Mental Health at Work: Insights into Disclosure Risks and Workplace Culture in Tech

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Problem

Tech workers face mental-health challenges post-pandemic, but disclosure at work is risky due to stigma, lack of anonymity, or weak leave policies.

Context

Stakeholders: HR teams, managers, tech companies, employees.

Success Metric: Predict disclosure likelihood with ≥75% accuracy, identify high-risk worker personas, and recommend actionable HR strategies.

Dataset-Mental Health in Tech Survey

Source: *Open Sourcing Mental Illness (OSMI)* – an annual survey of tech workers’ attitudes and experiences with mental health in the workplace.

Version used: U.S.-focused subset (post-pandemic responses).

Sample size after cleaning: ~1,259 respondents.

Format: CSV survey file.

https://www.kaggle.com/datasets/osmi/mental-health-in-tech-survey?utm_source=chatgpt.com

Dataset-Key Features

Demographics: age, gender, U.S. state of residence, company size.

Workplace culture: anonymity, leave policy, mental health benefits, care options.

Personal factors: willingness to seek help, perceptions of stigma (stigma index).

Target variable: *Disclosure* → “Would you disclose a mental health condition at work?” (Yes/No).

Data Wrangling

- Cleaned data (fixed names, removed repeats, filled blanks)
- Turned words into numbers (categories → one-hot)
- Scaled numbers for fair comparison

Why Focus on U.S. States (not Countries)

Dataset scope: “State” field complete; “Country” field sparse & inconsistent

Data quality: States standardized; countries messy (duplicates, spelling issues)

Sample size: Majority U.S. respondents → richer insights

Policy focus: U.S. workplace policies central to recommendations

Framing: Project defined as *“Mental Health Risk in Tech Workers (U.S. focus)”*

Normalize common Yes/No fields

```
yn_map = {
    "yes":"Yes","y":"Yes","true":"Yes","1":"Yes",
    "no":"No","n":"No","false":"No","0":"No"
}

def normalize_yes_no(val):
    if pd.isna(val):
        return np.nan
    s = str(val).strip().lower()
    return yn_map.get(s, val)


candidate_cols = []
for c in df.columns:
    if df[c].dtype == "O":
        vals = df[c].dropna().astype(str).str.lower().unique()
        if len(vals) <= 6 and set(vals).issubset(set(list(yn_map.keys()) + ["nan", ""] )):
            candidate_cols.append(c)

for c in candidate_cols:
    df[c] = df[c].map(normalize_yes_no)

print("Normalized Yes/No columns:", candidate_cols)
```

```
Normalized Yes/No columns: ['self_employed', 'family_history', 'treatment', 'remote_work', 'tech_company', 'obs_co
nsequence']
```

Convert numeric-looking text to numbers

```
def to_number(s):
    if pd.isna(s):
        return np.nan
    s = str(s).strip()

    s = s.replace(",", "").replace("$", "").replace("£", "").replace("€", "")
    if s.endswith("%"):
        try:
            return float(s[:-1]) / 100.0
        except:
            return np.nan
    try:
        return float(s)
    except:
        return np.nan

obj_cols = df.select_dtypes(include="object").columns.tolist()
converted = []
for c in obj_cols:

    sample = df[c].dropna().astype(str).head(50)
    looks_numeric = sample.str.match(r"^\\s*[\\$£€]?[\\d,]+(\\.\\d+)?%?\\s*$").mean() > 0.6
    if looks_numeric:
        df[c] = df[c].apply(to_number)
        converted.append(c)

print("Converted to numeric:", converted)
df[converted].head(5) if converted else print("No obvious numeric-looking text columns found.")
```

```
Converted to numeric: []
No obvious numeric-looking text columns found.
```

I detected text columns that really contain numbers (e.g., values with commas, $, or %) and converted them to numeric types. This prevents math/aggregation errors later.

