, y_test.shape)
print('_'*30)
```


```
print('_'*30)
```


```
(940, 23) (940,)
------------------------------
(314, 23) (314,)
______________________________
```

In [20]:
```
from sklearn.pipeline import Pipeline
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier as RFC
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.tree import DecisionTreeClassifier as DT
```

In [ ]:
```
Random forest Classifier
```

In [ ]:
```
from sklearn.pipeline import Pipeline
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier as RFC
```

```python
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.tree import DecisionTreeClassifier as DT
```

In [24]:

```python
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier as RFC
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score

# Define the steps for the pipeline
steps_rfc = [('Scaler', StandardScaler()), ('clf', RFC(n_estimators=40))]

# Create the pipeline
clf_rfc = Pipeline(steps=steps_rfc)

# Fit the pipeline to your training data
clf_rfc.fit(X_train, y_train)

# Make predictions on the test data
y_pred_rfc = clf_rfc.predict(X_test)

# Calculate and print the accuracy
print('RFC accuracy: ', accuracy_score(y_true=y_test, y_pred=y_pred_rfc) * 100)
```

```
RFC accuracy:  83.43949044585987
```

In [ ]:

```
K Nearest Neighbor
```

In [25]:

```python
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier as RFC
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
steps_knn = [('Scaler', StandardScaler()),
             ('clf', KNN(n_neighbors = 5))]



clf_knn = Pipeline(steps=steps_knn)


clf_knn.fit(X_train, y_train)

y_pred_knn = clf_knn.predict(X_test)
print('KNN accuracy :', accuracy_score(y_true=y_test, y_pred=y_pred_knn)*100)
```


```python
y_pred_knn = clf_knn.predict(X_test)
print('KNN accuracy :', accuracy_score(y_true=y_test, y_pred=y_pred_knn)*100)
```


```
KNN accuracy : 74.84076433121018
```

In [ ]:

```
Support vector Classifier
```

In [26]:

```python
steps_svc = [('Scaler', StandardScaler()),
             ('clf', SVC())]



clf_svc = Pipeline(steps=steps_svc)


clf_svc.fit(X_train, y_train)

y_pred_svc = clf_svc.predict(X_test)
print('SVC accuracy :', accuracy_score(y_true=y_test, y_pred=y_pred_svc)*100)
```

```
SVC accuracy : 79.61783439490446
```

In [ ]:
```
Decision Tree
```

In [27]:
```python
steps_dt = [('Scaler', StandardScaler()),
            ('clf', DT())]



clf_dt = Pipeline(steps=steps_dt)


clf_dt.fit(X_train, y_train)

y_pred_dt = clf_dt.predict(X_test)
print('DT accuracy :', accuracy_score(y_true=y_test, y_pred=y_pred_dt)*100)
```

```
DT accuracy : 75.15923566878982
```

In [ ]:
```
Tuning
```

In [28]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
```

In [29]:
```python
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
```

In [31]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [32]:
```python
rf_classifier = RandomForestClassifier()
```

In [33]:
```python
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
```

In [34]:
```python
grid_search = GridSearchCV(estimator=rf_classifier, param_grid=param_grid, cv=5, n_jobs=-1, ver
grid_search.fit(X_train, y_train)
```


In [34]:
```python
grid_search = GridSearchCV(estimator=rf_classifier, param_grid=param_grid, cv=5, n_jobs=-1, ver
grid_search.fit(X_train, y_train)
```


```
Fitting 5 folds for each of 324 candidates, totalling 1620 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 32 concurrent workers.
[Parallel(n_jobs=-1)]: Done  98 tasks      | elapsed:    5.2s
[Parallel(n_jobs=-1)]: Done 301 tasks      | elapsed:   10.7s
[Parallel(n_jobs=-1)]: Done 584 tasks      | elapsed:   18.3s
[Parallel(n_jobs=-1)]: Done 949 tasks      | elapsed:   28.2s
[Parallel(n_jobs=-1)]: Done 1394 tasks      | elapsed:   40.2s
[Parallel(n_jobs=-1)]: Done 1620 out of 1620 | elapsed:   46.3s finished
```

