DAC_PHASE4

Date: 26-10-2023
Team ID:716
Project Title: Public Health Awareness Campaign Analysis

Introduction

In this, we are building upon our analysis efforts by utilizing IBM Cognos for data visualization and integrating code, potentially in Python, for advanced data analysis. Our primary objective remains the assessment of the public health awareness campaign's effectiveness and impact. We will design interactive dashboards and reports in IBM Cognos to visually represent campaign reach, awareness levels, and impact metrics, offering valuable insights for stakeholders. Furthermore, we will use code to perform in-depth analysis, including calculating engagement rates, conducting demographic analysis, and running statistical tests, enabling us to provide comprehensive findings that can inform decisions and contribute to the betterment of our communities.

Import necessary libraries

```
import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

print('Successfully imported')
```

This dataset contains the following data:

* Timestamp

* Age

* Gender

* Country

* state: If you live in the United States, which state or territory do you live in?

* self_employed: Are you self-employed?

* family_history: Do you have a family history of mental illness?

* treatment: Have you sought treatment for a mental health condition?

* work_interfere: If you have a mental health condition, do you feel that it interferes with your work?

* no_employees: How many employees does your company or organization have?

* remote_work: Do you work remotely (outside of an office) at least 50% of the time?

* tech_company: Is your employer primarily a tech company/organization?

* benefits: Does your employer provide mental health benefits?

* care_options: Do you know the options for mental health care your employer provides?

* wellness_program: Has your employer ever discussed mental health as part of an employee wellness program?

* seek_help: Does your employer provide resources to learn more about mental health issues and how to seek help?

* anonymity: Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?

* leave: How easy is it for you to take medical leave for a mental health condition?

* mental_health_consequence: Do you think that discussing a mental health issue with your employer would have negative consequences?

* phys_health_consequence: Do you think that discussing a physical health issue with your employer would have negative consequences?

* coworkers: Would you be willing to discuss a mental health issue with your coworkers?

* supervisor: Would you be willing to discuss a mental health issue with your direct supervisor(s)?

* mental_health_interview: Would you bring up a mental health issue with a potential employer in an interview?

* phys_health_interview: Would you bring up a physical health issue with a potential employer in an interview?

* mental_vs_physical: Do you feel that your employer takes mental health as seriously as physical health?

* obs_consequence: Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?

* comments: Any additional notes or comments

Read Dataset

```
data = pd.read_csv('/kaggle/input/mental-health-in-tech-survey/survey.csv')

data.head()
```

Preprocessing and Cleaning dataset

```
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()))
```

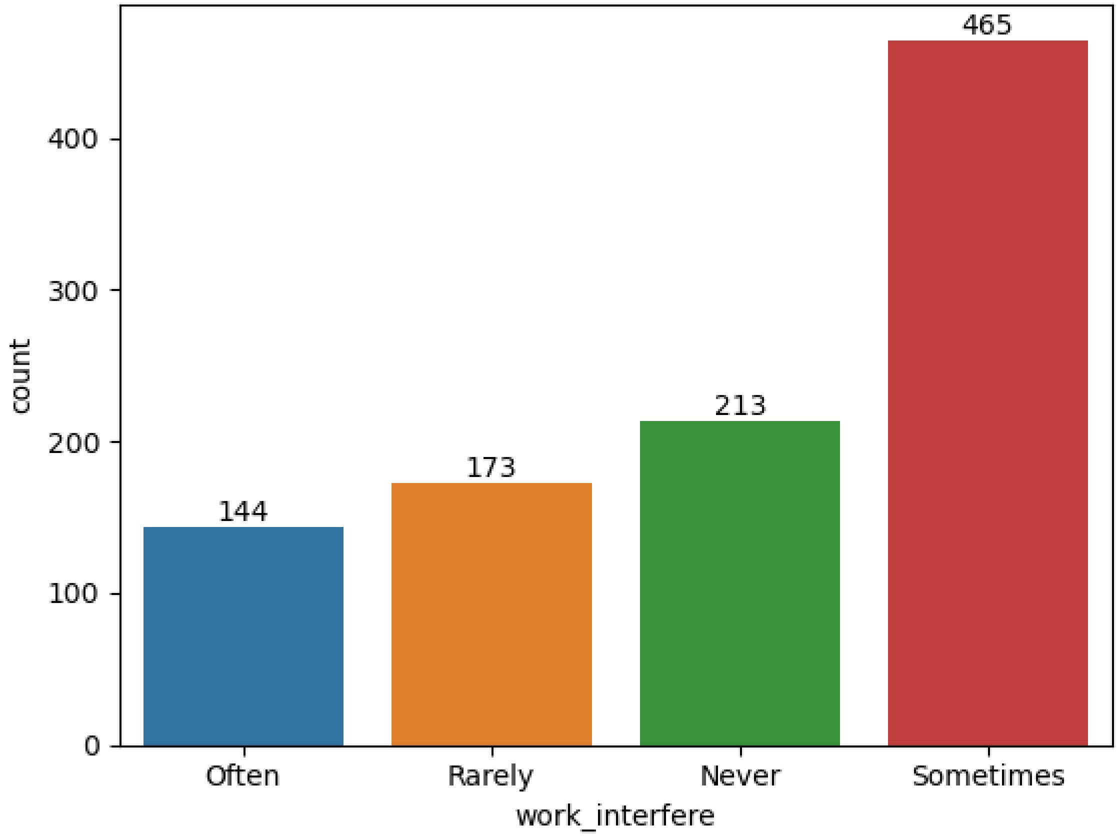
There is 1892 missing data in our dataset

