Public Health Awareness Project

Phase 3 Submission

In Phase 3 of the project, the loading and preprocessing the dataset has been done. Along with that, we have also started building the public health awareness campaign analysis using IBM Cognos for visualization.
We have defined the analysis objectives and collect campaign data from the source shared, processed and cleaned the collected data and ensured its quality and accuracy.

ANALYSIS OBJECTIVES

1. Audience Reach:

a. Assess the extent of campaign reach within the tragediennes:

- Identify the total number of individuals or entities reached by the campaign, such as the number of social media followers, email subscribers, or event attendees.

- Measure reach over time to understand whether the campaign reached its target audience continuously or experienced spikes during specific events or promotions.

b. Measure geographical and demographic coverage:

- Use demographic data to determine the age, gender, education level, income, and other characteristics of the audience reached.

- Analyze geographical data to assess where the audience is located, whether locally, nationally, or internationally.

- Identify any gaps in the demographic or geographic coverage to tailor future campaigns to reach underserved populations.

2. Awareness Levels:

a. Evaluate changes in awareness levels before and after the campaigns.

- Conduct surveys or collect data to measure the baseline level of awareness regarding the public health issue before launching the campaign.

- After the campaign, reevaluate awareness levels to measure the campaign's impact in terms of increased awareness.

b. Identify the most successful messages or topics:

- Analyze which campaign messages, slogans, or content were the most effective in increasing awareness.

- Determine which communication channels (e.g., social media, email newsletters, educational materials) were most effective in delivering these messages.

3. Campaign Impact:

a. Quantify the overall impact on public health behavior and knowledge:

- Use surveys, data collection, or interviews to assess behavioral changes, such as an increase in vaccination rates, adoption of healthier habits, or better understanding of a health issue.

- Measure changes in knowledge, such as increased awareness of symptoms, preventive measures, or available resources related to the public health issue.

b. Analyze correlations between engagement metrics and behavioral changes:

- Explore how campaign engagement metrics (e.g., social media likes, shares, comments, click-through rates) relate to actual behavioral changes or increases in knowledge.

- Investigate whether higher engagement with campaign content correlates with a greater impact on public health behavior and knowledge.

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-health-in-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.

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

Import necessary libraries

```
#imports necessary libraries to do basic things on the dataset
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt


print('Successfully imported')
```

```
Successfully imported
```

Read Dataset

+ Code + Text

```
#Reading data
data = pd.read_csv('survey.csv')
data.head()
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes
1	2014-08-27 11:29:37	44	M	United States	IN	NaN	No	No
2	2014-08-27 11:29:44	32	Male	Canada	NaN	NaN	No	No
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	NaN	Yes	Yes
4	2014-08-27 11:30:22	31	Male	United States	TX	NaN	No	No

5 rows × 27 columns

Preprocessing and Cleaning dataset

```
#Check the dataset for missing data
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 1892 missing data in our dataset
```

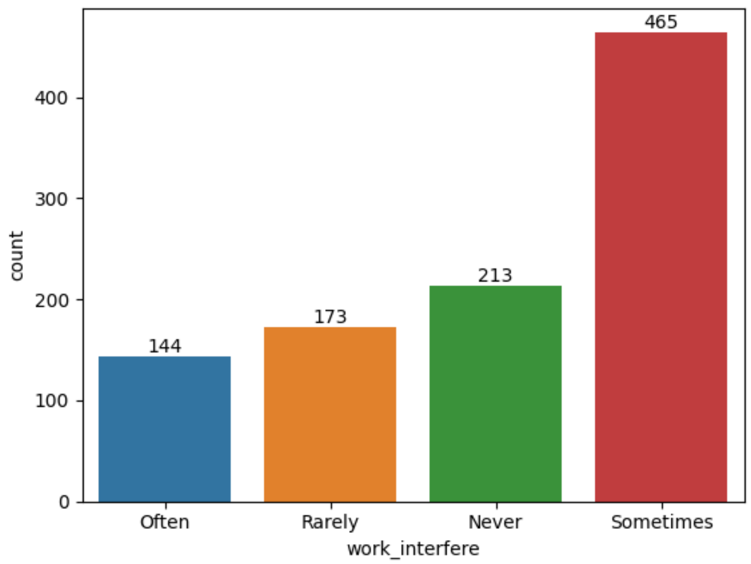
```
#Check our missing data from which columns and how many unique features they have.
frame = pd.concat([data.isnull().sum(), data.nunique(), data.dtypes], axis = 1, sort= False)
frame
```

	0	1	2
Timestamp	0	1246	object
Age	0	53	int64
Gender	0	49	object
Country	0	48	object
state	515	45	object
self_employed	18	2	object
family_history	0	2	object
treatment	0	2	object
work_interfere	264	4	object
no_employees	0	6	object
remote_work	0	2	object
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

```
#Look at what is in the 'Work_interfere' column to choose a suitable method to fill nan values.
data['work_interfere'].unique()
```

```
array(['Often', 'Rarely', 'Never', 'Sometimes', nan], dtype=object)
```

```
#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]);
```

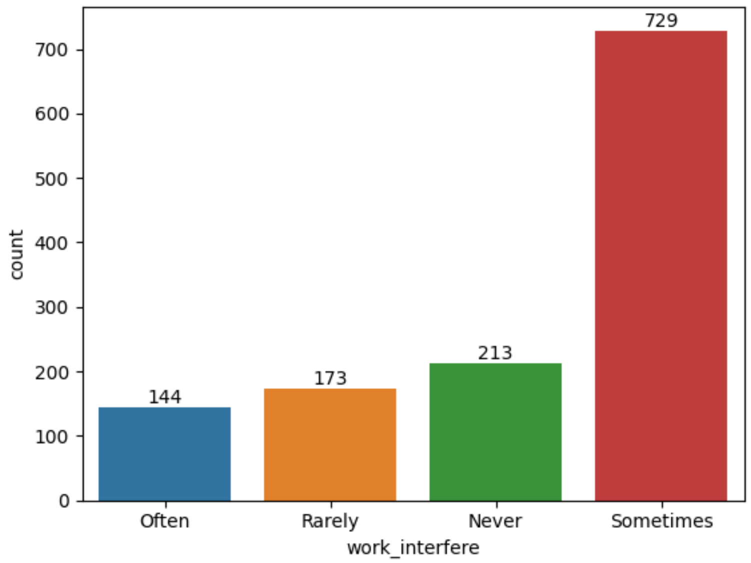



```
from sklearn.impute import SimpleImputer
import numpy as np
columns_to_drop = ['state', 'comments', 'Timestamp']
for column in columns_to_drop:
    if column in data.columns:
        data = data.drop(columns=[column])


