Combatting Depression In NUS

Group 2

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Brief Overview Of Depression

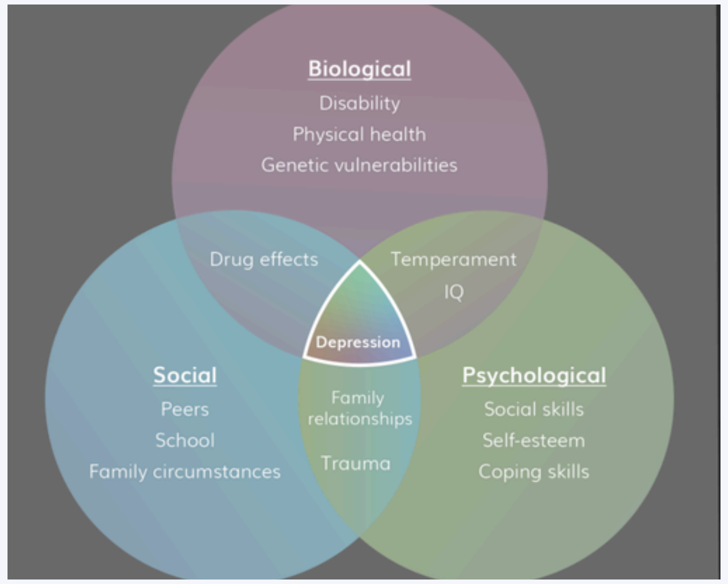
- Depression is a common mental health condition characterized by persistent low mood, loss of interest, fatigue and difficulty functioning in daily life.

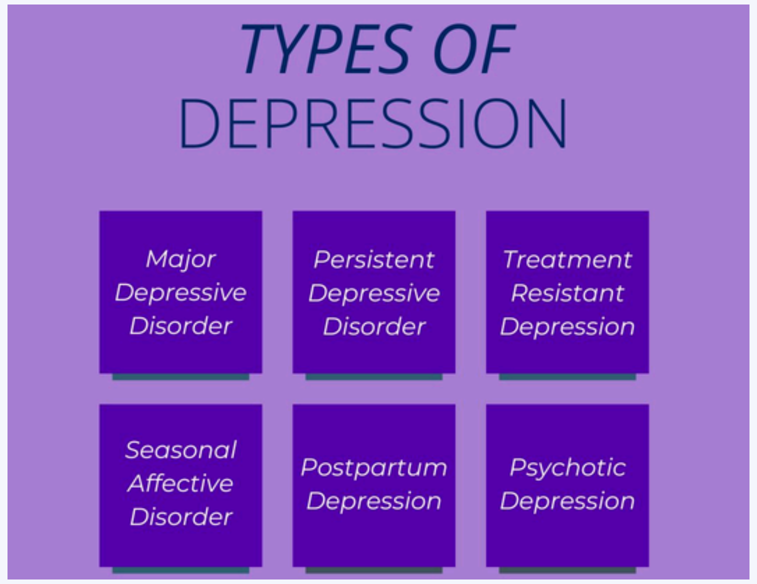
- It affects thoughts, emotions, behaviour and physical health. It is more than just temporary sadness.

- Depression results from a combination of biological, psychological and social factors. Prolonged stress and lack of support can increase vulnerability.

- According to WHO, 3.8% of the global population (~280 million people) experience depression. In Singapore, depression rates are higher at 6 - 7%.

- Categories most affected by depression include young adults (15 to 29 years old) and women





Why Is Depression Concerning?

Leading Cause Of Disability Worldwide Depression significantly reduces quality of life and functioning across personal, academic and social domains	**Increases Risk Of Suicide** Depression is a major risk factor for suicidal thoughts and behaviors, particularly among young people
Impairs Physical Health Depression is linked to negative physical outcomes, including heightened risk for cardiovascular disease and chronic conditions	**Economic And Productivity Burden** Depression contributes to a loss of productivity and increased healthcare costs globally

Our Problem Statement

"University Healthcare Centre (UHC) counsellors face challenges in providing continuous and timely support to NUS students experiencing depression, due to unavoidable intervals between counselling sessions.

These gaps in monitoring and intervention may contribute to delayed detection of symptom deterioration, increasing the risk of relapse or worsening depressive episodes."

National University of Singapore

3 Jobs to be Done

Detect Deterioration Early

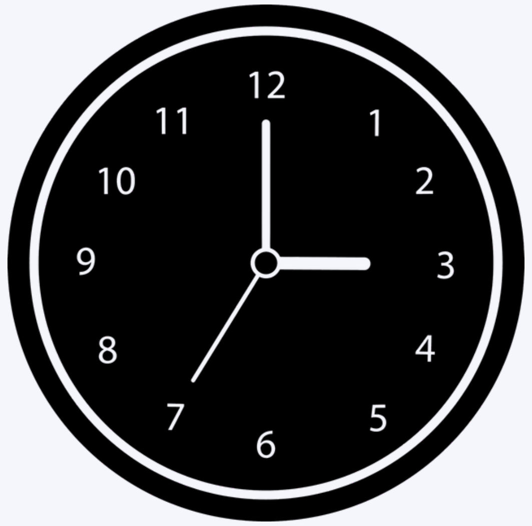
When a student's depressive symptoms worsen between sessions, I want to detect early warning signs so that intervention can occur without his / her condition deteriorating further.

Prioritize High-Risk Students

When counsellors manage multiple cases, I want to identify which students require urgent attention so that limited session capacity can be delegated effectively, without providing insufficient support for at-risk students.

Monitor Trends at Population Level

When UHC evaluates service demand, I want to identify trends in symptom severity and relapse patterns so that resource allocation and policy decisions can be adjusted, without compromising the welfare of students.



Datasets We Considered

- **Target Population:** Our problem statement focuses on NUS students and UHC counselling services.
- **Data Limitation:** Data on depression prevalence and counselling utilization among NUS students is confidential and may not be publicly accessible.
- **Current Approach:** Use broader Singapore population data with age-based filtering to approximate the university-aged demographic (15-24 years).

NUS
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No Data?

Fret not!
Zoom out!

Datasets We Considered

IHME Global Burden of Disease Depressive-disorders Dataset

- Provides nationally representative estimates of depression prevalence in Singapore.
- Disaggregated by age group, sex, and both percentage rates and absolute case counts.
- By extracting data for the 15–29 age range, we can estimate how common depression is among university-aged youths in Singapore.

population_group	measure	location	sex	age	cause	metric	year	val	upper	lower
All Population	Prevalence	Singapore	Male	15-19 years	Depressive disorders	Number	2000	2427.700826	3124.489839	1904.421655
All Population	Prevalence	Singapore	Female	15-19 years	Depressive disorders	Number	2000	2483.994263	3180.195073	1991.948197
All Population	Prevalence	Singapore	Both	15-19 years	Depressive disorders	Number	2000	4911.695089	6313.030076	3902.623496
All Population	Prevalence	Singapore	Male	15-19 years	Depressive disorders	Percent	2000	0.017408273	0.022347324	0.013849496
All Population	Prevalence	Singapore	Female	15-19 years	Depressive disorders	Percent	2000	0.020593509	0.026206822	0.016364438
All Population	Prevalence	Singapore	Both	15-19 years	Depressive disorders	Percent	2000	0.018885142	0.024239139	0.015037481
All Population	Prevalence	Singapore	Male	20-24 years	Depressive disorders	Number	2000	2936.81746	3718.449193	2296.789439

Future Dataset Considerations

Aim to obtain additional datasets capturing:

- Counselling utilization/frequency
- Effectiveness of counselling sessions

Use comparable international or university-level counselling datasets as benchmarks.

Conduct our own student surveys in NUS

Data Analysis and Exploration

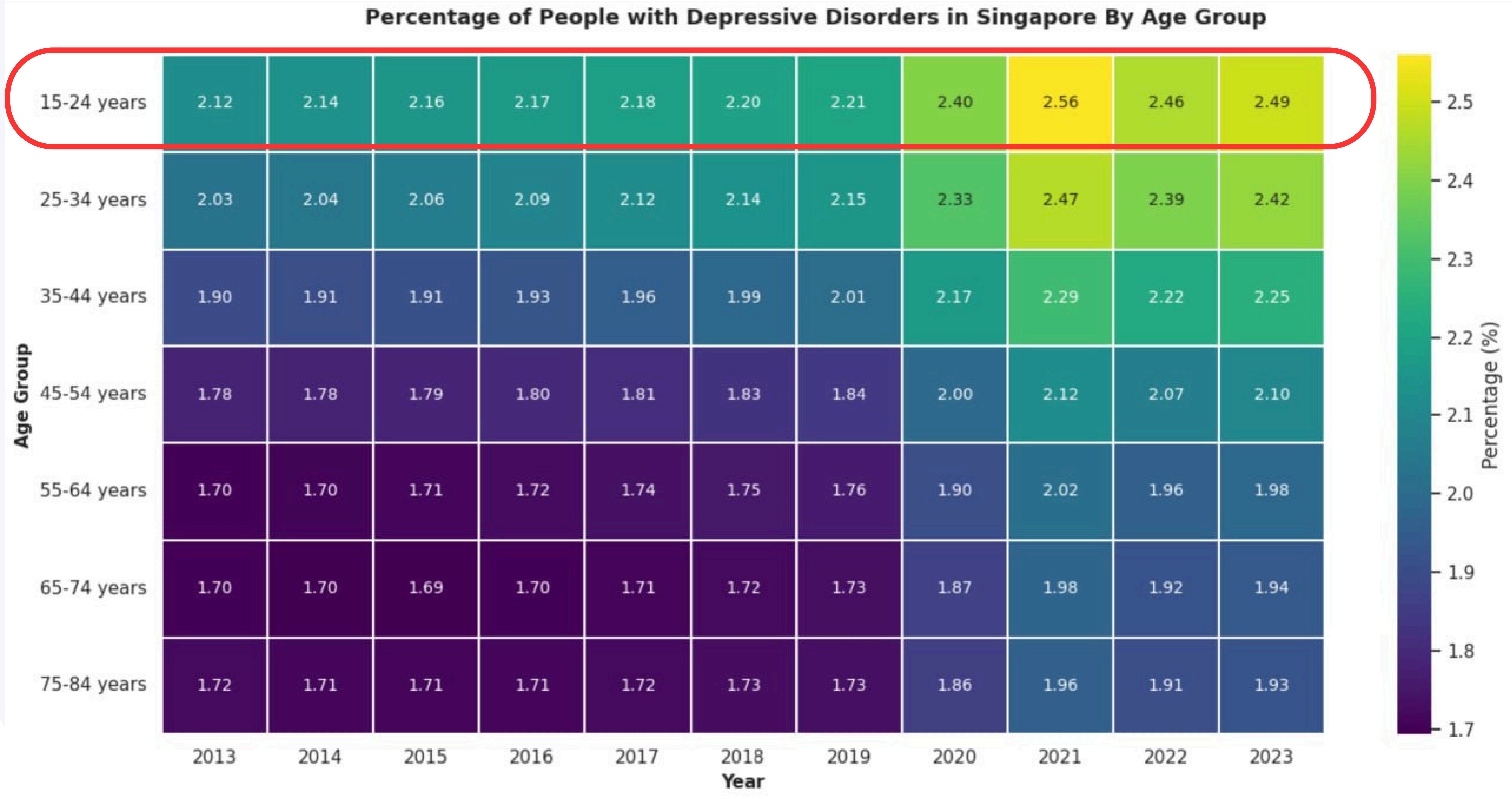
Demographic Patterns: Age

Observation:

- Individuals aged 15-24 consistently report the highest rates of depression compared to other age groups

Interpretation:

- 15-24 age group represents a high-risk segment
- This age range overlaps with university student populations



Data Analysis and Exploration

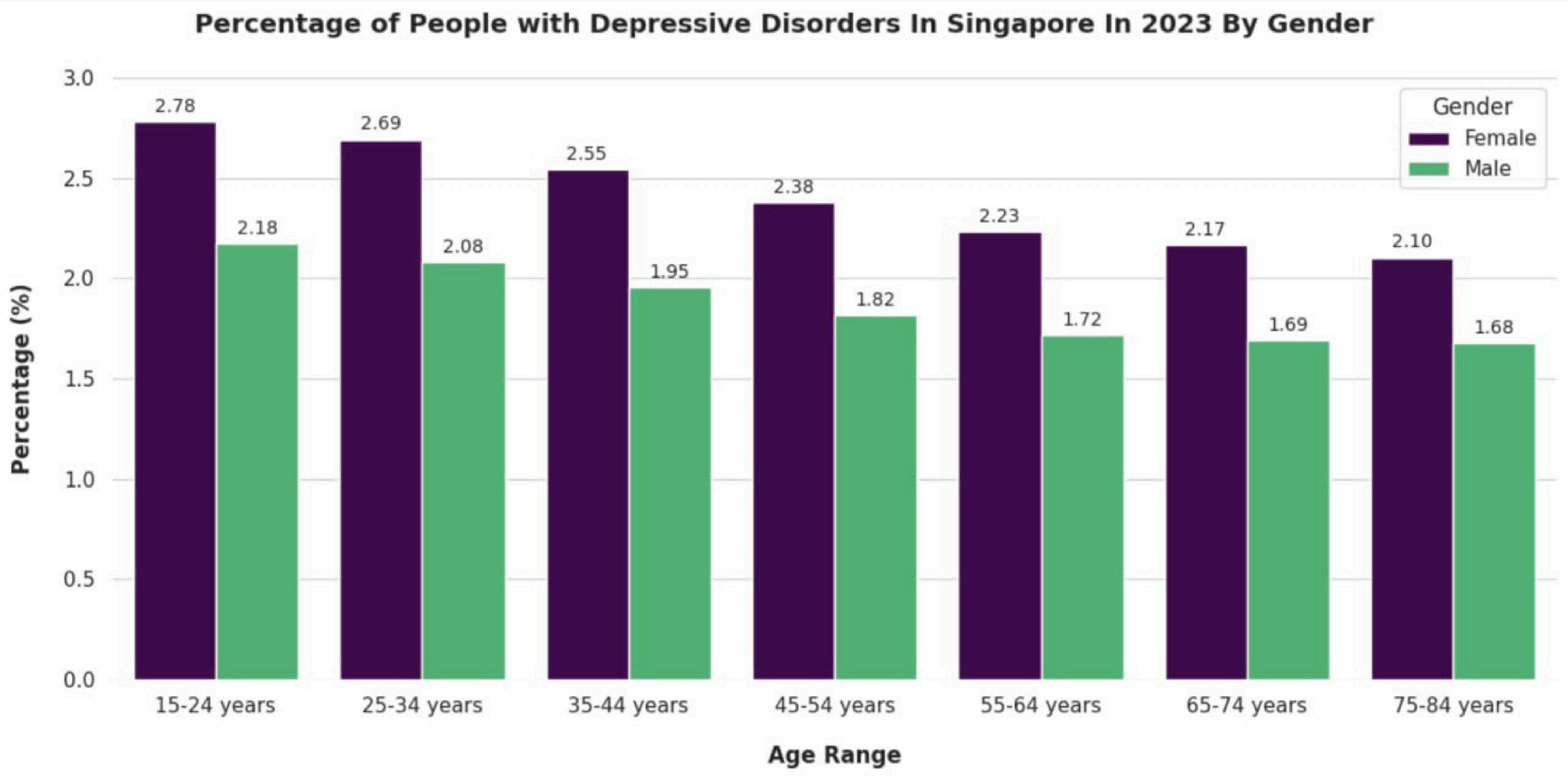
Demographic Patterns: Gender, Age

Observation:

- Depression prevalence rate is higher among females than males across all age groups
- Young females (15-24) represent the highest-risk demographic

Interpretation:

- Gender is correlated to depression risk, suggesting that female university students may face greater vulnerability



Data Analysis and Exploration

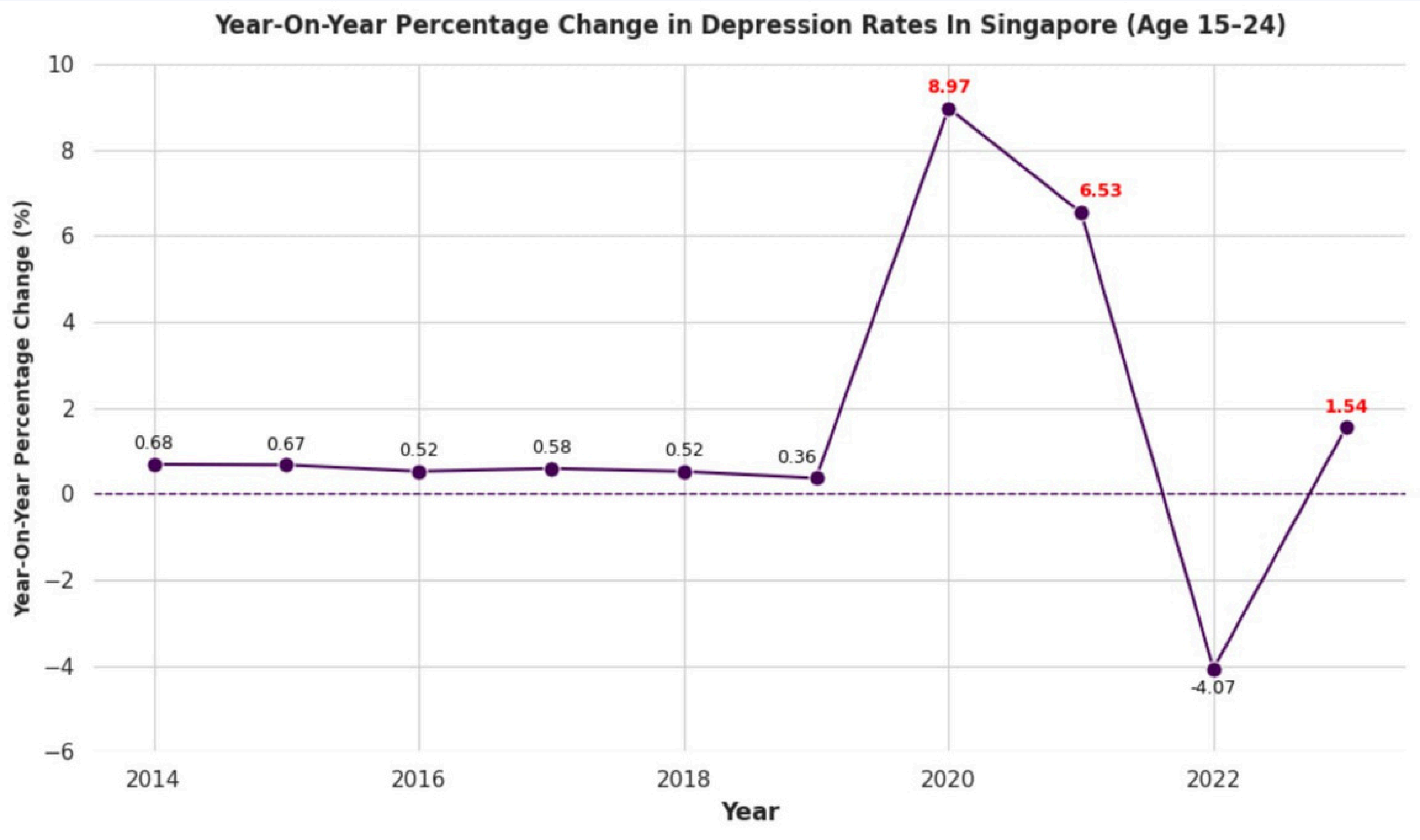
Anomalies and Volatility

Observation:

- **Pre-Pandemic (2014-2019):** Stable growth from 2014-2019
- **During Pandemic (2020-2021):** Significant spike in 2020 (+8.97%)
- **Post-Pandemic (2022-2023):** Depression rates fell in 2022 but increased again in 2023, suggesting continued instability

Interpretation:

- Youth depression rates are sensitive to external stressors, therefore it should be monitored consistently



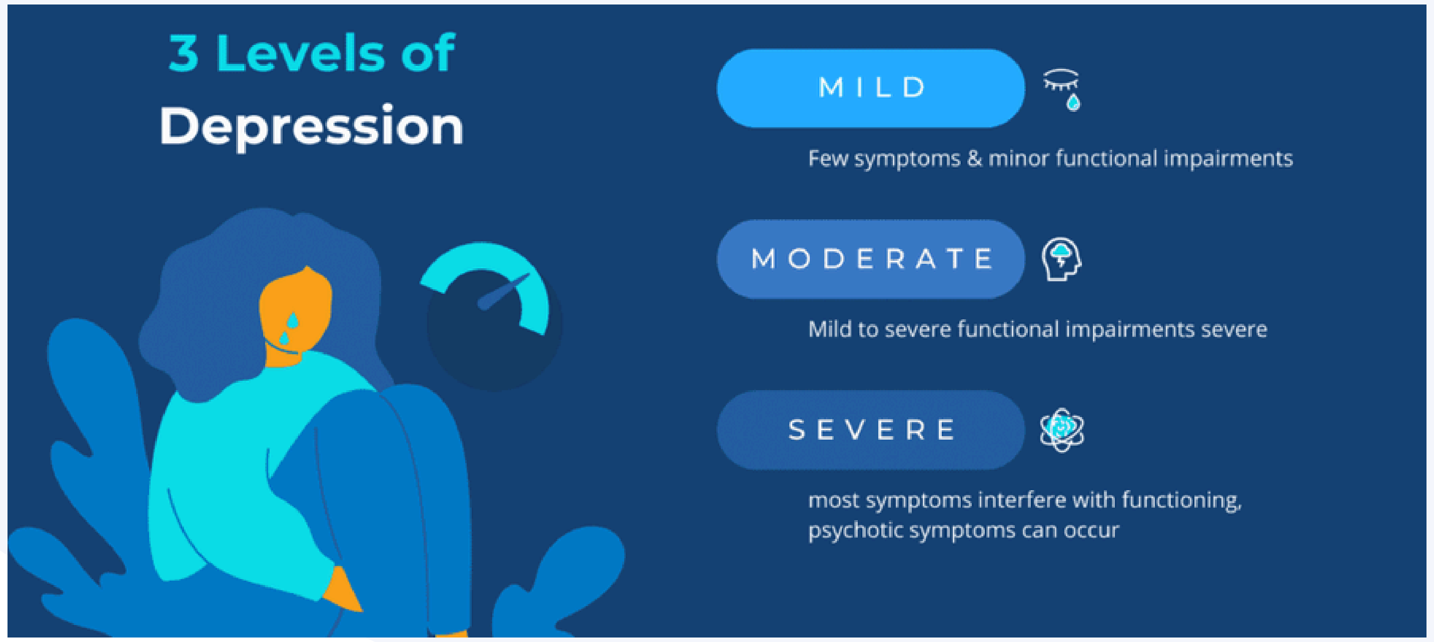
Potential Prediction Targets

Identify Students at High Risk

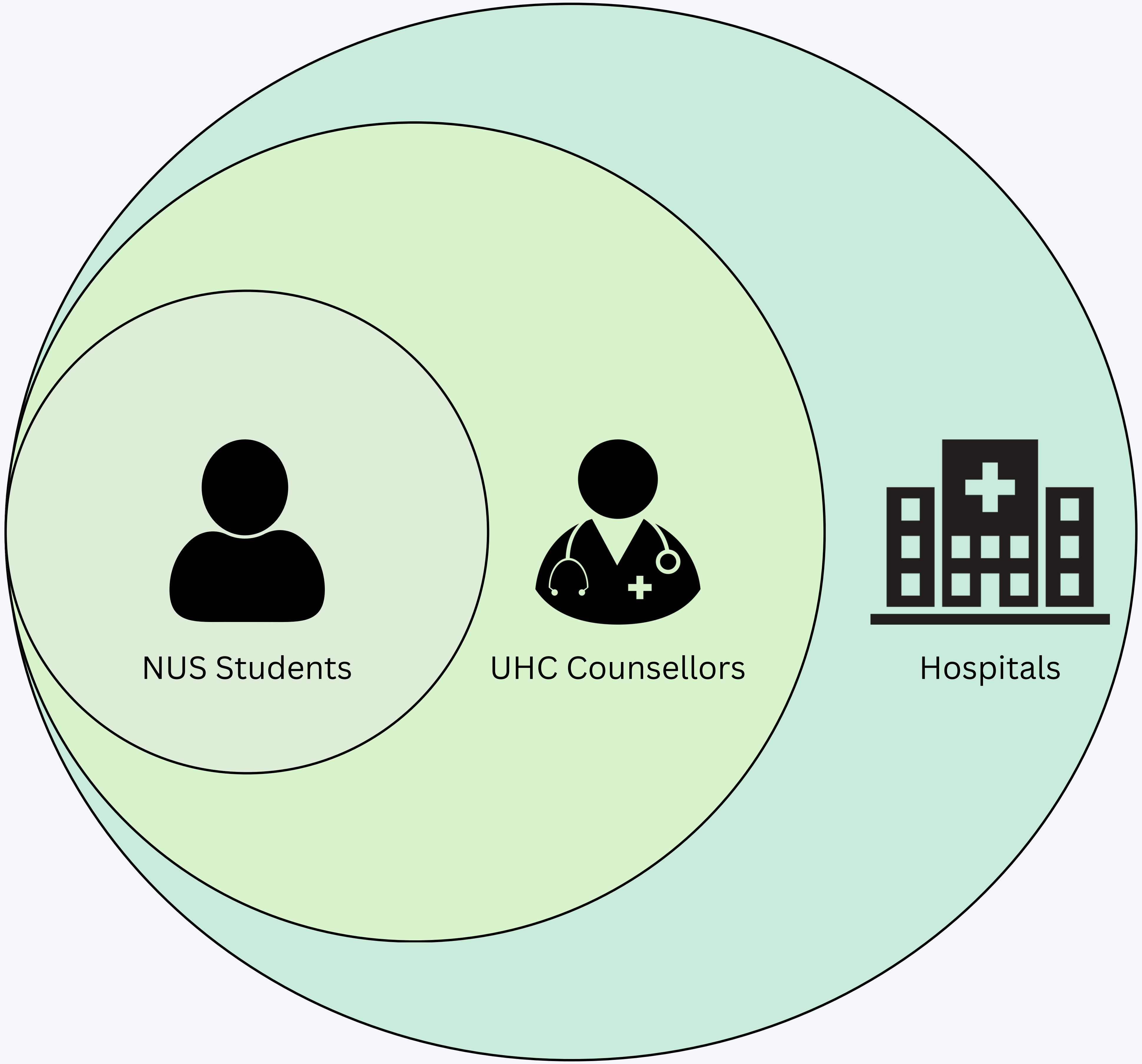
- Predict probability of risk classes among university students
- Eg. No Depression, Mild Depression, Moderate Depression, Severe Depression

Flag Elevated Risk Between Sessions

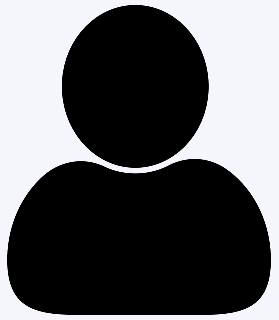
- Use predicted risk classes to prioritise students who may require earlier follow-up or additional monitoring



Stakeholders Involved



Needs And Constraints Of Stakeholders



NUS Students

UHC Counsellors

Hospitals

	NUS Students	UHC Counsellors	Hospitals
Needs	• Continuous emotional support • Early detection of worsening symptoms	• Reliable symptom tracking • Ability to prioritize high-risk students	• Timely referrals • Complete case documentation
Constraints	• Reluctance to seek help • Academic workload • Symptoms may deteriorate unnoticed between sessions	• Limited appointment slots • High caseload • No inter-session monitoring visibility	• Often receive cases after escalation

How To Measure Success?

Year-On-Year Percentage Change In Depression Prevalence

- Compute annual percentage change in depression prevalence for ages 15 to 24 in NUS
- Compare trends before and after the implementation
- **Success: Consecutive years of decline and stabilization in percentage change**

Trend Slope Reduction Over Time

- Run Linear Regression on the depression prevalence rates (pre vs post implementation)
- Compare the magnitude, as well as the direction of the two slopes
- **Success: Flatter or negative slopes after the intervention**

Changes In Average Time Interval Between Counselling Sessions

- Compute the mean number of days between counselling sessions per student
- Compare average day interval before and after the rollout
- **Success: Shorter and more consistent session gaps**

Changes In Average Counselling Session Scores

- Track average depression symptom scores (eg. PHQ-9) as well as satisfaction ratings
- Compare pre-intervention and post-intervention averages in scores and ratings
- **Success: Lower symptom severity and higher satisfaction ratings**

How To Handle Poor Performance Of Models?

Models and methods that we might be using for the project include

- Several **classical ML models** for depression prediction
- **Sentiment analysis** in raw text from NUS students and counsellors
- **LLMs** for text classification and prompt tuning

If models don't perform well (eg. poor accuracy)

First diagnose the root causes of the problem (ie. determine why the performance is poor?)
Possible issues include **class imbalance, noisy text data, feature weaknesses** and **small dataset size**

Improve Classical ML Models

- Apply **class weighting** or **SMOTE**
- Perform **hyperparameter tuning**
- Use **ensemble models/TD-IDF**

Improve Sentiment Analysis

- Use **emotion classification** instead of just sentiment (detect features like **self-blame, hopeless, rumination** etc.)

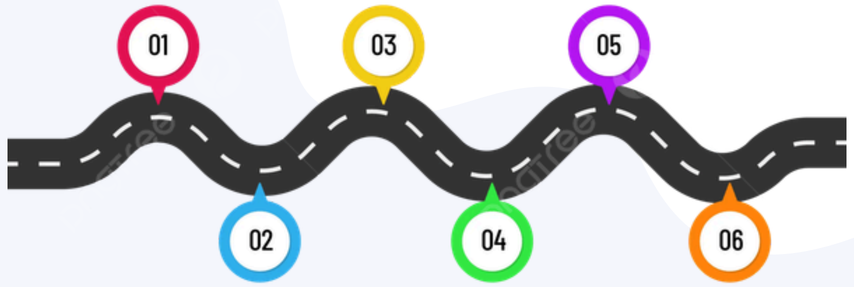
Improve LLM Models

- Use **few shot prompting**
- Use **chain-of-thought reasoning**
- Add **Retrieval-Augmented Generation** (RAG)

Transparently Report Limitations

Be honest and **state limitations in data** such as **small dataset size**, **self-reported biasness**, **using text-only signals** and **no longitudinal individual tracking**

Brief Project Roadmap



Phase 1: Problem Framing & Signal Identification
- Construct problem statement
- Identify key risk signals
- Define success metrics and evaluation criteria

Weeks 4 & 5

Phase 2: Finding Relevant Datasets
- Source population and counselling-level datasets
- Assess data completeness and relevance

Weeks 5 & 6

Phase 3: Exploratory Data Analysis & Insights
- Analyze trends from graphs
- Identify patterns and potential risk indicators
- Generate insights to guide model and app design

Recess Week

Phase 4: Calculating Initial Metric Results
- Compute baseline metrics (YoY change, scores etc.)
- Establish pre-implementation benchmarks

Recess Week

Phase 5: Build Predictive Models
- Develop multiple models (eg. Logistic Regression, XGBoost)
- Conduct sentiment analysis and possible LLM implementation
- Evaluate using accuracy, precision, recall, F1-score

Weeks 7 & 8

Week 9

Phase 6: Build Depression App in Figma
- Design user journey for students and counsellors
- Prototype dashboards for risk alerts and monitoring
- Integrate predictive outputs into intuitive UI flows

Week 10

Phase 7: App Testing & Actionable Integration
- Validate logic and workflow consistency
- Connect risk scores to recommended interventions
- Simulate real-world use cases and refine usability

Week 11

Phase 8: Product & Evaluation Framework
- Finalize evaluation metrics
- Define long-term impact measurement plan
- Prepare scalability and deployment considerations

Week 12

Phase 9: Final Presentation
- Present problem, methodology and solution
- Demonstrate predictive insights and app prototype
- Share evaluation framework and future roadmap

START!

COMPLETE!

Thank You!

We will gladly answer your questions 🙂

References

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