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

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

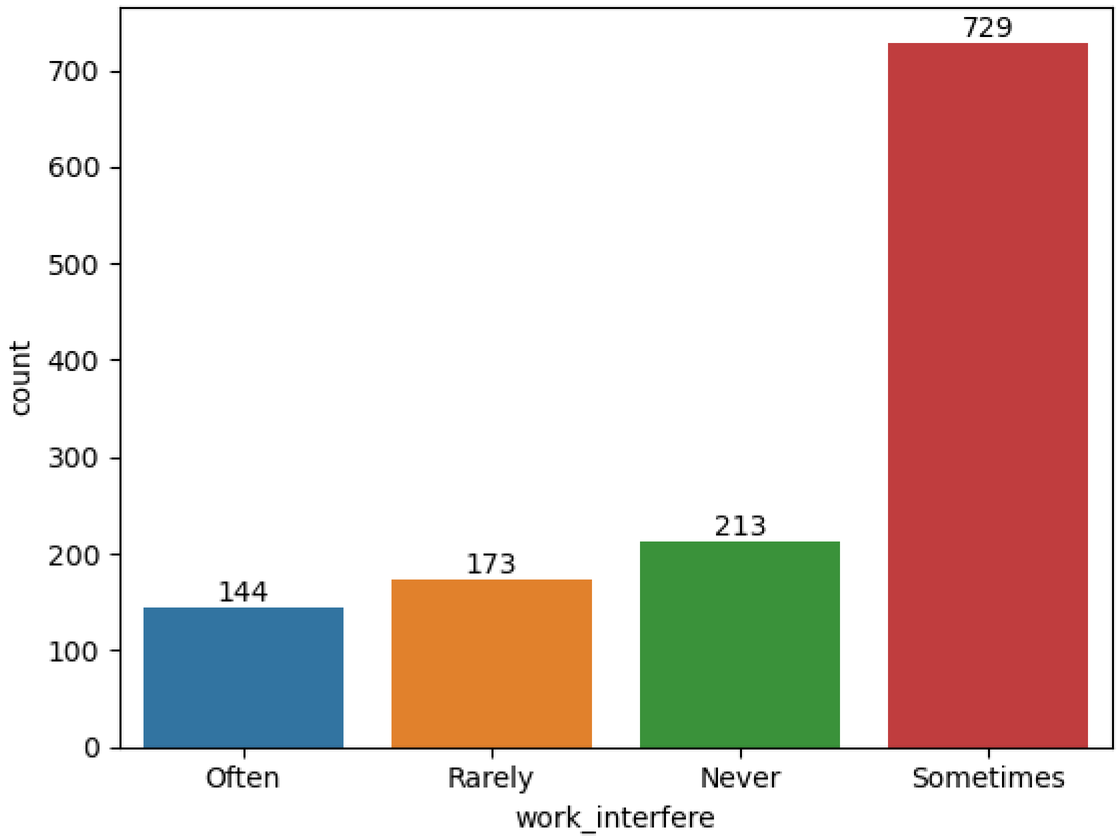
array(['Often', 'Rarely', 'Never', 'Sometimes', nan], dtype=object)

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




```
#For filling nan values i used SimpleImputer but you can use fillnan function too
from sklearn.impute import SimpleImputer
data = data.drop(columns=['state', 'comments', 'Timestamp', ])
# Fill in missing values in work_interfere column
```

```
data['work_interfere'] = SimpleImputer(strategy =
'most_frequent').fit_transform(data['work_interfere'].values.reshape(-1,1))

data['self_employed'] = SimpleImputer(strategy =
'most_frequent').fit_transform(data['self_employed'].values.reshape(-1,1))

data.head()


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())
```

Output

```
['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
```

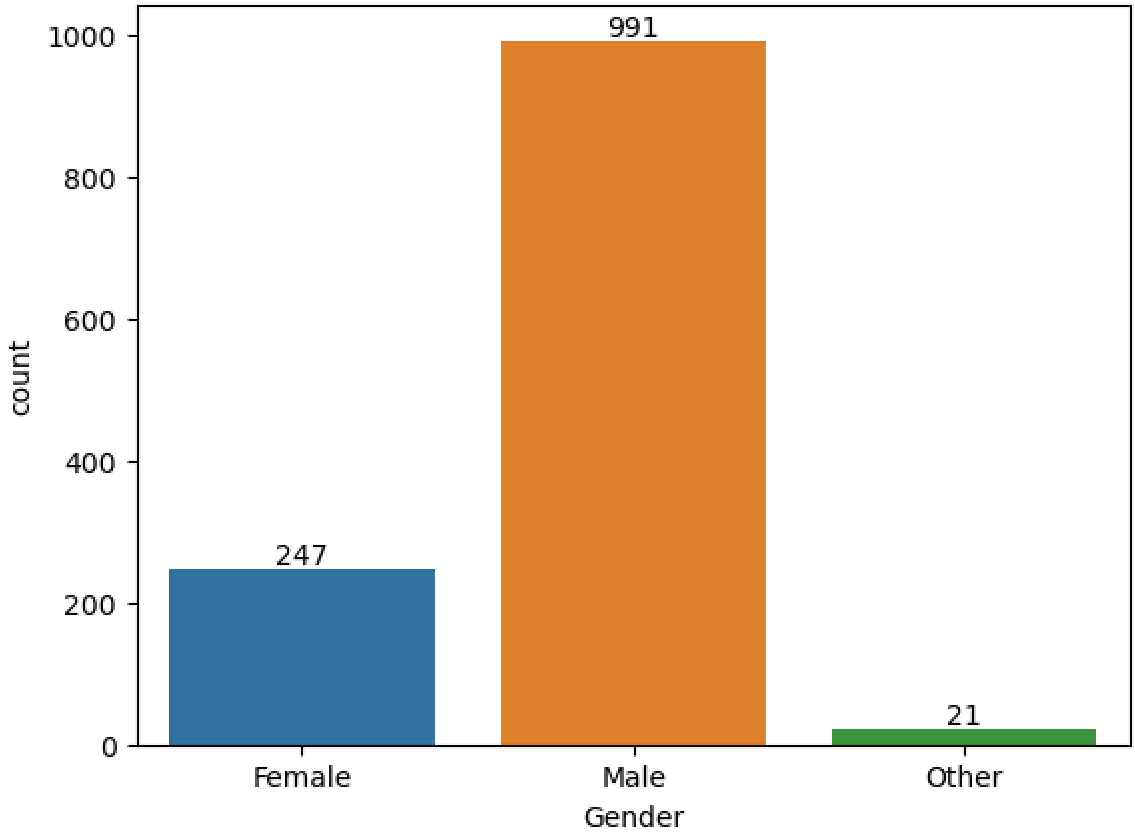
```
#Gender data contains dictation problems, nonsense answers, and too unique Genders.
#_So Let's clean it and organize it into Male, Female, and other categories

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())
```

Output

['Female' 'Male' 'Other']

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

Output




```
#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()))
```

Output

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())
```

Output

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

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

Output