Out[34]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': [None, 10, 20, 30],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [100, 200, 300]},
             verbose=2)
```

In [37]:
```python
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)
```

```
Best Hyperparameters: {'max_depth': None, 'max_features': 'log2', 'min_samples_leaf': 2, 'min_s
amples_split': 10, 'n_estimators': 100}
```

In [36]:
```
best_rf_classifier = RandomForestClassifier(**best_params)
best_rf_classifier.fit(X_train, y_train)
```

Out[36]:
```
RandomForestClassifier(max_features='log2', min_samples_leaf=2,
                       min_samples_split=10)
```

In [39]:
```
y_pred = best_rf_classifier.predict(X_test)
```

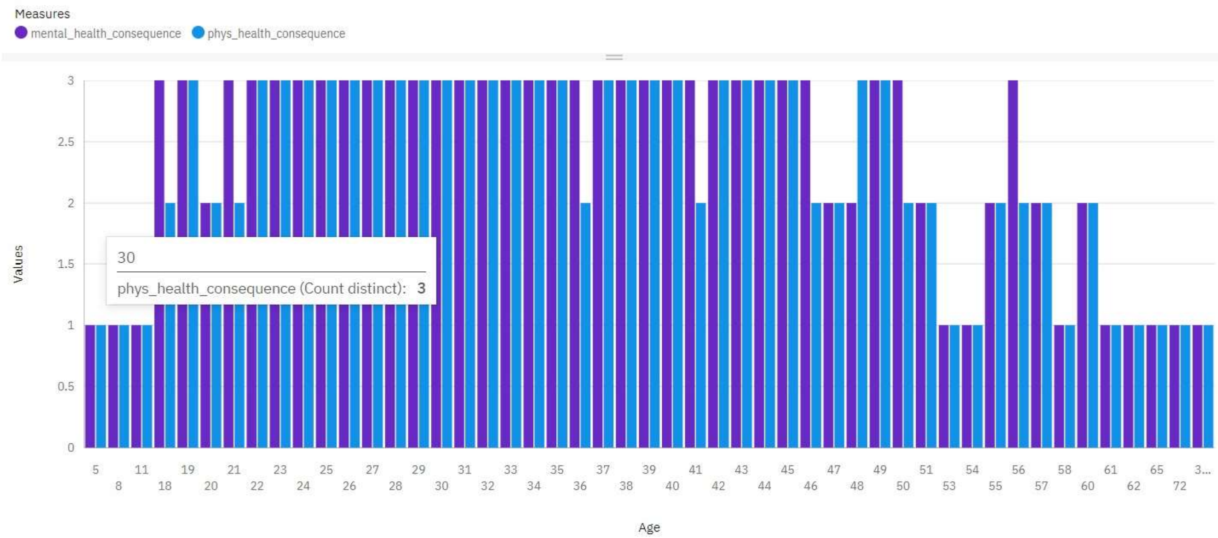
In [40]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.8446215139442231
Precision: 0.8092105263157895
Recall: 0.924812030075188
F1 Score: 0.863157894736842
```

In [ ]:

BOTH THE PYTHON CODE AND VISUALIZATION DOCUMENT HAVE BEEN INCLUDED BELOW.

