AN ANALYSIS OF

Mental Health in the Tech Industry

A 2014 dataset dive by Team 1 - Taylor Bauer

```
data = pd.read_csv("mental-health.csv")
data.columns
```

```
Index(['Timestamp', 'Age', 'Gender', 'Country', 'state', 'self_employed',
       'family_history', 'treatment', 'work_interfere', 'no_employees',
       'remote_work', 'tech_company', 'benefits', 'care_options',
       'wellness_program', 'seek_help', 'anonymity', 'leave',
       'mental_health_consequence', 'phys_health_consequence', 'coworkers',
       'supervisor', 'mental_health_interview', 'phys_health_interview',
       'mental_vs_physical', 'obs_consequence', 'comments'],
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfere	no_employees	...	leave	mental_health_consequence
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes	Often	6-25	...	Somewhat easy	No
1	2014-08-27 11:29:37	44	M	United States	IN	NaN	No	No	Rarely	More than 1000	...	Don't know	Maybe
2	2014-08-27 11:29:44	32	Male	Canada	NaN	NaN	No	No	Rarely	6-25	...	Somewhat difficult	No
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	NaN	Yes	Yes	Often	26-100	...	Somewhat difficult	Yes
4	2014-08-27 11:30:22	31	Male	United States	TX	NaN	No	No	Never	100-500	...	Don't know	No
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1254	2015-09-12 11:17:21	26	male	United Kingdom	NaN	No	No	Yes	NaN	26-100	...	Somewhat easy	No
1255	2015-09-26 01:07:35	32	Male	United States	IL	No	Yes	Yes	Often	26-100	...	Somewhat difficult	No
1256	2015-11-07 12:36:58	34	male	United States	CA	No	Yes	Yes	Sometimes	More than 1000	...	Somewhat difficult	Yes
1257	2015-11-30 21:25:06	46	f	United States	NC	No	No	No	NaN	100-500	...	Don't know	Yes
1258	2016-02-01 23:04:31	25	Male	United States	IL	No	Yes	Yes	Sometimes	26-100	...	Don't know	Maybe

1259 rows × 27 columns

phys_health_consequence	coworkers	supervisor	mental_health_interview	phys_health_interview	mental_vs_physical	obs_consequence	comments
No	Some of them	Yes	No	Maybe	Yes	No	NaN
No	No	No	No	No	Don't know	No	NaN
No	Yes	Yes	Yes	Yes	No	No	NaN
Yes	Some of them	No	Maybe	Maybe	No	Yes	NaN
No	Some of them	Yes	Yes	Yes	Don't know	No	NaN
...	...	...	...	...	...	...	...
No	Some of them	Some of them	No	No	Don't know	No	NaN
No	Some of them	Yes	No	No	Yes	No	NaN
Yes	No	No	No	No	No	No	NaN
No	No	No	No	No	No	No	NaN
No	Some of them	No	No	No	Don't know	No	NaN

The Data: Mental Health in Tech Survey - 2014

- **Origin:**
  - Kaggle
- **Demographic Information:**
  - Age, Gender, State, Country, Employment Status
- **Mental Health Information:**
  - Treatment sought for mental health, family history, work interference
- **Workplace Details:**
  - Tech company affiliation, benefits provided by employer, awareness of mental health care options, and more.
- **Attitudes and Perceptions:**
  - Willingness to discuss mental health with coworkers, supervisors, job interviews, and comparison to attitudes about physical health
- **Several other data features**

Data Queries

WHAT VARIABLES CONTRIBUTE TO SOUGHT MENTAL HEALTH TREATMENT?

State-Wise

Question: Are there specific states where technology employees more likely to seek mental health treatment?

Impact of Remote Work

Question: Does remote work influence tech employees seeking mental health treatment?

Awareness and Comfortability

Question: Are there differences in sought mental health treatment based on awareness of resources and comfort level of discussing mental health issues with coworkers or supervisors?

Gender

Question: Does gender have an impact on seeking mental health treatment?

Benefits!

- Inclusive, assistive, and increased workplace for employees.
- Improving remote work conditions and practices.
- Supporting employee well-being to improve productivity.
- Identifying regional disparities.
- **Mental Health Awareness in the workplace.**

Data Preparation

CLEANING & ORGANIZING

Several of columns were dropped due to the analysis focusing on the following variables:

- treatment (target)
- age
- gender
- country (US)
- state
- remote_work
- seek_help
- coworkers
- supervisors
- tech_company (Yes)

```
# dropping all null values
survey = survey.dropna().reset_index(drop=True)
```

```
survey.head()
```

	Age	Gender	Country	state	self_employed	treatment	remote_work	tech_company	seek_help	coworkers	supervisor
0	46	male	United States	MD	Yes	No	Yes	Yes	Don't know	Yes	Yes
1	29	Male	United States	NY	No	Yes	No	Yes	No	Some of them	Some of them
2	31	male	United States	NC	Yes	No	Yes	Yes	No	Some of them	Some of them
3	46	Male	United States	MA	No	Yes	Yes	Yes	No	Some of them	Yes
4	41	Male	United States	IA	No	Yes	No	No	Don't know	No	No

Data Preparation

CLEANING & ORGANIZING

```
# dropping all null values
survey = survey.dropna().reset_index(drop=True)
survey.head()
```

Dropped all entries with null values - to increase the quality of analysis

```
# only usa entries
df1 = survey[survey["Country"] == "United States"]
df1 = df1.reset_index(drop=True)
```

Focused in on analysis solely for entries in the United States of America

```
# only those who are employed by company
df2  = df1[df1["self_employed"] == "No"]
df2 = df2.reset_index(drop=True)
```

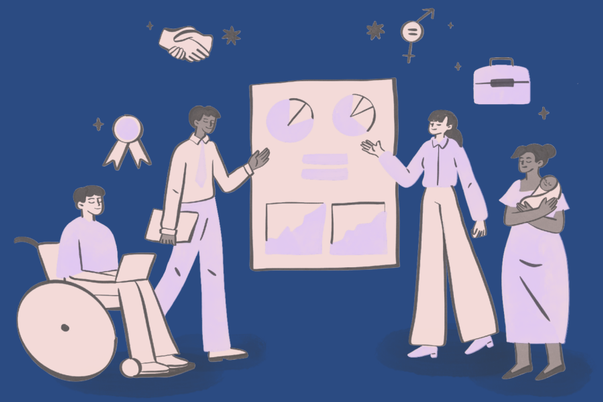
Concentration of company empoyees - some picked features relate to company environment

