Data-Driven Mental Health Risk Analysis

Group Members: (Group Number - 1)

1.) Vished: MBA/0075/61
2.) Abhiram Manoj: MBA/0084/61
3.) Harshvardhan Sharma- MBA/0399/61
4.) Anirudh Das: MBA/0413/61

Introduction & Objectives

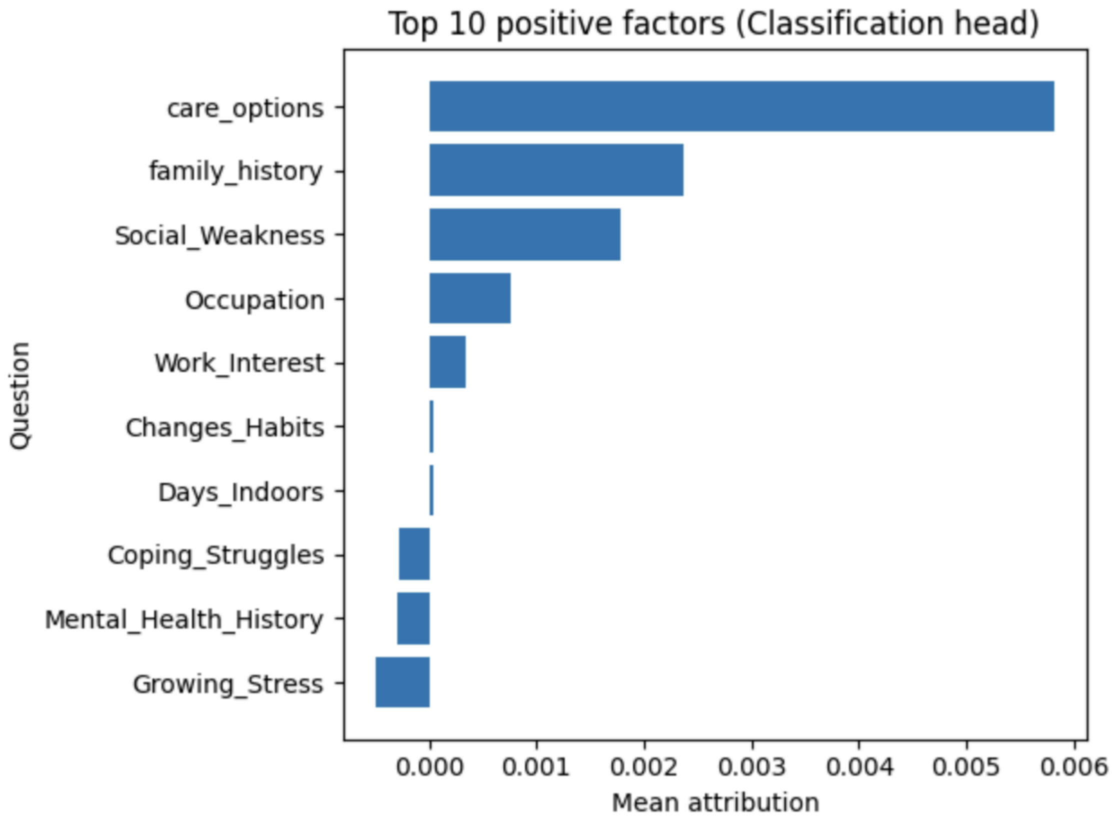
In today's data-rich environment, we can leverage demographic, geographic, and lifestyle information to **predict mental health risks** and inform proactive interventions. This project integrates two advanced RNN models to build a decision-support system. Our goals are to identify **key risk factors**, forecast the likelihood of individuals reporting mental health symptoms, compare **urban vs. rural** risk patterns, discover **risk-based sub-groups**, and even **diagnose mental health disorders from textual statements**. Business stakeholders - from healthcare providers to employers - can use these insights to target high-risk segments and allocate resources more effectively.