# Fill in missing values in work_interfere column
data['work_interfere'] = np.ravel(SimpleImputer(strategy = 'most_frequent').fit_transform(data['work_interfere'].values.reshape(-1,1)))
data['self_employed'] = np.ravel(SimpleImputer(strategy = 'most_frequent').fit_transform(data['self_employed'].values.reshape(-1,1)))

data.head()
```

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_employees	remote_work	tech_company	...	anon
0	37	Female	United States	No	No	Yes	Often	6-25	No	Yes	...	
1	44	M	United States	No	No	No	Rarely	More than 1000	No	No	...	Don'
2	32	Male	Canada	No	No	No	Rarely	6-25	No	Yes	...	Don'
3	31	Male	United Kingdom	No	Yes	Yes	Often	26-100	No	Yes	...	
4	31	Male	United States	No	No	No	Never	100-500	Yes	Yes	...	Don'

5 rows × 24 columns

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




```
#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())
```

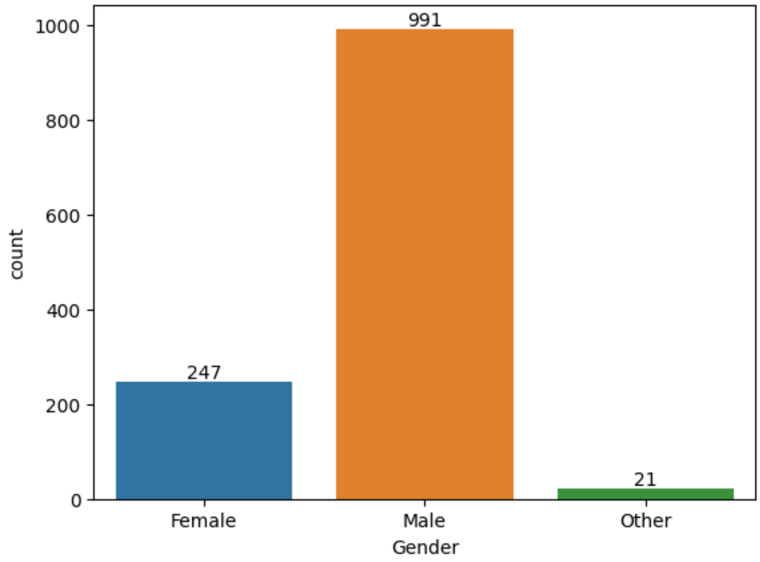
```
['Female' 'M' 'Male' 'male' 'female' 'm' 'Male-ish' 'maile' 'Trans-female'
 'Cis Female' 'F' 'something kinda male?' 'Cis Male' 'Woman' 'f' 'Mal'
 'Male (CIS)' 'queer/she/they' 'non-binary' 'Femake' 'woman' 'Make' 'Nah'
 'All' 'Enby' 'fluid' 'Genderqueer' 'Female ' 'Androgyne' 'Agender'
 'cis-female/femme'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

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

number of unique Gender in our dataset is : 49
```

```
#Gender data contains dictation problems, nonsense answers, and too unique Genders.
#_So Let's clean it and organize it into Male, Female, and other categories

data['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)

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

data["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',], 'Other', inplace = True)

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

```
['Female' 'Male' 'Other']
```

```
#Plot Genders column after cleaning and new categorizing
ax = sns.countplot(data=data, x='Gender');
ax.bar_label(ax.containers[0]);
```




```
#Our data is clean now ? let's see.
if data.isnull().sum().sum() == 0:
    print('There is no missing data')
else:
    print('There is {} missing data'.format(data.isnull().sum().sum()))
```

```
There is no missing data
```

```
#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
```

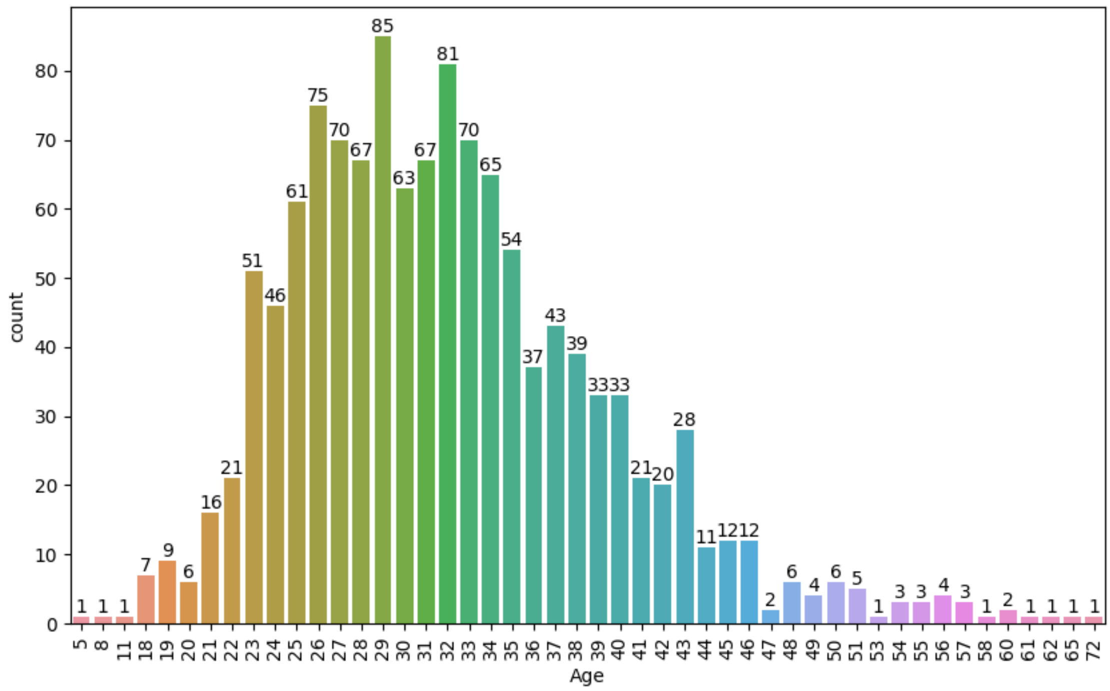
```
#Look unique data in Age column
data['Age'].unique()
```

```
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,         -29,          43,
                56,          60,          54,         329,          55,
       99999999999,          48,          20,          57,          58,
                47,          62,          51,          65,          49,
             -1726,           5,          53,          61,           8,
                11,          -1,          72])
```

```
#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())
```