```
# work in a primarily tech company
df3 = df2[df2["tech_company"] == "Yes"]
df3 = df3.reset_index(drop=True)
```

Wanted analysis to deal with companies who were primarily regarded as a “Tech Company”

Data Preparation

CLEANING & ORGANIZING



```
# checking gender values
gender = df3["Gender"]
gender.unique()
```

```
array(['Male', 'male', 'Female', 'female', 'M', 'Male-ish', 'maile',
       'Trans-female', 'F', 'Cis Male', 'm', 'Male (CIS)', 'f',
       'queer/she/they', 'non-binary', 'Femake', 'Make', 'Genderqueer',
       'Female ', 'Male ', 'Man', 'msle', 'Female (trans)',
       'Female (cis)', 'Mail', 'cis male', 'Woman'], dtype=object)
```

- Due to the gender survey question being free response, there were numerous different gender entries
- Ultimately, I wanted to change the values to make it easier for future use
- I struggled with choosing the values to categorize, because I wanted to respect participants gender identities

```
# replacing female identifying entries with "Female"
f_replace = ["Female", "female", "Trans-female", "F", "f", "Femake", "Female ",
             "Female (trans)", "Female (cis)", "Woman"]
df3["Gender"] = df3["Gender"].replace(f_replace, "Female")

# replacing male identifying entries with "Male"
m_replace = ["Male", "male", "M", "maile", "Cis Male", "m", "Male (CIS)",
             "Make", "Male ", "Man", "msle", "Mail", "cis male"]
df3["Gender"] = df3["Gender"].replace(m_replace, "Male")

# replacing non-conforming identifying entries with "Non-comforming"
nc_replace = ["Male-ish", "queer/she/they", "non-binary", "Genderqueer"]
df3["Gender"] = df3["Gender"].replace(nc_replace, "Non-Comforming")
```

- Decided these could possibly best fit into three categories, which would help with my future data exploration
- “Female” maps to those who identified as cis-female or trans-woman
- “Male” maps to entries who identify with male, as there were no trans-men entries
- “Non-Conforming” maps to those who were uncertain or non-conforming to gender roles

Data Preparation

CLEANING & ORGANIZING

```
# checking age col
df3["Age"].unique()
```

```
array([ 29,  46,  33,  35,  34,  42,  40,  27,  50,  30,  38,  22,  32,
        24,  36,  23,  25,  31,  44,  28,  45,  18,  39,  26,  43,  37,
        41,  60,  54, 329,  21,  55,  57,  58,  48,  47,  62,  56,  49,
         5,  20,  51,  53,  19], dtype=int64)
```

- In addition to gender, age was also a free response survey question
- This can lead to typos and incorrect values in the data set
- Wanted to ensure all ages were realistic so any descriptive statistics on age were not skewed