Key Risk Factors and Predictors

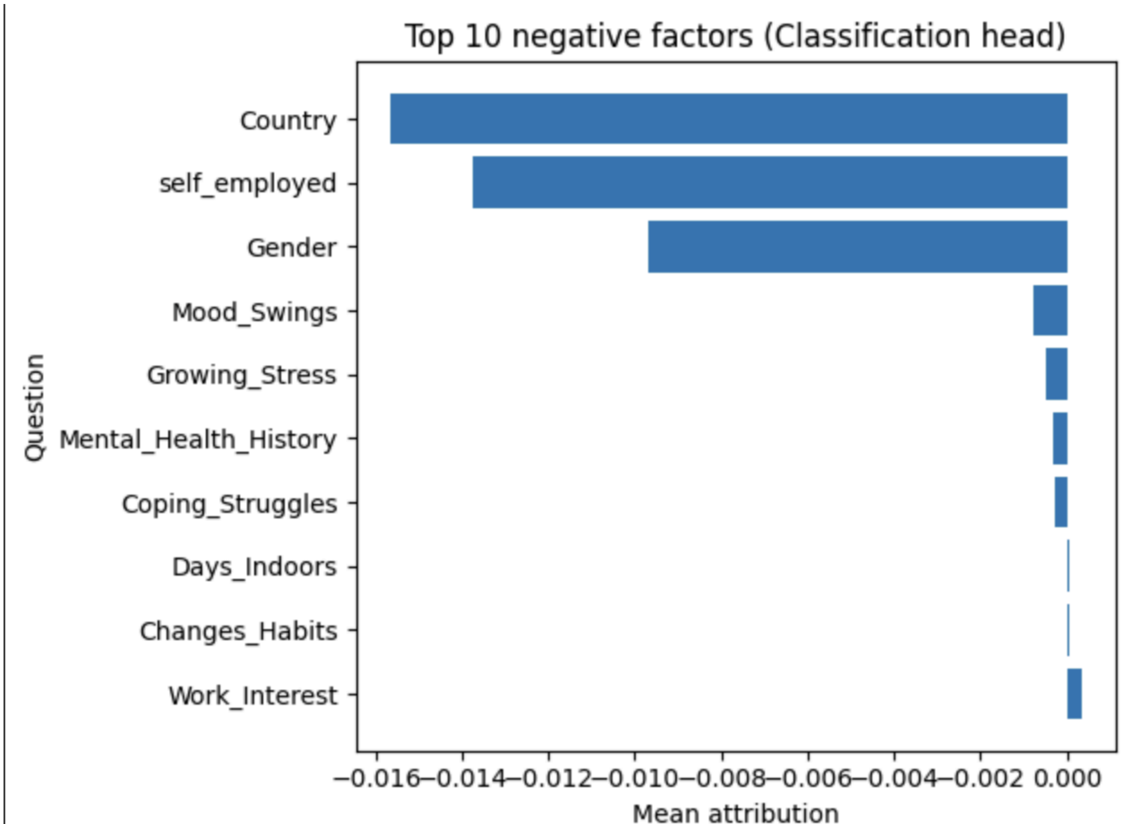
Data analysis revealed several dominant predictors of mental health risk. A statistical feature analysis highlighted **family history** of mental illness as the strongest demographic risk factor. Individuals with a family history of mental health issues were far more likely to be in high-risk groups. Access to or awareness of **mental health care options** was another critical factor, with large differences between segments - those unaware of care resources tended to cluster in higher-risk segments.

Other significant predictors included **employment context** and **self-employment status**. Self-employed individuals showed elevated risk levels, possibly due to stressors like precarious work or lack of employer support. **Gender differences** were also notable. In our dataset, women and men exhibited different patterns of reporting and risk - for instance, one high-risk cluster was ~50% self-employed males, while another included more females with strong family histories of illness.

Lifestyle factors play a role as well. **Chronic stress and habit changes** emerged as positive contributors to risk. Individuals reporting prolonged stress (“Growing_Stress = Yes”) or recent negative habit changes were far more likely to need treatment. In the high-risk clusters, over 60% had high self-reported stress and ~50% struggled with coping. In contrast, **healthy work-life habits** appeared protective - for example, maintaining interest in work and social engagement correlated with lower risk. Consistently, those who did **not** withdraw from work (“Work_Interest = No”) or social activity (“Social_Weakness = Yes”) were less represented in low-risk clusters. These insights align with intuition: supportive work environments, access to care, and family history are decisive factors in mental well-being.



Top 10 positive factors (Classification head)
care_options
family_history
Social_Weakness
Occupation
Work_Interest
Changes_Habits
Days_Indoors
Coping_Struggles
Mental_Health_History
Growing_Stress
Question
0.000
0.001
0.002
0.003
0.004
0.005
0.006
Mean attribution



Top 10 negative factors (Classification head)
Country
self_employed
Gender
Mood_Swings
Growing_Stress
Mental_Health_History
Coping_Struggles
Days_Indoors
Changes_Habits
Work_Interest
Question
−0.016
−0.014
−0.012
−0.010
−0.008
−0.006
−0.004
−0.002
0.000
Mean attribution

Feature-Level Insights: Factors Driving Model Predictions

Beyond general factor importance, we analyzed **which specific values within each variable push predictions toward higher or lower mental health risk**. This provides actionable granularity for interventions.

