Mental Health in Tech – EDA Submission

This notebook explores the 2014 OSMI Mental Health in Tech survey. It follows the assignment sections: data understanding, preprocessing, univariate and bivariate analysis, attitudes, geographic and remote insights, predictive signals, and a concise summary with recommendations.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from collections import Counter

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, roc_auc_score

import os

pd.set_option('display.max_columns', None)
df = pd.read_csv(r"/Users/shivalimuthukumar/Desktop/Mental_Health_A
print("Loaded shape:", df.shape)
df.head(10)
```

```
/Users/shivalimuthukumar/anaconda3/lib/python3.11/site-packages/pa
ndas/core/arrays/masked.py:61: UserWarning: Pandas requires versio
n '1.3.6' or newer of 'bottleneck' (version '1.3.5' currently inst
alled).
  from pandas.core import (

Loaded shape: (1259, 27)
```

Out[1]:

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	wor
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	2014-08-27 11:31:22	33	Male	United States	TN	NaN	Yes	No
6	2014-08-27 11:31:50	35	Female	United States	MI	NaN	Yes	Yes
7	2014-08-27 11:32:05	39	M	Canada	NaN	NaN	No	No
8	2014-08-27 11:32:39	42	Female	United States	IL	NaN	Yes	Yes
9	2014-08-27 11:32:43	23	Male	Canada	NaN	NaN	No	No

Section A: Data Understanding and Preprocessing

Task 1: Load and Inspect the Data

In [2]:

```
print("\nBasic info:")
print(df.info())

print("\nMissing values per column:")
print(df.isna().sum().sort_values(ascending=False))

print("\nFirst 10 rows:")
df.head(10)
```

```
Basic info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Timestamp                  1259 non-null   object
 1   Age                        1259 non-null   int64 
 2   Gender                     1259 non-null   object
 3   Country                    1259 non-null   object
 4   state                      744 non-null    object
 5   self_employed              1241 non-null   object
 6   family_history             1259 non-null   object
 7   treatment                  1259 non-null   object
 8   work_interfere             995 non-null    object
 9   no_employees               1259 non-null   object
 10  remote_work                1259 non-null   object
 11  tech_company               1259 non-null   object
 12  benefits                   1259 non-null   object
 13  care_options               1259 non-null   object
 14  wellness_program           1259 non-null   object
```

```
 15  seek_help                  1259 non-null   object
 16  anonymity                  1259 non-null   object
 17  leave                      1259 non-null   object
 18  mental_health_consequence  1259 non-null   object
 19  phys_health_consequence    1259 non-null   object
 20  coworkers                  1259 non-null   object
 21  supervisor                 1259 non-null   object
 22  mental_health_interview    1259 non-null   object
 23  phys_health_interview      1259 non-null   object
 24  mental_vs_physical         1259 non-null   object
 25  obs_consequence            1259 non-null   object
 26  comments                   164 non-null    object
dtypes: int64(1), object(26)
memory usage: 265.7+ KB
None

Missing values per column:
comments                     1095
state                         515
work_interfere                264
self_employed                  18
seek_help                       0
obs_consequence                 0
mental_vs_physical              0
phys_health_interview           0
mental_health_interview         0
supervisor                      0
coworkers                       0
phys_health_consequence         0
mental_health_consequence       0
leave                           0
anonymity                       0
Timestamp                       0
wellness_program                0
Age                             0
benefits                        0
tech_company                    0
remote_work                     0
no_employees                    0
treatment                       0
family_history                  0
Country                         0
Gender                          0
care_options                    0
dtype: int64

First 10 rows:
```

Out[2]:

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	wor
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes	
	2014-08-27			United					

1	11:29:37	44	M	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	2014-08-27 11:31:22	33	Male	United States	TN	NaN	Yes	No
6	2014-08-27 11:31:50	35	Female	United States	MI	NaN	Yes	Yes
7	2014-08-27 11:32:05	39	M	Canada	NaN	NaN	No	No
8	2014-08-27 11:32:39	42	Female	United States	IL	NaN	Yes	Yes
9	2014-08-27 11:32:43	23	Male	Canada	NaN	NaN	No	No

Task 2: Data Cleaning

Rules applied:

- Keep respondents with 18 <= Age <= 100.
- Standardize Gender into Male, Female, or Other using keyword mapping.
- Fill key categorical NaNs with 'Not answered' to retain rows for plots.
- Drop columns primarily free-text or identifiers not needed for EDA (Timestamp and comments).

In [5]:

```
def clean_gender(g):
    if pd.isna(g):
        return "Not answered"
    s = str(g).strip().lower()
    # Common male indicators
    male_kw = ["m", "male", "man", "cis male", "cis-male", "male (c
    # Common female indicators
    female_kw = ["f", "female", "woman", "cis female", "cis-female"
    # Heuristics
    if any(k in s for k in female_kw):
        return "Female"
    if any(k in s for k in male_kw):
        return "Male"
    # Keywords within longer phrases
    if "trans" in s and "female" in s:
        return "Female"
    if "trans" in s and "male" in s:
        return "Male"
    if "female" in s:
        return "Female"
    if "male" in s:
        return "Male"
    # Otherwise bucket as Other for clarity
    return "Other"
```

In [7]:

```
df_orig = df.copy()

# Drop irrelevant columns if present
for col in ["Timestamp", "comments"]:
    if col in df.columns:
        df.drop(columns=[col], inplace=True)

# Age filtering
if "Age" in df.columns:
    df = df[(df["Age"] >= 18) & (df["Age"] <= 100)]

# Gender standardization
if "Gender" in df.columns:
    df["Gender"] = df["Gender"].apply(clean_gender)

# For plotting, replace missing in selected categoricals
fill_cols = [
    "self_employed","family_history","treatment","work_interfere","
    "remote_work","tech_company","benefits","care_options","wellnes
    "seek_help","anonymity","leave","mental_health_consequence","ph
    "coworkers","supervisor","mental_health_interview","phys_health
    "mental_vs_physical","obs_consequence","Country","state"
]
for c in fill_cols:
```

```
    if c in df.columns:
        df[c] = df[c].fillna("Not answered")

print("Shape after cleaning:", df.shape)

# Save cleaned CSV
df.to_csv(r"/Users/shivalimuthukumar/Desktop/Mental_Health_Assignme
print("Saved cleaned dataset to:", r"/Users/shivalimuthukumar/Deskt
df.head(5)
```