```
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])
```

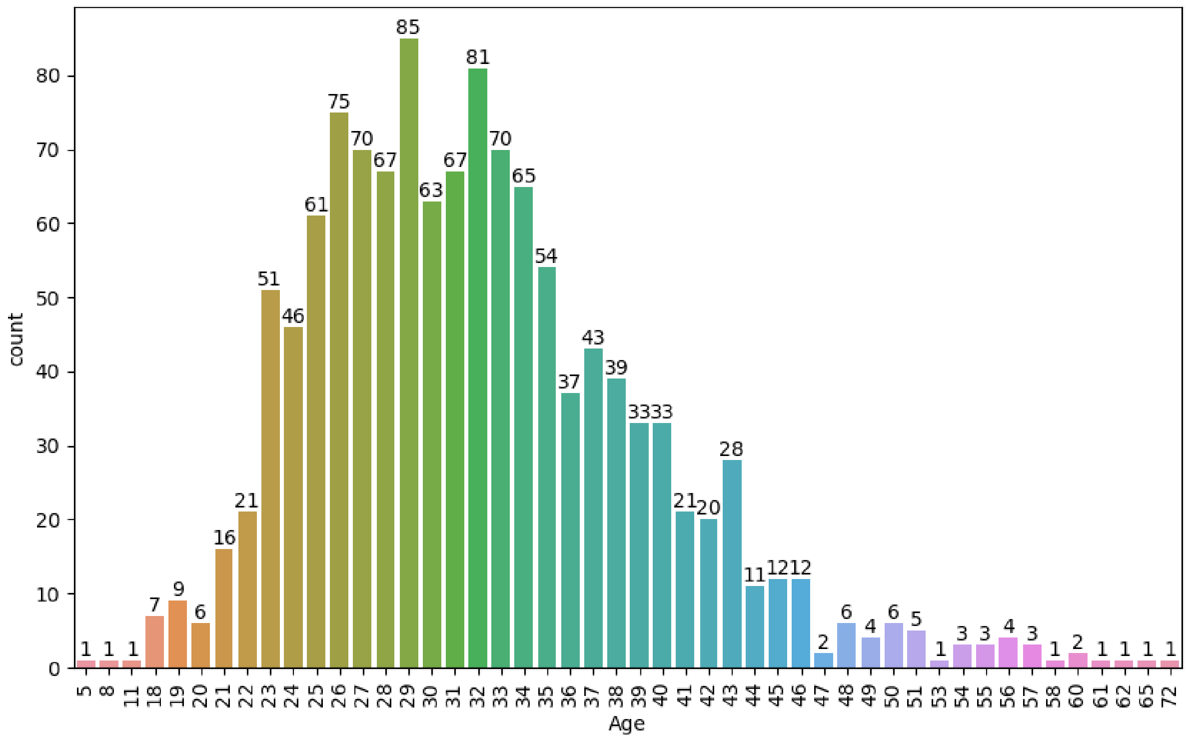
```
#We had a lot of nonsense answers in the Age column too
#This filtering will drop entries exceeding 100 years and those indicating negative values.
data.drop(data[data['Age']<0].index, inplace = True)
data.drop(data[data['Age']>99].index, inplace = True)

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

Output

```
[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);
```

Output



#In this plot moreover on Age distribution we can see treatment distribution by age

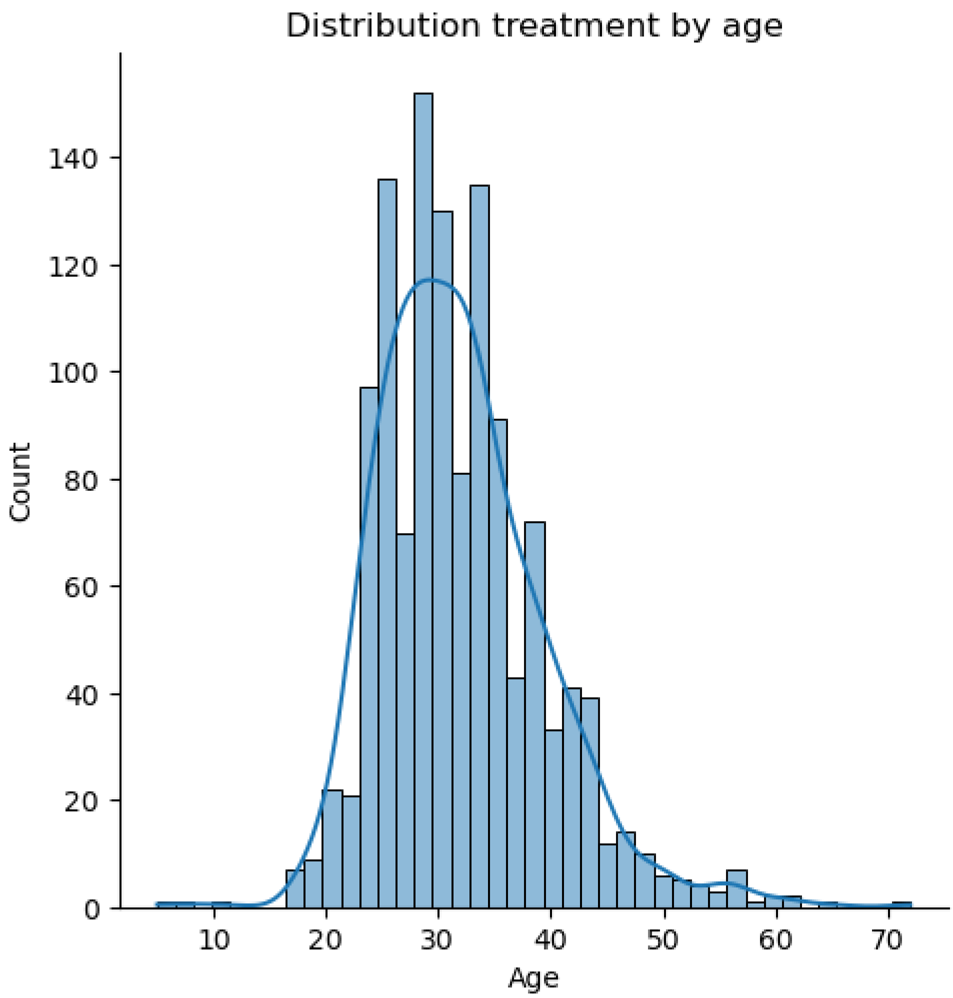
plt.figure(figsize=(10, 6));

sns.displot(data['Age'], kde = 'treatment');

plt.title('Distribution treatment by age');