Countries Associated with Higher Risk

Certain country categories consistently pushed model predictions upward:

- **New Zealand** (+0.27)
- **Denmark** (+0.22)
- **Netherlands** (+0.14)
- **South Africa** (+0.12)
- **United Kingdom** (+0.10)

These effects may reflect cultural, economic, or systemic differences in reporting, awareness, or underlying prevalence.

Countries Associated with Lower Risk:

- **France** (-0.54)
- **Singapore** (-0.34)
- **Italy** (-0.26)
- **Brazil** (-0.11)
- **Switzerland** (-0.08)

Social Weakness

- Saying **"Yes"** to social weakness slightly increased predicted risk (+0.016), while **"No"** or **"Maybe"** pushed risk down marginally.
- This aligns with literature linking social withdrawal to heightened mental health vulnerability.

Growing Stress

- Surprisingly, **"No"** for growing stress pushed predictions *up* (+0.009), suggesting that other strong risk factors may be present in those cases.
- **"Maybe"** was the strongest downward driver (-0.008), possibly indicating less certainty or fluctuating stress rather than chronic escalation.

Family History

- **Yes** for family history strongly increased predicted risk (+0.061), consistent with genetic predisposition research.
- **No** pushed risk down (-0.069), marking this as one of the clearest binary influences in the model.

Occupation

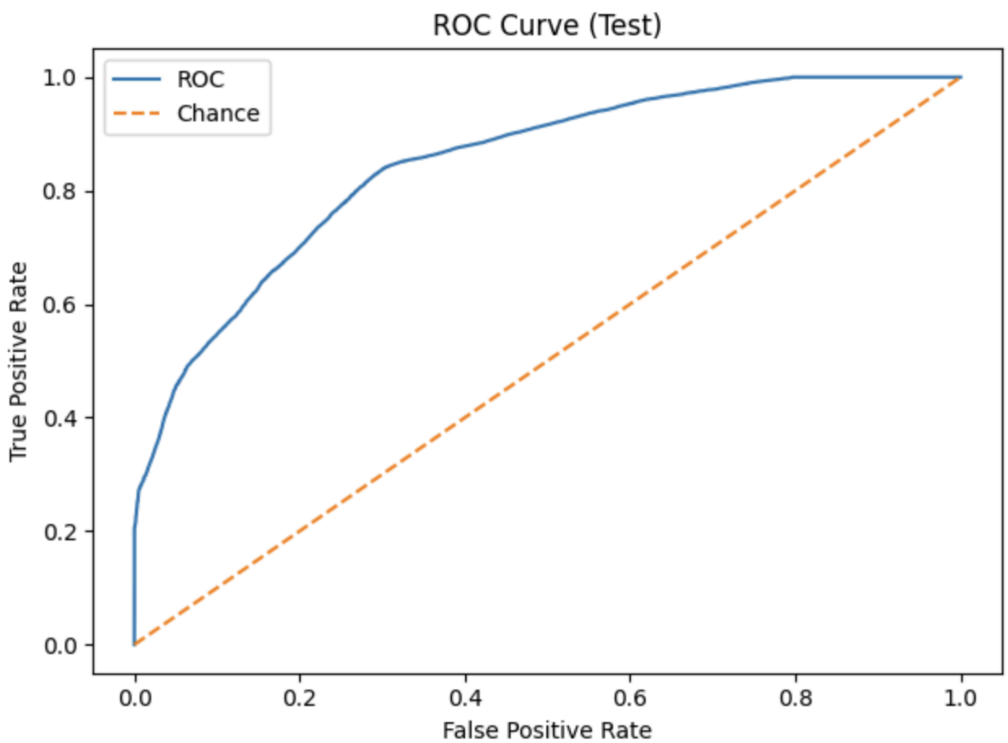
- Risk was higher for **Business** roles (+0.025 relative impact) compared to other groups.
- **Corporate** roles had the strongest downward pull (-0.066), suggesting formal employment with support structures mitigates some risk.