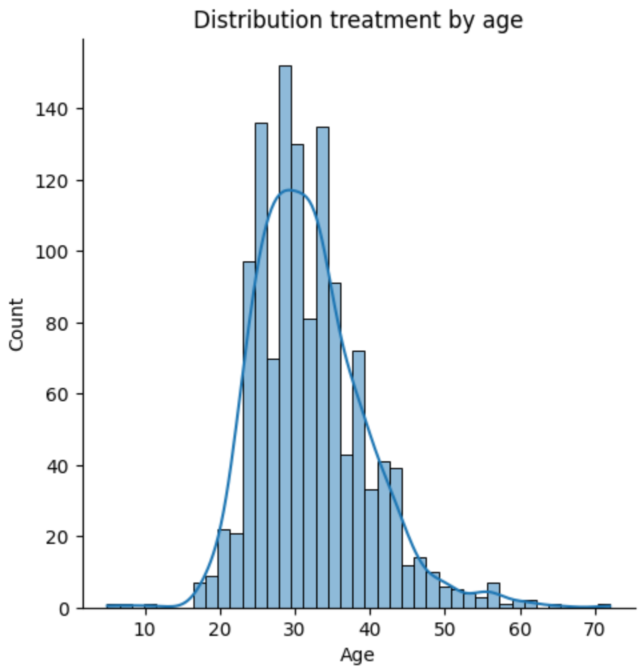
```
[37 44 32 31 33 35 39 42 23 29 36 27 46 41 34 30 40 38 50 24 18 28 26 22
 19 25 45 21 43 56 60 54 55 48 20 57 58 47 62 51 65 49  5 53 61  8 11 72]
```

```
#Let's see the Age distribution in this dataset.
plt.figure(figsize = (10,6))
age_range_plot = sns.countplot(data = data, x = 'Age');
age_range_plot.bar_label(age_range_plot.containers[0]);
plt.xticks(rotation=90);
```

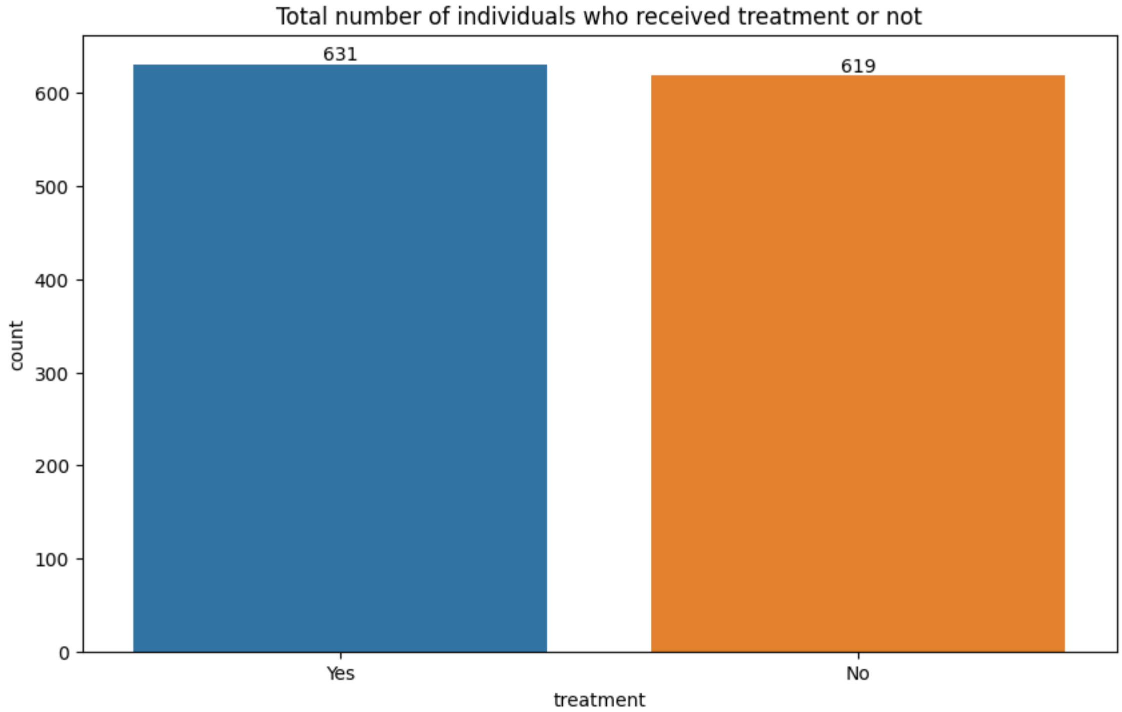



```
#In this plot moreover on Age distribution we can see treatment distribution by age
plt.figure(figsize=(10, 6));
sns.displot(data['Age'], kde = 'treatment');
plt.title('Distribution treatment by age');
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
<Figure size 1000x600 with 0 Axes>
```




```
#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');
```




```
#Check Dtypes
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1250 entries, 0 to 1258
Data columns (total 24 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Age                        1250 non-null   int64 
 1   Gender                     1250 non-null   object
 2   Country                    1250 non-null   object
 3   self_employed              1250 non-null   object
 4   family_history             1250 non-null   object
 5   treatment                  1250 non-null   object
 6   work_interfere             1250 non-null   object
 7   no_employees               1250 non-null   object
 8   remote_work                1250 non-null   object
 9   tech_company               1250 non-null   object
 10  benefits                   1250 non-null   object
 11  care_options               1250 non-null   object
 12  wellness_program           1250 non-null   object
 13  seek_help                  1250 non-null   object
 14  anonymity                  1250 non-null   object
 15  leave                      1250 non-null   object
 16  mental_health_consequence  1250 non-null   object
 17  phys_health_consequence    1250 non-null   object
 18  coworkers                  1250 non-null   object
 19  supervisor                 1250 non-null   object
 20  mental_health_interview    1250 non-null   object
 21  phys_health_interview      1250 non-null   object
 22  mental_vs_physical         1250 non-null   object
 23  obs_consequence            1250 non-null   object
dtypes: int64(1), object(23)
memory usage: 244.1+ KB
```

```
#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_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']
#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'>
Index: 1250 entries, 0 to 1258
```

```
Data columns (total 24 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Age                        1250 non-null   int64
 1   Gender                     1250 non-null   int64
 2   Country                    1250 non-null   int64
 3   self_employed              1250 non-null   int64
 4   family_history             1250 non-null   int64
 5   treatment                  1250 non-null   int64
 6   work_interfere             1250 non-null   int64
 7   no_employees               1250 non-null   int64
 8   remote_work                1250 non-null   int64
 9   tech_company               1250 non-null   int64
 10  benefits                   1250 non-null   int64
 11  care_options               1250 non-null   int64
 12  wellness_program           1250 non-null   int64
 13  seek_help                  1250 non-null   int64
 14  anonymity                  1250 non-null   int64
 15  leave                      1250 non-null   int64
 16  mental_health_consequence  1250 non-null   int64
 17  phys_health_consequence    1250 non-null   int64
 18  coworkers                  1250 non-null   int64
 19  supervisor                 1250 non-null   int64
 20  mental_health_interview    1250 non-null   int64
 21  phys_health_interview      1250 non-null   int64
 22  mental_vs_physical         1250 non-null   int64
 23  obs_consequence            1250 non-null   int64
dtypes: int64(24)
memory usage: 244.1 KB
```

```
#Let's check Standard deviation
data.describe()
```