```
# dropping entry
survey_clean = df3[(df3["Age"] != 329) & (df3["Age"] != 5)].reset_index(drop=True)
```

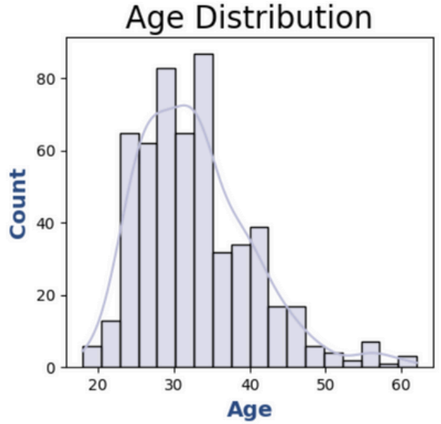
- Found two outliers for the context - entries were dropped

	Age	Gender	Country	state	self_employed	treatment	remote_work	tech_company	seek_help	coworkers	supervisor
0	29	Male	United States	NY	No	Yes	No	Yes	No	Some of them	Some of them
1	46	Male	United States	MA	No	Yes	Yes	Yes	No	Some of them	Yes
2	33	Male	United States	CA	No	Yes	No	Yes	Yes	Yes	Yes
3	33	Male	United States	TN	No	No	No	Yes	Don't know	Some of them	No
4	35	Female	United States	CA	No	Yes	Yes	Yes	Don't know	Yes	Yes

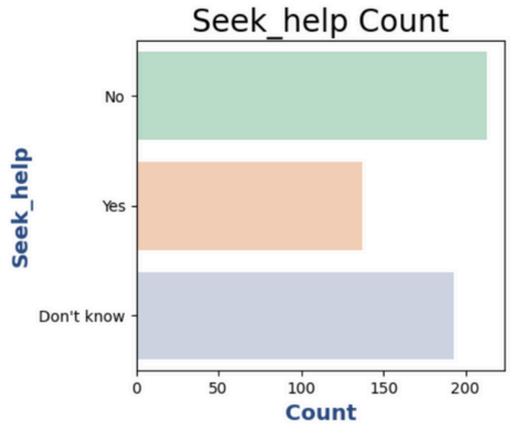
Hypothesis

- Remote work will have a fairly substantial impact on whether treatment is sought
- Women will have sought more treatment
- There will be less elder people and more young people