mental_health_consequence and phys_health_consequence by Age



Narrative insights

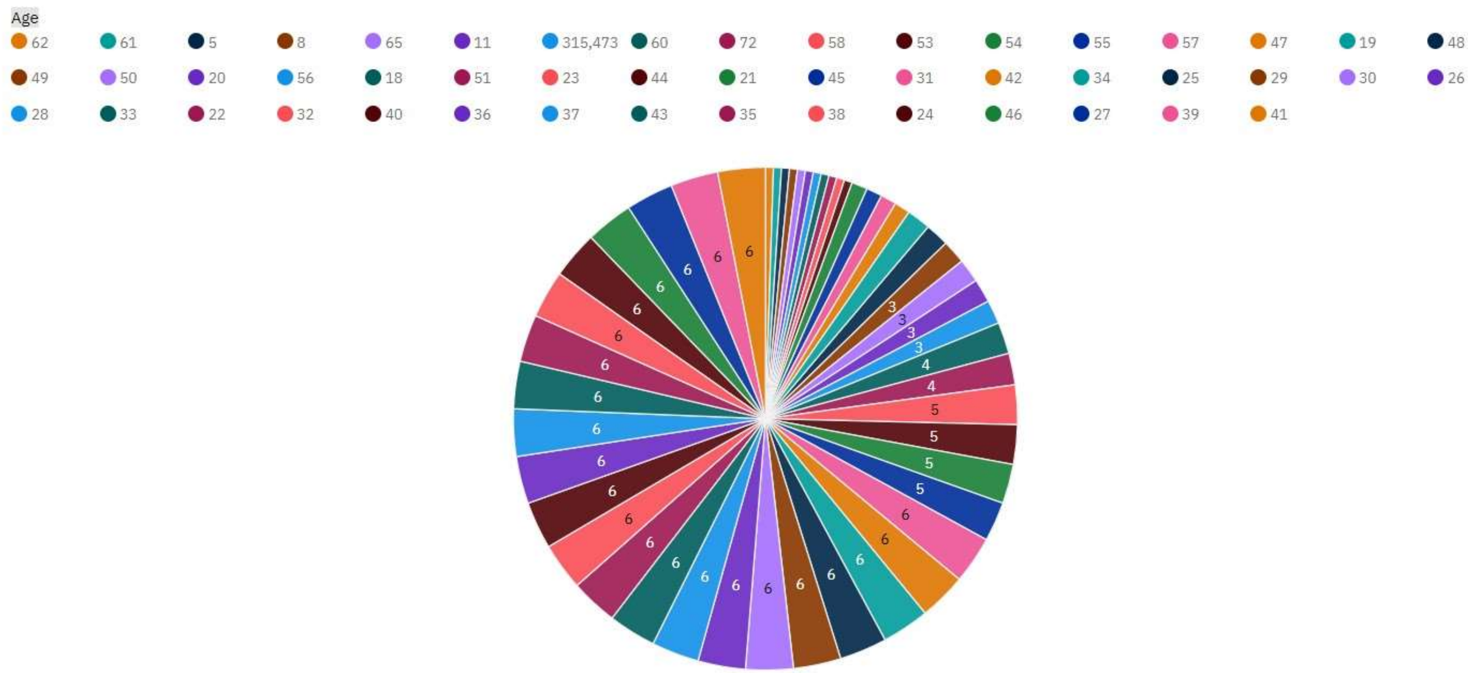
Suggested insights (3)