```
Shape after cleaning: (1251, 25)
Saved cleaned dataset to: /Users/shivalimuthukumar/Desktop/Mental_
Health_Assignment/survey_clean.csv
```

Out[7]:

	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfer
0	37	Female	United States	IL	Not answered	No	Yes	Ofte
1	44	Male	United States	IN	Not answered	No	No	Rare
2	32	Male	Canada	Not answered	Not answered	No	No	Rare
3	31	Male	United Kingdom	Not answered	Not answered	Yes	Yes	Ofte
4	31	Male	United States	TX	Not answered	No	No	Neve

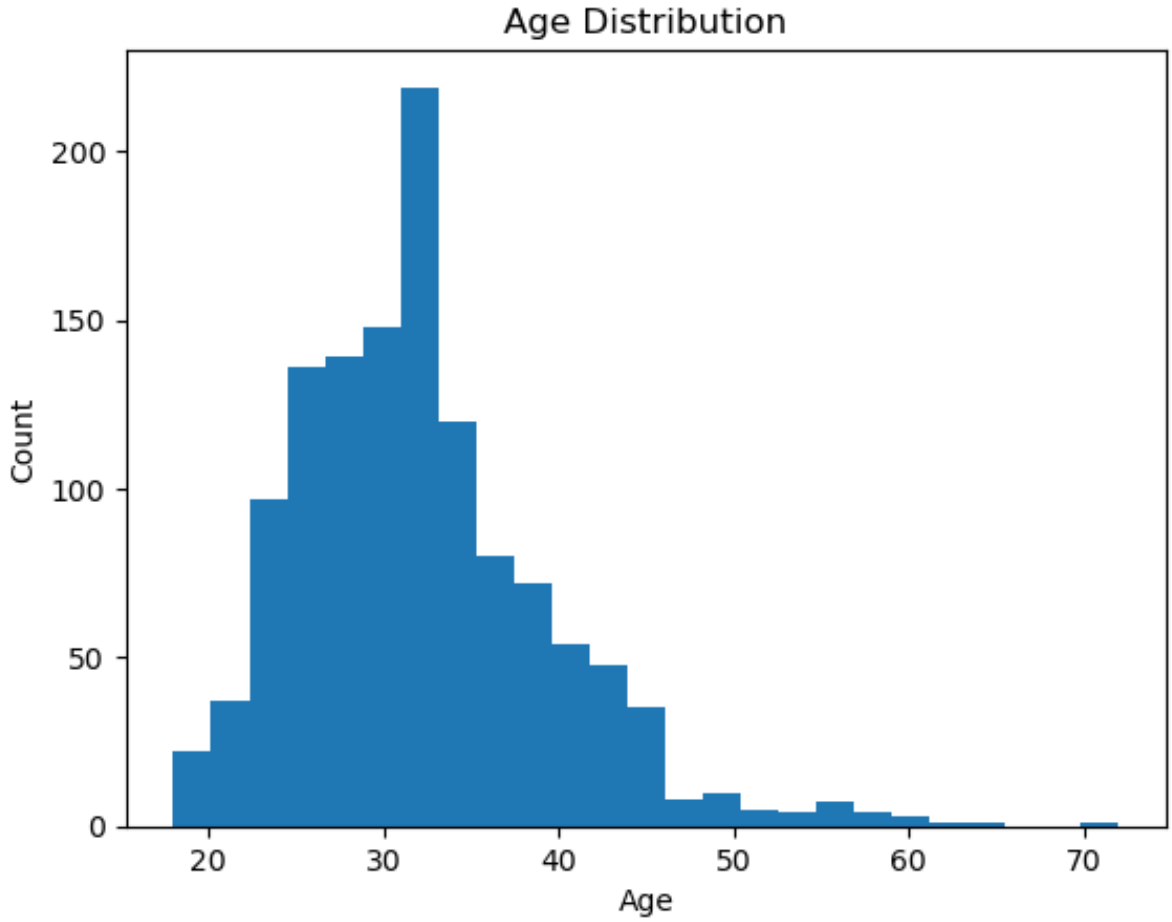
Section B: Univariate Analysis

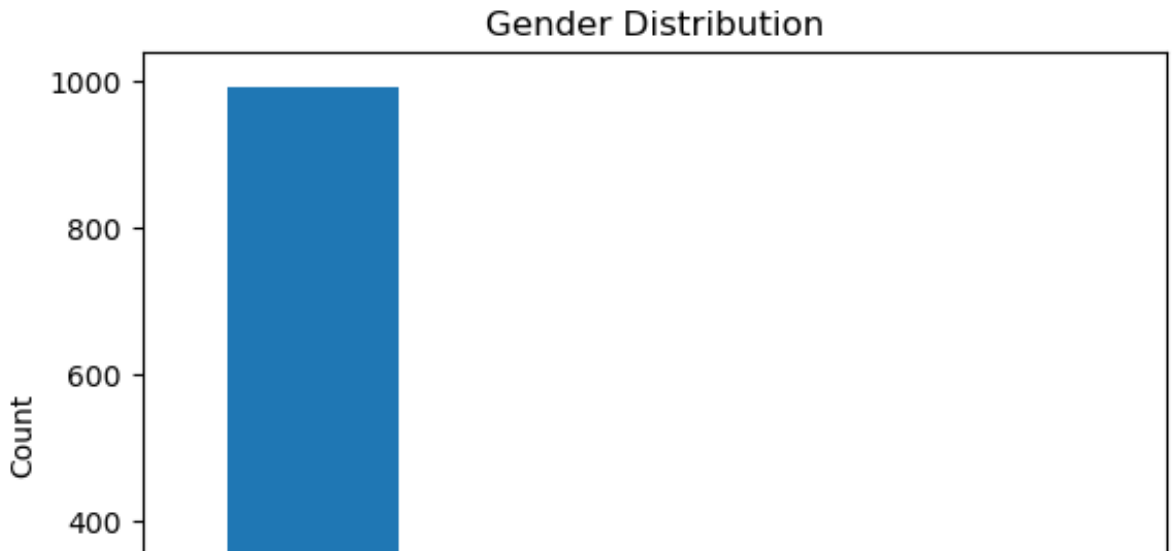
Task 3: Demographic Overview

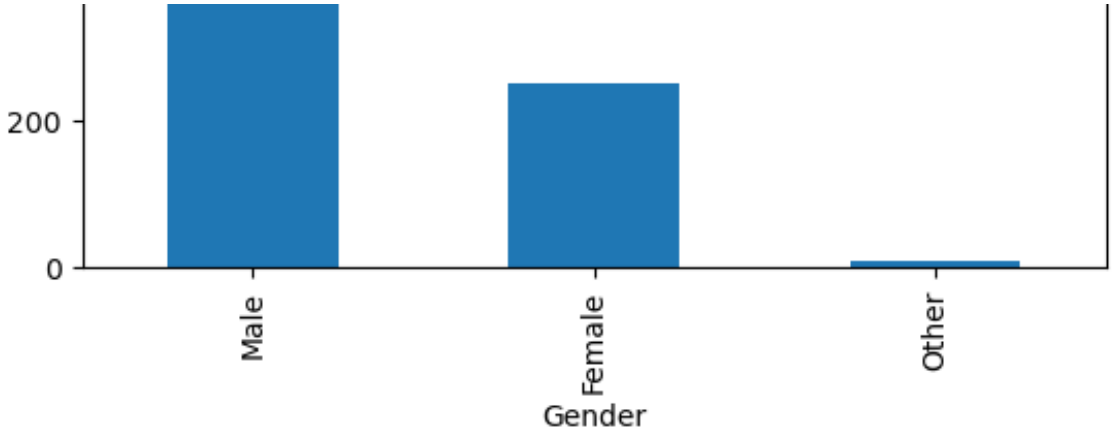
In [8]:

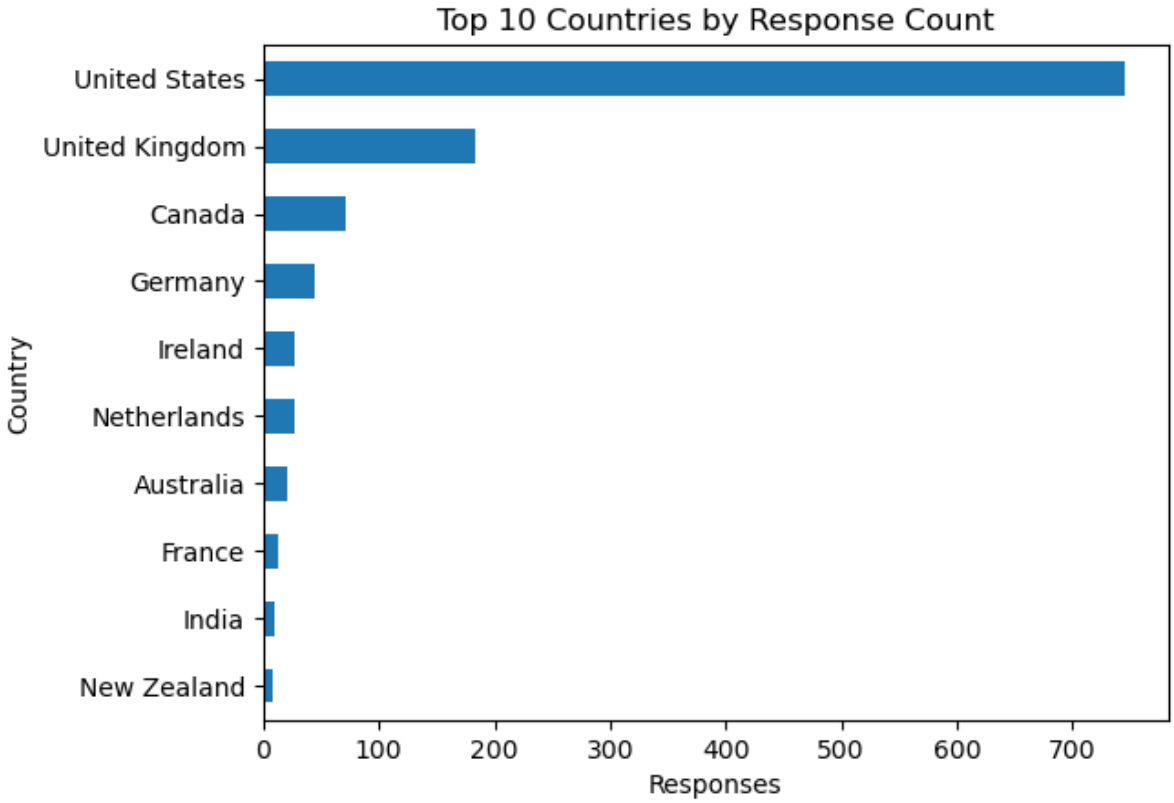
```
# Age distribution
if "Age" in df.columns:
    plt.figure()
    df["Age"].dropna().plot(kind="hist", bins=25)
    plt.title("Age Distribution")
    plt.xlabel("Age")
    plt.ylabel("Count")
    plt.show()

# Gender distribution
if "Gender" in df.columns:
    plt.figure()
    df["Gender"].value_counts().plot(kind="bar")
    plt.title("Gender Distribution")
    plt.xlabel("Gender")
    plt.ylabel("Count")
```

```
    plt.show()

# Country-wise response count (Top 10)
if "Country" in df.columns:
    plt.figure()
    df["Country"].value_counts().head(10).sort_values().plot(kind="
    plt.title("Top 10 Countries by Response Count")
    plt.xlabel("Responses")
    plt.ylabel("Country")
    plt.show()
```





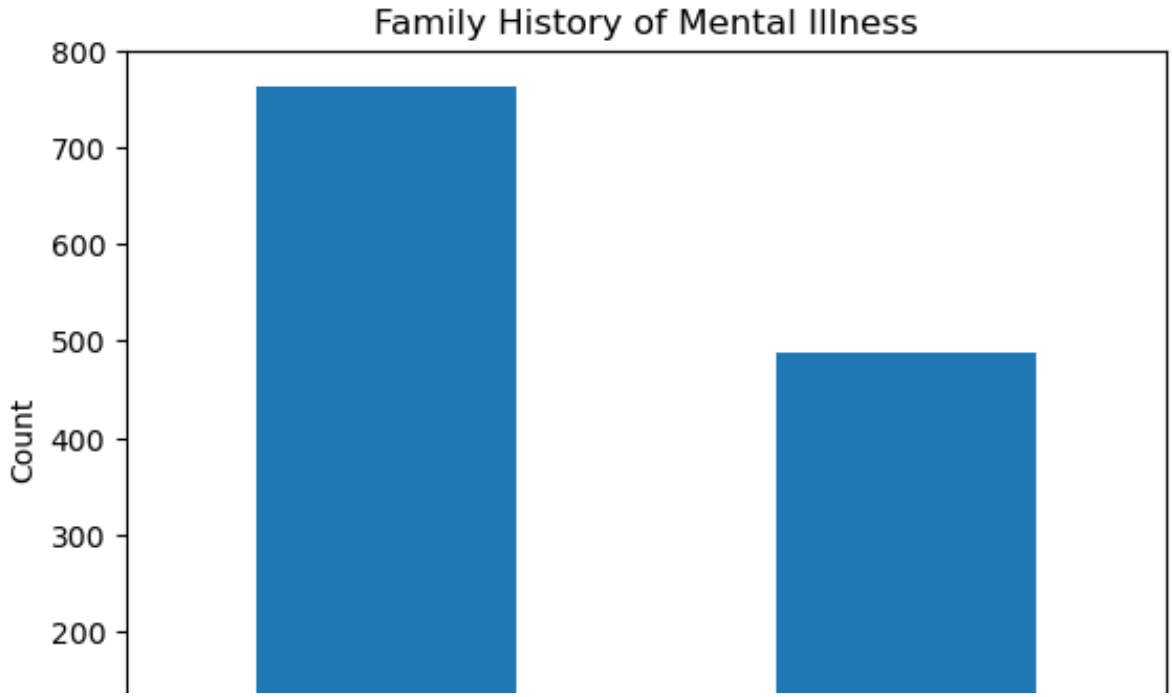




Task 4: Mental Health Context

In [9]:

```
def bar_count(col, title):
    if col in df.columns:
        plt.figure()
        df[col].value_counts().plot(kind="bar")
        plt.title(title)
        plt.xlabel(col)
        plt.ylabel("Count")
        plt.show()
        print(df[col].value_counts())