- More supportive and comfortable atmospheres will have less sought treatment

Descriptive Stats - Variable Distributions

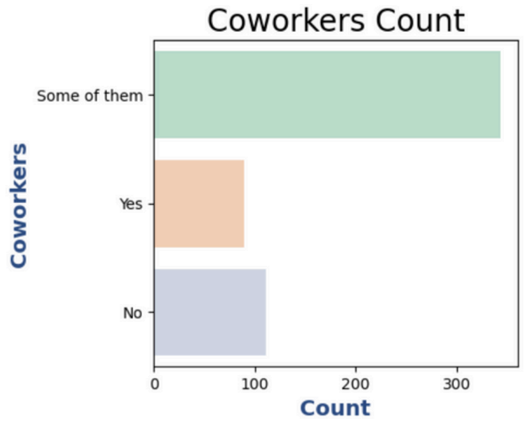


count: 543
mean: 32.8
std: 7.53
min: 18
max: 62



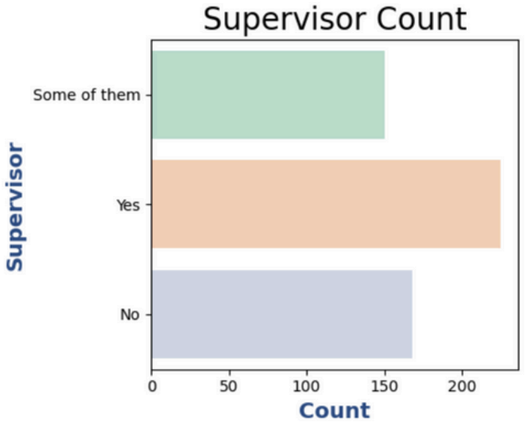
Frequency Count
Yes: 137
No: 213
Don't know: 193

Percentage:
Yes: 25.2
No: 39.2
Don't know: 35.5



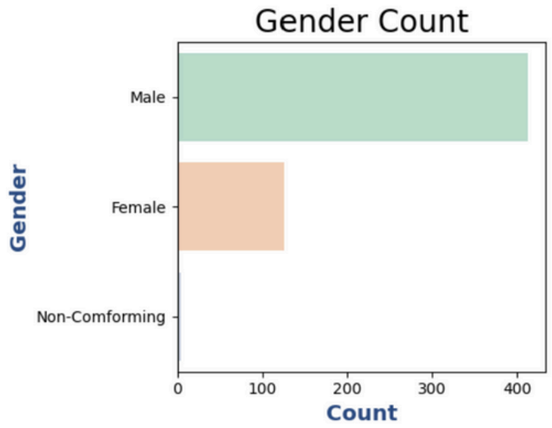
Frequency Count
Yes: 89
No: 111
Some of them: 343

Percentage:
Yes: 16.4
No: 20.4
Some of them: 63.2



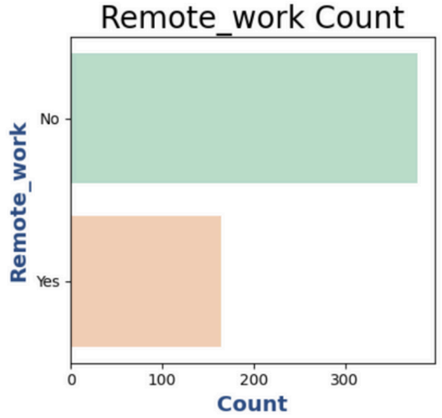
Frequency Count
Yes: 225
No: 168
Some of them: 150

Percentage:
Yes: 41.4
No: 30.9
Some of them: 27.6



Frequency Count
Male: 413
Female: 126
Non-Conforming: 4

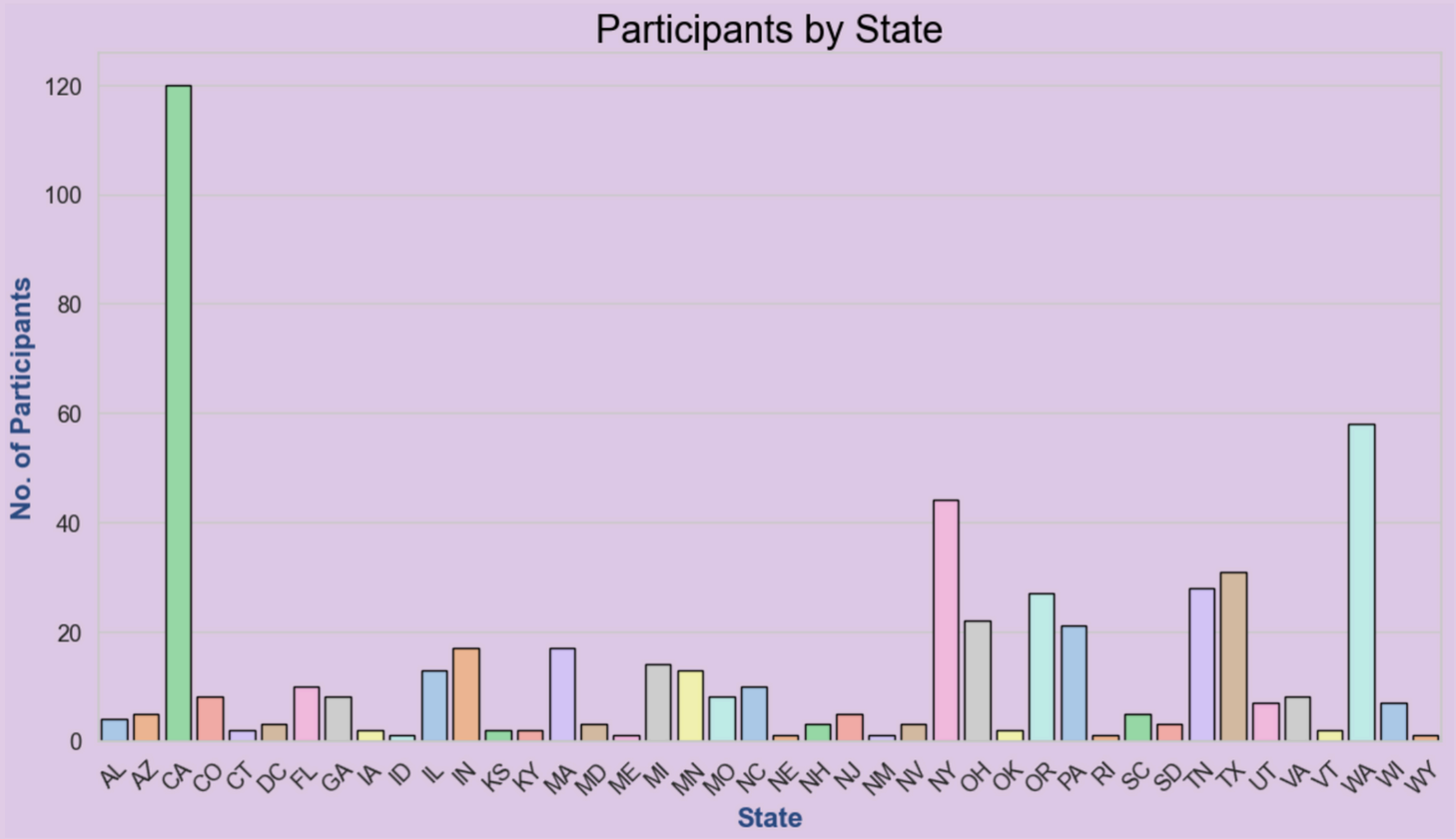
Percentage:
Male: 76.1
Female: 23.2
Non-Conforming: 0.7



Frequency Count
Yes: 164
No: 379

Percentage:
Yes: 30.2
No: 69.8

Descriptive Stats - Variable Distributions