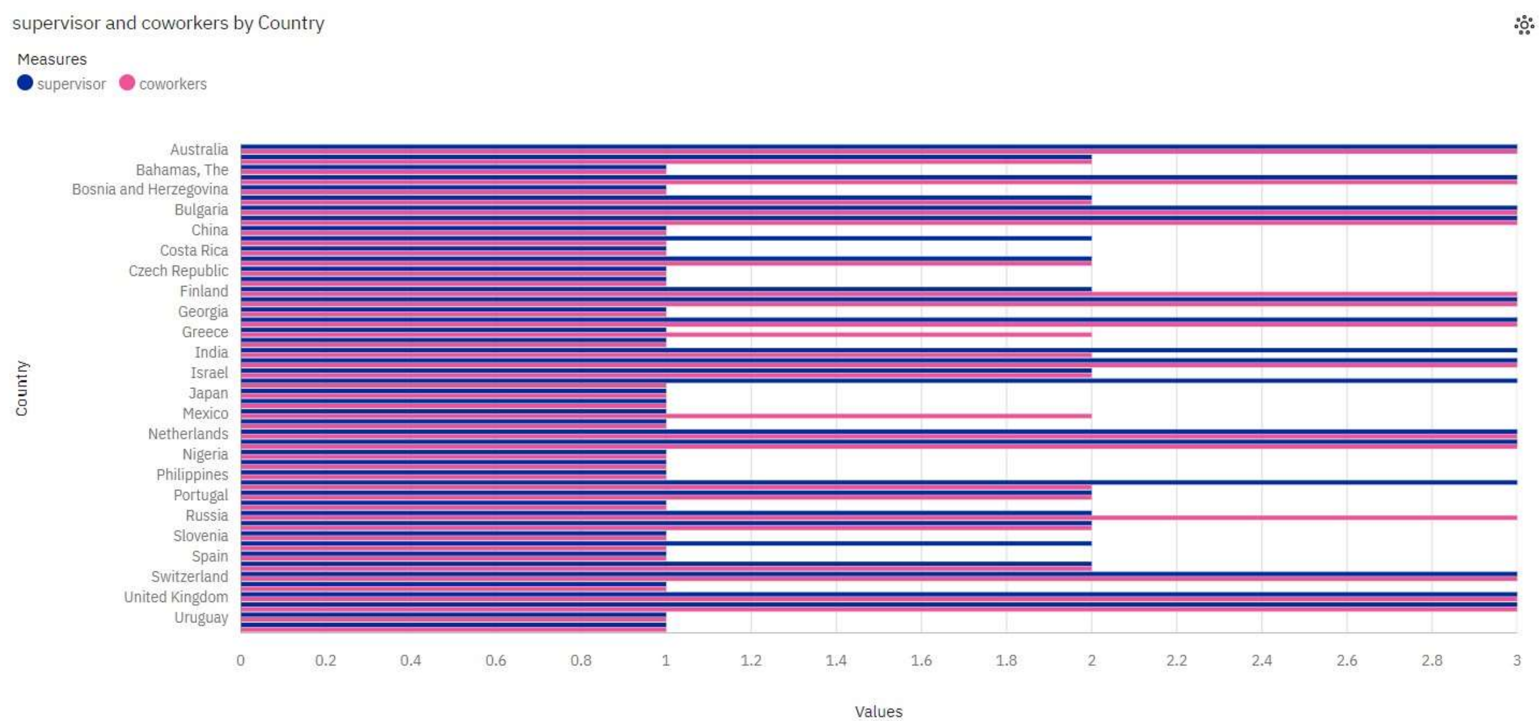
Age 26 has the highest **phys_health_consequence** due to **Country United States**.

Age 18 has the highest **Count distinct mental_health_consequence** but is ranked #**26** in **Count distinct phys_health_consequence**.

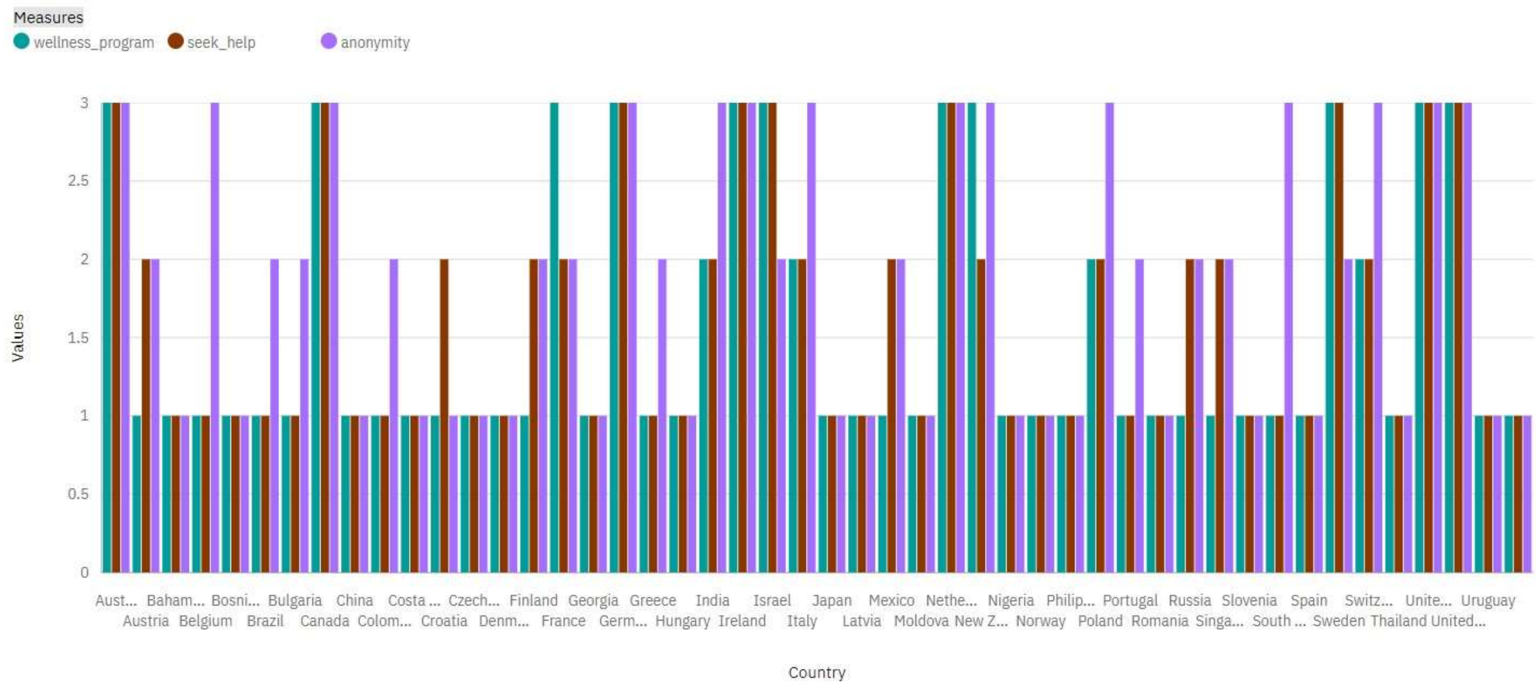
Country United States has the highest **phys_health_consequence** at **99**, out of which **Age 22** contributed the most at **3**.