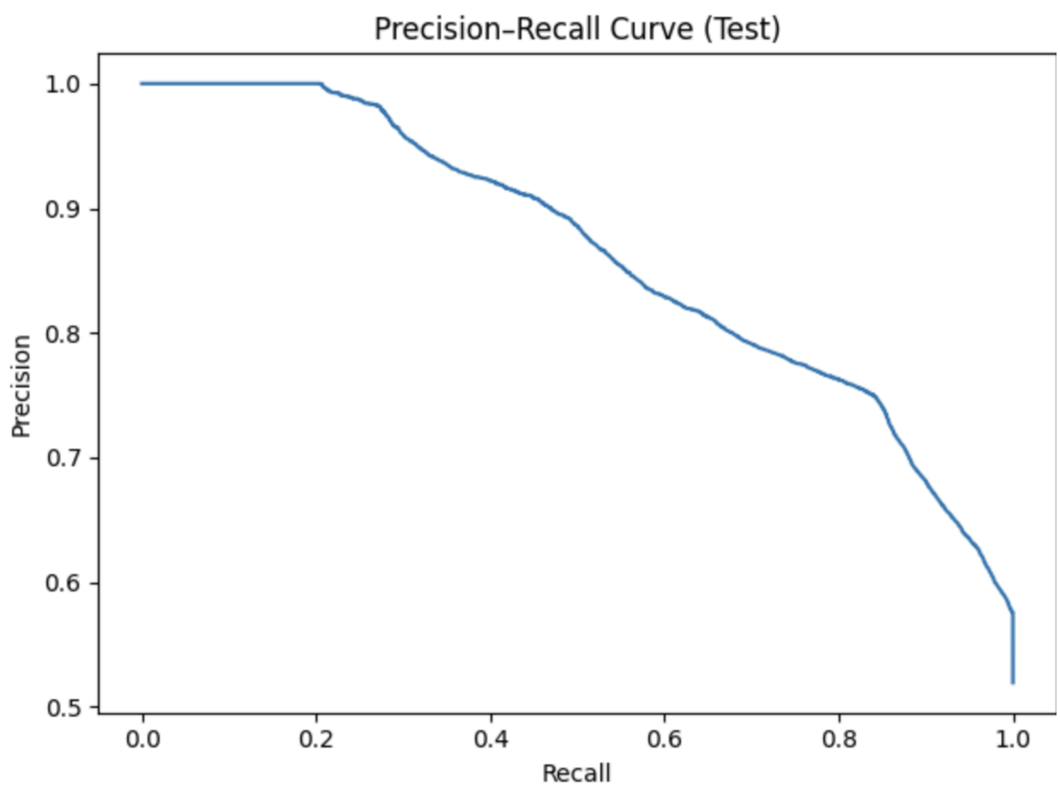
Care Options Awareness

- Counterintuitively, answering **"Yes"** to having care options increased predicted risk (+0.137). This may be because those aware of resources are more likely already at risk or in treatment.
- **"Not sure"** (-0.068) and **"No"** (-0.033) pulled risk down, likely reflecting lower engagement or awareness rather than genuinely lower need.