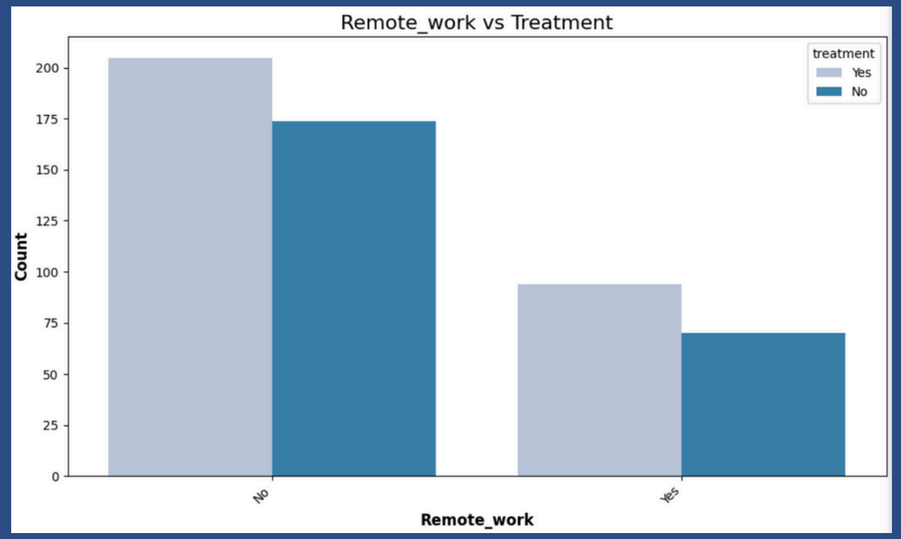


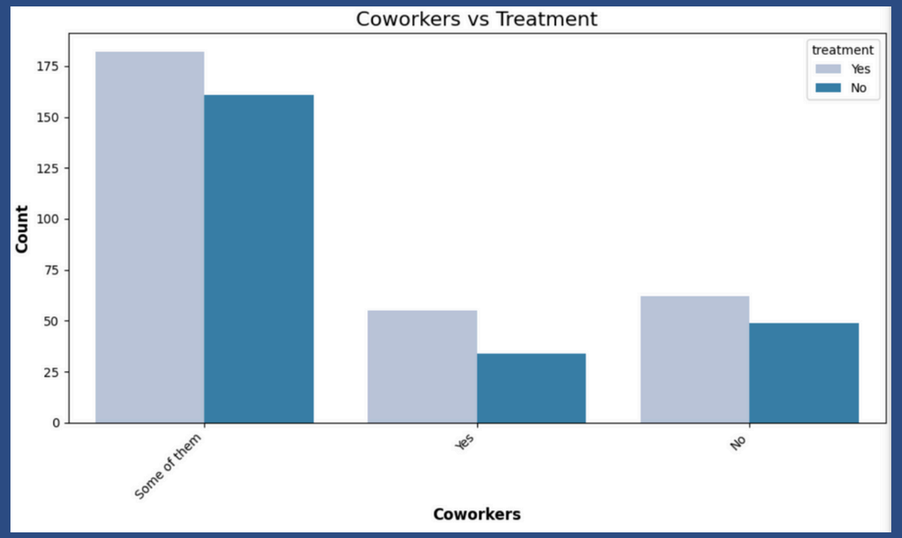
Frequency Counts for States

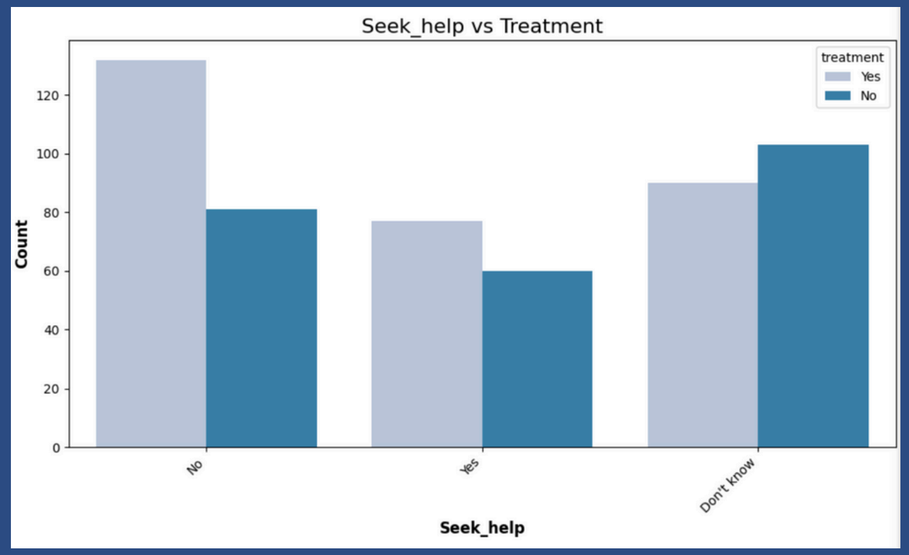
AL	4
AZ	5
CA	120
CO	8
CT	2
DC	3
FL	10
GA	8
IA	2
ID	1
IL	13
IN	17
KS	2
KY	2
MA	17
MD	3
ME	1
MI	14
MN	13
MO	8

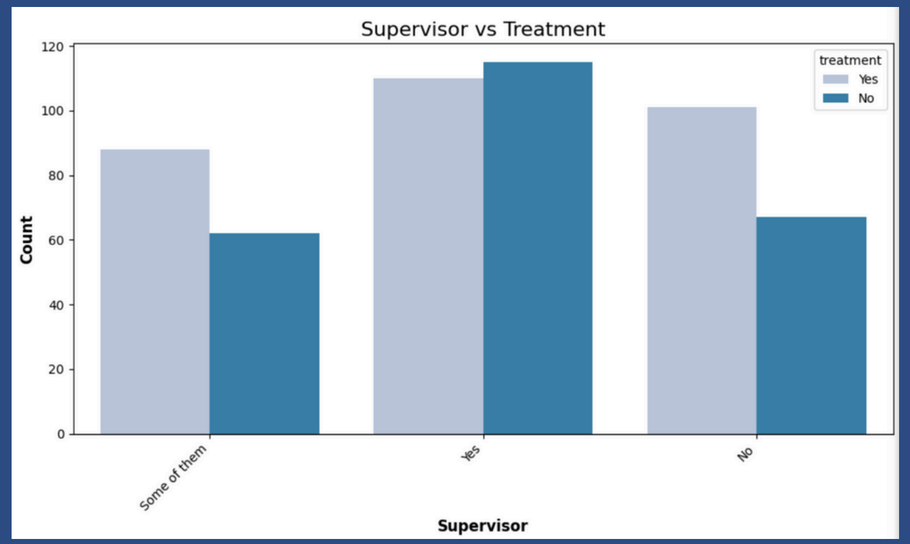
NC	10
NE	1
NH	3
NJ	5
NM	1
NV	3
NY	44
OH	22
OK	2
OR	27
PA	21
RI	1
SC	5
SD	3
TN	28
TX	31
UT	7
VA	8
VT	2
WA	58
WI	7
WY	1

Variable Interactions









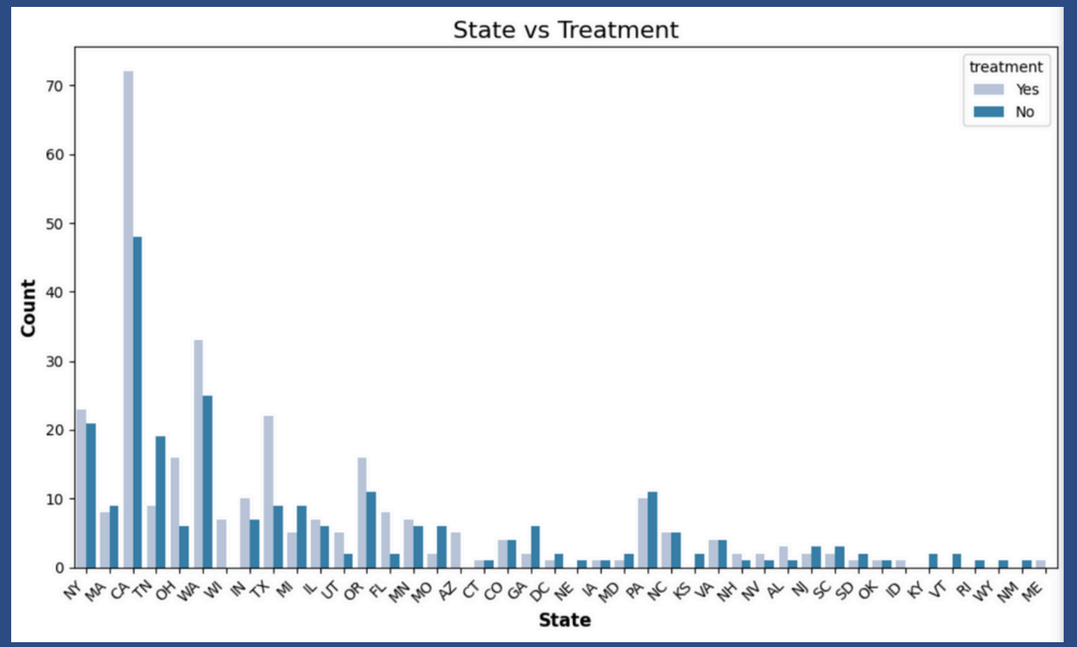
Variable Interactions

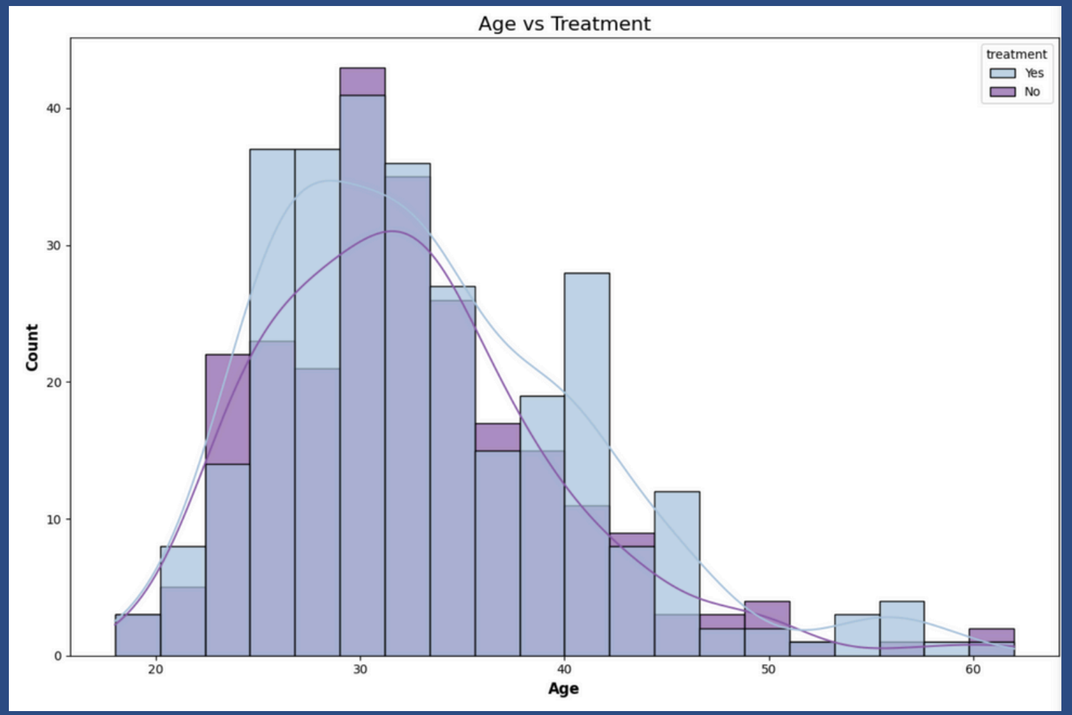
California:

- Seems to have the highest number of sought treatment.
  - However, also has the largest number of tech workers

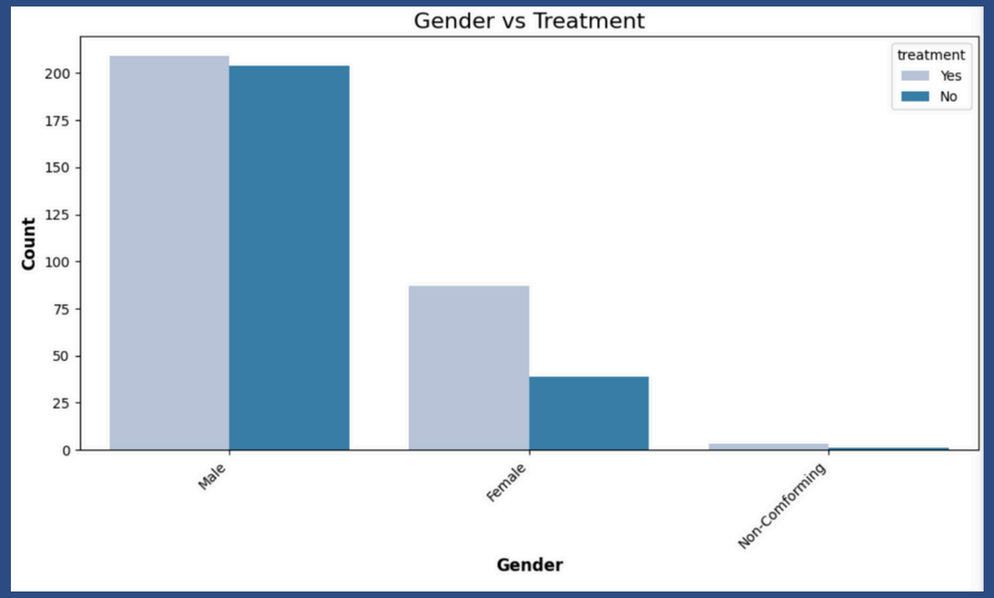
Mean age for treatment:

- **Yes** (sought treatment):
  - 33.19
- **No** (did not seek treatment)
  - 32.25
- Not a large difference in age