no_employees by Age

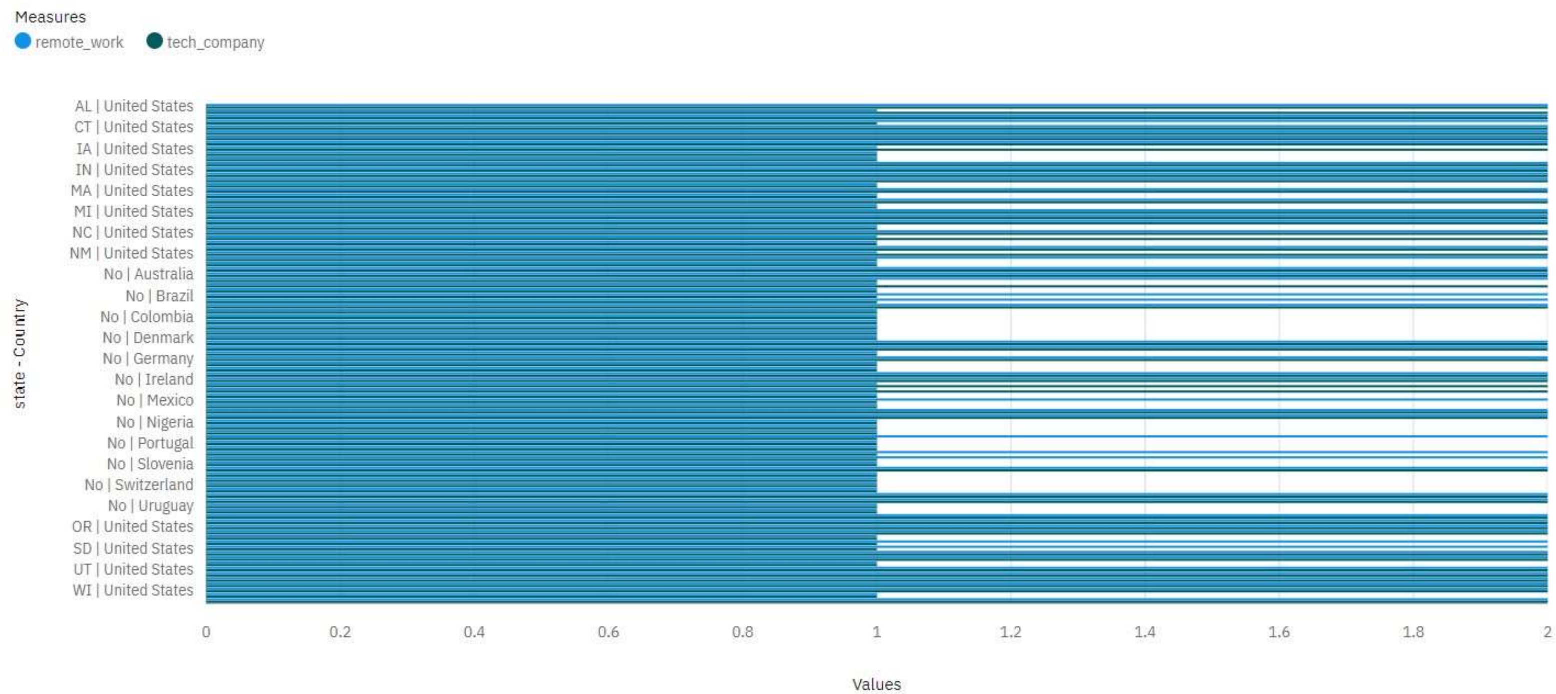


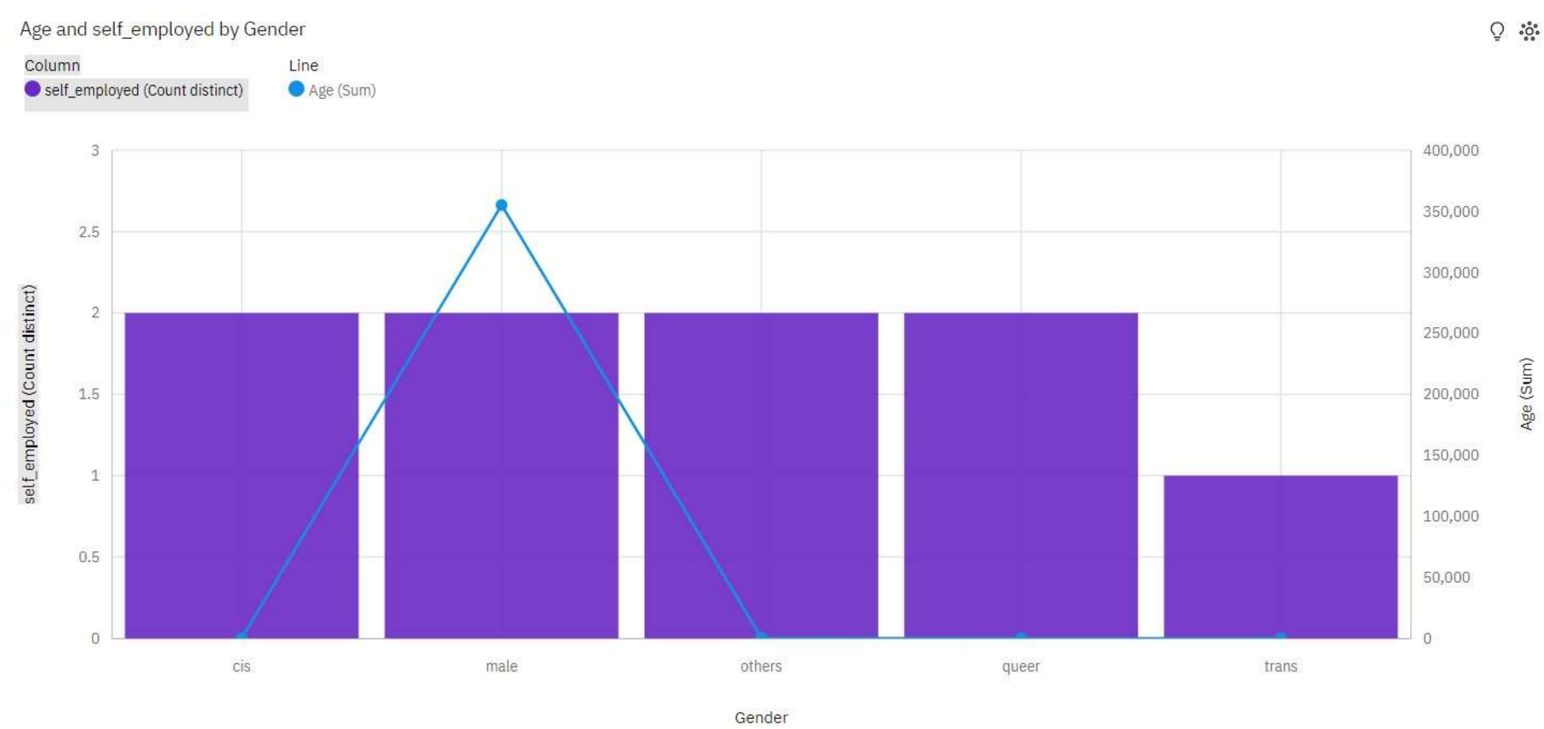

supervisor and coworkers by Country
Measures
supervisor
coworkers
Country
Australia
Bahamas, The
Bosnia and Herzegovina
Bulgaria
China
Costa Rica
Czech Republic
Finland
Georgia
Greece
India
Israel
Japan
Mexico
Netherlands
Nigeria
Philippines
Portugal
Russia
Slovenia
Spain
Switzerland
United Kingdom
Uruguay
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