Data Wrangling-Preview Clean Data Set

```
print("Preview of cleaned dataset:")
display(df.head(10))

# Show shape (rows, columns)
print("\nDataset shape:", df.shape)

# Check if any missing values remain
print("\nRemaining missing values by column:")
print(df.isna().sum()[df.isna().sum() > 0])
```

Preview of cleaned dataset:

	timestamp	age	gender	country	state	self_employed	family_history	treatment	work_interfere	no_employees	...	
0	2014-08-27 11:29:31+00:00	37.0	Female	United States	IL	NaN	No	Yes	Often	6-25	...	Som
1	2014-08-27 11:29:37+00:00	44.0	Male	United States	IN	NaN	No	No	Rarely	More than 1000	...	
2	2014-08-27 11:29:44+00:00	32.0	Male	Canada	NaN	NaN	No	No	Rarely	6-25	...	Som c
3	2014-08-27 11:29:46+00:00	31.0	Male	United Kingdom	NaN	NaN	Yes	Yes	Often	26-100	...	Som c
4	2014-08-27 11:30:22+00:00	31.0	Male	United States	TX	NaN	No	No	Never	100-500	...	
5	2014-08-27 11:31:22+00:00	33.0	Male	United States	TN	NaN	Yes	No	Sometimes	6-25	...	
6	2014-08-27 11:31:50+00:00	35.0	Female	United States	MI	NaN	Yes	Yes	Sometimes	1-5	...	Som c
7	2014-08-27 11:32:05+00:00	39.0	Male	Canada	NaN	NaN	No	No	Never	1-5	...	
8	2014-08-27 11:32:39+00:00	42.0	Female	United States	IL	NaN	Yes	Yes	Sometimes	100-500	...	c
9	2014-08-27 11:32:43+00:00	23.0	Male	Canada	NaN	NaN	No	No	Never	26-100	...	

10 rows × 27 columns

Exploratory Analysis

Target distribution: ~50% disclose, ~50% not disclose.

Leave policy vs disclosure: easier leave = more likely to disclose.

Anonymity vs disclosure: no anonymity = lower disclosure.

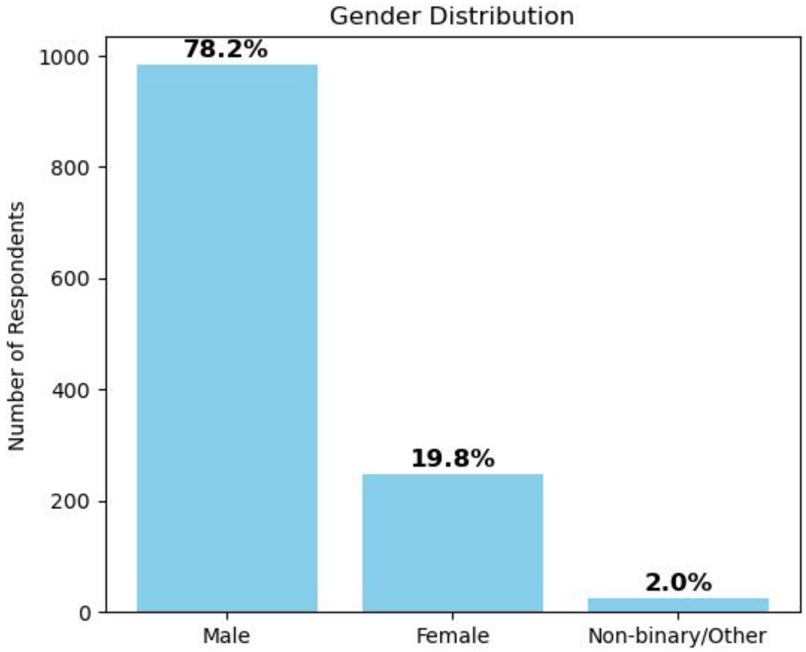
Stigma index correlation: higher stigma → lower disclosure.