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_employees	remote_work	tecl
count	1250.00000	1250.00000	1250.000000	1250.000000	1250.000000	1250.000000	1250.000000	1250.000000	1250.000000	12
mean	32.02400	0.81760	37.792800	0.114400	0.390400	0.504800	2.128000	2.786400	0.298400	
std	7.38408	0.42388	13.334981	0.318424	0.488035	0.500177	1.165806	1.738733	0.457739	
min	5.00000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	27.00000	1.00000	42.000000	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000	
50%	31.00000	1.00000	45.000000	0.000000	0.000000	1.000000	3.000000	3.000000	0.000000	
75%	36.00000	1.00000	45.000000	0.000000	1.000000	1.000000	3.000000	4.000000	1.000000	
max	72.00000	2.00000	46.000000	1.000000	1.000000	1.000000	3.000000	5.000000	1.000000	

8 rows × 24 columns

```
from sklearn.preprocessing import MaxAbsScaler, StandardScaler

data['Age'] = MaxAbsScaler().fit_transform(data[['Age']])
data['Country'] = StandardScaler().fit_transform(data[['Country']])
data['work_interfere'] = StandardScaler().fit_transform(data[['work_interfere']])
data['no_employees'] = StandardScaler().fit_transform(data[['no_employees']])
data['leave'] = StandardScaler().fit_transform(data[['leave']])

data.describe()
```

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_employees	remote_work
count	1250.000000	1250.00000	1.250000e+03	1250.000000	1250.000000	1250.000000	1.250000e+03	1.250000e+03	1250.000000
mean	0.444778	0.81760	3.979039e-17	0.114400	0.390400	0.504800	-1.193712e-16	-1.705303e-17	0.298400
std	0.102557	0.42388	1.000400e+00	0.318424	0.488035	0.500177	1.000400e+00	1.000400e+00	0.457739
min	0.069444	0.00000	-2.835244e+00	0.000000	0.000000	0.000000	-1.826077e+00	-1.603187e+00	0.000000
25%	0.375000	1.00000	3.156273e-01	0.000000	0.000000	0.000000	-9.679583e-01	-1.027826e+00	0.000000
50%	0.430556	1.00000	5.406895e-01	0.000000	0.000000	1.000000	7.482798e-01	1.228972e-01	0.000000
75%	0.500000	1.00000	5.406895e-01	0.000000	1.000000	1.000000	7.482798e-01	6.982587e-01	1.000000
max	1.000000	2.00000	6.157103e-01	1.000000	1.000000	1.000000	7.482798e-01	1.273620e+00	1.000000

8 rows × 24 columns

Split the data to train and test

```
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)
```

```
(937, 23) (937,)
------------------------------
(313, 23) (313,)
______________________________
```

```
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
```

Random Forest Classifier

```
steps_rfc = [('Scaler', StandardScaler()),
             ('clf', RFC(n_estimators = 40))]
```

```
clf_rfc = Pipeline(steps=steps_rfc)
```

```
clf_rfc.fit(X_train, y_train)

y_pred_rfc = clf_rfc.predict(X_test)
print('RFC accuracy: ', accuracy_score(y_true=y_test, y_pred=y_pred_rfc)*100)
```

```
RFC accuracy:  69.6485623003195
```

K nearest neighbor

```
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)
```

```
KNN accuracy : 58.78594249201278
```

Support vector Classifier

```
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 : 71.24600638977637
```

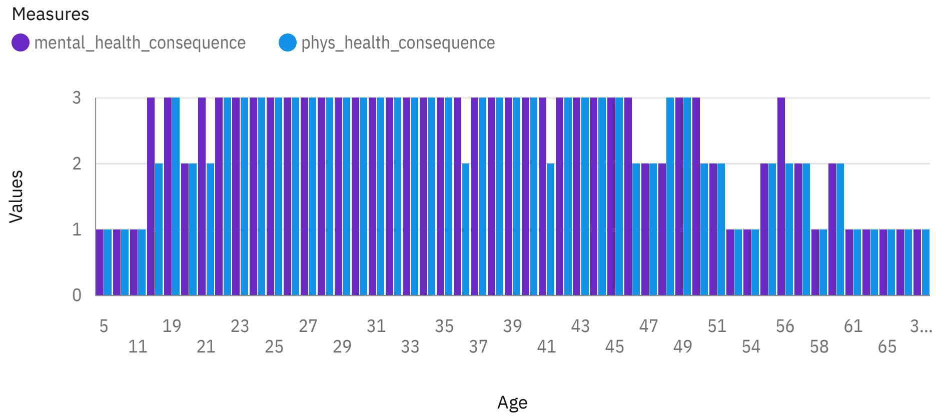
Decision Tree

```
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)
```

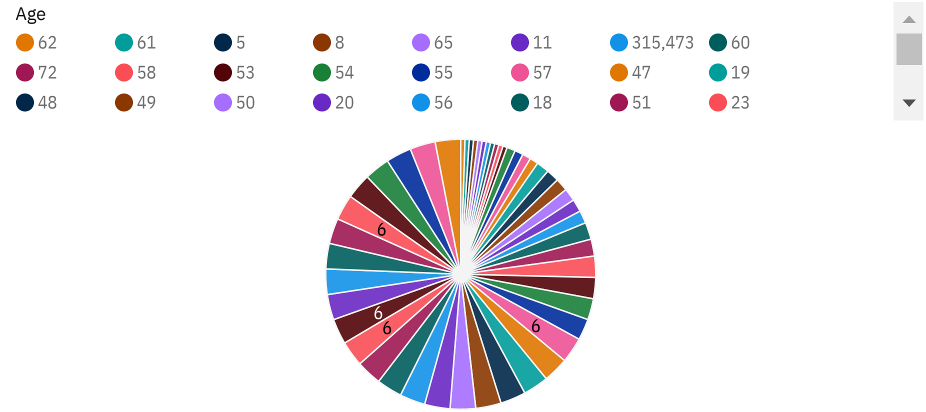
```
DT accuracy : 65.814696485623
```

Tab 1

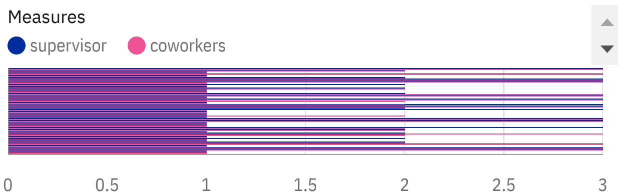
mental_health_consequence and phys_health_consequence by Age