  - Similar to mean age of entire dataset
  - Could be due to numerous tech workers are typically this age in industry



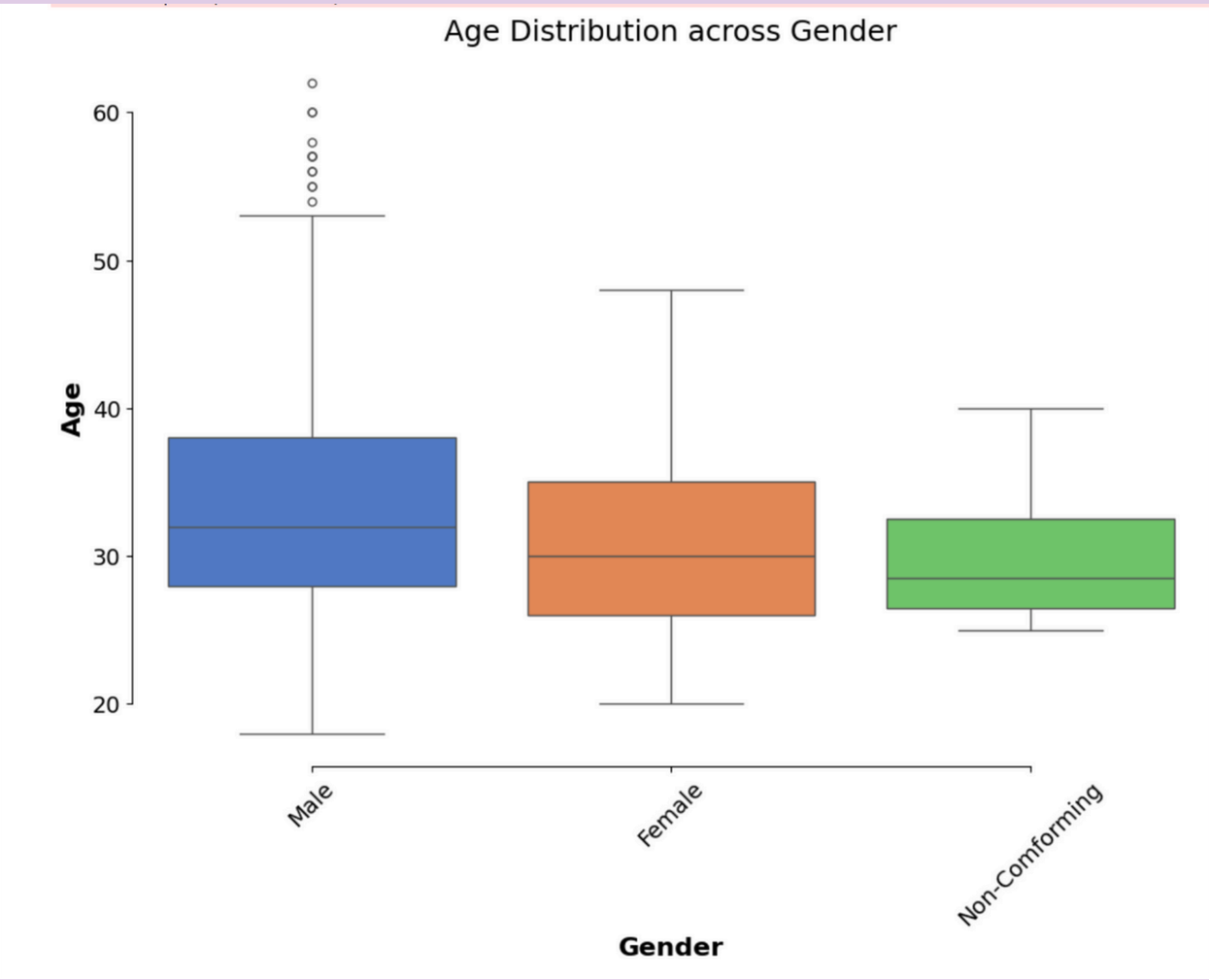


Gender	Yes	No
Female	69.0%	20.0%
Male	50.6%	44.0%
Non-Conforming	75.0%	1.3%



Variable Interactions

- Percentages are low due to low representation of other genders
- Women have seem to have sought treatment more
- Men seem to border on not seeking vs seeking
- Difficult to draw conclusions on non-conforming genders with such low entries



Data Anomalies

- High outliers in age category - mainly men
  - Older men typically work more than older women
  - Older prominent men figures in industry
- Majority of variables are categorical Chi-Squared Test
- P-Values for chosen variables vs. Treatment:
  - Age: 0.7508
  - Gender: 0.4275
  - State: 0.5354
  - Remote Work: 0.2010
  - Coworkers: 0.8696
  - Supervisor: 0.9360