Demographics (age, gender, company size): small differences, but culture/benefits more predictive.

Target Distribution (Disclosure Yes/No)

Chart type: Bar chart

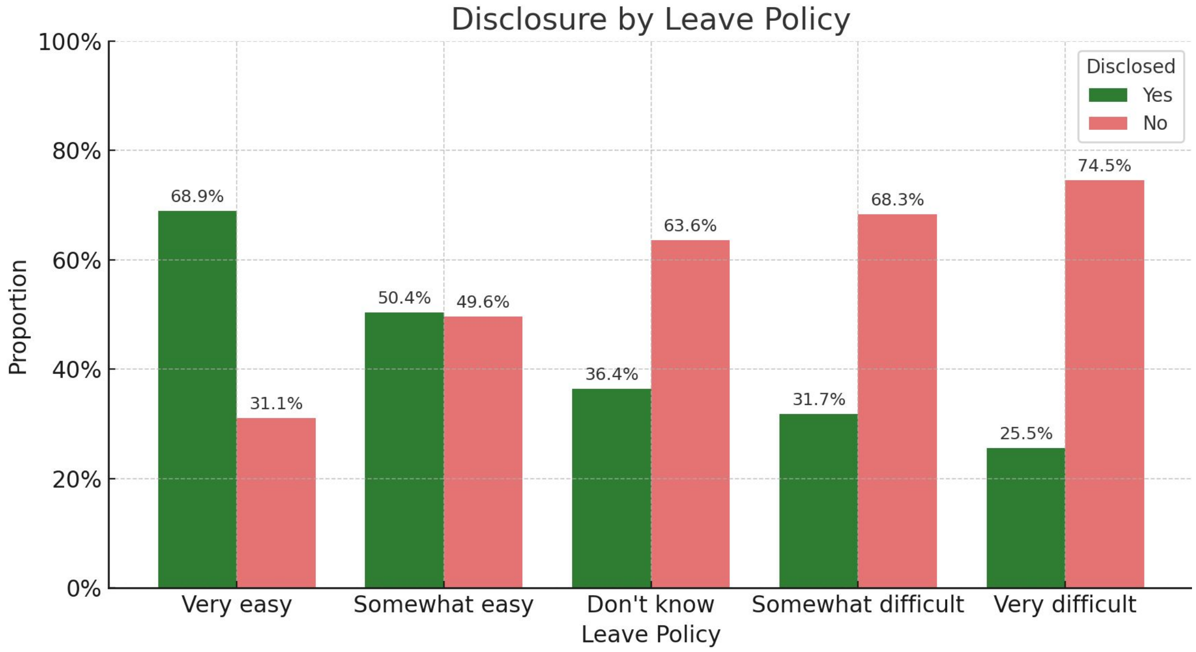
Caption: “Disclosure is balanced (~50% yes vs. 50% no), making classification feasible.”



Leave Policy vs Disclosure

Grouped bar chart: disclosure rate across leave policy categories (very easy → very difficult).