bar_count("family_history", "Family History of Mental Illness")
bar_count("treatment", "Sought Treatment")
bar_count("work_interfere", "Work Interference Due to Mental Health
bar_count("self_employed", "Self-employment Status")
```

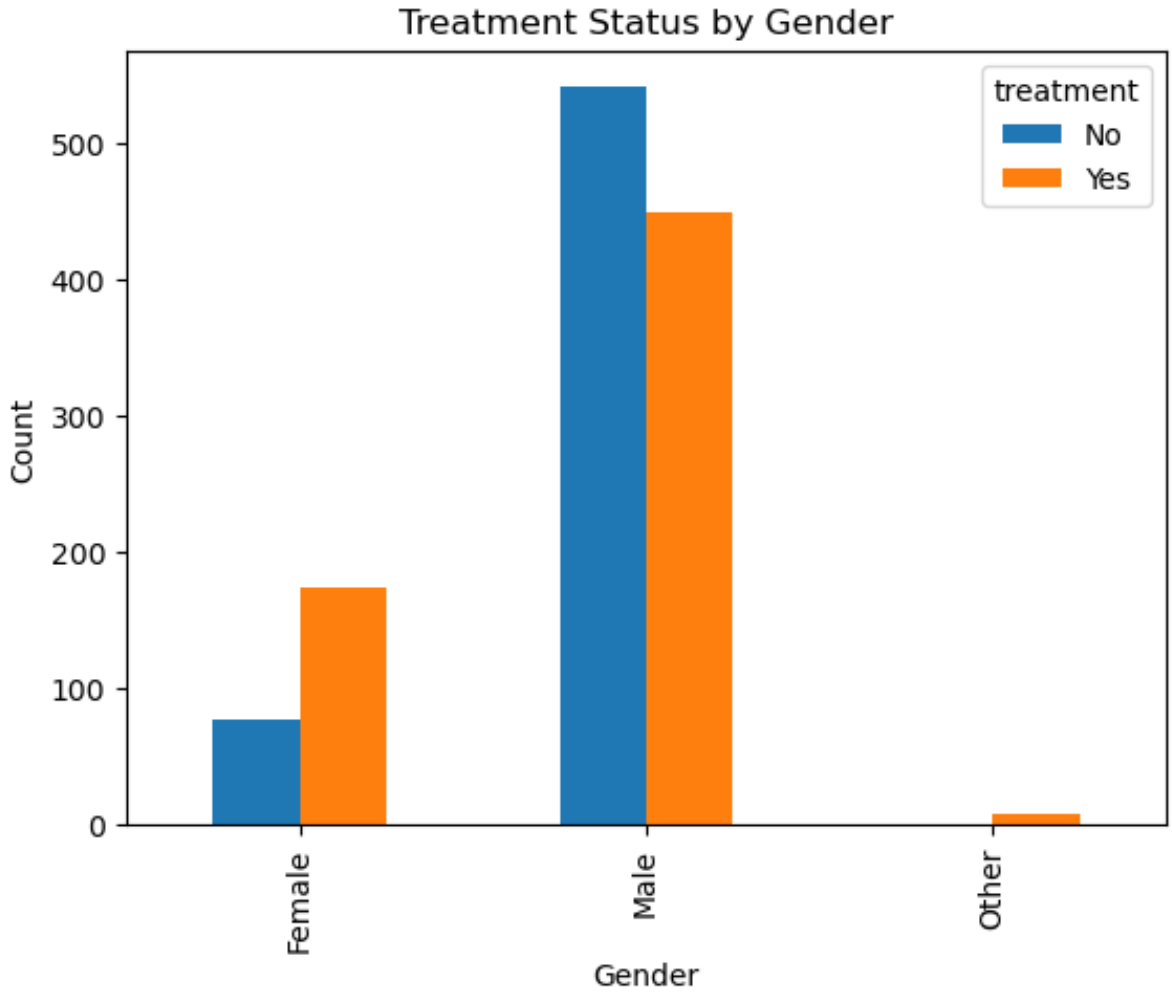


Section C: Bivariate Analysis

Task 5: Gender and Treatment

In [10]:
```
if set(["Gender","treatment"]).issubset(df.columns):
    ct = pd.crosstab(df["Gender"], df["treatment"])
    print(ct)
    ct.plot(kind="bar", stacked=False)
    plt.title("Treatment Status by Gender")
    plt.xlabel("Gender")
    plt.ylabel("Count")
    plt.show()
```

```
treatment   No  Yes
Gender
Female      78  174
Male       540  449
Other        1    9
```

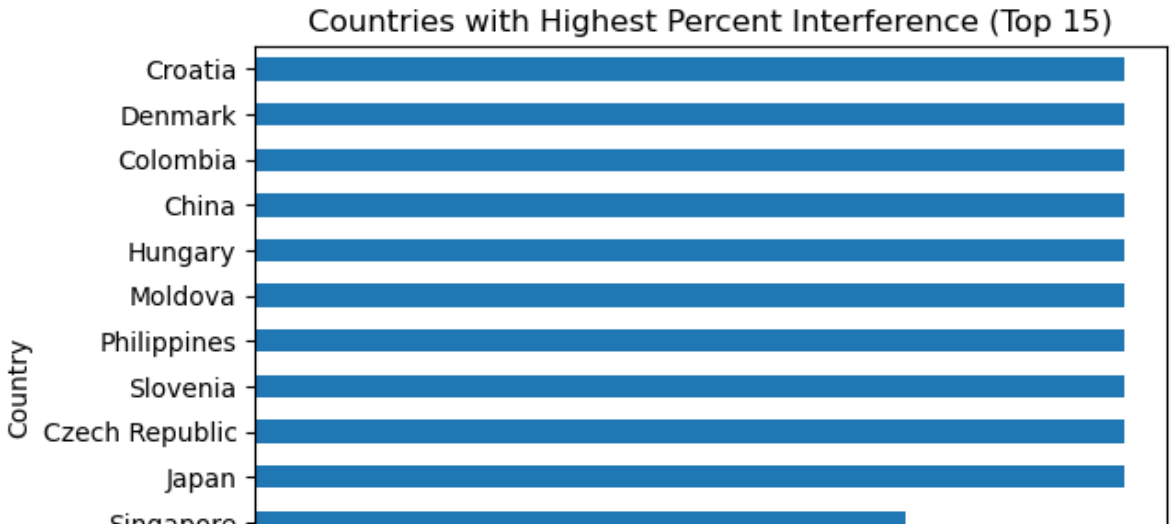


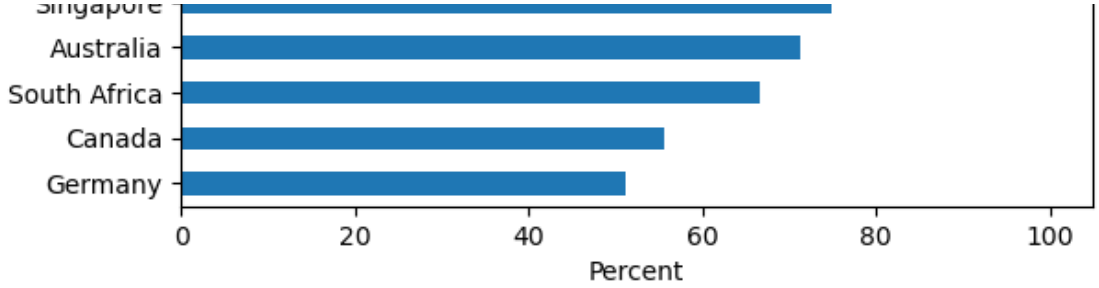
Task 6: Country and Work Interference

In [11]:
```
set(["Country","work_interfere"]).issubset(df.columns):
 # Consider 'Often' and 'Sometimes' as interference; adjust if dif
```

```
interfering = df["work_interfere"].str.lower().isin(["often","some
by_country = df.groupby("Country").apply(lambda x: (interfering.lo
by_country = (by_country * 100).round(1)
print(by_country.head(15))
plt.figure()
by_country.head(15).sort_values().plot(kind="barh")
plt.title("Countries with Highest Percent Interference (Top 15)")
plt.xlabel("Percent")
plt.ylabel("Country")
plt.show()
```

```
Country
Japan             100.0
Czech Republic    100.0
Slovenia          100.0
Philippines       100.0
Moldova           100.0
Hungary           100.0
China             100.0
Colombia          100.0
Denmark           100.0
Croatia           100.0
Singapore          75.0
Australia          71.4
South Africa       66.7
Canada             55.6
Germany            51.1
dtype: float64

/var/folders/76/h0hd92ws6r7cjlnr540_frr40000gn/T/ipykernel_66387/3
262336241.py:4: FutureWarning: DataFrameGroupBy.apply operated on
the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the o
peration. Either pass `include_groups=False` to exclude the groupi
ngs or explicitly select the grouping columns after groupby to sil
ence this warning.
  by_country = df.groupby("Country").apply(lambda x: (interfering.
loc[x.index]).mean()).sort_values(ascending=False)
```



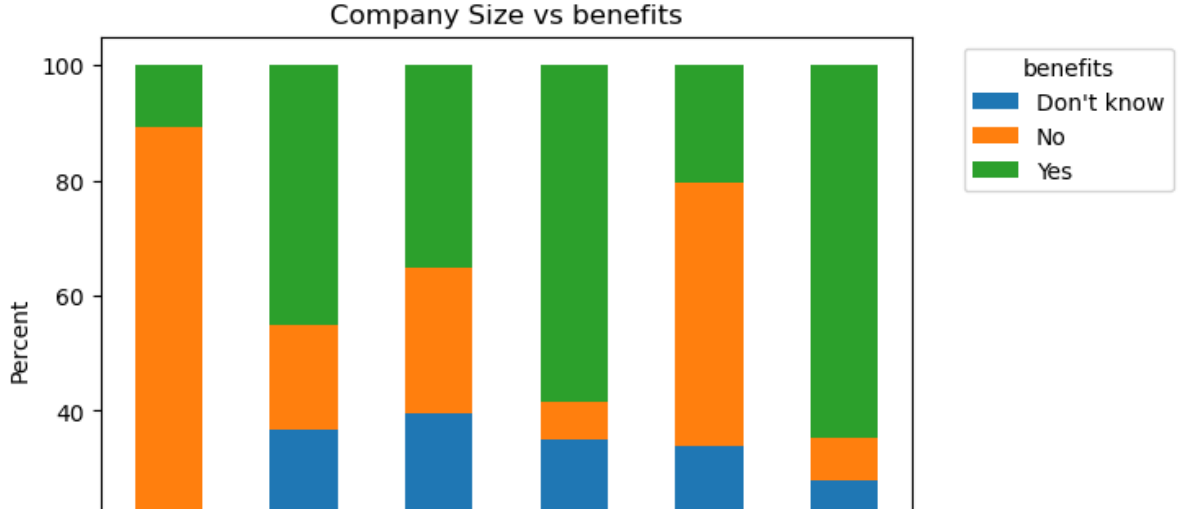


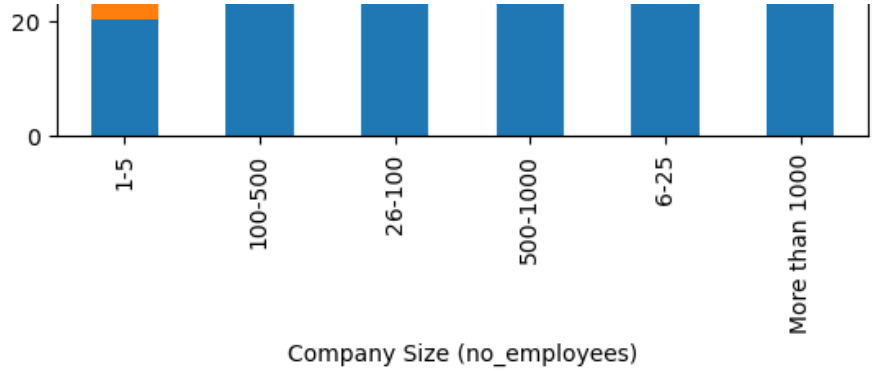
Task 7: Company Size and Benefits

In [12]:

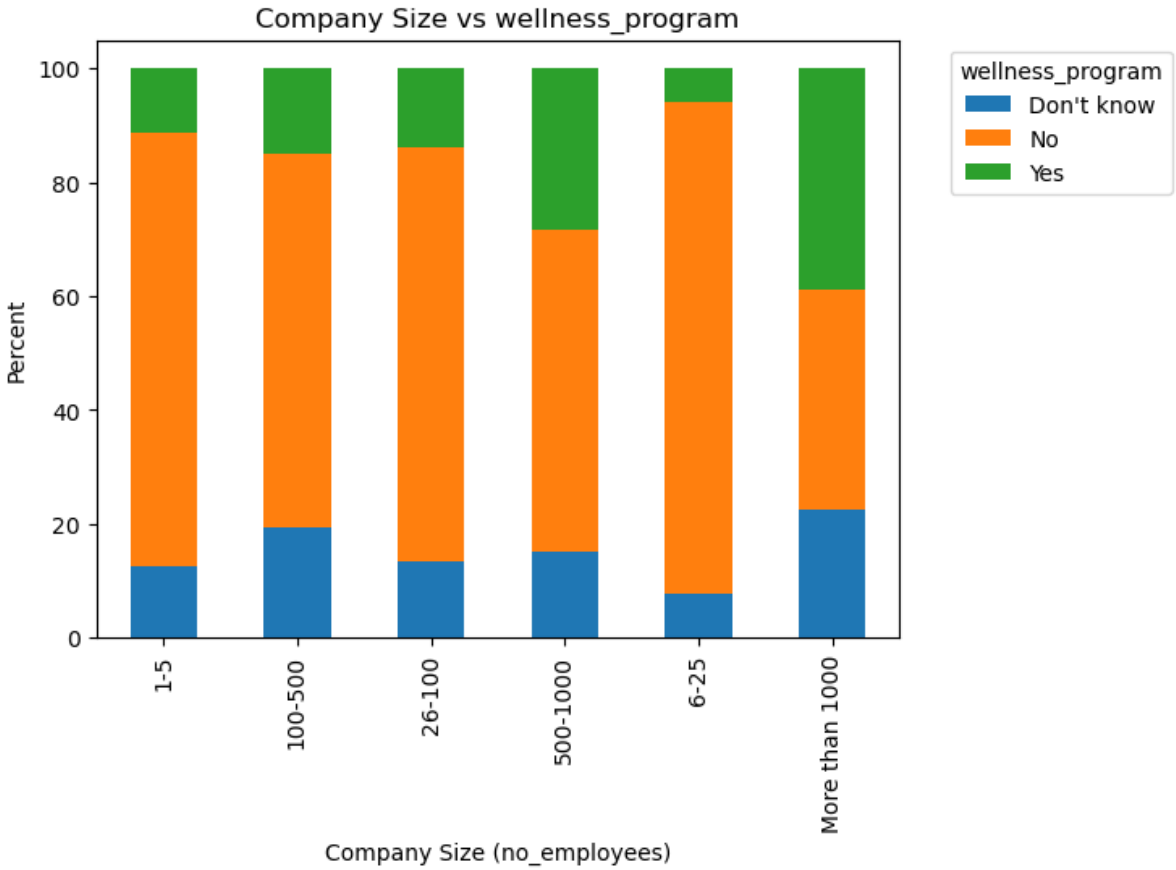
```
targets = ["benefits","wellness_program","care_options"]
if "no_employees" in df.columns:
    for t in targets:
        if t in df.columns:
            ct = pd.crosstab(df["no_employees"], df[t], normalize="
            print(f"\nno_employees vs {t} (row-normalized)")
            print((ct*100).round(1))
            (ct*100).plot(kind="bar", stacked=True)
            plt.title(f"Company Size vs {t}")
            plt.xlabel("Company Size (no_employees)")
            plt.ylabel("Percent")
            plt.legend(title=t, bbox_to_anchor=(1.05, 1), loc="uppe
            plt.show()
```