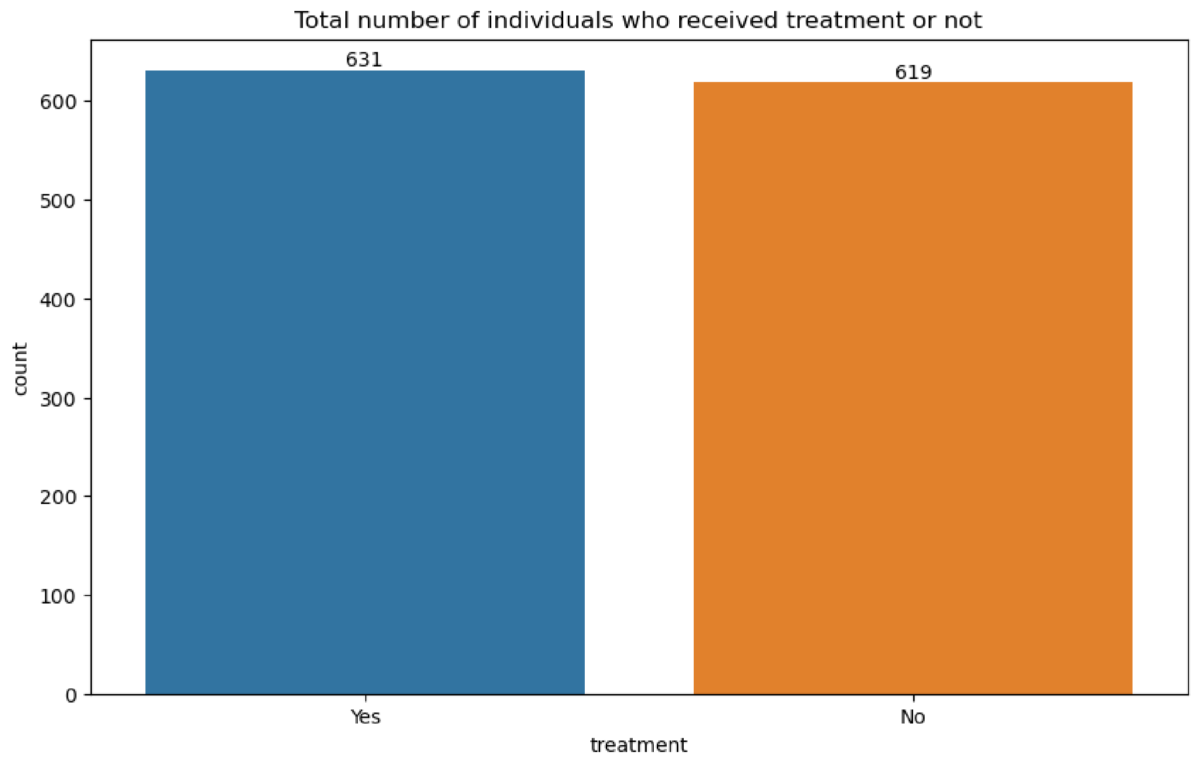
Output

<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');
```



data.info()

Output

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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
...
 22  mental_vs_physical         1250 non-null   object
 23  obs_consequence            1250 non-null   object
dtypes: int64(1), object(23)
```

```
#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()
```

Output

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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
...
 22  mental_vs_physical         1250 non-null   int64
 23  obs_consequence            1250 non-null   int64
dtypes: int64(24)
```

```
data.describe()
```

```
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()
```

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)
```

Output

```
(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
```

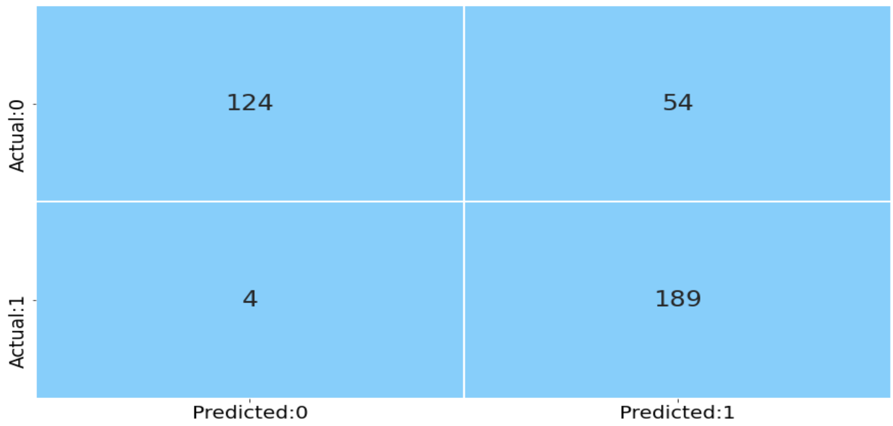
```
from sklearn.tree import DecisionTreeClassifier as DT
```

Support Vector Machine

```
svclassifier = SVC(kernel = 'linear')

# fit the model
svc_model=svclassifier.fit(X_train, y_train)

# predict the values
y_pred = svclassifier.predict(X_test)
```

linkcode

```
# call the function to plot the confusion matrix
plot_confusion_matrix(svc_model)
```




```
test_report = get_test_report(svc_model)

# print the performace measures
print(test_report)
```

	precision	recall	f1-score	support
0	0.97	0.70	0.81	178
1	0.78	0.98	0.87	193

Output

accuracy			0.84	371
macro avg	0.87	0.84	0.84	371

weighted avg 0.87 0.84 0.84 371

Input

kappa_value = kappa_score(svc_model)

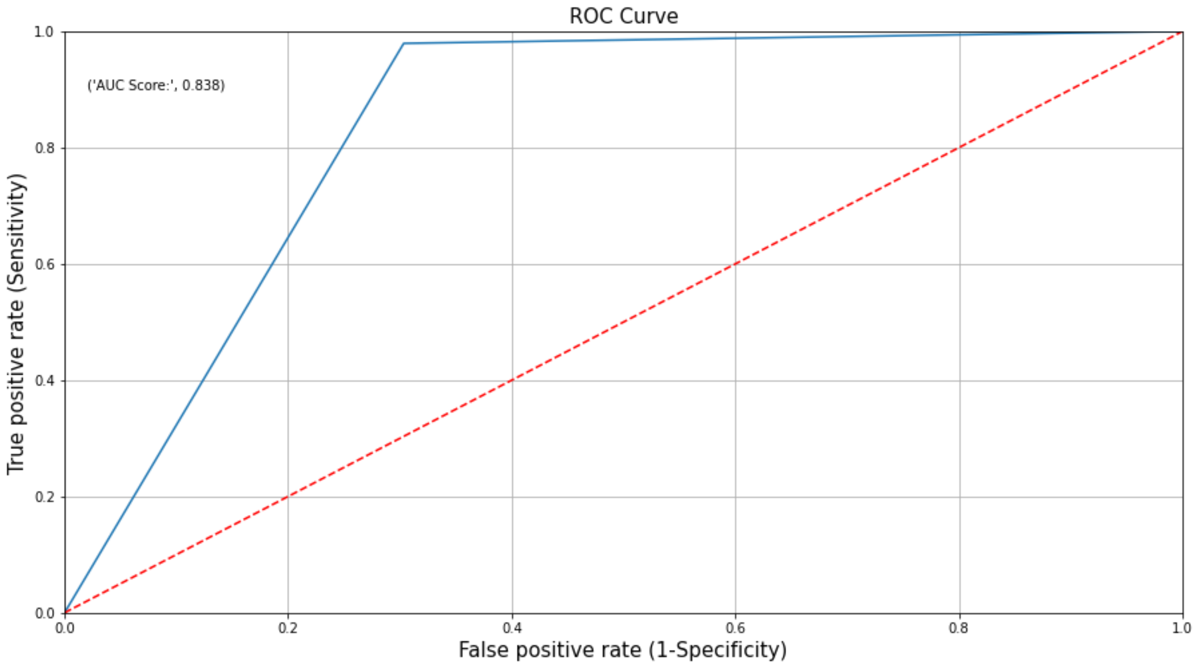
print the kappa value

print(kappa_value)