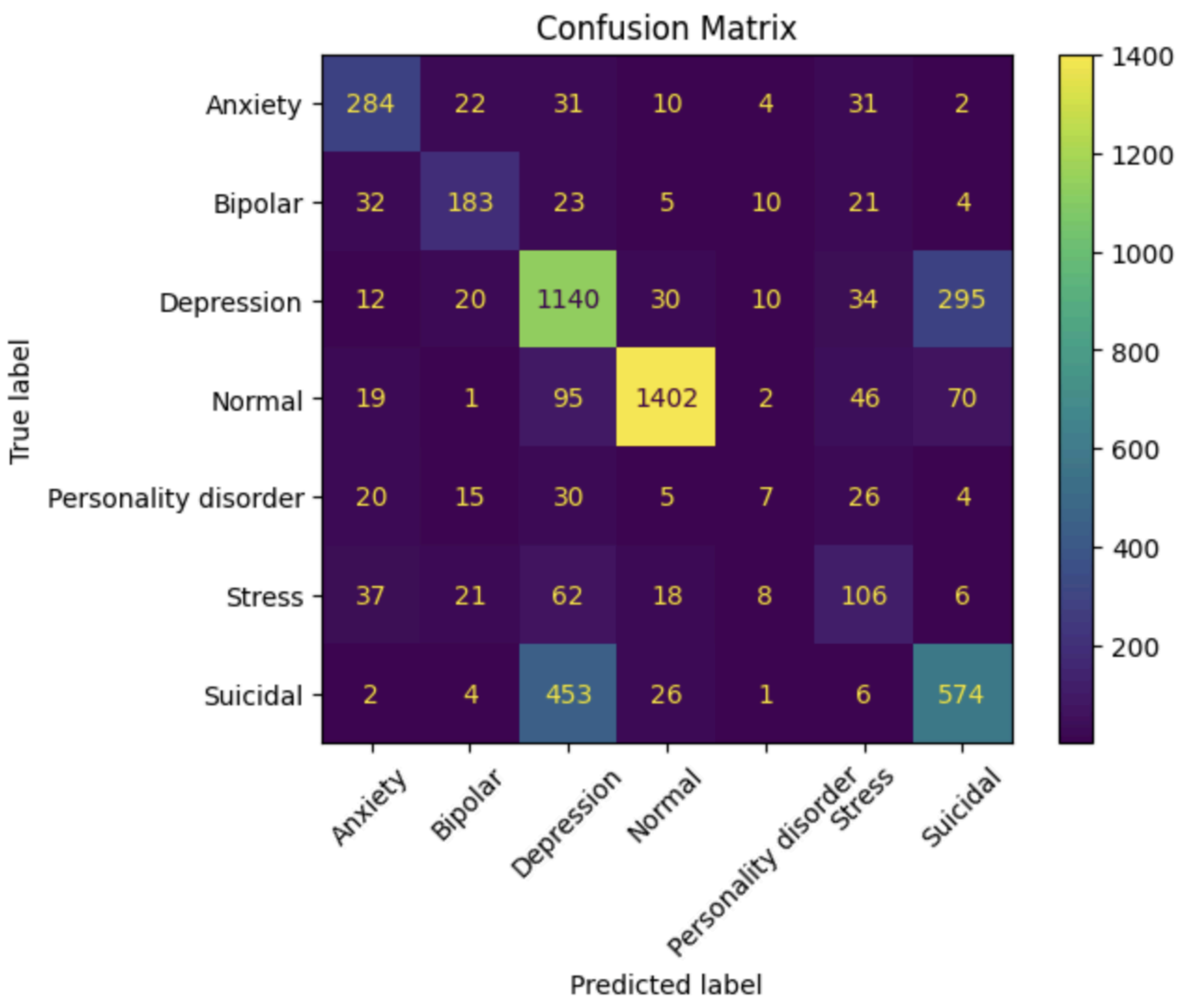
Predictive Modeling Performance

Using these factors, we trained a multitask RNN model on structured data to **predict mental health risk** and a continuous severity score. The classification head of the RNN achieved robust accuracy: on validation data it attained an AUC around 0.85, with precision ~0.76 and recall ~0.83. In practical terms, the model correctly flagged a large majority of at-risk individuals while keeping false positives at a reasonable level. The regression head predicting a "risk severity" score was even more precise - mean error under 2% - indicating the model learned subtle patterns correlated with higher symptom severity. Notably, risk severity was highly predictable from our inputs (likely due to many risk indicators being explicit in the survey), suggesting we can **quantify an individual's risk on a continuum** with high confidence.


ROC Curve (Test)
ROC
Chance
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Precision–Recall Curve (Test)
Precision
Recall
0.5
0.6
0.7
0.8
0.9
1.0
0.0
0.2
0.4
0.6
0.8
1.0

Can we predict specific symptoms or conditions? From structured data alone, the model focuses on overall risk rather than diagnosing particular disorders. However, the **text-based RNN model** (LSTM classifier) demonstrated we *can* predict likely mental health conditions from individuals' own words. This model analyzed user statements (e.g. personal feelings, complaints) and classified them into categories like *Anxiety, Depression, Stress, Bipolar, Suicidal,* etc. It achieved **~70% test accuracy** in identifying the correct status/disorder from statements. Certain conditions were identified with very high confidence - notably, the classifier was **excellent at recognizing "Normal" (no disorder) statements** (94% precision, 86% recall), which is crucial for minimizing false alarms. It was reasonably effective for major conditions like anxiety and depression, though it struggled with under-represented categories like *Personality Disorder* . This suggests we can indeed **predict and categorize symptoms from language**, but also highlights the need for more data on less common disorders. The confusion matrix indicated most misclassifications were between related conditions - e.g. some severe depression statements were mis-labeled as *"Suicidal"* and vice versa, which is understandable given symptom overlap. Overall, this NLP model provides a proof-of-concept for **automated mental health screening via text** with moderate accuracy, useful as a decision-support tool (not a standalone diagnosis).