```
no_employees vs benefits (row-normalized)
benefits        Don't know    No   Yes
no_employees
1-5                   20.3  69.0  10.8
100-500               36.6  18.3  45.1
26-100                39.6  25.3  35.1
500-1000              35.0   6.7  58.3
6-25                  33.9  45.7  20.4
More than 1000        27.8   7.5  64.8
```



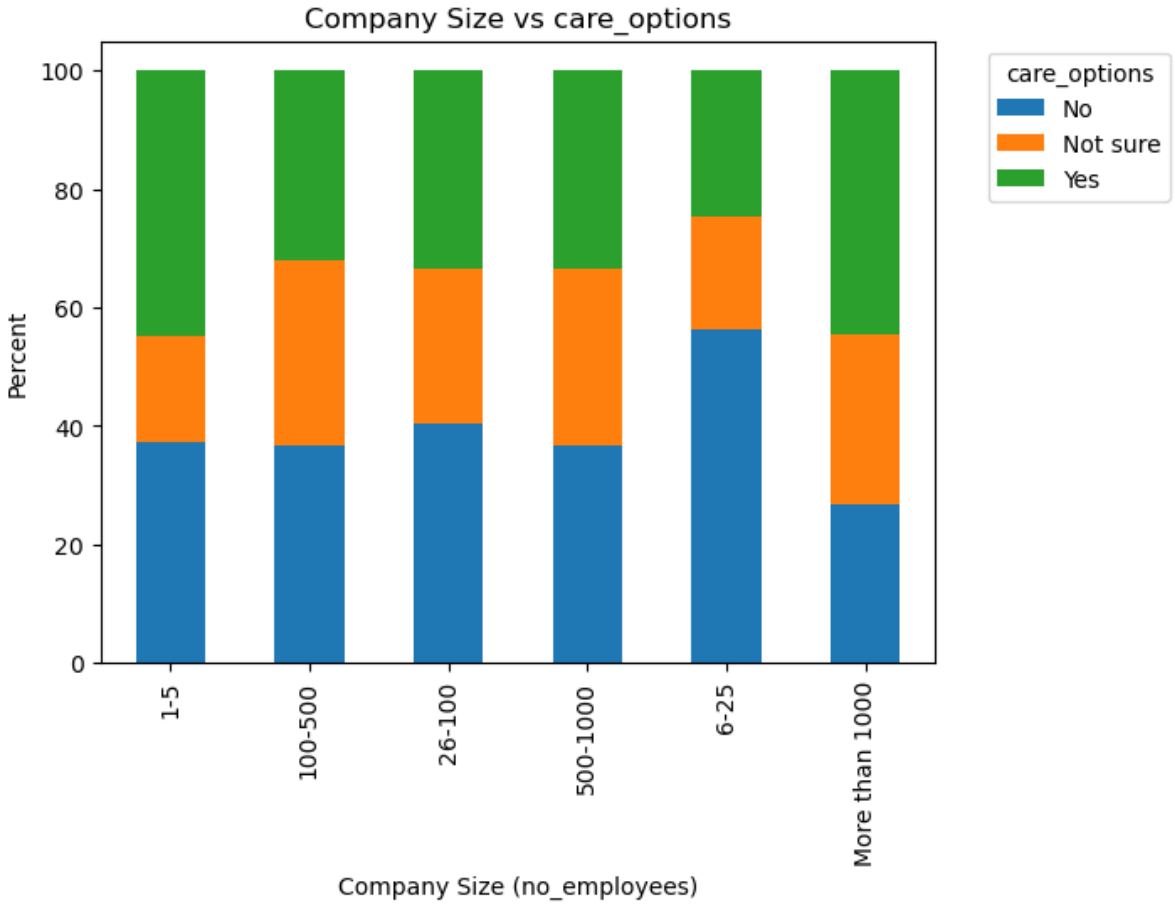



```
no_employees vs wellness_program (row-normalized)
wellness_program  Don't know    No   Yes
no_employees
1-5                       12.7  75.9  11.4
100-500                   19.4  65.7  14.9
26-100                    13.5  72.6  13.9
500-1000                  15.0  56.7  28.3
6-25                       7.6  86.5   5.9
More than 1000            22.4  38.8  38.8
```




```
no_employees vs care_options (row-normalized)
care_options      No  Not sure   Yes
no_employees
1-5             37.3      17.7  44.9
100-500         36.6      31.4  32.0
26-100          40.3      26.4  33.3
```