wellness_program, seek_help and anonymity by Country



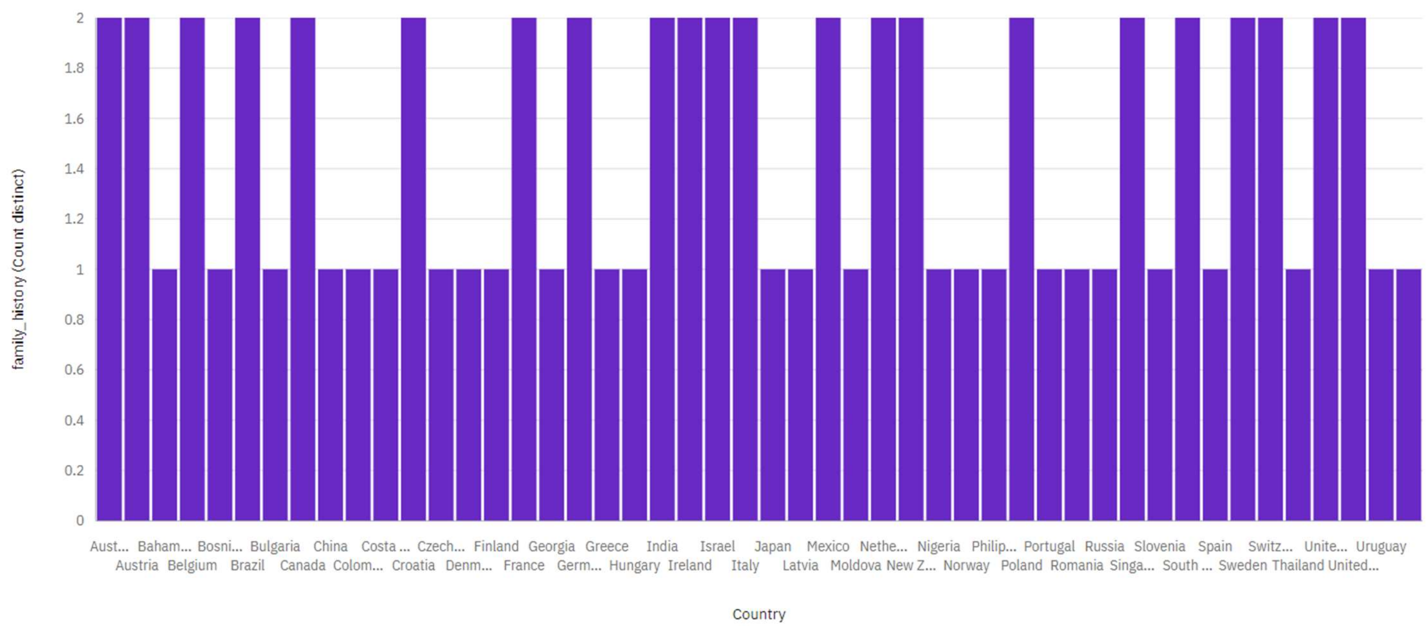
remote_work and tech_company by state and Country





Age and self_employed by Gender
Column
self_employed (Count distinct)
Line
Age (Sum)
3
2.5
2
1.5
1
0.5
0
400,000
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
self_employed (Count distinct)
Age (Sum)
cis
male
others
queer
trans
Gender

family_history by Country



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