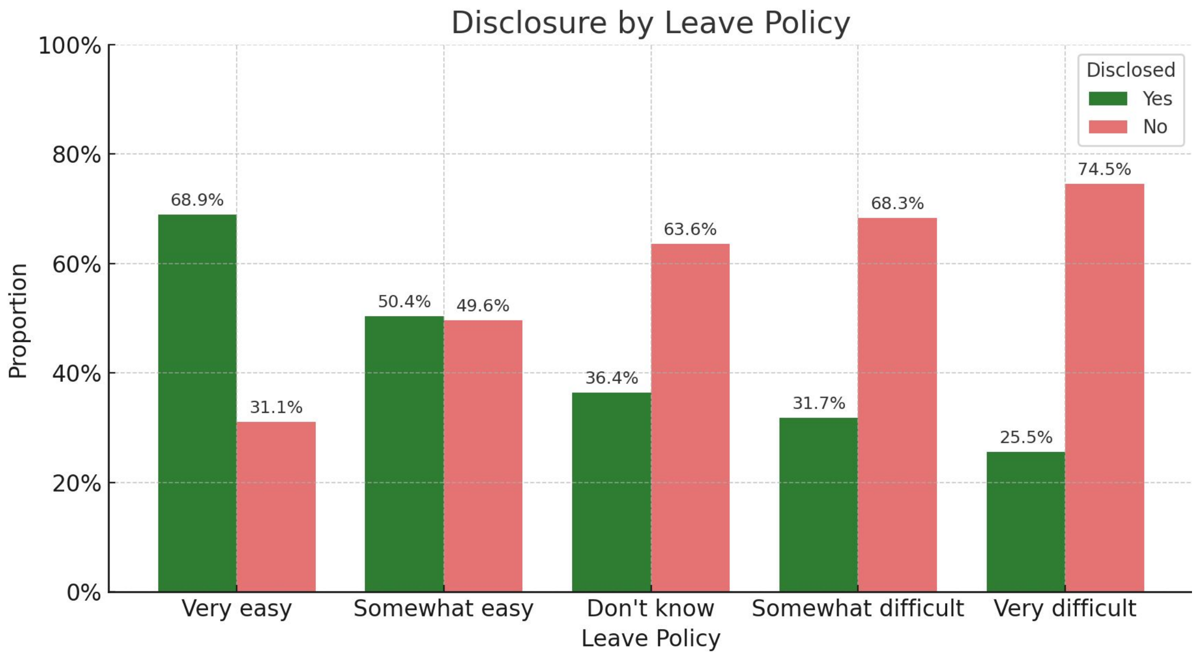
Clear link: easier leave → higher disclosure.



Anonymity vs Disclosure

Chart type: Grouped bar chart

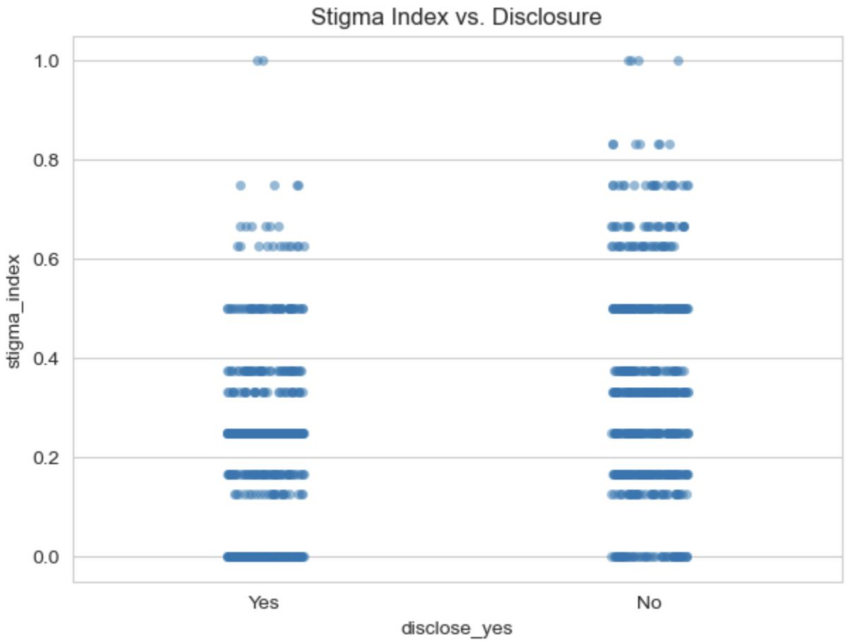
Caption: “Lack of anonymity reduces disclosure; safe channels increase openness.”