```
500-1000          36.7      30.0  33.3
6-25              56.4      19.0  24.6
More than 1000    26.7      28.8  44.5
```

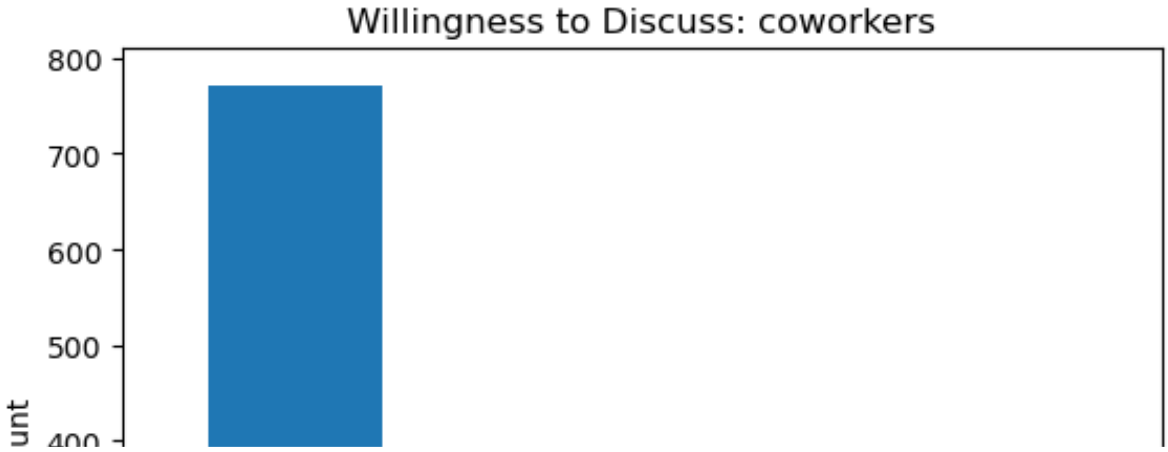


Section D: Attitudes Toward Mental Health

Task 8: Discussion Comfort

In [13]:
```
for col in ["coworkers","supervisor","mental_health_interview"]:
    if col in df.columns:
        ct = df[col].value_counts(normalize=True)*100
        print(f"{col} distribution (%):\n", ct.round(1))
        plt.figure()
        df[col].value_counts().plot(kind="bar")
        plt.title(f"Willingness to Discuss: {col}")
        plt.xlabel(col)
        plt.ylabel("Count")
        plt.show()
```

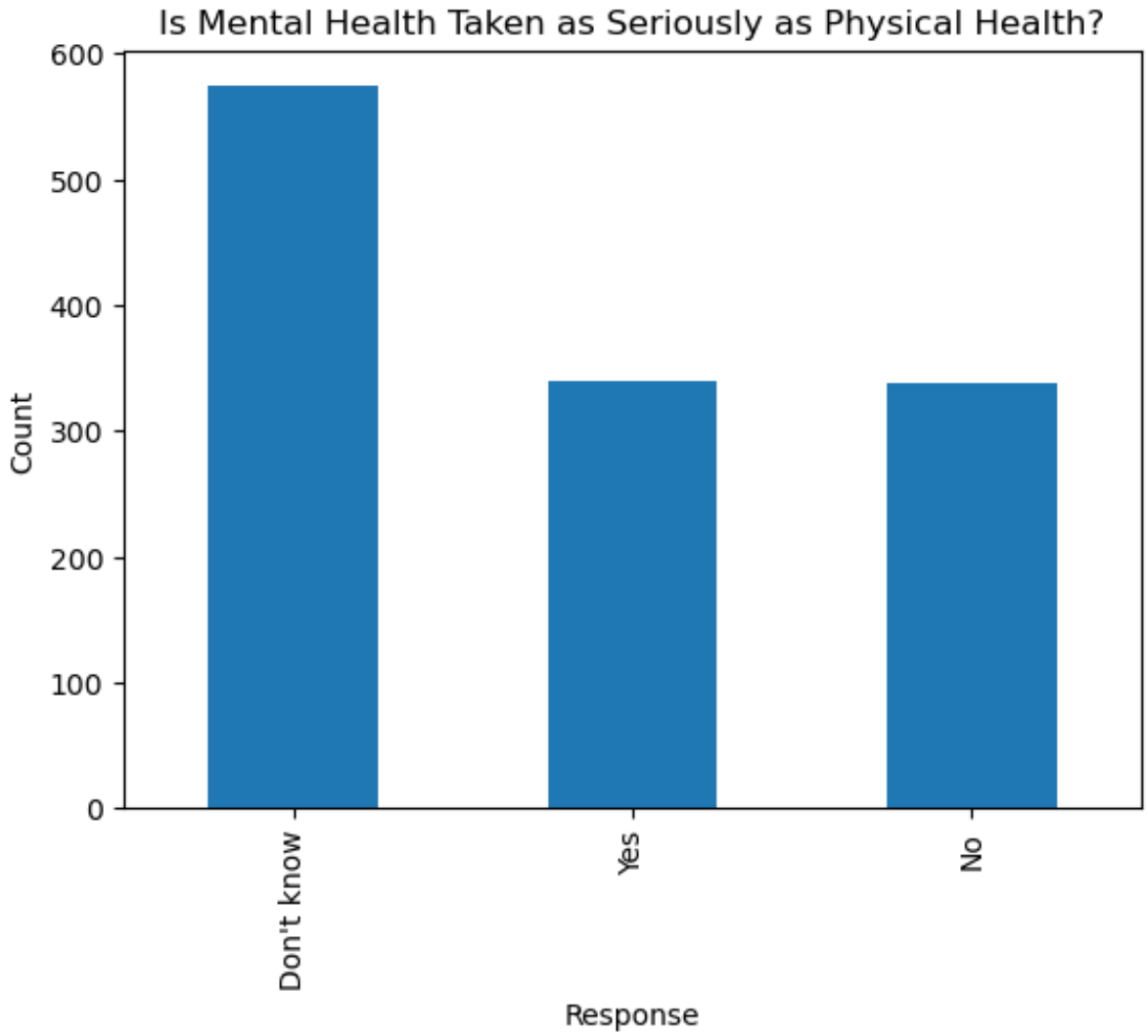
```
coworkers distribution (%):
 coworkers
Some of them    61.6
No              20.6
Yes             17.7
Name: proportion, dtype: float64
```



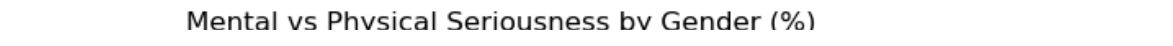
Task 9: Mental vs Physical Health Perceptions

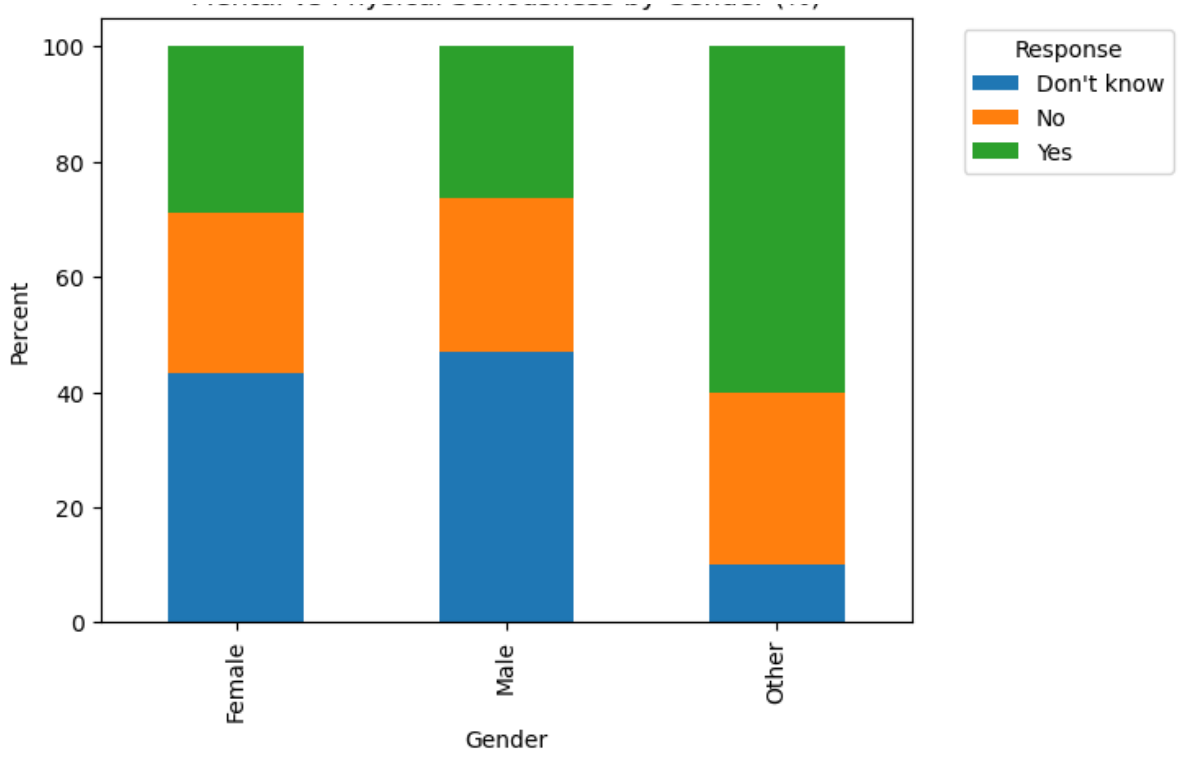
In [14]:
```
cols_needed = ["mental_vs_physical","Gender","tech_company"]
if set(cols_needed).issubset(df.columns):
    # Overall
    plt.figure()
    df["mental_vs_physical"].value_counts().plot(kind="bar")
    plt.title("Is Mental Health Taken as Seriously as Physical Heal
    plt.xlabel("Response")
    plt.ylabel("Count")
    plt.show()

    # By Gender
    ct = pd.crosstab(df["Gender"], df["mental_vs_physical"], normal
    print("By Gender (%):\n", ct.round(1))
    (ct).plot(kind="bar", stacked=True)
    plt.title("Mental vs Physical Seriousness by Gender (%)")
```

```
    plt.xlabel("Gender")
    plt.ylabel("Percent")
    plt.legend(title="Response", bbox_to_anchor=(1.05, 1), loc="upp
    plt.show()

    # By Tech Company
    ct2 = pd.crosstab(df["tech_company"], df["mental_vs_physical"],
    print("By Tech Company (%):\n", ct2.round(1))
    (ct2).plot(kind="bar", stacked=True)
    plt.title("Mental vs Physical Seriousness by Employer Type (%)"
    plt.xlabel("tech_company")
    plt.ylabel("Percent")
    plt.legend(title="Response", bbox_to_anchor=(1.05, 1), loc="upp
    plt.show()
```

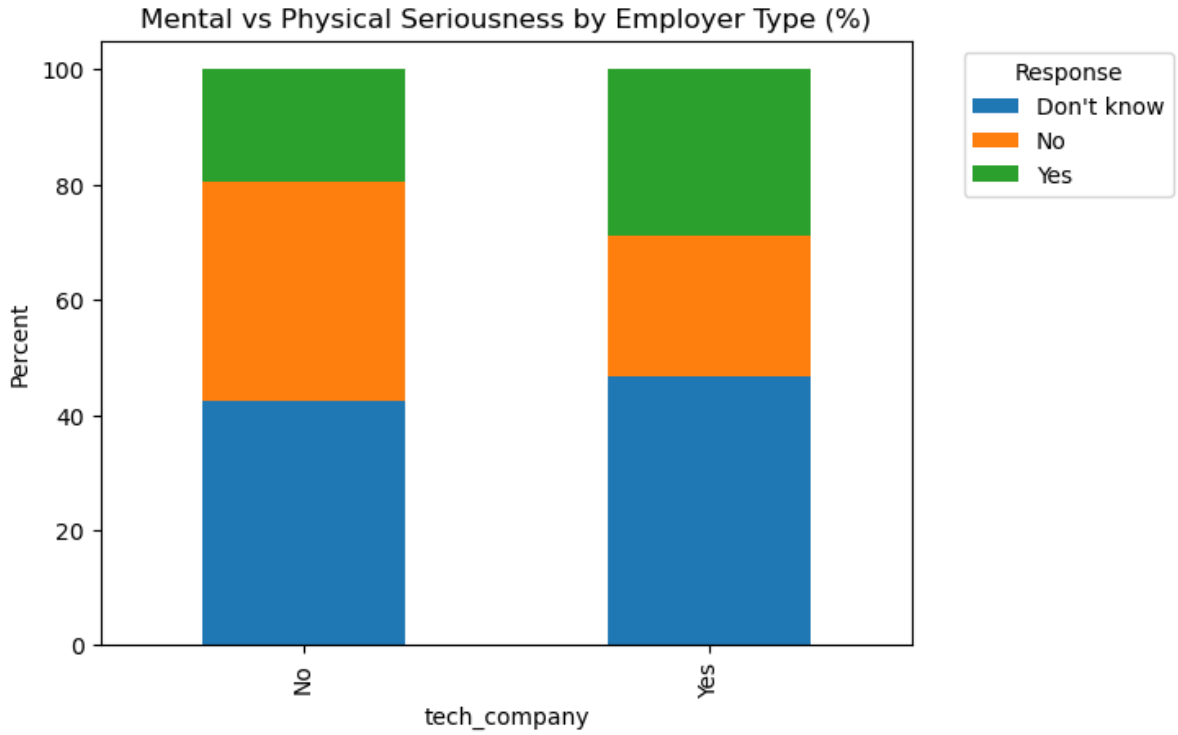



```
By Gender (%):
 mental_vs_physical  Don't know    No   Yes
Gender
Female                    43.3  27.8  29.0
Male                      46.9  26.8  26.3
Other                     10.0  30.0  60.0
```