  - Seek Help: 0.0676

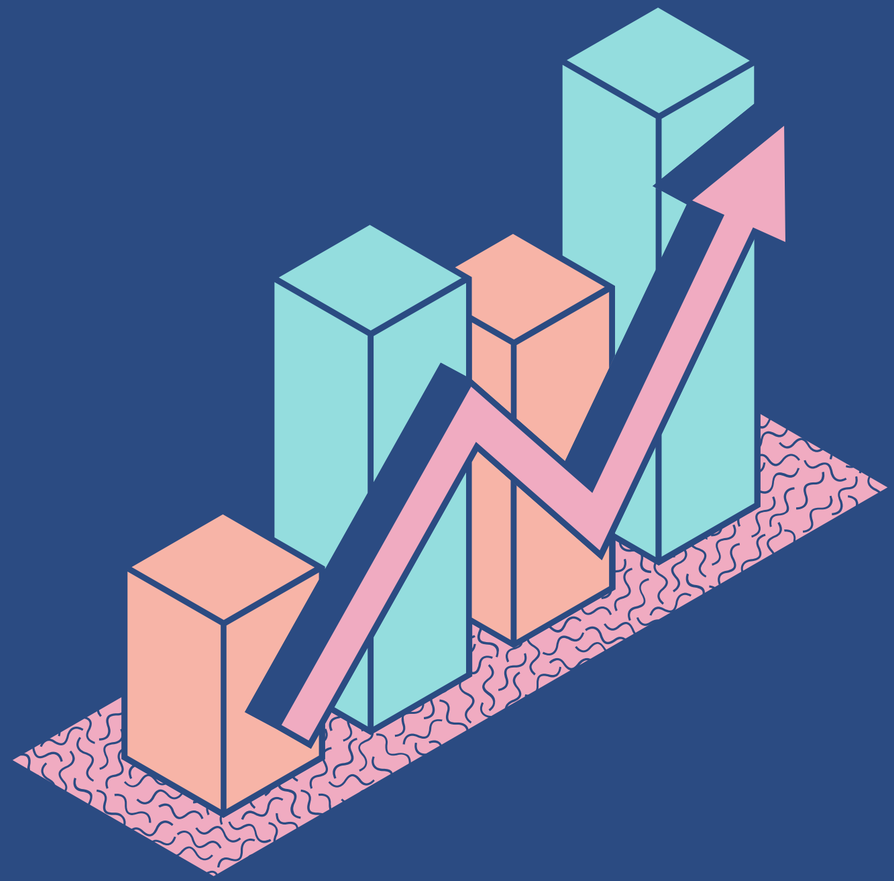
Cramer’s V

Cramer's V for Treatment versus:

- Age: 0.2681
- Gender: 0.1601
- State: 0.3134
- Remote Work: 0.0258
- Seek Help: 0.1338
- Coworkers: 0.0639
- Supervisor: 0.1050

What this tells us:

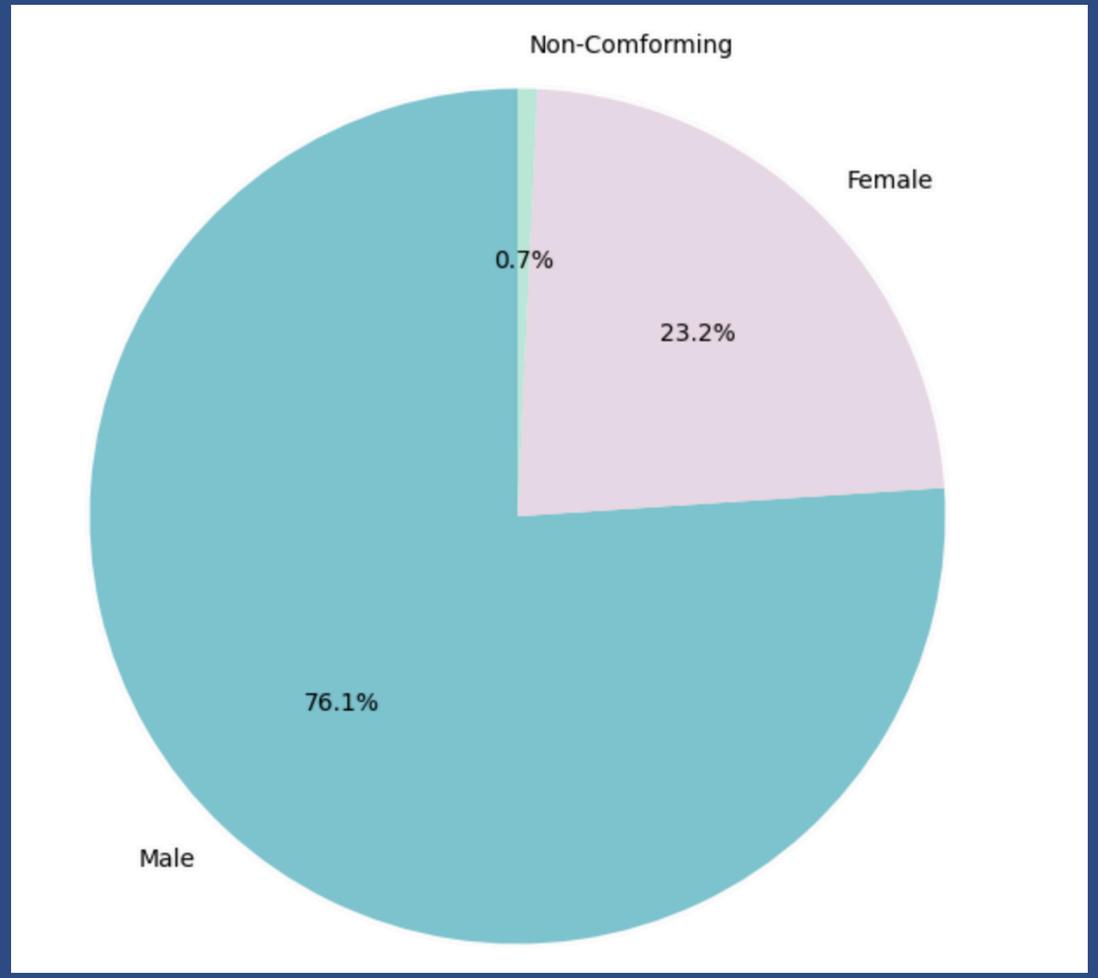
- Strength and relevance of association between variables
- Closer to zero - weaker association
- None of the variables are statistically significant



Data Anomalies

GENDER

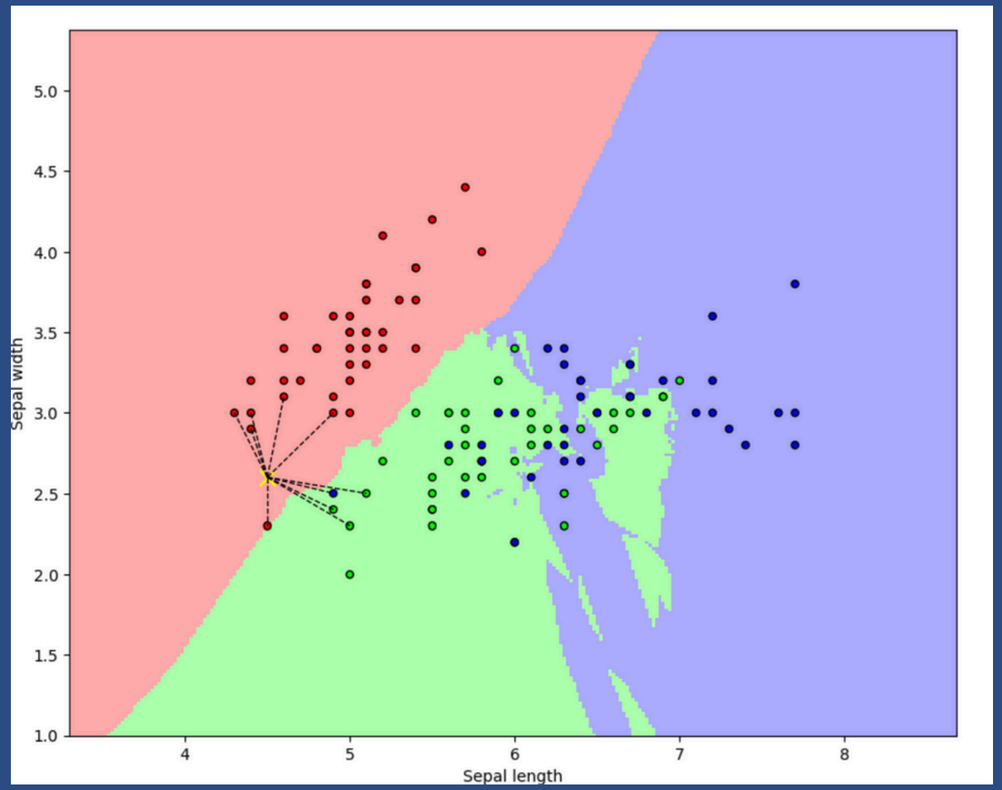
- **Less significance than expected - P: 0.4275**
  - Could be due to oversaturation of men in dataset
  - There were four non-conforming entries, cannot accurately represent with low numbers
- **Potential fixes:**
  - Introduce more women and non-conforming genders into dataset to assist with imbalance



Modelling the Data One Hot & Transforming