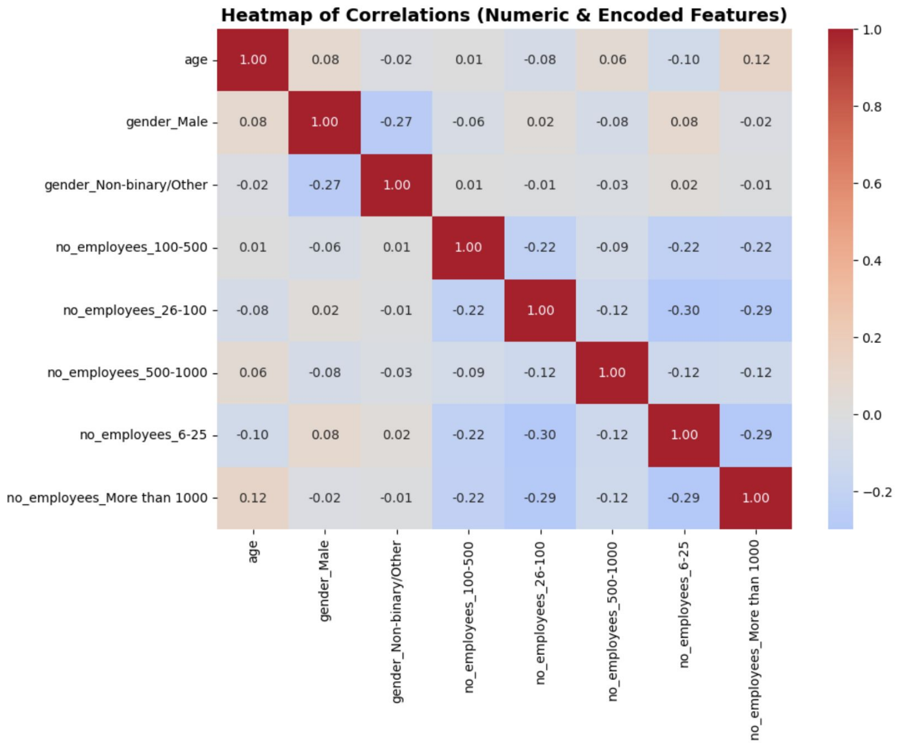
Stigma Index vs Disclosure

Chart type:Strip plot (categorical scatter/jitter) of stigma_index by disclosure (“Yes” vs “No”).

Caption: “Workers who say **No** to disclosure show **higher stigma scores** overall—dots cluster higher than the **Yes** group (mean ≈ 0.58 vs 0.37)—supporting: higher stigma → lower disclosure.”



Demographics (age, gender, company size): small differences, but culture/benefits more predictive.



Modeling

Methods tried: Logistic Regression, Random Forest (with balanced class weights).

Why Logistic Regression?

- Interpretable (stakeholders can act on coefficients).
- Performed best (ROC-AUC 0.806 on test).

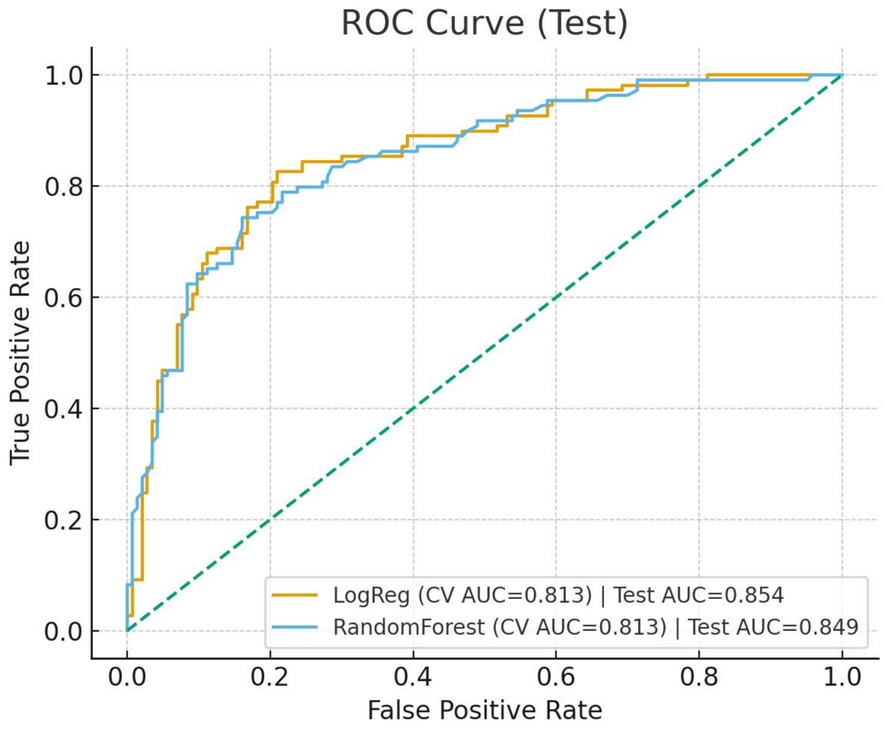
Validation: Stratified 80/20 split, 5-fold CV on training.