```
By Tech Company (%):
 mental_vs_physical  Don't know    No   Yes
tech_company
No                         42.5  38.1  19.5
Yes                        46.6  24.6  28.8
```

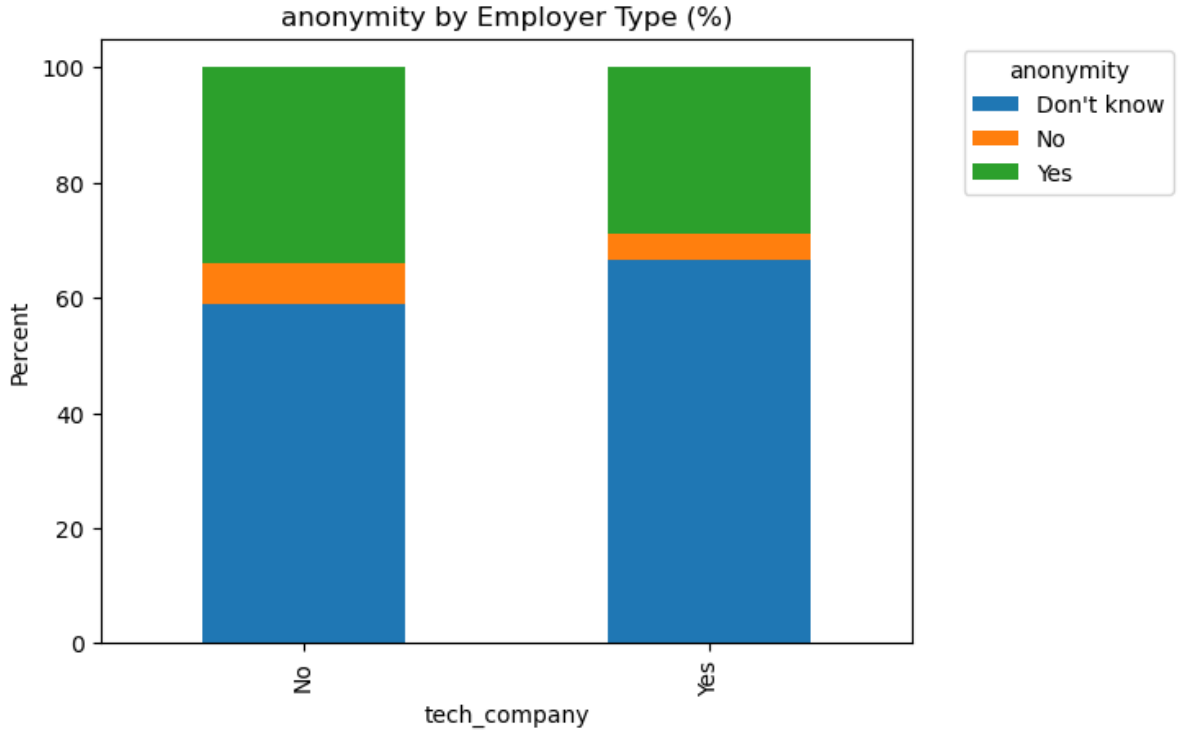


Task 10: Anonymity and Consequences

In [15]:

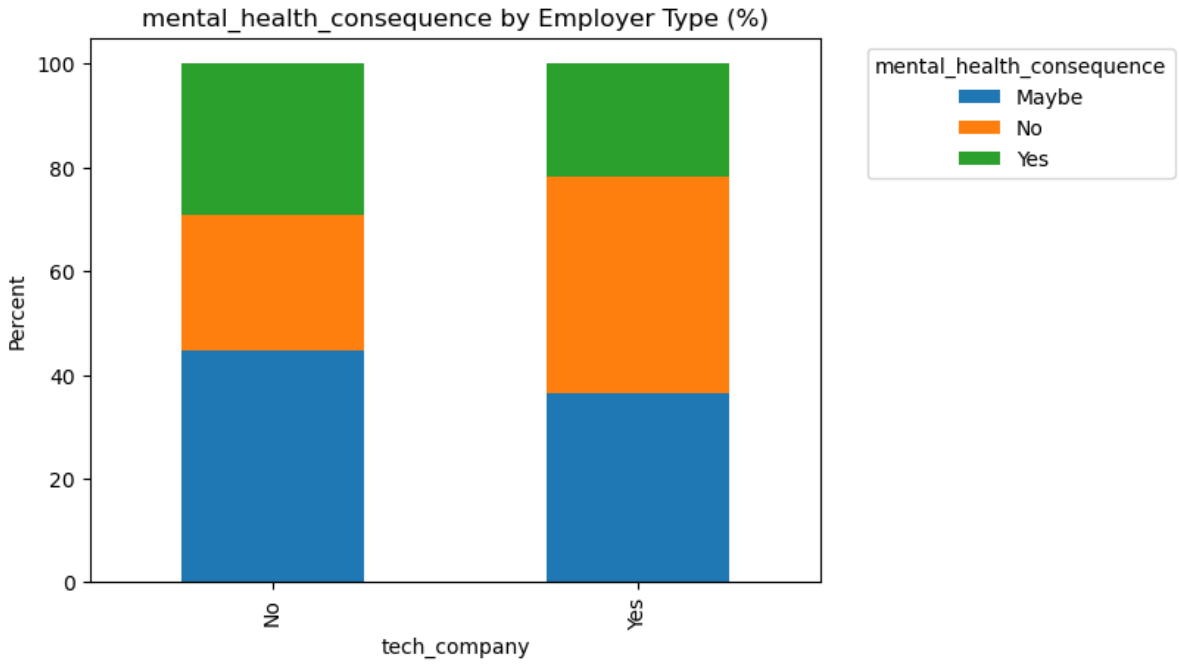
```
for col in ["anonymity","mental_health_consequence"]:
    if set(["tech_company", col]).issubset(df.columns):
        ct = pd.crosstab(df["tech_company"], df[col], normalize="in
        print(f"{col} by tech_company (%):\n", ct.round(1))
        (ct).plot(kind="bar", stacked=True)
        plt.title(f"{col} by Employer Type (%)")
        plt.xlabel("tech_company")
        plt.ylabel("Percent")
        plt.legend(title=col, bbox_to_anchor=(1.05, 1), loc="upper
        plt.show()

# Remote vs non-remote for the same perceptions
for col in ["anonymity","mental_health_consequence"]:
    if set(["remote_work", col]).issubset(df.columns):
        ct = pd.crosstab(df["remote_work"], df[col], normalize="ind
        print(f"{col} by remote_work (%):\n", ct.round(1))
        (ct).plot(kind="bar", stacked=True)
        plt.title(f"{col} by Remote Work Status (%)")
        plt.xlabel("remote_work")
        plt.ylabel("Percent")
        plt.legend(title=col, bbox_to_anchor=(1.05, 1), loc="upper
        plt.show()
```

```
anonymity by tech_company (%):
 anonymity     Don't know   No   Yes
tech_company
No                  58.8  7.1  34.1
Yes                 66.5  4.7  28.8
```

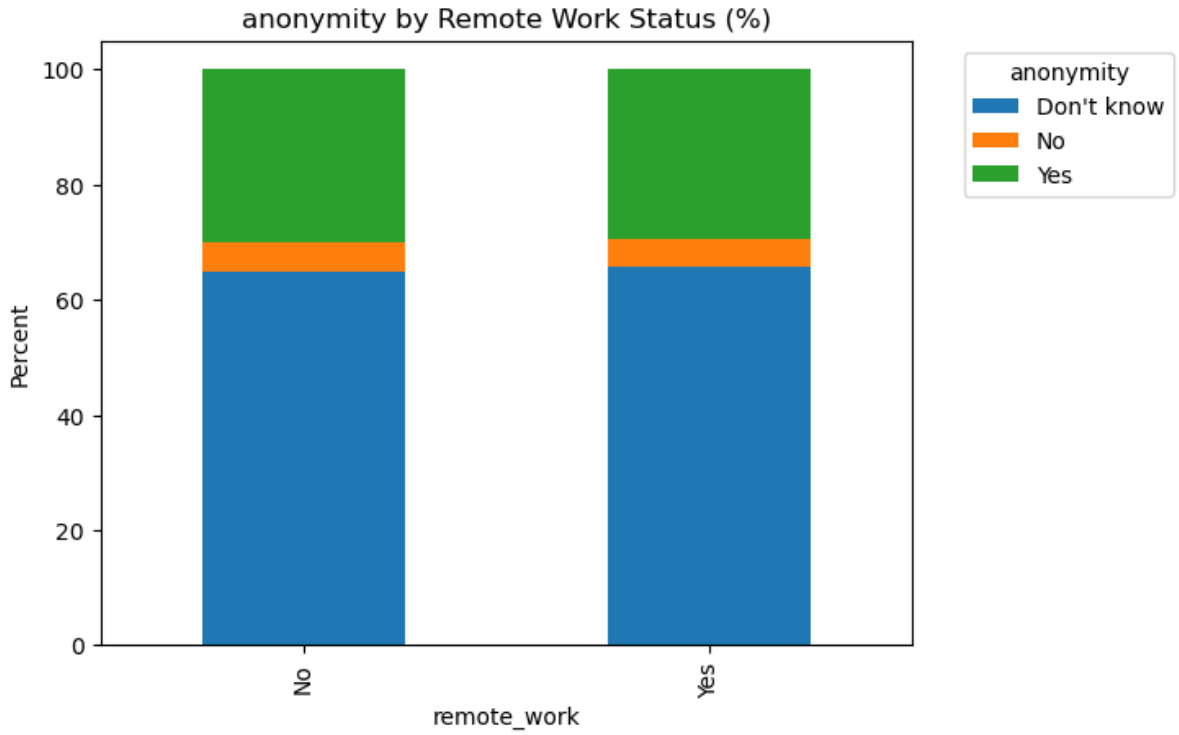



```
mental_health_consequence by tech_company (%):
```

```
 mental_health_consequence  Maybe    No   Yes
tech_company
No                          44.7  26.1  29.2
Yes                         36.6  41.8  21.7
```

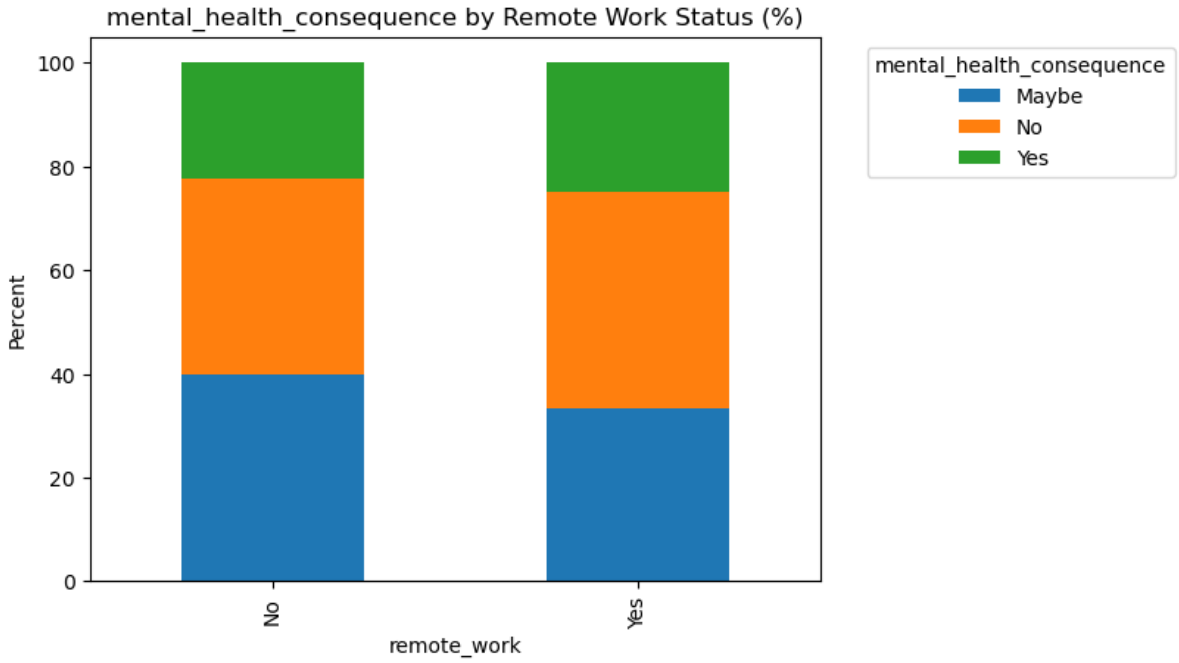