```
# cols needed
feats = ["Gender", "state", "remote_work", "seek_help", "coworkers", "supervisor"]

# mapping
y = survey_clean["treatment"].map({"Yes": 1, "No": 0})

# one hot encoding
one_hot = OneHotEncoder()

# fit & transform
encoded = one_hot.fit_transform(survey_clean[feats]).toarray()

# encoded into df
en_survey = pd.DataFrame(encoded, columns=one_hot.get_feature_names_out(feats))

# reset index
survey_clean.reset_index(drop=True, inplace=True)
df.reset_index(drop=True, inplace=True)

# need to add age since it is already numeric
X = pd.concat([survey_clean[["Age"]], en_survey], axis=1)
```

```
# knn classifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
```



Example of KNN from arise.com

K-Nearest Neighbors

Why not other model?

- KNN is easier to understand - could not find very good resources in regards to survey data and machine learning
- Used for classification and a categorical target variable (which I have)
- KNN does not make assumptions about linearity

Performance

Model Accuracy: 0.55

Explanation:

- Correctly predicts 55.05% of time
- Not effective for predictions

Confusion Matrix

True negatives: 21	False positive: 23
False negatives: 26	True positive: 39

```
Classification Report:
              precision    recall  f1-score   support

          No       0.45      0.48      0.46        44
         Yes       0.63      0.60      0.61        65

    accuracy                           0.55       109
   macro avg       0.54      0.54      0.54       109
weighted avg       0.56      0.55      0.55       109
```

- Tends to predict yes more than no
- Fixes:
  - Review features used (feature engineering)
  - Changing number of n-neighbors
  - Fine tuning other parameters
- Performance is *moderate* - could try different models

Thank you!