Modeling Approach & Validation

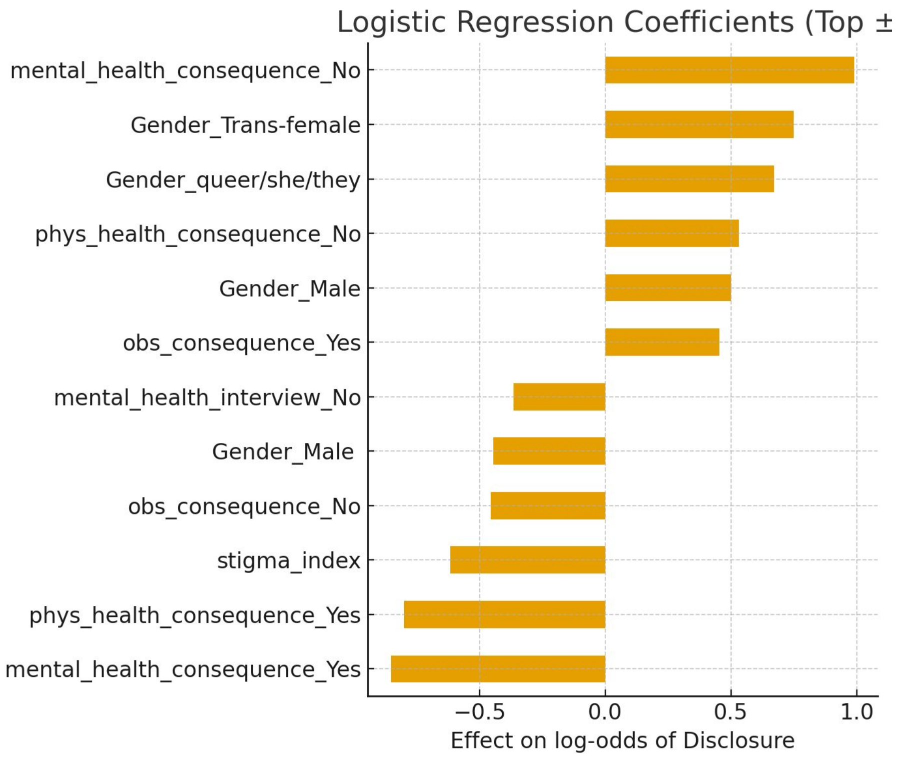
Goal: Predict disclosure (Yes/No).

Models tried: Logistic Regression, Random Forest (**class_weight='balanced'**).