0.6833632537743901

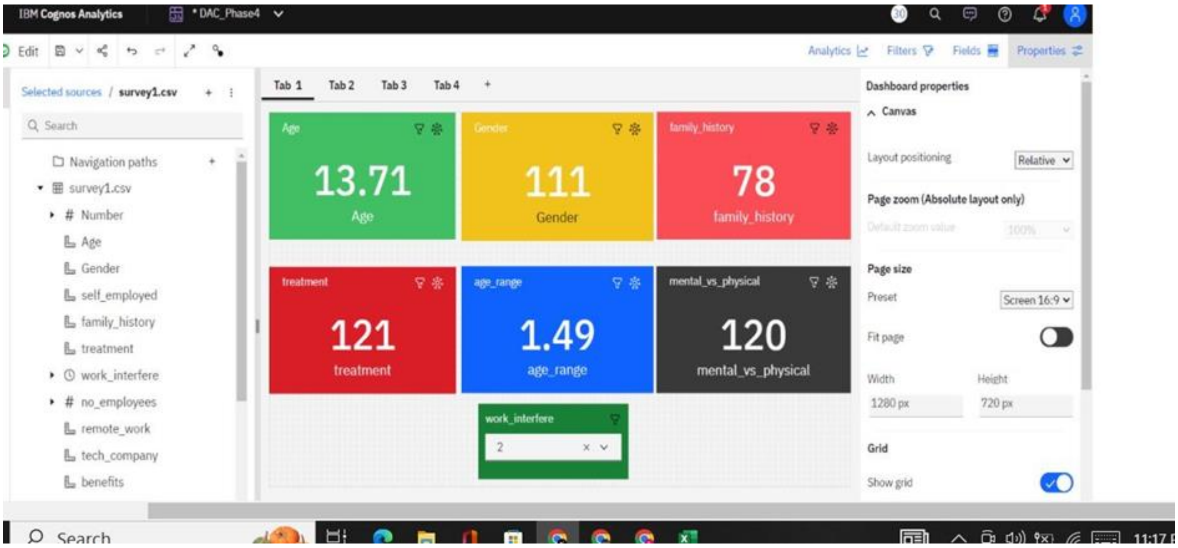
plot_roc(svc_model)

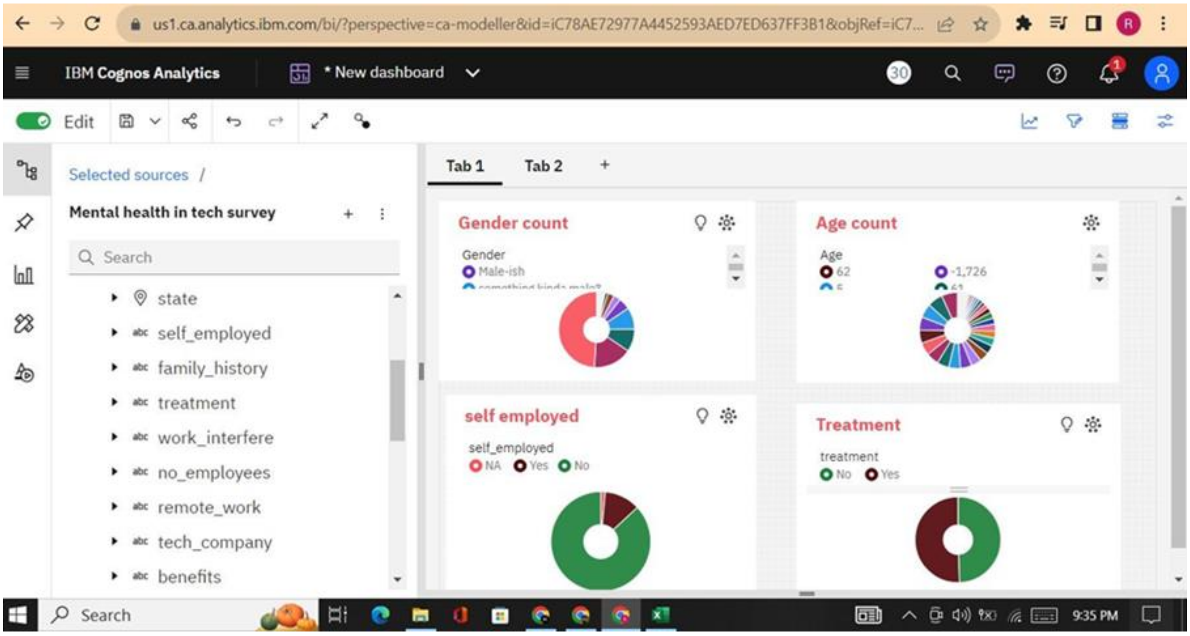
Output

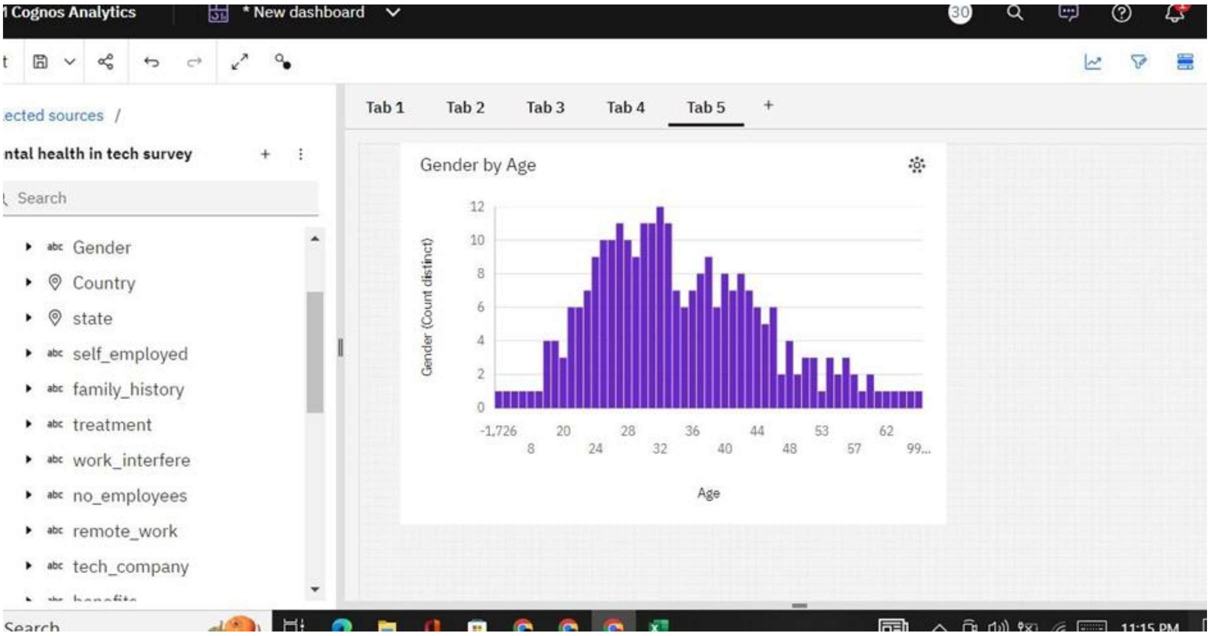


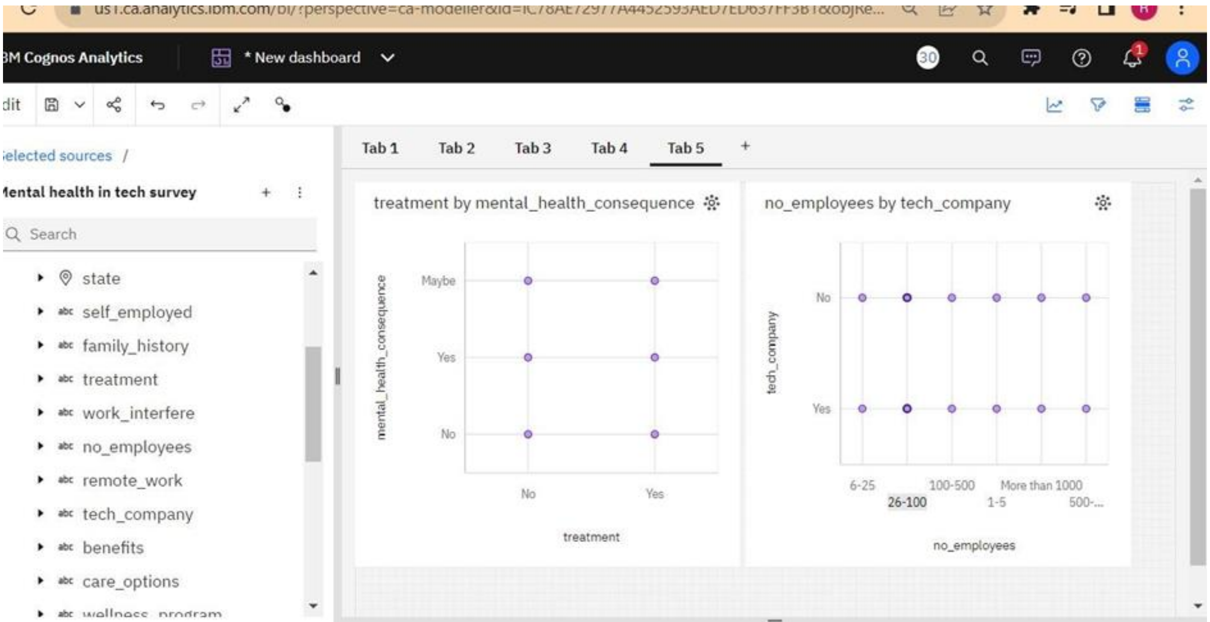
Accuracy 0.84

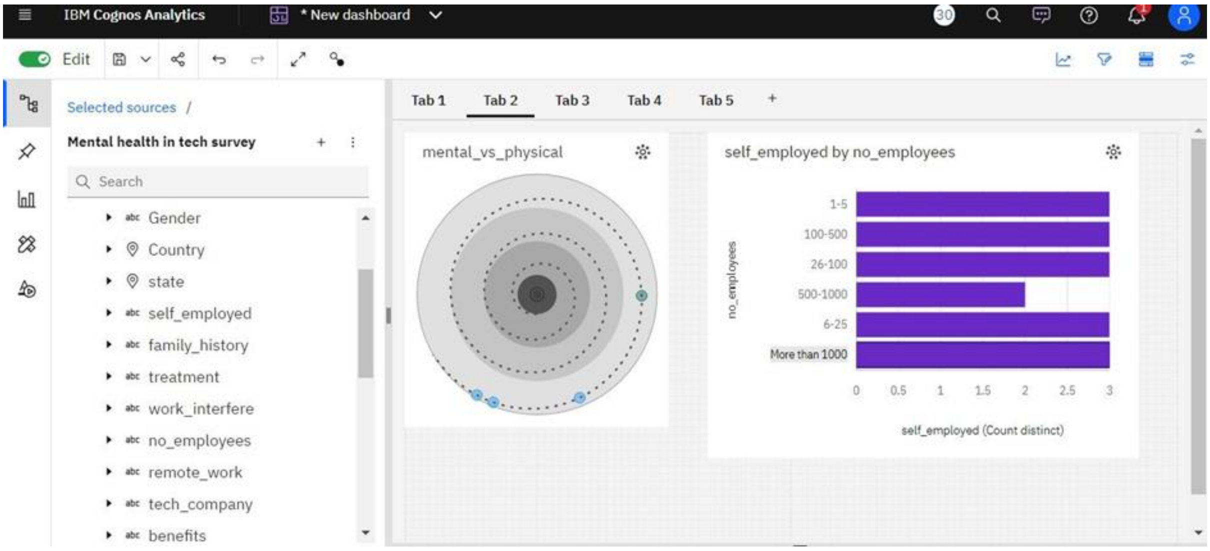
Dashboard and Report in IBM COGNOS

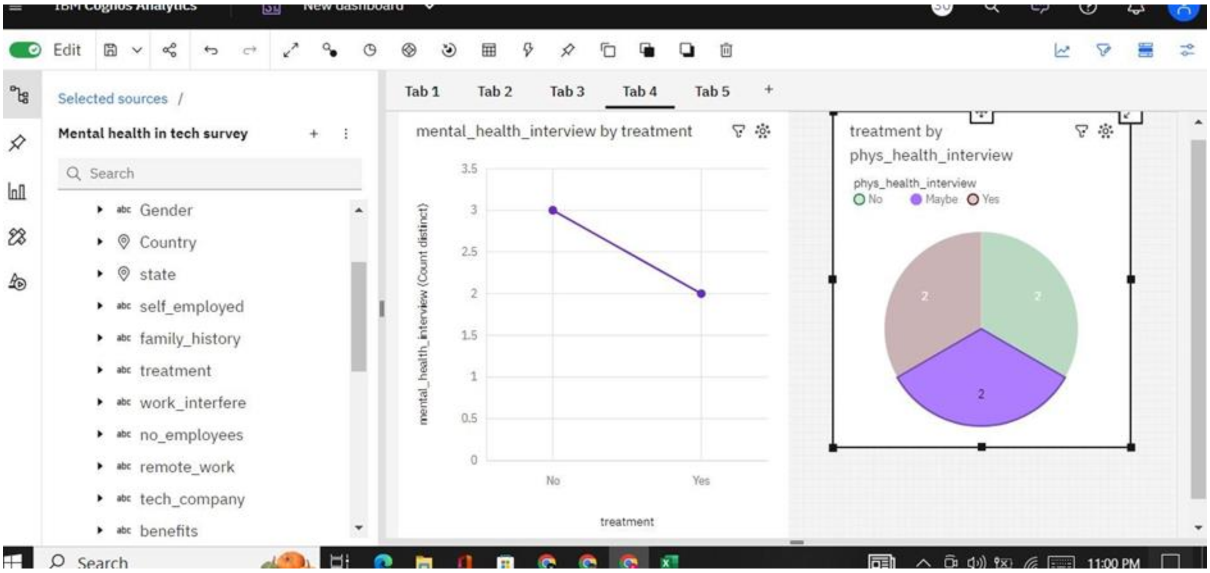

IBM Cognos Analytics
* DAC_Phase4
Edit
Analytics
Filters
Fields
Properties
Selected sources / survey1.csv
Search
Navigation paths
survey1.csv
Number
Age
Gender
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
benefits
Tab 1
Tab 2
Tab 3
Tab 4
13.71
Age
111
Gender
78
family_history
121
treatment
1.49
age_range
120
mental_vs_physical
work_interfere
Dashboard properties
Canvas
Layout positioning
Relative
Page zoom (Absolute layout only)
Page size
Preset
Screen 16:9
Fit page
Width
Height
1280 px
720 px
Grid
Show grid
Search