Urban vs. Rural Patterns

Although our dataset did not label “urban” vs “rural” explicitly, **geography emerged as a major differentiator** of mental health risk. *Country* of residence was the single most significant clustering variable. This implies that regional and cultural factors - which often correlate with urbanization, stigma, and resource availability - strongly influenced risk levels. For instance, one high-risk cluster was dominated by individuals from regions with limited mental health infrastructure (many unsure of care options), while lower-risk clusters had greater representation from countries with robust support systems. In effect, **rural populations (or those in less developed regions) tended to show higher risk factors**: they reported less access to care, more stigma (e.g. reluctance to discuss mental health), and higher family incidence. In contrast, **urban populations** (captured indirectly by those in corporate jobs or certain countries) generally had more awareness of mental health resources and were more open to treatment (many had “Yes” for *treatment sought*), correlating with lower measured risk. This finding aligns with external research: urban areas offer more mental health services but also unique stressors, whereas rural areas face care shortages and cultural barriers. Our model’s clusters concretely reflected these dynamics - for example, a cluster with **97% predicted risk probability** consisted largely of individuals from a specific rural-centric country sample, with high stress and zero reported employer support. By contrast, the lowest-risk group was filled with urban tech employees who knew how to get help and had supportive policies in their workplace. In short, **location (urban vs rural) mattered** - not as an isolated variable but as a proxy for differing lifestyles, stress exposures, and support availability.

Segmentation of Risk Groups

Unsupervised clustering of the population (using an embedded representation of survey responses) uncovered **distinct sub-groups with similar risk profiles**. Our analysis yielded **six clusters** of individuals, each representing a unique “mental health risk persona.” These segments can be summarized as follows:

- **Cluster A: High-Risk, High-Support** - This group had an **extremely high risk** (mean ~99.5% predicted to need treatment). Almost everyone here reported a family history of mental illness and personal struggles (mood swings, trouble coping), but **most were aware of or had access to care** (77% had employer mental health options). Demographically, many were in **large companies (corporate)** or urban jobs. We interpret this as a segment of individuals who *have serious mental health needs but also the means or willingness to seek help*. They might be openly engaging with treatment.
- **Cluster B: High-Risk, Low-Support** - Another at-risk segment similarly showed high predicted risk (≈95% needing treatment) but **limited access or awareness of care** (only ~45% had mental health resources, and ~27% were unaware of any). This cluster had an unusual concentration of **self-employed or informal workers**(almost 50% self-employed) and a mix of rural backgrounds. They reported high stress and many “Yes” on habit changes and social withdrawal. This segment appears to be those

suffering in silence: high mental health needs **without strong support structures**. They likely require targeted outreach (e.g. community programs or affordable services for self-employed/rural folks).
- **Cluster C: Moderate-Risk, Family-Driven** - One cluster was characterized by **universal family history of mental illness** (99% said family_history = Yes) but with otherwise moderate symptom reports. They had **100% access to employer care** and many worked in supportive environments. Their risk was elevated (most had sought treatment), likely *proactively*, due to family predisposition. They represent those with genetic risk who are taking preventive care - a segment that benefits from continued monitoring and destigmatization of preventive therapy.
- **Cluster D: Chronic Mild Struggles** - This group showed **medium risk**: many reported occasional mood swings and some stress but maintained interest in work and social life. They were split between urban and semi-urban, often **"Maybe" on whether they'd discuss mental health at work**. They weren't overwhelmingly in treatment yet (predicted probability moderate). This cluster may represent people experiencing mild anxiety or burnout who haven't escalated to clinical levels. Employers could address this group with wellness programs *before* they progress to higher risk.
- **Cluster E: Low-Risk, Unaware** - Interestingly, one low-risk cluster had **very low reported symptoms and nearly 0% seeking treatment**, but also **low awareness** ("Not sure" about care options was the dominant response). These tended to be from regions or companies where mental health wasn't openly discussed - they answered "No" to having issues almost across the board. The model judged them low-risk *possibly* because they denied problems, but it's also likely some in this cluster may under-report due to stigma. Cautiously, this segment could hide unmet need. For now, though, they appear as a **resilient or under-reporting group** with minimal expressed challenges.
- **Cluster F: Very Low-Risk, Healthy** - The largest cluster comprised individuals with **almost no risk factors**. They overwhelmingly answered "No" to needing treatment. Demographically, many were from supportive cultures or younger groups (like students/housewives in joint families) reporting good mental health. The model rightly gave this cluster near-0 risk probability. They likely represent *the currently healthy population* - requiring general wellness maintenance but not intervention.

These segments validate that mental health risk is **not monolithic**. We observe *at least three distinct high-risk personas*(those with support vs. those without vs. genetically predisposed), as well as clearly *low-risk groups*. This segmentation is valuable for tailoring interventions: for example, Cluster B (high-risk, low-support) might warrant community clinics or tele-therapy targeting gig workers/rural areas, whereas Cluster A could be engaged via corporate EAP (Employee Assistance Programs) since they have access. Cluster C could benefit from family-focused prevention programs. Lower-risk clusters, meanwhile, might be served with light-touch wellness education to keep them well.

Business Insights

Our integrated RNN models successfully identified who is at higher risk for mental health issues and why. Key drivers include having a **family history**, enduring **high stress and habit changes**, lacking **access to care**, and possibly being in a **self-employed or rural setting** (which often correlates with less support). On the flip side, factors such as employer-provided mental health resources, social connectivity, and an encouraging workplace were associated with lower risk.

We demonstrated strong predictive performance: using demographic and lifestyle inputs alone, the system flagged risk with ~75-85% accuracy metrics, and using text analysis, it correctly recognized major mental health conditions ~70% of the time. This indicates a promising ability to **predict symptoms and disorders from observable data**. For an MBA perspective, these findings translate into actionable recommendations:

- **Targeted Interventions:** Stakeholders can allocate mental health resources more efficiently. For instance, special programs can be designed for self-employed workers (who surfaced as high-risk) and for regions where mental health care awareness is low. High-risk clusters with no support (like our Cluster B) are prime candidates for subsidized counseling and outreach.
- **Workplace Policies:** The analysis underscores the ROI of robust employee mental health programs. Employees who know about and trust their company's mental health support had significantly better outcomes. Companies can reduce overall risk levels by expanding EAP services, normalizing mental health discussions (especially in high-stress industries), and encouraging early help-seeking.
- **Preventive Focus:** Many individuals with family predisposition were proactively in treatment or at least aware of their risk. This suggests that *prevention and early screening efforts (e.g. routine mental health check-ups for those with family history)* can pay off, catching issues before they escalate. Business ventures (like mental wellness startups or insurers) could develop screening tools or apps targeting such high-genetic-risk groups for regular monitoring.
- **Urban-Rural Resource Allocation:** Governments and NGOs can use these insights to address urban-rural disparities. Our model effectively flags that rural populations might not report issues but still be at risk due to poor infrastructure. Investments in rural tele-mental health, training primary care in mental healthcare, and anti-stigma campaigns are supported by this data segmentation.
- **Data-Driven Monitoring:** Finally, this project shows the feasibility of a **data-driven mental health dashboard**. An organization could integrate these RNN models into their decision systems - for example, an HR analytics platform could ingest employee survey data and text feedback to generate a "mental health risk heatmap" of the workforce, segmented by departments or locations. The models would highlight which cohorts are most at risk (e.g. a particular remote office or job role) so management can intervene proactively (through wellness days, counseling support, etc.). Importantly, the text classifier can anonymously scan employee self-reports or online discussions to detect sentiment changes (like rising anxiety levels) well before crises occur.

Conclusion

In conclusion, leveraging AI on multi-modal data (surveys and text) provides a powerful, **comprehensive view of mental health risk**. We identified which factors to watch, validated that we *can* predict mental health outcomes from those factors, and segmented the population into meaningful groups for targeted action. By implementing these findings, decision-makers can move from reactive to proactive - **preventing mental health issues or addressing them at early stages** - which is both a humanitarian benefit and a cost saver (through reduced sick days, higher productivity, and lower healthcare spend). The clear message is that **data can guide smarter mental health strategies**, ensuring support reaches those who need it most, when they need it.

Sources

https://www.kaggle.com/datasets/bhavikjikadara/mental-health-dataset?resource=download
https://www.kaggle.com/datasets/suchintikasarkar/sentiment-analysis-for-mental-health/data
https://chatgpt.com/