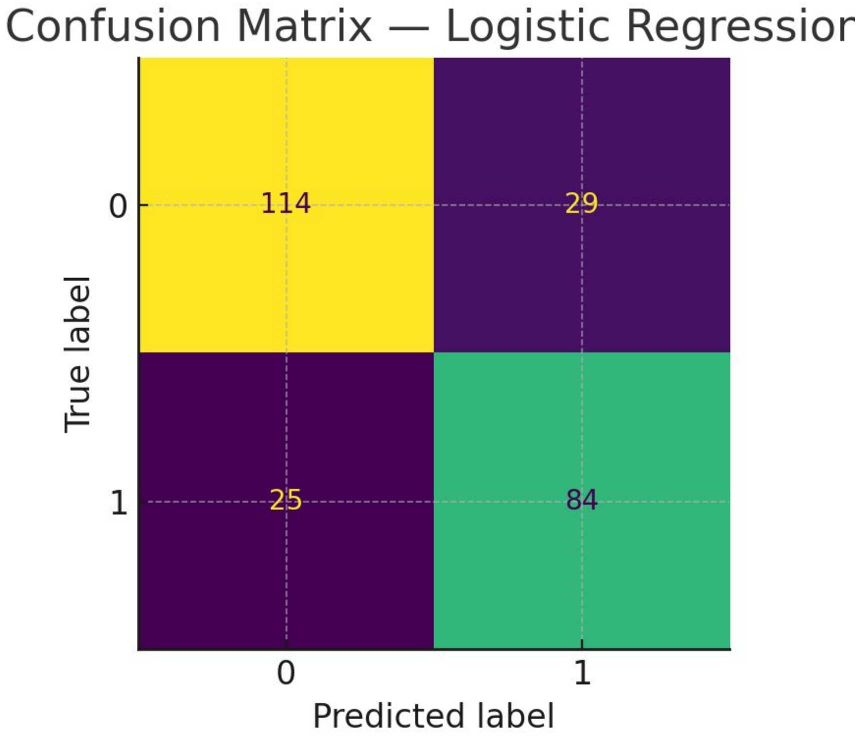
ROC Curve (Test) — LR vs RF



Logistic Regression — Top ± Coefficients



Confusion Matrix — Logistic Regression (Test)



Text metrics summary

	model	cv_auc	cv_f1	test_auc	test_f1	test_precision	test_recall	test_accuracy
0	LogReg	0.724	0.638	0.795	0.687	0.645	0.734	0.710
1	RF	0.679	0.576	0.668	0.562	0.584	0.541	0.635

- LogReg achieved the best generalization: **AUC ~0.80, F1 ~0.69**, with higher precision and recall than RF.”

How well does the model work?

- Logistic Regression generalizes well (Test ROC-AUC = 0.806; Balanced Acc ≈ 0.75).

ROC curve (test) with AUC label (0.806) and a faint diagonal baseline.

Mini metric strip (horizontal badges):
AUC 0.806 • F1 ≈ 0.69 • Precision ≈ 0.65 • Recall ≈ 0.73 • BalAcc ≈ 0.75

One-line note: "80.6% probability the model ranks a true discloser above a non-discloser."

What drives disclosure (and what to do)?

Reduce stigma: leadership messaging, MH training.

Clarify leave: simple, documented path (no manager friction).

Guarantee anonymity: confidential channels.

Visible benefits: advertise counseling & care options.

Recommendations

Stigma (strongest ↓): higher stigma → lower disclosure → Normalize MH talk: leadership messages, manager training, and peer stories.

Leave policy (↑): easier leave → higher disclosure → Simplify and publish steps; pre-approve/streamline MH time-off.

Anonymity (↑): safe channels → higher disclosure → Provide confidential/anonymous reporting & support (EAP, third-party) with no manager gatekeeping.

Benefits & care (↑, moderate): visible support → higher disclosure → Centralize and promote counseling/care options; remind regularly in onboarding and cadence.

Conclusion

Model works: Test AUC ≈ **0.81**.

Levers: stigma ↓, leave ↑, anonymity ↑, benefits ↑.

Do now: manager training + clear MH-leave flow + anonymous channels + benefits reminders.

Measure quarterly: disclosure rate, EAP use, retention.