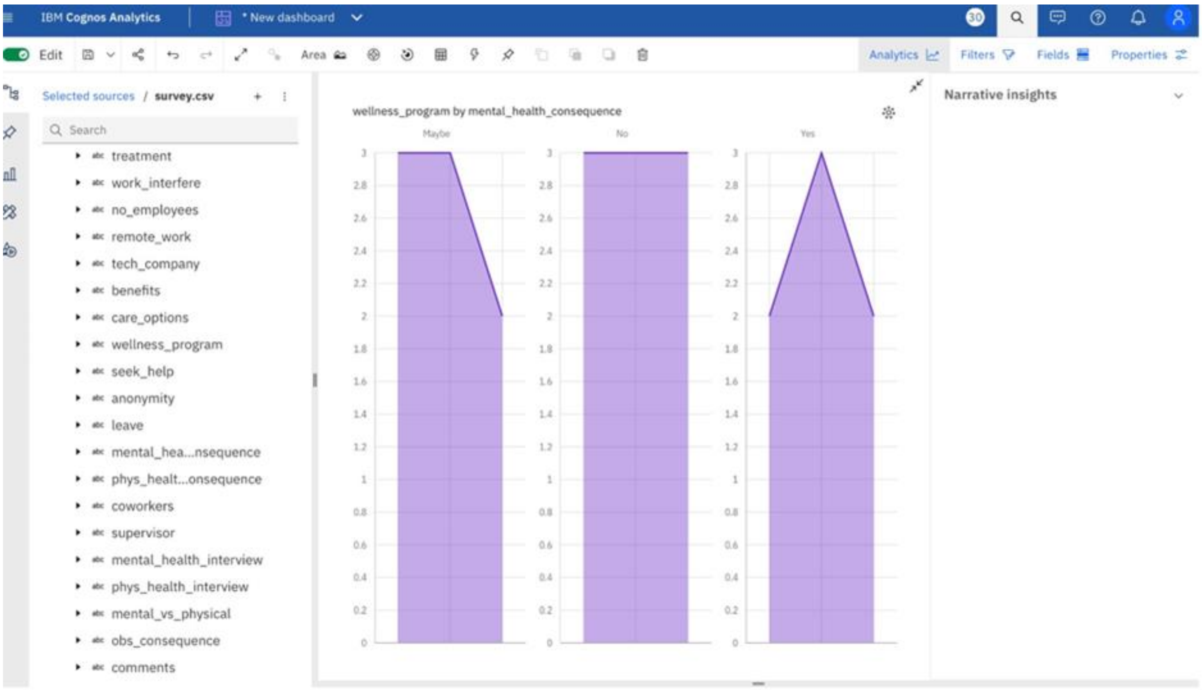

us1.ca.analytics.ibm.com/bi/?perspective=ca-modeller&id=iC78AE72977A4452593AED7ED637FF3B1&objRef=iC7...
IBM Cognos Analytics
* New dashboard
Edit
Selected sources /
Mental health in tech survey
Search
state
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
benefits
Tab 1
Tab 2
Gender count
Gender
Male-ish
Age count
Age
62
-1,726
self employed
self_employed
NA
Yes
No
Treatment
treatment
No
Yes
Search
9:35 PM


Cognos Analytics
* New dashboard
ected sources /
ntal health in tech survey
Search
Gender
Country
state
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
Gender by Age
Gender (Count distinct)
Age
12
10
8
6
4
2
0
-1,726
8
20
24
28
32
36
40
44
48
53
57
62
99...

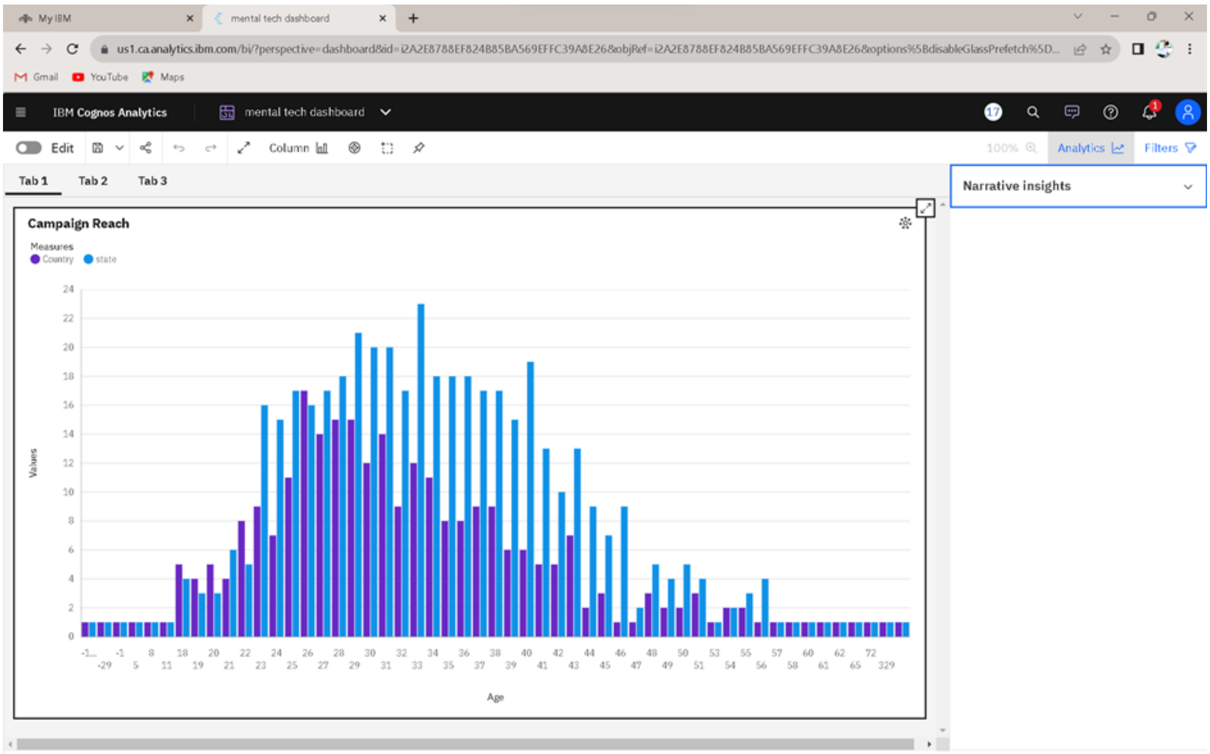

3M Cognos Analytics
* New dashboard
elected sources /
Mental health in tech survey
Search
state
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
benefits
care_options
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
treatment by mental_health_consequence
mental_health_consequence
Maybe
Yes
No
No
Yes
treatment
no_employees by tech_company
tech_company
No
Yes
6-25
26-100
100-500
1-5
More than 1000
500-...
no_employees


IBM Cognos Analytics
* New dashboard
Edit
Selected sources /
Mental health in tech survey
Search
Gender
Country
state
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
benefits
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
mental_vs_physical
self_employed by no_employees
1-5
100-500
26-100
500-1000
6-25
More than 1000
no_employees
0
0.5
1
1.5
2
2.5
3
self_employed (Count distinct)