```
anonymity by remote_work (%):
 anonymity    Don't know   No   Yes
remote_work
No                 64.9  5.2  29.9
Yes                65.8  4.9  29.4
```




```
mental_health_consequence by remote_work (%):
 mental_health_consequence  Maybe    No   Yes
```

```
remote_work
No                          40.0  37.7  22.3
Yes                         33.4  41.8  24.8
```



Section E: Geographic and Remote Work Insights

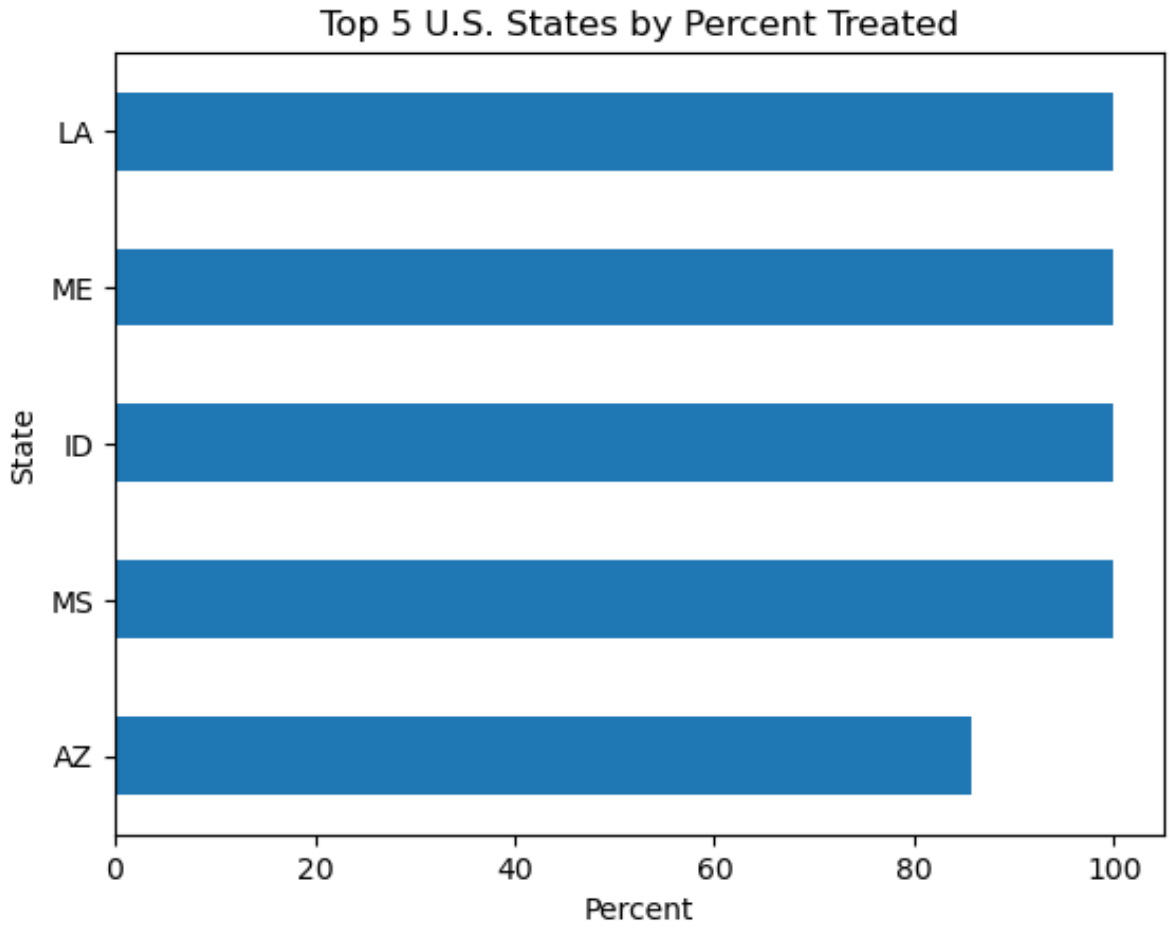
Task 11: U.S. State-wise Patterns

In [16]:

```
if set(["state","treatment"]).issubset(df.columns):
    # Compute % treated by state
    treated = df["treatment"].str.lower().eq("yes")
    state_rates = df.groupby("state").apply(lambda x: treated.loc[x
    state_rates = (state_rates*100).dropna().sort_values(ascending=
    top5 = state_rates.head(5).round(1)
    print("Top 5 states by percent treated (%):\n", top5)
    plt.figure()
    top5.sort_values().plot(kind="barh")
    plt.title("Top 5 U.S. States by Percent Treated")
    plt.xlabel("Percent")
    plt.ylabel("State")
    plt.show()
```

```
Top 5 states by percent treated (%):
 state
MS    100.0
ID    100.0
ME    100.0
LA    100.0
```

```
AZ     85.7
dtype: float64

/var/folders/76/h0hd92ws6r7cjlnr540_frr40000gn/T/ipykernel_66387/3
619783661.py:4: FutureWarning: DataFrameGroupBy.apply operated on
the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the o
peration. Either pass `include_groups=False` to exclude the groupi
ngs or explicitly select the grouping columns after groupby to sil
ence this warning.
  state_rates = df.groupby("state").apply(lambda x: treated.loc[x.
index].mean() if len(x)>0 else np.nan)
```



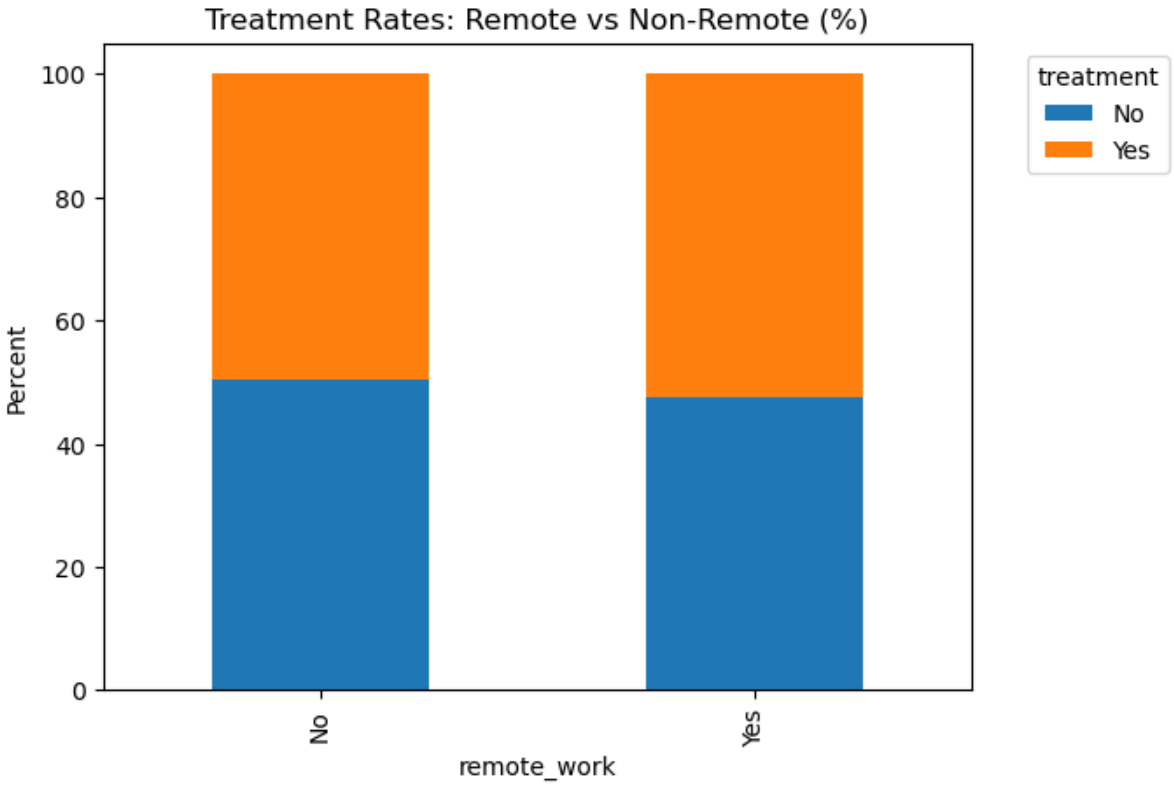
Task 12: Remote Work Effect

In [17]:

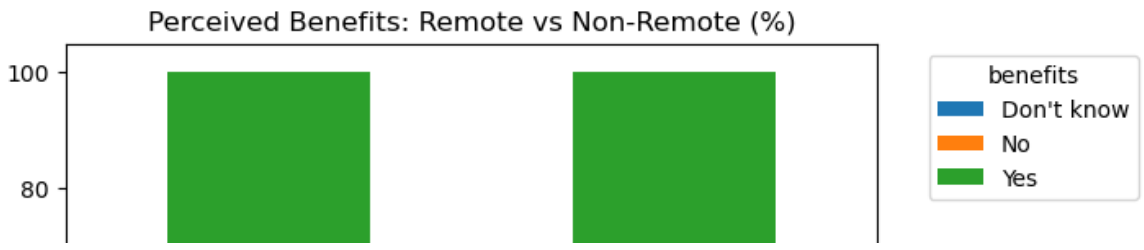
```
if set(["remote_work","treatment"]).issubset(df.columns):
    ct = pd.crosstab(df["remote_work"], df["treatment"], normalize=
    print("Treatment by remote_work (%):\n", ct.round(1))
    (ct).plot(kind="bar", stacked=True)
    plt.title("Treatment Rates: Remote vs Non-Remote (%)")
    plt.xlabel("remote_work")
    plt.ylabel("Percent")
    plt.legend(title="treatment", bbox_to_anchor=(1.05, 1), loc="up
    plt.show()
```

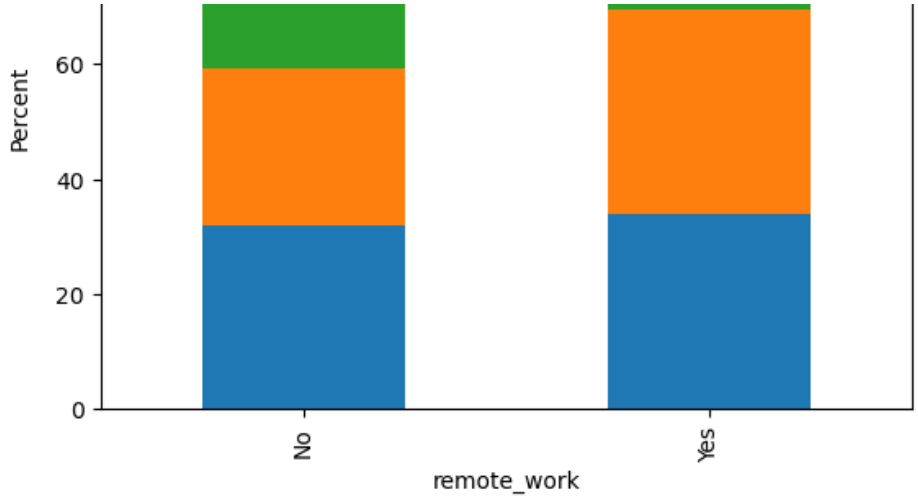
```
# Perception of support: use benefits as a proxy
if set(["remote_work","benefits"]).issubset(df.columns):
    ct2 = pd.crosstab(df["remote_work"], df["benefits"], normalize=
    print("Benefits by remote_work (%):\n", ct2.round(1))
    (ct2).plot(kind="bar", stacked=True)
    plt.title("Perceived Benefits: Remote vs Non-Remote (%)")
    plt.xlabel("remote_work")
    plt.ylabel("Percent")
    plt.legend(title="benefits", bbox_to_anchor=(1.05, 1), loc="upp
    plt.show()
```