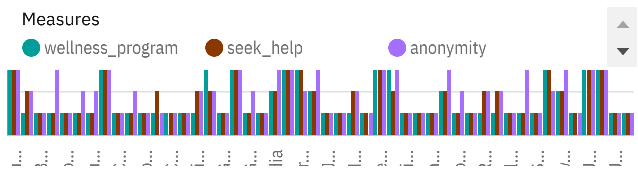
no_employees by Age



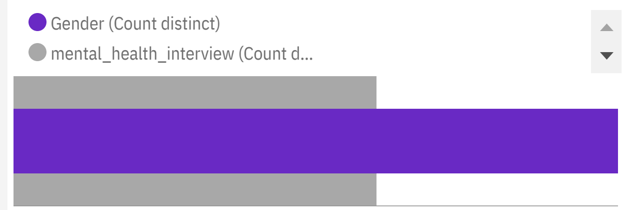
supervisor and coworkers by Country



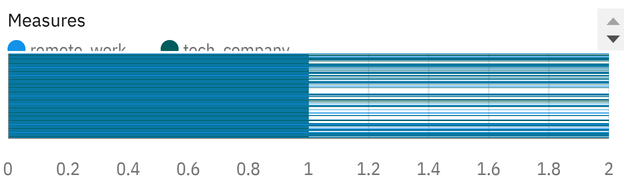
wellness_program, seek_help and anonymity by Country



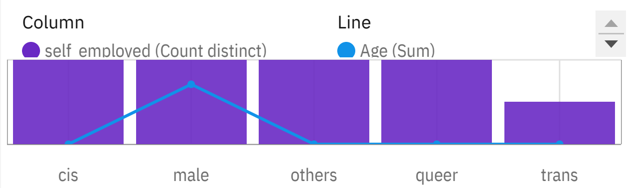
Gender, mental_health_interview, phys_health_interview



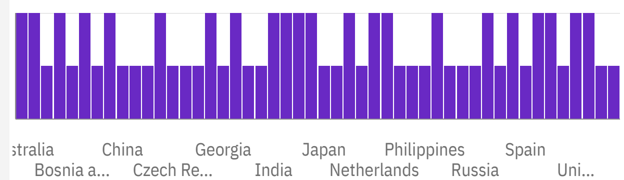
remote_work and tech_company by state and Country



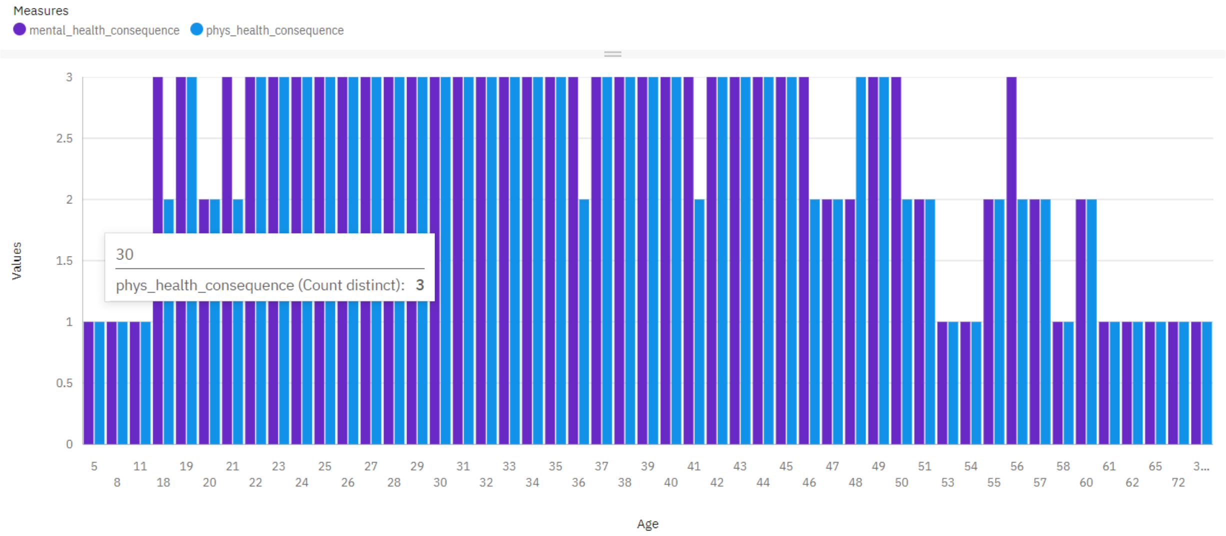
Age and self_employed by Gender



family_history by Country



mental_health_consequence and phys_health_consequence by Age



Narrative insights

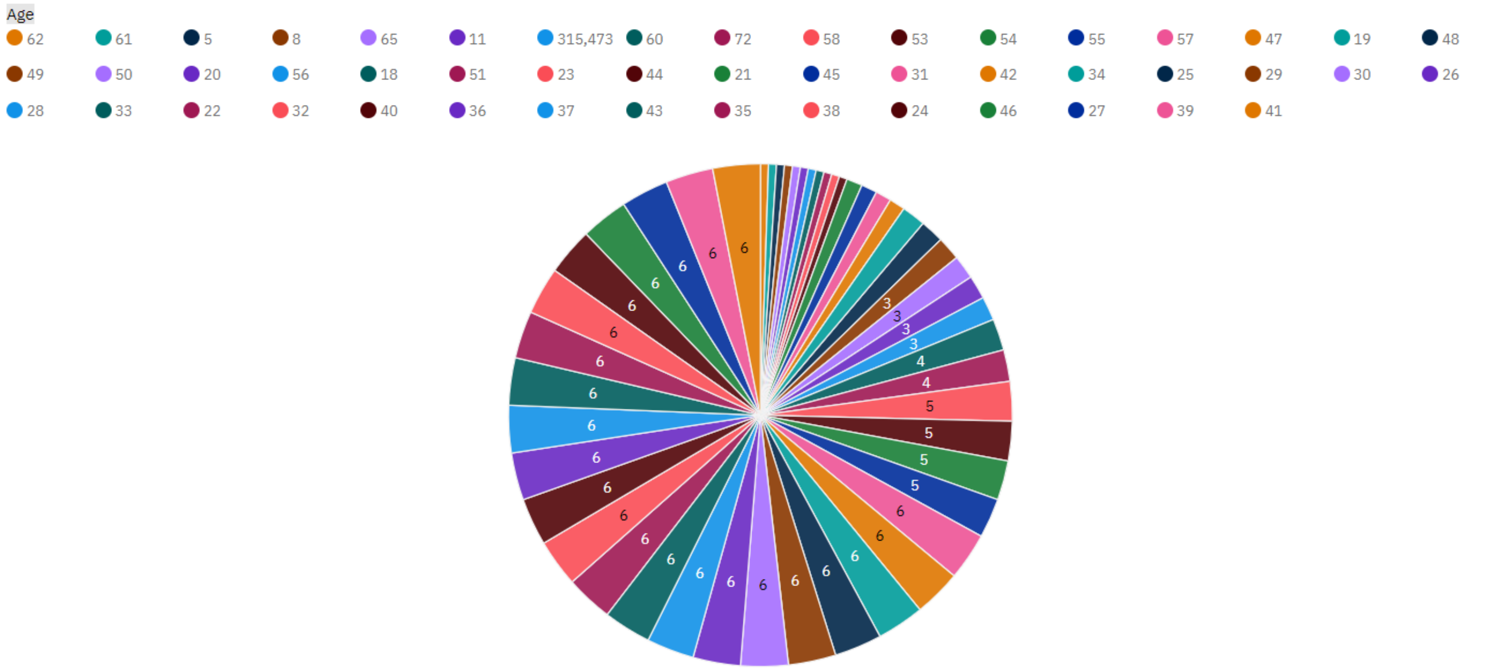
Suggested insights (3)

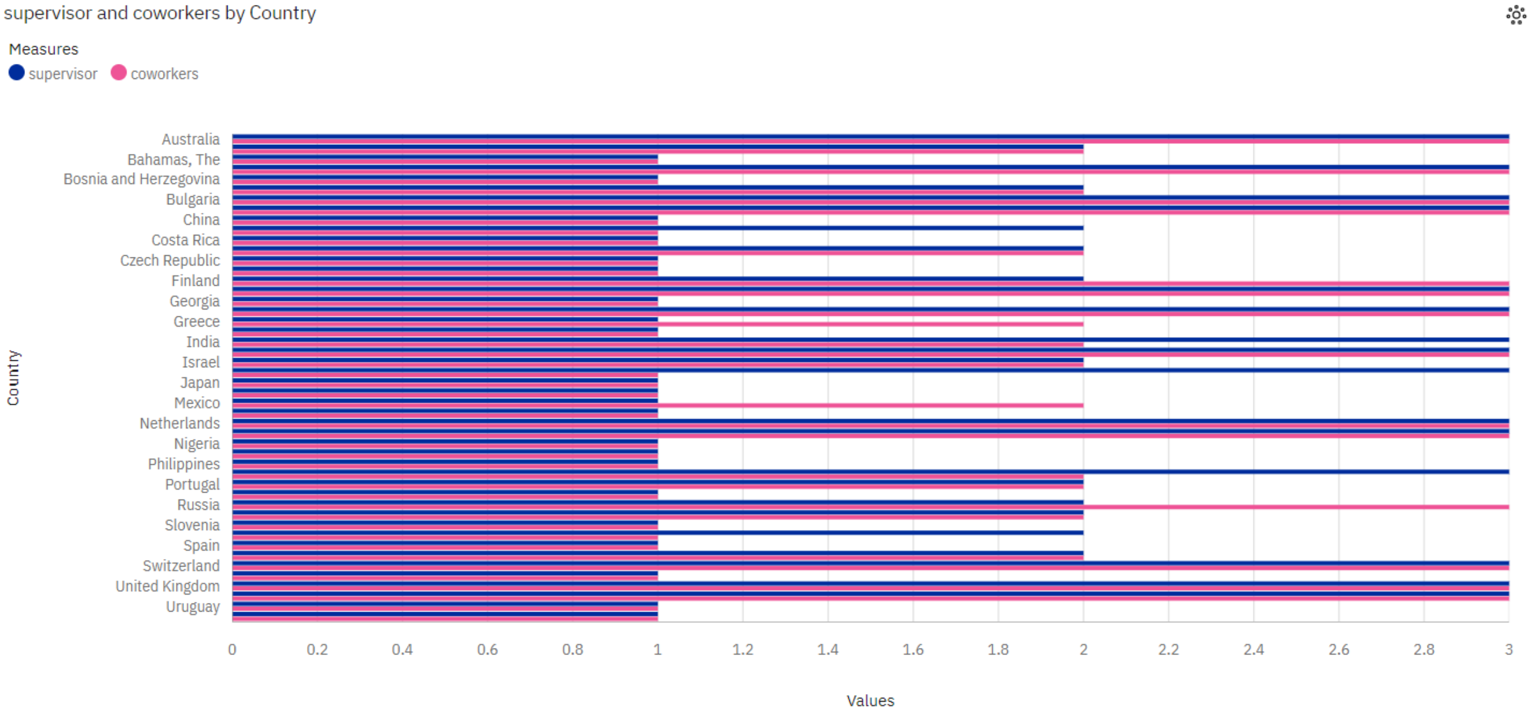
Age 26 has the highest **phys_health_consequence** due to **Country United States**.

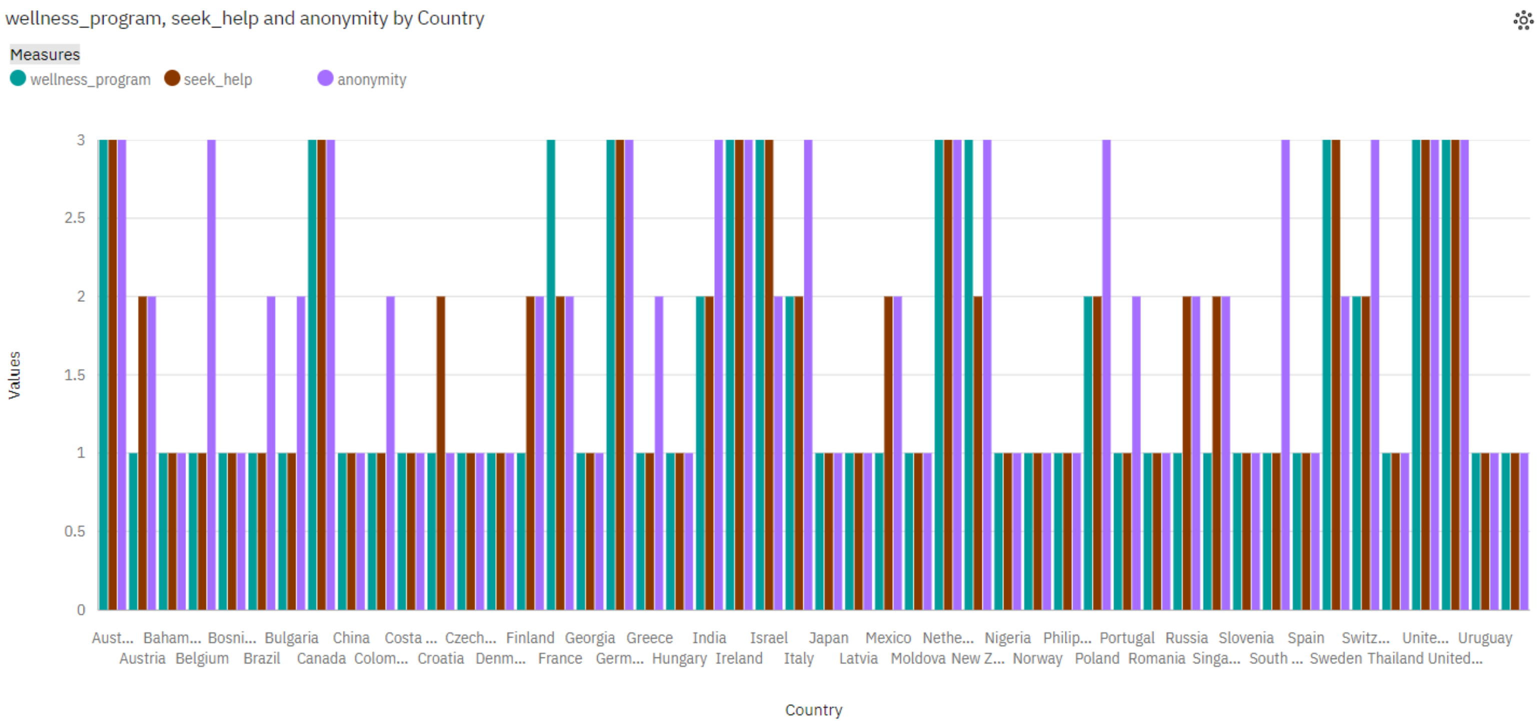
Age 18 has the highest **Count distinct mental_health_consequence** but is ranked #**26** in **Count distinct phys_health_consequence**.

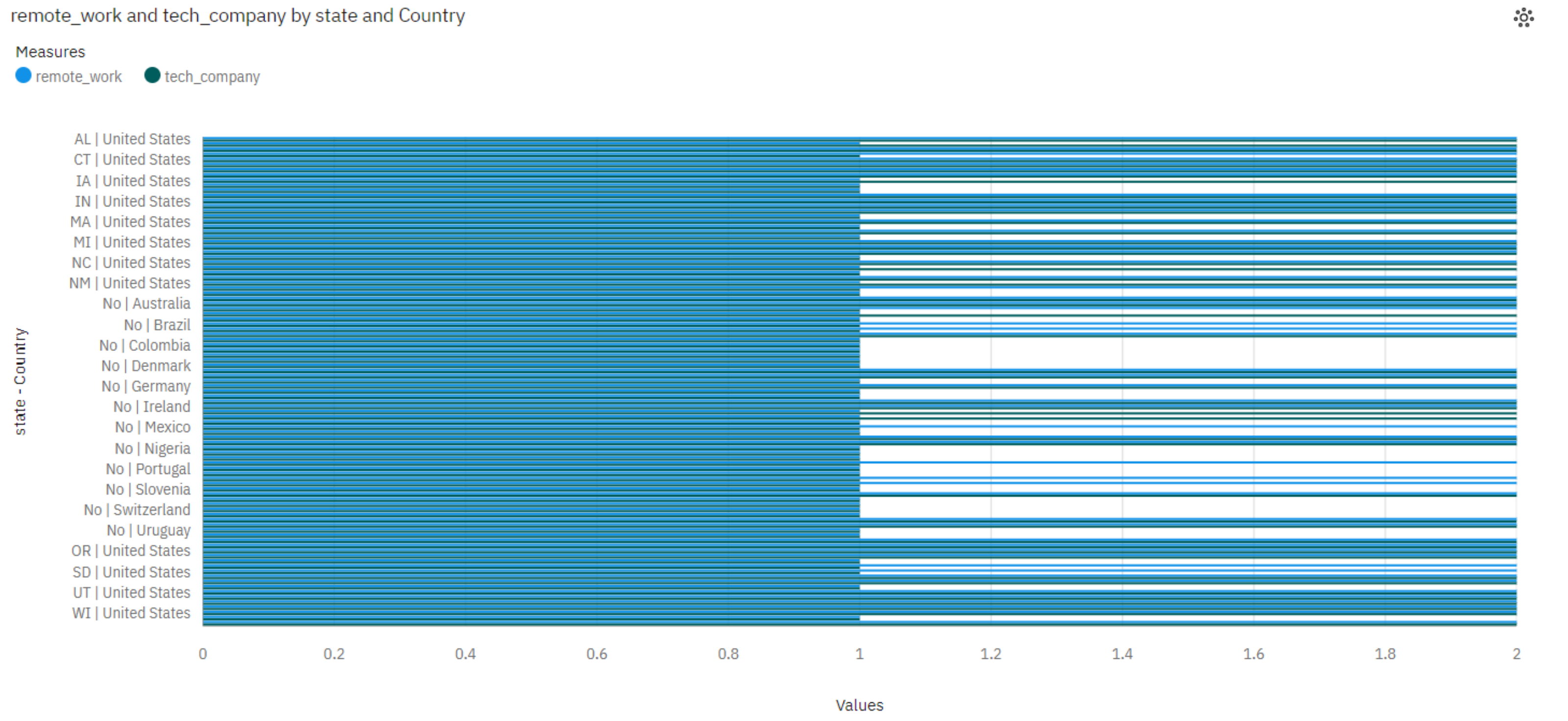
Country United States has the highest **phys_health_consequence** at **99**, out of which **Age 22** contributed the most at **3**.

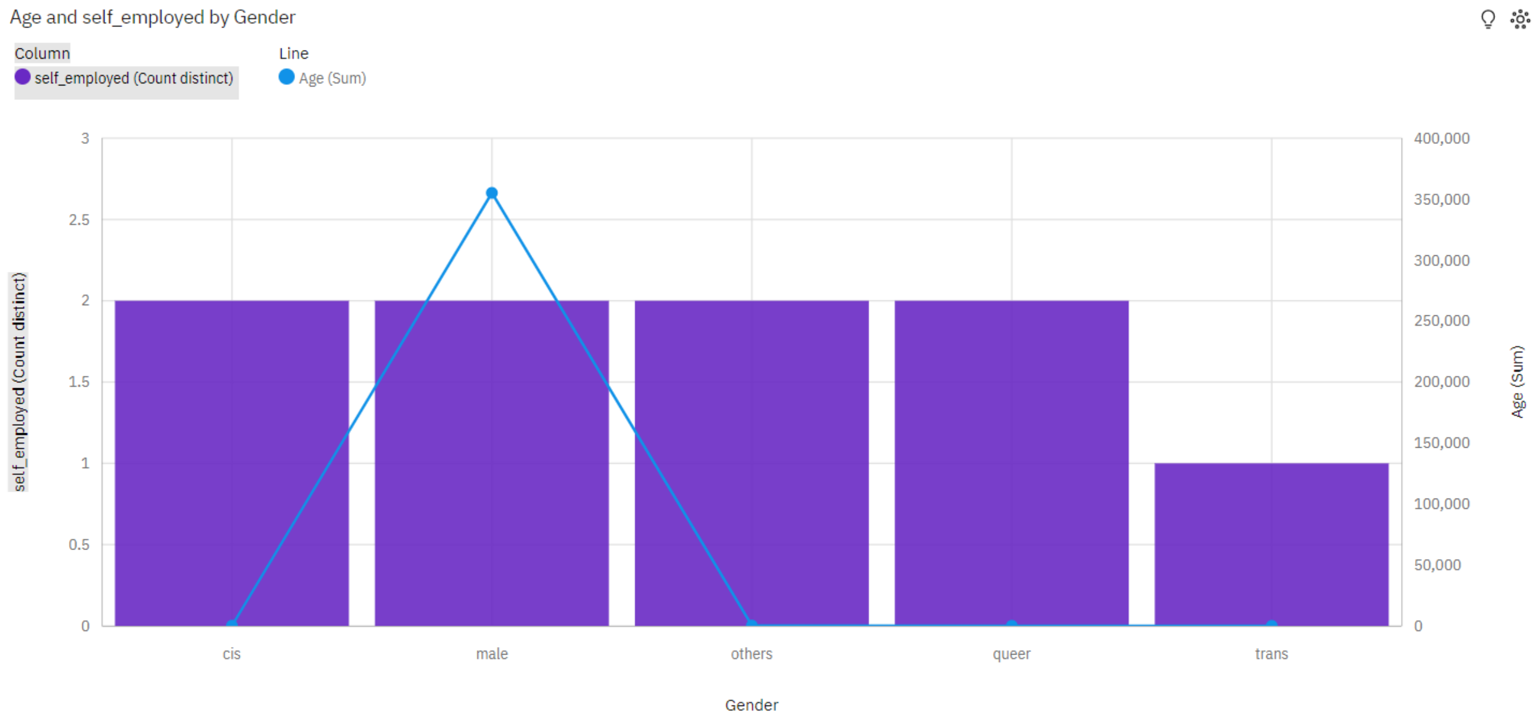
no_employees by Age

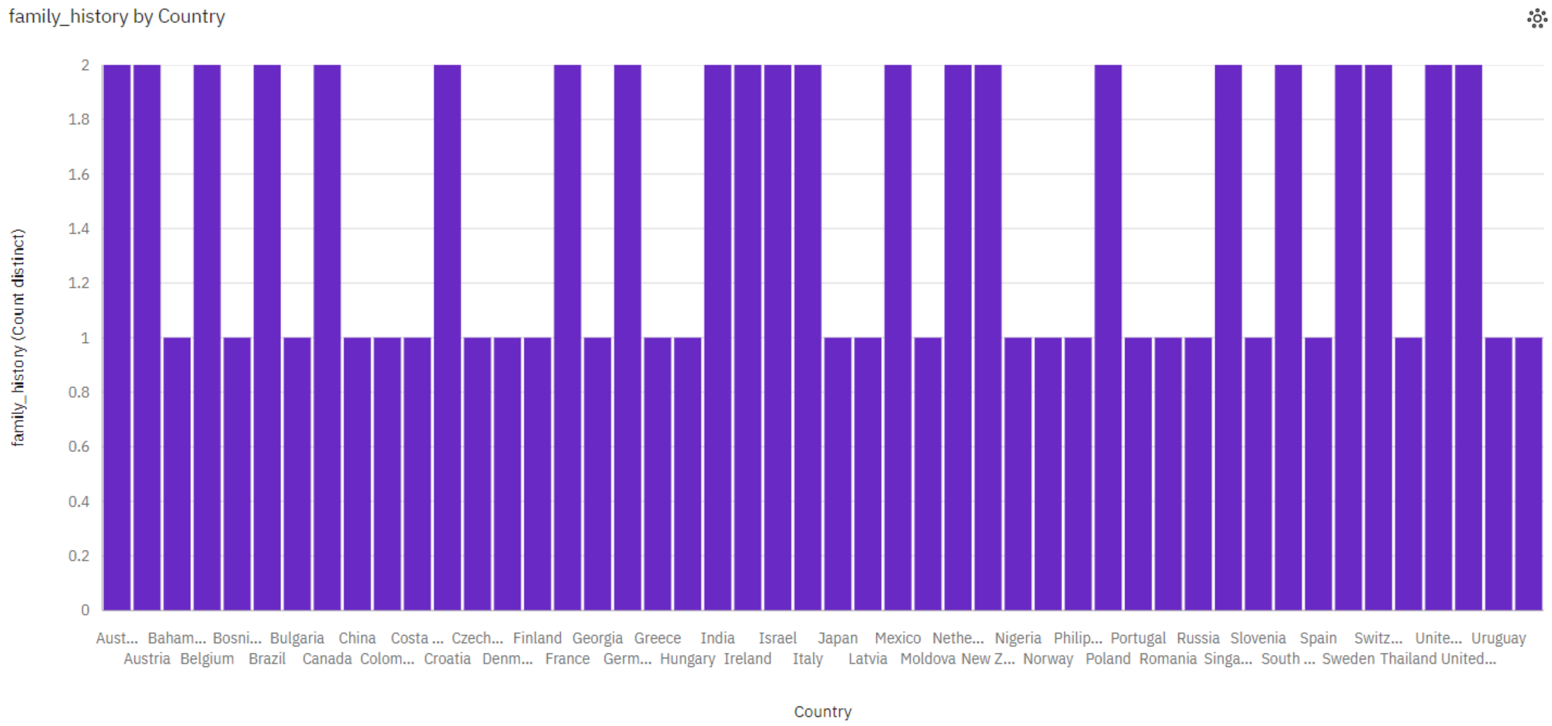



supervisor and coworkers by Country
Measures
supervisor
coworkers
Australia
Bahamas, The
Bosnia and Herzegovina
Bulgaria
China
Costa Rica
Czech Republic
Finland
Georgia
Greece
India
Israel
Japan
Mexico
Netherlands
Nigeria
Philippines
Portugal
Russia
Slovenia
Spain
Switzerland
United Kingdom
Uruguay
Country
0
0.2
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
Measures
wellness_program
seek_help
anonymity
Values
3
2.5
2
1.5
1
0.5
0
Aust...
Austria
Baham...
Belgium
Bosni...
Brazil
Bulgaria
Canada
China
Colom...
Costa ...
Croatia
Czech...
Denm...
Finland
France
Georgia
Germ...
Greece
Hungary
India
Ireland
Israel
Italy
Japan
Latvia
Mexico
Moldova
Nethe...
New Z...
Nigeria
Norway
Philip...
Poland
Portugal
Romania
Russia
Singa...
Slovenia
South ...
Spain
Sweden
Switz...
Thailand
Unite...
United...
Uruguay
Country


remote_work and tech_company by state and Country
Measures
remote_work
tech_company
AL | United States
CT | United States
IA | United States
IN | United States
MA | United States
MI | United States
NC | United States
NM | United States
No | Australia
No | Brazil
No | Colombia
No | Denmark
No | Germany
No | Ireland
No | Mexico
No | Nigeria
No | Portugal
No | Slovenia
No | Switzerland
No | Uruguay
OR | United States
SD | United States
UT | United States
WI | United States
state - Country
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Values


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
family_history (Count distinct)
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Aust... Baham... Bosni... Bulgaria China Costa ... Czech... Finland Georgia Greece India Israel Japan Mexico Nethe... Nigeria Philip... Portugal Russia Slovenia Spain Switz... Unite... Uruguay
Austria Belgium Brazil Canada Colom... Croatia Denm... France Germ... Hungary Ireland Italy Latvia Moldova New Z... Norway Poland Romania Singa... South ... Sweden Thailand United...
Country

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