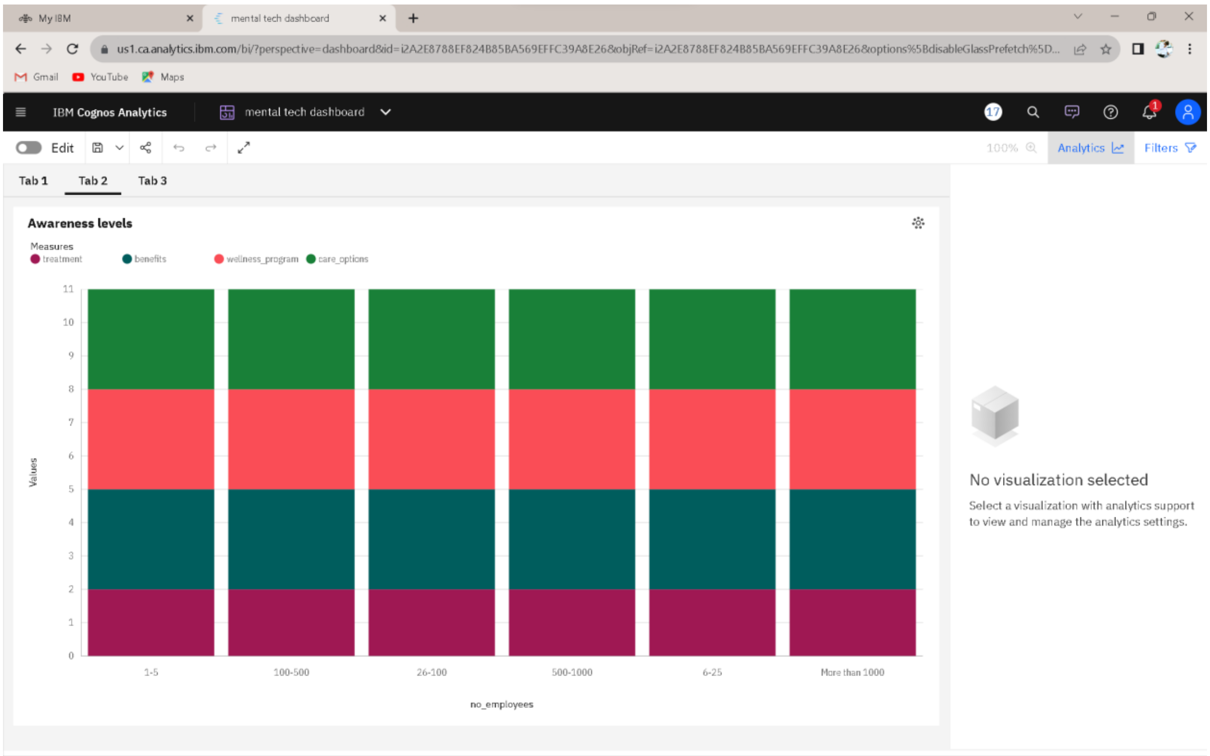

Edit
Selected sources /
Mental health in tech survey
Search
Gender
Country
state
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
benefits
Tab 1
Tab 2
Tab 3
Tab 4
Tab 5
mental_health_interview by treatment
3.5
3
2.5
2
1.5
1
0.5
0
mental_health_interview (Count distinct)
No
Yes
treatment
treatment by phys_health_interview
phys_health_interview
No
Maybe
Yes
2
2
2
Search
11:00 PM

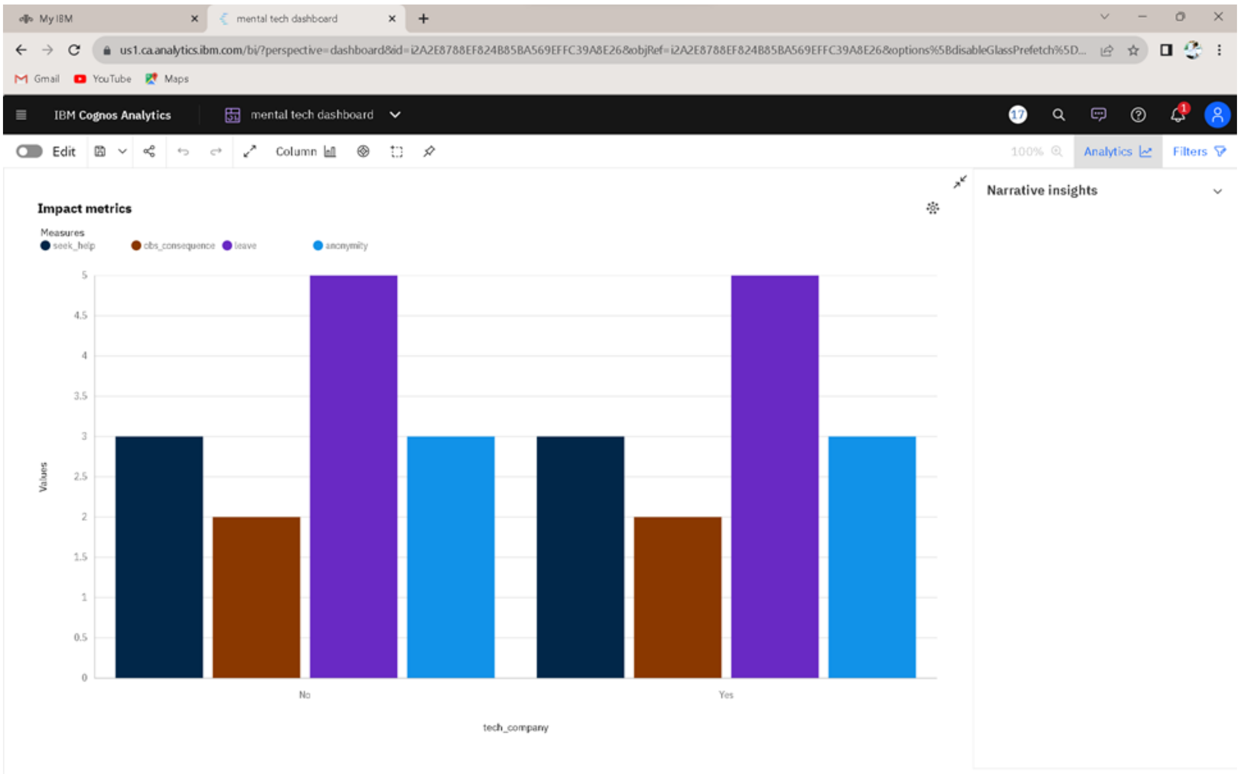


CAMPAIGN REACH



AWARENESS LEVEL





Conclusion:

It has focused on the assessment of a public health awareness campaign's effectiveness and impact. We have employed IBM Cognos for data visualization and integrated code, possibly in Python, for advanced data analysis. Through the creation of interactive dashboards and reports, we have effectively visualized campaign reach, awareness levels, and impact metrics, providing actionable insights for campaign organizers, healthcare professionals, and policymakers. Additionally, our use of code for in-depth analysis, including calculating engagement rates, conducting demographic analysis, and running statistical tests, has yielded comprehensive findings. This combined approach equips us to contribute to healthier communities by supporting informed decision-making and promoting public health initiatives.