```
Treatment by remote_work (%):
 treatment      No   Yes
remote_work
No            50.3  49.7
Yes           47.4  52.6
```




```
Benefits by remote_work (%):
 benefits      Don't know    No   Yes
remote_work
No                  31.9  27.2  40.9
Yes                 34.0  35.6  30.5
```



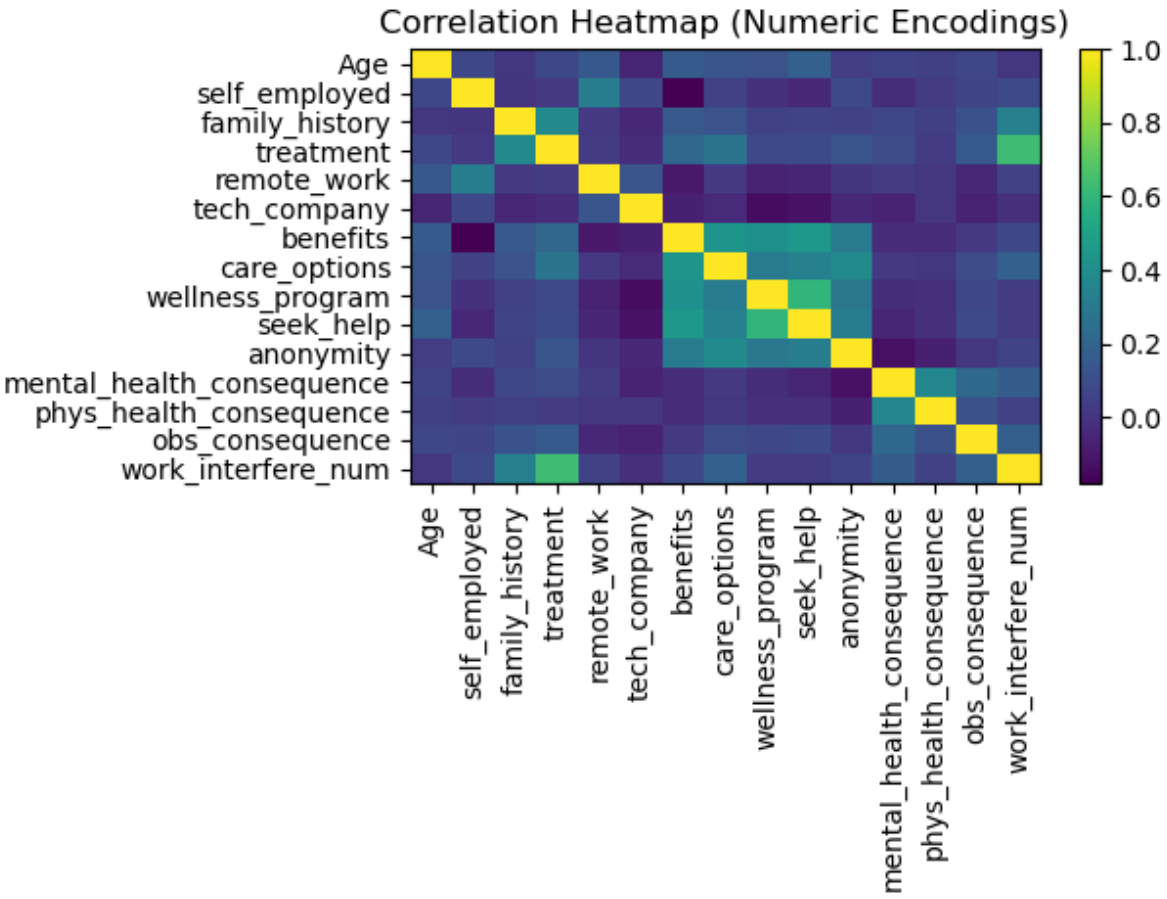


Section F: Predictive Insights

Task 13: Correlation Analysis

In [18]:

```
df_corr = df.copy()

# Simple binary encoding for common Yes/No style columns
yn_cols = [
    "self_employed","family_history","treatment","remote_work","tec
    "benefits","care_options","wellness_program","seek_help","anony
    "mental_health_consequence","phys_health_consequence","obs_cons
]
for c in yn_cols:
    if c in df_corr.columns:
        df_corr[c] = df_corr[c].map({"Yes":1, "No":0}).fillna(0)

# Encode work_interfere to ordinal-like scale if present
if "work_interfere" in df_corr.columns:
    mapping = {"Never":0, "Rarely":1, "Sometimes":2, "Often":3}
    df_corr["work_interfere_num"] = df_corr["work_interfere"].map(m

# Choose numeric columns for correlation
num_cols = [c for c in df_corr.columns if pd.api.types.is_numeric_d
corr = pd.DataFrame()
if len(num_cols) > 1:
    corr = df_corr[num_cols].corr()
    plt.figure()
    plt.imshow(corr, aspect="auto")
    plt.colorbar()
    plt.title("Correlation Heatmap (Numeric Encodings)")
    plt.xticks(range(len(num_cols)), num_cols, rotation=90)
    plt.yticks(range(len(num_cols)), num_cols)
    plt.tight_layout()
    plt.show()
corr.head(10)
```



Out[18]:

	Age	self_employed	family_history	treatment	remote_work	tech_c
Age	1.000000	0.073365	0.009101	0.073627	0.146906	-(
self_employed	0.073365	1.000000	0.002551	0.016442	0.313863	(
family_history	0.009101	0.002551	1.000000	0.376674	0.014278	-(
treatment	0.073627	0.016442	0.376674	1.000000	0.026507	-(
remote_work	0.146906	0.313863	0.014278	0.026507	1.000000	(
tech_company	-0.058081	0.076326	-0.049646	-0.032521	0.132026	
benefits	0.153344	-0.180272	0.149020	0.207857	-0.098437	-(
care_options	0.124218	0.048415	0.121513	0.272083	0.017635	-(
wellness_program	0.122016	-0.011551	0.047900	0.080151	-0.069569	-(
seek_help	0.180278	-0.044546	0.055355	0.085215	-0.053862	-(

Task 14: Strong Predictors (Optional Model)

In [19]:

```
model_output = {}
if "treatment" in df.columns:
    # Target: treatment == Yes
    y = df["treatment"].map({"Yes":1, "No":0}).fillna(0)
    X = df.drop(columns=[c for c in df.columns if c == "treatment"]

    # Select features (exclude free text already dropped)
    cat_cols = [c for c in X.columns if X[c].dtype == object]
    num_cols  = [c for c in X.columns if pd.api.types.is_numeric_dt

    pre = ColumnTransformer(
        transformers=[
            ("cat", OneHotEncoder(handle_unknown="ignore"), cat_col
            ("num", "passthrough", num_cols)
        ]
    )

    clf = Pipeline(steps=[("pre", pre),
                          ("lr", LogisticRegression(max_iter=200, n_

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_

    try:
        clf.fit(X_train, y_train)
        preds = clf.predict(X_test)
        proba = clf.predict_proba(X_test)[:,1]
        print("Classification report:")
        print(classification_report(y_test, preds, digits=3))
        try:
            print("ROC AUC:", round(roc_auc_score(y_test, proba), 3
        except Exception as e:
            print("ROC AUC could not be computed:", e)
    except Exception as e:
        print("Model training failed:", e)
else:
    print("Column 'treatment' not found; skipping model step.")
```

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

           0      0.874     0.761     0.814       155
           1      0.792     0.892     0.839       158

    accuracy                          0.827       313
   macro avg      0.833     0.827     0.827       313
weighted avg      0.833     0.827     0.827       313

ROC AUC: 0.896
```

Section G: Summary and Recommendations

The following bullet points summarize key findings and suggestions based on the above analysis. Edit if you derive more precise insights after reviewing the charts.

In [20]:
```
y_points = [
 Age responses cluster between early 20s and 40s, consistent with a
 Gender distribution is imbalanced toward Male, with smaller Female
 A notable share of respondents report work interference associated
 Larger companies tend to report more benefits and awareness of care
 Comfort discussing mental health varies: respondents are more willi
 Perceptions that mental health is taken as seriously as physical he
 Remote work status shows differences in treatment rates and perceiv


endations = [
 Expand mental health benefits and clearly communicate care options,
 Normalize conversations about mental health through manager trainin
 Provide targeted resources for remote employees to ensure equitable


"Key Insights:")
in summary_points:
int(s)

"\nRecommendations:")
in recommendations:
int(r)
```

```
Key Insights:
- Age responses cluster between early 20s and 40s, consistent with
a tech workforce age profile.
- Gender distribution is imbalanced toward Male, with smaller Fema
le and Other groups.
- A notable share of respondents report work interference associat
ed with mental health, especially in select countries.
- Larger companies tend to report more benefits and awareness of c
are options than smaller organizations.
- Comfort discussing mental health varies: respondents are more wi
lling with coworkers than in interviews.
- Perceptions that mental health is taken as seriously as physical
health differ by gender and by whether the employer is a tech comp
any.
- Remote work status shows differences in treatment rates and perc
eived benefits.

Recommendations:
- Expand mental health benefits and clearly communicate care optio
ns, particularly in smaller companies.
- Normalize conversations about mental health through manager trai
ning and peer programs to reduce perceived consequences.
- Provide targeted resources for remote employees to ensure equita
ble access and support.
```

In [ ]: