# Asian Institute of Technology

## School of Engineering and Technology

## AT82.04 Business Intelligence and Analytics

***Final Report: Mental Health Analytics and Prediction in University Students***

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# Introduction

Mental health conditions such as depression, anxiety, and stress are increasingly common among university students, driven by factors such as academic pressure, social isolation, financial burdens, and the psychological challenges of transitioning into adulthood. Despite growing awareness, these conditions often go undiagnosed or untreated, resulting in diminished academic performance, reduced quality of life, and long-term psychological harm.

A 2021 systematic review [2] across six ASEAN countries—including Cambodia, Laos, Malaysia, Myanmar, Thailand, and Vietnam—revealed alarming statistics:

- 29% of students reported symptoms of depression (with 7.6% classified as severe),
- 42.4% experienced anxiety (18.9% severe),
- 16.4% reported stress-related symptoms.
- Additional concerns included disordered eating (13.9%) and 12-month suicidality rates ranging from 7% to 8%. These findings underscore a critical need for early detection and intervention in the student population.

These numbers not only highlight the current mental health burden among university students but also reflect a year-over-year increase in reported cases globally. Despite growing evidence, mental health is still under prioritized in many educational systems, with limited institutional frameworks for early detection, monitoring, and intervention. The persistent stigma surrounding mental illness, combined with insufficient campus resources, has led to a gap between students' needs and the support they receive. Without proactive measures, the long-term academic, social, and emotional consequences may deepen, making it critical to integrate data-driven solutions that can support student well-being at scale.

This project addresses that need by leveraging machine learning (ML) to classify mental health risks—anxiety, stress, and depression—based on students' self-reported survey data aligned with DSM-5 criteria. In addition to predictive modeling, an interactive analytics dashboard was developed to visualize risk levels, demographic trends, and contributing factors. University counselors and mental health practitioners can use this tool to identify at-risk students, make data-driven decisions, and deploy personalized support strategies.

By integrating AI-powered prediction, real-time visualization, and actionable recommendations, this study offers a scalable solution to promote mental well-being in higher education settings and support a more resilient academic environment.

## Research Objectives

1. To identify the most effective machine learning algorithms for classifying depression, anxiety, and panic attack symptoms in university students using survey data.
    a. Identify which model account for the best accuracy, precision, recall and F1 score
2. To determine key predictive features that contribute most significantly to the classification of each mental health condition.
    a. Analyze the relationship between mental health and other variable (Sleep quality, stress, Academic Engagement, Mental health support)
    b. Which Course, year and Age of University Student are likely to face mental health
3. To design and implement a web-based analytics system for forecasting and monitoring mental health risks among university students, integrating predictive modeling with visual analytics to support data-driven decision-making by university support staff.

## Why is it important

Understanding and addressing mental health issues among university students is more important than ever. With rising rates of depression, anxiety, stress and related disorders, educational institutions must take a proactive approach to promote well-being on campus. Leveraging data and technology to identify and support students at risk can lead to meaningful improvements not only in individual lives but also in academic outcomes and campus culture. The benefits of investing in mental health prediction and support systems are wide-ranging, as outlined below

- For better resource allocation – ensures support services are directed where they're needed most
- Early prevention and intervention – allows action before symptoms escalate
- Better understanding and support for young people – addresses students' unique emotional challenges
- Reduces long-term mental health costs – lowers future treatment and crisis management expenses
- Improves academic performance and retention – helps students stay focused and succeed
- Helps identify at-risk individuals before crisis – supports timely outreach and care
- Supports data-driven mental health strategies – informs more effective policy and programming
- Promotes a healthier, more inclusive campus environment – fosters student well-being and belonging

# Understanding Mental Health

Mental health refers to an individual's emotional, psychological, and social well-being. It affects how people think, feel, and act, and also influences how they handle stress, relate to others, and make decisions. For university students, mental health is particularly important, as it directly impacts academic performance, interpersonal relationships, and long-term development. While mental health exists on a spectrum, certain psychological conditions—when persistent or intense—can significantly interfere with daily functioning. Among university students, the most commonly reported mental health issues include anxiety, stress, and depression. These conditions often overlap and may intensify one another, yet they each present with distinct characteristics and implications.

## Anxiety

Anxiety is characterized by excessive worry, nervousness, or fear that is disproportionate to the situation at hand. While occasional anxiety is a normal response to stressful events like exams or deadlines, persistent anxiety can disrupt concentration, decision-making, and sleep. Students with high anxiety levels may experience symptoms such as:

- Feeling on edge or restless
- Uncontrollable worry
- Trouble relaxing
- Irritability
- Physical symptoms like a racing heart or shortness of breath

In academic settings, anxiety often stems from performance pressure, uncertainty about the future, and fear of failure. Without intervention, anxiety can escalate to conditions such as generalized anxiety disorder (GAD) or panic disorder.

## Stress

Stress is the body's natural response to demands or threats, and in small amounts, it can be motivating. However, chronic or high levels of stress can be harmful to both mental and physical health. Among students, stress typically arises from juggling coursework, exams, finances, social expectations, and part-time jobs. Symptoms may include:

- Feeling overwhelmed or out of control
- Difficulty focusing or sleeping
- Frequent headaches or fatigue
- Emotional outbursts or mood swings
- Reduced academic performance

Prolonged stress is associated with burnout and can increase vulnerability to other mental health issues, such as anxiety and depression.

## Depression

Depression is a mood disorder marked by persistent sadness, loss of interest or pleasure in daily activities, and negative changes in thinking, behavior, and physical well-being. Unlike temporary emotional lows, depression can last weeks or months and significantly impact daily functioning. Common symptoms include:

- Loss of motivation and energy
- Feelings of worthlessness or hopelessness
- Changes in appetite and sleep
- Trouble concentrating
- Thoughts of self-harm or suicide

In university students, depression is often underreported due to stigma or lack of awareness. Early recognition is essential for providing emotional support, therapy, or medical intervention.

**Table: Comparison of Mental Health Conditions Among University Students**

| Aspect | Anxiety | Stress | Depression |
|---|---|---|---|
| Definition | Persistent worry, fear, or nervousness disproportionate to the situation | Emotional or physical tension in response to pressure or demands | A mood disorder marked by prolonged sadness, hopelessness, and disinterest |
| Common Triggers | uncertainty, public speaking, fear of failure | Academic workload, deadlines, time pressure | Social isolation, poor academic performance, low self-esteem |
| Psychological Symptoms | Overthinking, fearfulness, irritability | Feeling overwhelmed, loss of control, frustration | Hopelessness, negative self-perception, suicidal thought |
| Physical Symptoms | Rapid heartbeat, restlessness, insomnia | Fatigue, headaches, sleep disturbances | Sleep/appetite changes, fatigue, psychomotor slowing |
| Duration | Can be chronic and persistent without intervention | Usually short-term, but can become chronic if unmanaged | Symptoms persist for weeks or months and interfere with daily functioning |
| Diagnosis Tool Example | GAD-7, DSM-5 Criteria for Generalized Anxiety Disorder | Perceived Stress Scale (PSS), DSM-5 for Acute Stress Disorder | PHQ-9, DSM-5 Criteria for Major Depressive Disorder |
| Treatment | Counseling, CBT, mindfulness, medication | Time management training, relaxation techniques, therapy | Psychotherapy, antidepressants, peer support, crisis intervention |
| Impact on Academics | Affects concentration, increases procrastination | Reduces productivity, causes burnout | Severe decline in motivation and academic engagement |

Table 1: Mental Health Comparison

# Dataset

The dataset consists of 1,978 rows and 39 columns. It contains comprehensive information on university students, capturing both demographic details and indicators of mental health status.

### Demographic Variables

The following demographic features are included:

- Year: The year the data was collected
- Gender: Student's self-identified gender
- University: Institution attended by the student
- Department: Academic department or major
- Academic Year: Student's year of study (e.g., 1st year, 2nd year)
- CGPA: Cumulative Grade Point Average
- Scholarship: Did the student received waiver or scholarship from university

### Mental Health Classification

The remaining variables are categorized into three groups corresponding to mental health conditions based on the DSM-5 criteria:

**Anxiety**

Students were asked to respond to the following questions on a 1–5 Likert scale, where 1 indicates "Never" and 5 indicates "Always":

1. How often have you felt nervous, anxious, or on edge due to academic pressure?
2. How often have you been unable to stop worrying about your academic affairs?
3. How often have you had trouble relaxing due to academic pressure?
4. How often have you been easily annoyed or irritated because of academic pressure?
5. How often have you worried too much about academic affairs?
6. How often have you felt so restless due to academic pressure that it was hard to sit still?
7. How often have you felt afraid, as if something awful might happen?

These questions aim to assess anxiety levels specifically related to academic stressors, following the DSM-5 framework, which includes symptoms such as restlessness or feeling keyed up or on edge, fatigue, difficulty concentrating, irritability, muscle tension, and sleep disturbances [3].

**Stress**

Students were asked to respond to the following questions on a 1–5 Likert scale, where 1 indicates "Never" and 5 indicates "Always"

1. How often have you felt upset due to something that happened in your academic affairs?
2. How often have you felt as if you were unable to control important things in your academic affairs?
3. How often have you felt nervous and stressed because of academic pressure?
4. How often did you felt as if you could not cope with all the mandatory academic activities? (e.g, assignments, quiz, exams)
5. How often have you felt confident about your ability to handle your academic / university problems?
6. How often do you felt as if things in your academic life is going on your way?
7. How often are you able to control irritations in your academic / university affairs?
8. How often did you felt as if your academic performance was on top?
9. How often do you got angered due to bad performance or low grades that is beyond your control?
10. How often have you felt as if academic difficulties are piling up so high that you could not overcome them?

These questions aim to assess anxiety levels specifically related to academic stressors, following the DSM-5 framework, which includes symptoms such as recurrent stress, irritability, a sense of pressure, physiological distress, difficulty expressing positive emotions, and trouble concentrating [4].

**Depression**

Students were asked to respond to the following questions on a 1–5 Likert scale, where 1 indicates "Never" and 5 indicates "Always"

1. How often have you had little interest or pleasure in doing things
2. How often have you been feeling down, depressed or hopeless
3. How often have you had trouble falling or staying asleep, or sleeping too much
4. How often have you been feeling tired or having little energy
5. How often have you had poor appetite or overeating
6. How often have you been feeling bad about yourself - or that you are a failure or have let yourself or your family down
7. How often have you been having trouble concentrating on things, such as reading books or watching television?
8. How often have you moved or spoke too slowly for other people to notice? Or you've been moving a lot more than usual because you've been restless?
9. How often have you had thoughts that you would be better off dead, or of hurting yourself

These questions aim to assess depression levels specifically related to academic stressors, following the DSM-5 framework, which includes symptoms such as depressed mood, loss of interest or pleasure, significant weight loss or gain, insomnia or hypersomnia, psychomotor agitation or retardation, fatigue, feelings of worthlessness, diminished ability to concentrate, and recurrent thoughts of death or suicide [5]. For each mental health state, the scores from the relevant questions were summed and categorized into different levels of severity. For Anxiety: Minimal Anxiety (0-4), Mild Anxiety (5-9), Moderate Anxiety (10-14) and Severe Anxiety (15-21). For Stress: Low Stress (0-13), Moderate Stress (14-26) and High Perceived Stress (27-40). For Depression: No Depression (0), Minimal Depression (1-4), Mild Depression (5-9), Moderate Depression (10-14), moderate severe Depression (15-19), severe Depression (20-27).

| 1. Age | 2. Gender | 3. University | 4. Department | 5. Academic Year | 6. Current CGPA | 7. Did you receive a waiver or scholarship at your university? |
|---|---|---|---|---|---|---|
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | Fourth Year or Equivalent | 2.50 - 2.99 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.00 - 3.39 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.40 - 3.79 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.40 - 3.79 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | Yes |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | Third Year or Equivalent | 2.50 - 2.99 | No |
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | No |
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | Yes |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.40 - 3.79 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | Yes |
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | No |
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | No |
| 18-22 | Male | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 2.50 - 2.99 | No |
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | Third Year or Equivalent | 2.50 - 2.99 | No |
| 18-22 | Female | Independent University, Bangladesh (IUB) | Engineering - CS / CSE / CSC / Similar to CS | First Year or Equivalent | 3.80 - 4.00 | Yes |

Figure 1: Example from the dataset

| e too slowly for other people to notice? Or you've been moving a lot more than usual because you've been restless? | 9. In a semester, how often have you had thoughts that you would be better off dead, or of hurting yourself? | Depression Value | Depression Label |
|---|---|---|---|
| 1 | 1 | 11 | Moderate Depression |
| 1 | 1 | 9 | Mild Depression |
| 2 | 1 | 16 | Moderately Severe Depression |
| 1 | 1 | 9 | Mild Depression |
| 1 | 1 | 9 | Mild Depression |
| 2 | 2 | 18 | Moderately Severe Depression |
| 1 | 0 | 3 | Minimal Depression |
| 0 | 0 | 14 | Moderate Depression |
| 2 | 2 | 18 | Moderately Severe Depression |
| 2 | 0 | 19 | Moderately Severe Depression |
| 2 | 2 | 18 | Moderately Severe Depression |
| 3 | 3 | 23 | Severe Depression |
| 1 | 1 | 9 | Mild Depression |
| 2 | 3 | 20 | Severe Depression |
| 2 | 2 | 18 | Moderately Severe Depression |
| 0 | 3 | 20 | Severe Depression |
| 2 | 2 | 18 | Moderately Severe Depression |
| 0 | 0 | 9 | Mild Depression |
| 0 | 0 | 3 | Minimal Depression |
| 1 | 0 | 6 | Mild Depression |
| 0 | 0 | 0 | No Depression |

Figure 2: Example from the dataset

# Data Insight

## Demographic Insight:

The following visualizations provide insights into the dataset by exploring both individual variables and relationships between variables. These charts help us better understand the distribution of key features and how they interact with one another.

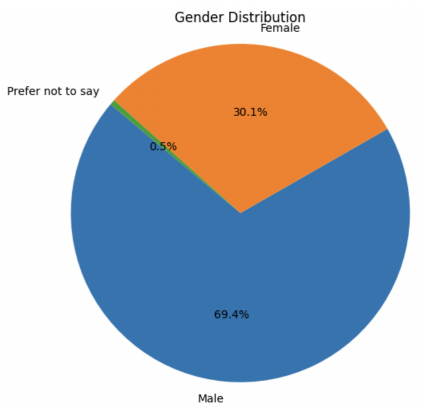



Figure 3: Gender Distribution in the Dataset

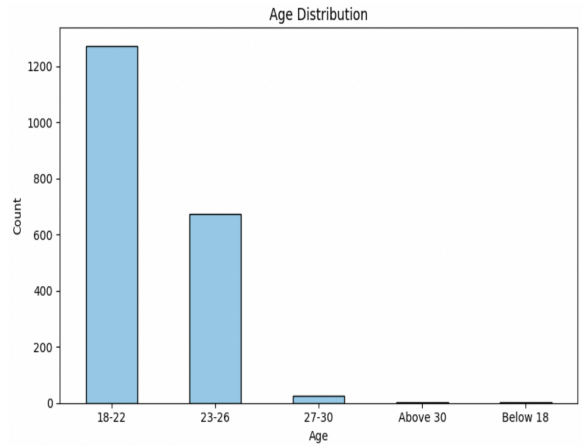



Figure 4: Age Distribution in the Dataset

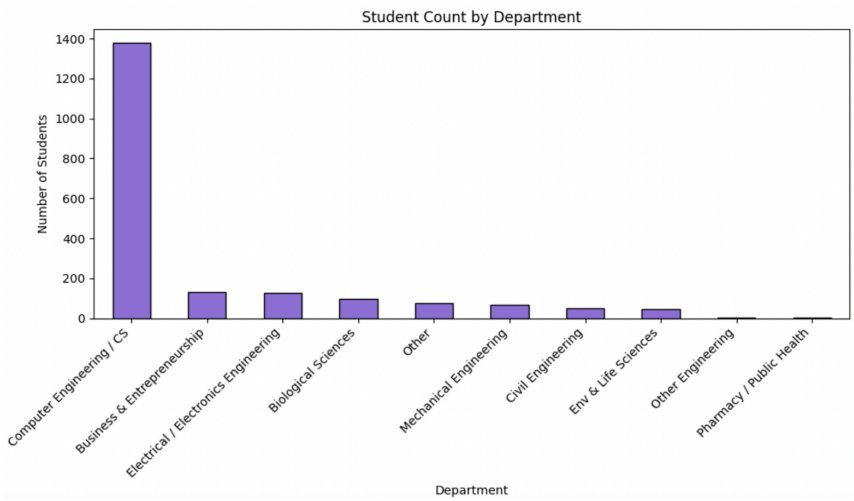



Figure 5: Student Count per Department

The Gender Distribution(Figure 3) pie chart shows that the majority of students in the dataset are male, comprising approximately 69.4% of the total respondents. Female students account for 30.1%, while a very small portion (0.5%) chose not to disclose their gender. This indicates a notable gender imbalance, with male students being more than twice as represented as female students. The Age Distribution bar chart (Figure 4) further reveals that most respondents fall into the younger age group, with the majority aged between 18–22 years which align with the dataset that most of the students are either a first or a second year university students, followed by a smaller but significant group aged 23–26. Very few students are in the 27–30, below 18, or above 30 age groups, highlighting that the dataset is predominantly composed of traditional university-age students. Finally, the Student Count by Department bar chart (Figure 5) illustrates a heavy concentration in the field of Computer Engineering / Computer Science (CS), which significantly outnumbers all other departments. Other fields such as Business & Entrepreneurship, Electrical Engineering, and Biological Sciences show relatively smaller counts,

while departments like Pharmacy/Public Health and Other Engineering are represented by very few students. This departmental skew suggests that mental health analyses based on academic background should carefully consider the overwhelming dominance of CS-related students in the sample.

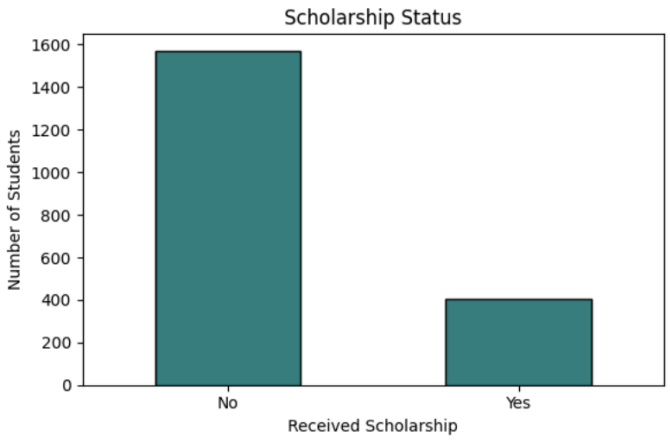



Figure 6: Scholarship count

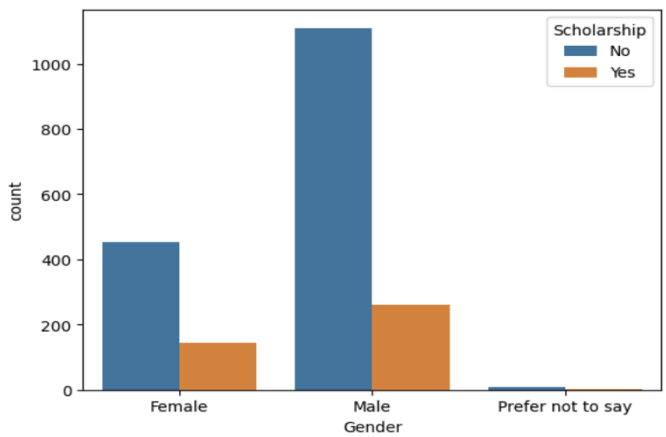



Figure 7: Gender and Scholarship count

The Scholarship Status bar chart (Figure 6) demonstrates that the majority of students, around 1571, did not receive a scholarship, while only 406 students were scholarship recipients. This suggests that financial assistance is relatively limited across the student population. Additionally, the Scholarship by Gender bar chart (Figure 7) provides a more detailed breakdown, showing that male students made up the largest group of scholarship recipients (262) as well as non-recipients (1110), reflecting their overall dominance in the dataset. Female students accounted for 143 scholarship recipients and 452 non-recipients, while a very small group of students who preferred not to disclose their gender reported only one scholarship recipient and nine non-recipients. Overall, these patterns indicate that scholarship opportunities are scarce for all genders, but proportionally male students received more scholarships simply because they make up the majority of the dataset.

**Demographic impact on Mental Health Insight:**

To explore the potential impact of demographic variables on anxiety levels, we examined the association between the anxiety label and a range of factors, including age group, gender, department, academic year, CGPA, and scholarship status. The results suggest that gender ($p < 0.001$), department ($p = 0.009$), and academic year ($p < 0.001$) are statistically significant predictors of anxiety, indicating meaningful differences in anxiety prevalence across these groups. In contrast, age group ($p = 0.058$), CGPA ($p = 0.105$), and scholarship status ($p = 0.069$) were not statistically significant, suggesting that these factors may not play a strong role in predicting anxiety within this dataset. Based on these findings, further analysis will focus on gender, department, and academic year to better understand how these characteristics relate to students' anxiety levels.

Moving on, the relationship between stress levels and demographic characteristics, we analyzed associations with age group, gender, department, academic year, CGPA, and scholarship status. The results show statistically significant associations with age group ($p < 0.001$), gender ($p < 0.001$), department ($p < 0.001$), academic year ($p < 0.001$), and CGPA ($p < 0.001$). These findings indicate that stress levels vary meaningfully across these demographic and academic dimensions. In contrast, scholarship status ($p = 0.816$) did not demonstrate a significant association with stress, suggesting it may have little influence on stress levels in this dataset. As a result, deeper analysis will focus on the significant predictors to better understand the drivers of stress among students.

Lastly, examining factors potentially contributing to depression among students, we assessed demographic and academic variables in relation to the depression label. Significant associations were observed for age group ($p = 0.002$), gender ($p < 0.001$), academic year ($p = 0.003$), and CGPA ($p = 0.040$), highlighting that

these variables may meaningfully affect depression outcomes. Department (p = 0.187) and scholarship status (p = 0.446) were not significantly associated with depression, indicating a more limited role in explaining depression variation within the sample. Consequently, further analysis will focus on the demographic and academic predictors that showed significant relationships with depression to inform targeted support strategies. Which all of the factors can be seen below.

| | Age | Gender | Department | Academic Year | CGPA | Scholarship |
|---|---|---|---|---|---|---|
| Anxiety Label | No, p = 0.058 | Yes, p < 0.001 | Yes, p = 0.009 | Yes, p < 0.001 | No, p = 0.105 | No, p = 0.069 |
| Stress Label | Yes, p < 0.001 | Yes, p < 0.001 | Yes, p < 0.001 | Yes, p < 0.001 | Yes, p < 0.001 | No, p = 0.816 |
| Depression Label | Yes, p = 0.002 | Yes, p < 0.001 | No, p = 0.187 | Yes, p = 0.003 | Yes, p = 0.040 | No, p = 0.446 |

Table 2: Impact of Demographic on Mental Health

Having established the statistical associations between mental health outcomes (anxiety, stress, and depression) and key demographic and academic variables, the next section will explore these relationships in greater depth. By examining how factors such as gender, age group, department, academic year, CGPA, and scholarship status influence students' mental health, we can gain a more nuanced understanding of which groups may be at greater risk and how these patterns manifest. This detailed analysis will provide critical insights to inform targeted interventions and support mechanisms tailored to specific student populations.

When examining the impact of age group on stress levels, the analysis shows that students aged 23–26 had slightly higher odds of experiencing moderate and high stress compared to those aged 18–22, but these differences were not statistically significant (moderate stress p = 0.098; high stress p = 0.094). Students aged 27–30 did not differ significantly from the 18–22 group in stress levels (moderate stress p = 0.567; high stress p = 0.971). For students above 30, there was a possible indication of higher moderate stress (odds ratio ~11, borderline p = 0.05), though with wide confidence intervals suggesting caution in interpretation, and no significant difference for high stress (p = 1.000). Results for students below 18 were considered unreliable due to a very small sample size and large standard errors. Regarding depression, age was not a significant predictor for minimal, mild, or moderate depression. However, for moderately severe depression, age was significantly associated (p = 0.048, odds ratio ~1.9 per year of age), with the 23–26 age group showing a significant positive coefficient (+0.650, p = 0.048), and the 27–30 group showing an even higher coefficient (+2.568, p = 0.002). Severe depression was also significantly associated with age (p = 0.008, odds ratio ~1.24 per year of age). Results for students above 30 and below 18 were again unreliable due to large standard errors, making them effectively meaningless for these comparisons. Overall, these findings suggest that while stress patterns did not show strong age group effects, moderately severe and severe depression appear to be more common in older student groups, particularly those aged 23–30.

Examining gender effects reveals several notable patterns across anxiety, stress, and depression outcomes. For anxiety, male students were significantly more likely to report mild anxiety compared to minimal anxiety (p = 0.031, odds ratio ~1.64), but showed no significant difference for moderate anxiety, and were actually less likely to report severe anxiety compared to minimal anxiety (p < 0.001, odds ratio ~0.64). In terms of stress, males were significantly more likely to experience both moderate stress (p < 0.001, odds ratio ~4.35) and high perceived stress (p < 0.001, odds ratio ~1.68) relative to females, highlighting an elevated stress burden among male students. Regarding depression, there were no significant gender differences for minimal or mild depression. However, males were significantly less likely to report moderate depression (p = 0.029, odds ratio ~0.72) and severe depression (p = 0.001, odds ratio ~0.61) compared to no depression, while moderately severe depression

showed only a borderline trend toward higher odds for males ($p = 0.065$). Overall, these findings suggest that male students may be more prone to mild anxiety and higher levels of stress, yet less likely to report moderate to severe depression symptoms compared to their female peers.

When considering department-level effects on mental health outcomes, several patterns emerge. For anxiety, students in “Other Engineering” fields were significantly more likely to report both mild ($p = 0.006$) and moderate anxiety ($p = 0.006$) compared to minimal anxiety, though the extremely large coefficients for these comparisons suggest that these estimates should be interpreted cautiously due to potential data instability. Civil Engineering students were significantly more likely to report severe anxiety compared to minimal anxiety ($p = 0.009$, odds ratio ~3.89), while Electrical/Electronics Engineering students also showed elevated odds of severe anxiety ($p = 0.025$, odds ratio ~2.32). For stress, no departments showed a significant effect for moderate stress compared to low stress. However, Electrical/Electronics Engineering students were significantly less likely to experience high stress ($p = 0.000$, odds ratio ~0.319), and Civil Engineering students also showed a reduced likelihood of high stress compared to low stress ($p = 0.000$, odds ratio ~0.193). Other departments did not demonstrate significant differences for these outcomes. Overall, these findings suggest that department affiliation may influence anxiety and stress experiences among students, although some extreme coefficient estimates warrant cautious interpretation.

Analysis of academic year effects revealed that year groups had a limited influence on mental health outcomes overall. For anxiety, no year groups significantly predicted mild or moderate anxiety compared to minimal anxiety. However, Year 2 students showed significantly higher odds of severe anxiety compared to graduates ($p = 0.019$, odds ratio ~2.19), and Year 3 students showed even higher odds ($p = 0.005$, odds ratio ~2.5), suggesting that anxiety may intensify during the middle academic years. Regarding stress, Year 2 students had borderline lower odds of moderate stress ($p = 0.054$, odds ratio ~0.35) and significantly lower odds of high stress ($p = 0.012$, odds ratio ~0.44) compared to graduates, while Year 3 students showed significantly reduced odds of moderate stress ($p = 0.018$, odds ratio ~0.27). In contrast, the academic year showed no significant associations with depression at any severity level. Overall, these findings indicate that academic year appears to play a stronger role in severe anxiety and stress outcomes than in depression, with Year 2 and Year 3 students showing distinct patterns compared to graduates.

The relationship between CGPA and mental health outcomes showed several notable patterns. For stress, students with higher GPAs (3.80–4.00) had significantly increased odds of experiencing mild stress compared to the baseline group (odds ratio ~3.66, $p = 0.001$), while those in the “Other” CGPA category demonstrated significantly lower odds of high stress (odds ratio ~0.61, $p = 0.014$). For depression, higher CGPA categories were generally associated with lower odds of more severe depression outcomes. Specifically, students with GPAs between 3.40–3.79 and 3.80–4.00 showed significantly lower odds of moderately severe depression compared to the reference group ($p = 0.018$ and $p = 0.040$, respectively), and lower odds of severe depression ($p = 0.026$ and $p = 0.023$, respectively). No CGPA categories showed significant effects on minimal, mild, or moderate depression (all $p > 0.05$). Overall, these results suggest that academic performance may act as a protective factor against more severe depression, though higher achievers may still be vulnerable to mild stress.

Analysis of scholarship status revealed no significant associations with any of the measured mental health outcomes, including anxiety, stress, and depression. Across all models and severity levels, scholarship receipt did not emerge as a significant predictor, with p-values consistently above conventional significance thresholds. This suggests that whether or not a student received a scholarship had minimal influence on their reported mental health status in this dataset.

**Example on the demographic impact on the actual Dataset:**

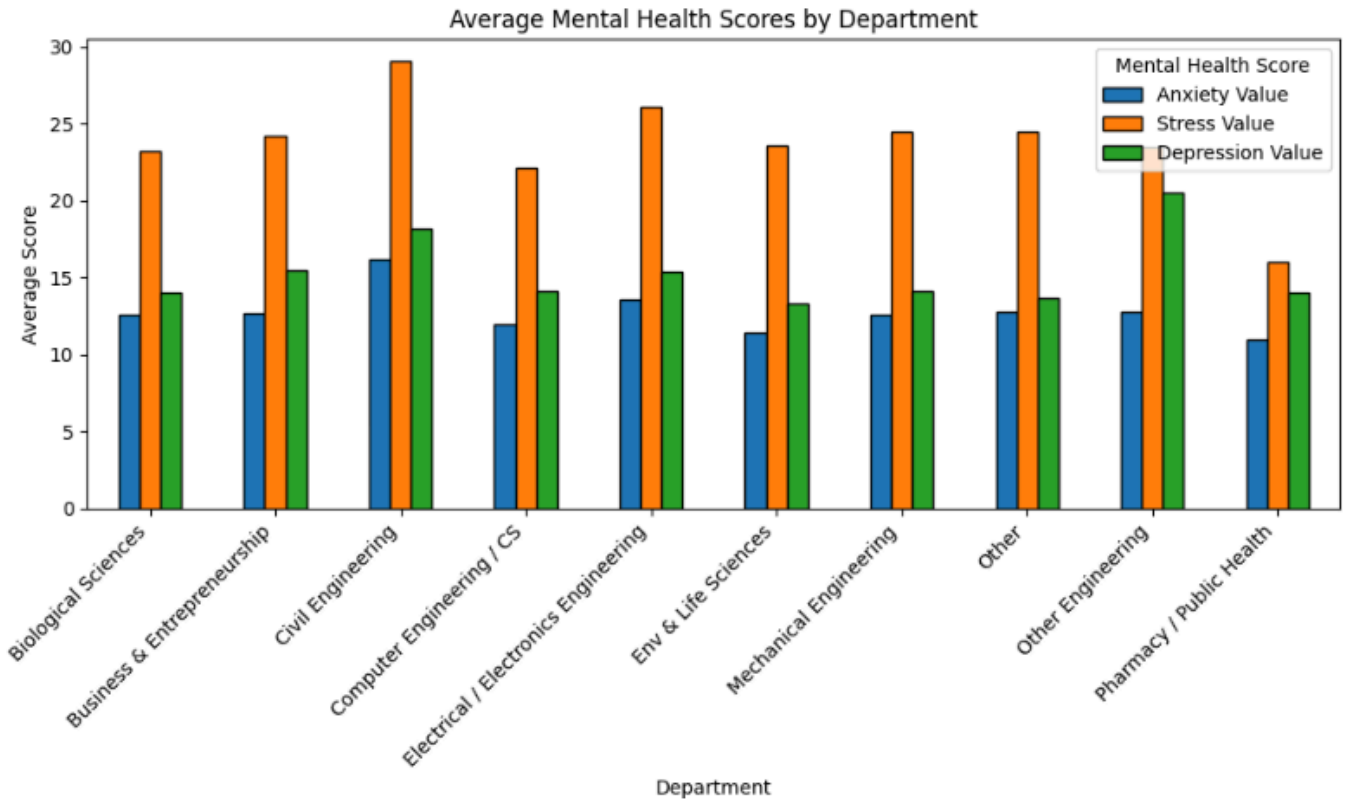



Figure 8: Average Mental Health Score by Department

The bar chart above (Figure 8) presents the average scores for anxiety, stress, and depression across various university departments, complementing the statistical test results. Overall, stress emerges as the most prominent mental health concern, with consistently higher average scores than both anxiety and depression in every department. Notably, students in the Computer Engineering / CS department exhibit the highest average stress scores, which aligns with the statistical findings showing stress is broadly elevated but department differences were generally not significant for moderate stress. Civil Engineering and Pharmacy / Public Health also display elevated scores across all three mental health dimensions, which supports the significant associations identified for severe anxiety in Civil Engineering, as well as some department-level effects on anxiety. While anxiety and depression averages appear lower than stress in most departments, the patterns in Business & Entrepreneurship and Other Engineering are consistent with statistical results that highlighted Other Engineering students having significantly higher odds of mild and moderate anxiety (albeit with unstable coefficients). These observations together suggest that mental health challenges vary by academic discipline, and the average patterns shown here reinforce the statistical evidence of certain departments particularly Civil and Other Engineering experiencing higher levels of psychological distress.

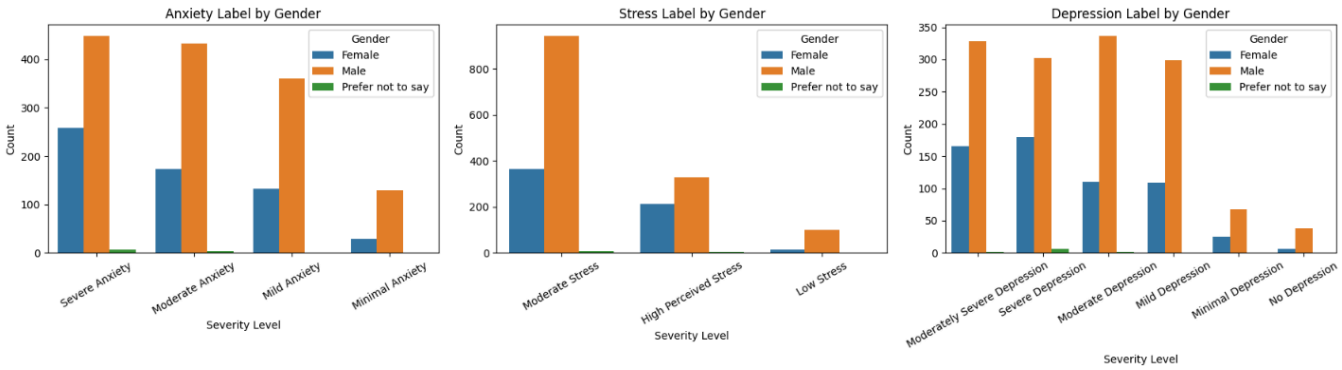



Figure 9: Mental Health Label by Gender

The charts above (Figure 9) display anxiety, stress, and depression severity levels by gender, supporting the statistical findings. In the Anxiety chart, male students consistently report higher counts across all severity levels, with particularly high representation in the "Severe Anxiety" and "Moderate Anxiety" groups. This pattern is consistent with the statistical results showing that males were significantly more likely to report mild anxiety but less likely to report severe anxiety compared to minimal anxiety, suggesting that while their reported counts are higher, their relative odds differ by severity. In the Stress chart, the majority of students fall under "Moderate Stress," with male students outnumbering females across all stress categories, which aligns with the significant statistical associations indicating that males had substantially higher odds of both moderate and high perceived stress. For Depression, male students again lead in count across nearly all severity levels, including “Moderately Severe” and “Severe Depression.” However, the statistical results showed that males were significantly less likely to have severe depression compared to females (odds ratio ~0.61), suggesting that while raw counts are higher for males, females may still be disproportionately affected in relative terms. Overall, these charts visually support the finding that male students report higher absolute counts of mental health symptoms across anxiety, stress, and depression, while the statistical models highlight differences in proportional risk by severity category.

### Mental Health Score Distribution:

To better understand the nature of this distress, we also examined which specific questions (symptoms) most strongly contribute to each mental health condition. This helps reveal why students might be classified under certain severity labels. For anxiety, the most impactful symptoms were related to overthinking (2.50), feeling fearful (2.49), and irritability (2.38), suggesting that cognitive and emotional hyperactivity are key drivers of high anxiety levels. For stress, the strongest predictors included feeling overwhelmed by academic tasks (2.80), loss of control (2.69), and emotional upset from academic events (2.63), highlighting academic workload and control as central stress triggers. In the case of depression, the most influential criteria were low self-worth (2.85), low energy or fatigue (2.85), and hopelessness (2.83), reflecting the deep emotional and physical exhaustion experienced by those with higher levels of depression. Taken together, these findings not only highlight demographic patterns in mental health experiences but also pinpoint the core psychological symptoms driving mental health severity. This dual perspective is essential for informing more targeted and effective student support strategies. These details are summarized in the table below.

| Anxiety Label (Scale 1-5) | |
|---|---|
| **Anxiety** - Overthinking | 2.503865 |
| **Anxiety** - Fearful | 2.488157 |
| **Anxiety** - Irritated | 2.384037 |
| **Anxiety** - Restless | 2.348243 |

| | |
|---|---|
| **Anxiety** - NervousOnEdge | 2.311155 |
| **Anxiety** - TroubleRelaxing | 2.179289 |
| **Anxiety** - UnstoppableWorry | 2.107453 |

Table 3: Anxiety Average Score

| Stress Label (Scale 1-5) | |
|---|---|
| **Stress** - OverwhelmedByTasks | 2.800701 |
| **Stress** - LossOfControl | 2.689903 |
| **Stress** - UpsetAcademic | 2.625816 |
| **Stress** - NervousStressed | 2.587992 |
| **Stress** - DifficultiesPileUp | 2.515592 |
| **Stress** - AngeredByGrades | 2.178229 |
| **Stress** - Performance | 1.755120 |
| **Stress** - OnTrack | 1.730849 |
| **Stress** - ConfidentHandling | 1.231693 |
| **Stress** - ControlIrritation | 1.207565 |

Table 4: Stress Average Score

| Depression Label (Scale 1-5) | |
|---|---|
| **Depression** - SelfWorth | 2.854508 |
| **Depression** - LowEnergy | 2.846311 |
| **Depression** - Hopeless | 2.829918 |
| **Depression** - Concentration | 2.649590 |
| **Depression** - SleepIssues | 2.645492 |
| **Depression** - AppetiteChange | 2.485656 |
| **Depression** - MovementChanges | 2.428279 |
| **Depression** - SuicidalThoughts | 2.350410 |
| **Depression** - LowInterest | 1.942623 |

Table 5: Depression Average Score

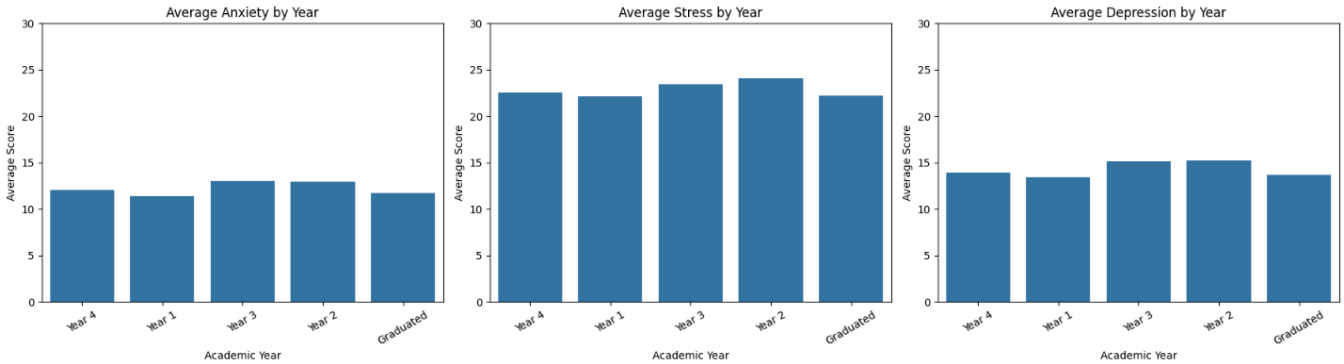
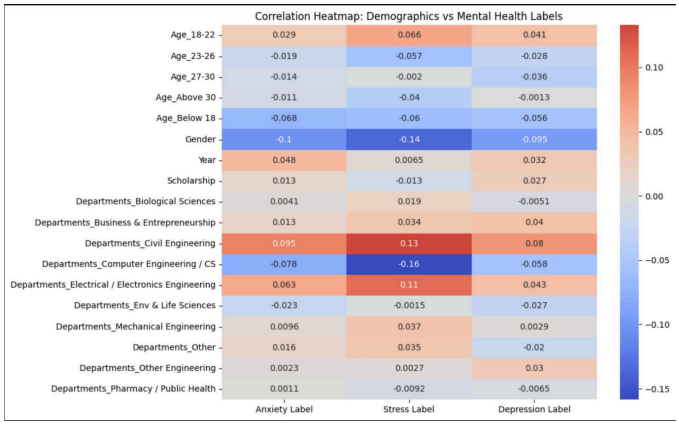



Figure 10: Average Mental Health Label by Year

The charts above (Figure 10) display the average scores for anxiety, stress, and depression across academic years. For anxiety, the average scores remain relatively consistent but with a slight increase among Year 2 and Year 3 students, which supports the statistical findings indicating higher odds of severe anxiety in these years compared to graduates. The Stress chart shows generally higher average scores across all groups, with Year 2 and Year 3 students reporting the highest stress scores. However, this pattern differs somewhat from the statistical analysis, which found that Year 2 and Year 3 students had lower odds of high stress compared to graduates, suggesting that while they report higher average stress, their relative risk for severe stress is actually reduced. For depression, Year 2 and Year 3 students again show slightly higher average scores, while Year 1 and Graduated students report the lowest. This descriptive trend is consistent with the overall pattern of distress during middle years, but statistical tests did not find significant academic year effects on depression severity. Overall, these charts help visualize the general mental health burden across academic years, while the statistical models clarify which patterns are significant.

Based on the analysis of question-level variation across severity levels, we can identify the top variables that have the greatest impact on each type of mental health condition. For Anxiety, the most influential question is "Overthinking", followed by "Fearful" and "Irritated". These results suggest that overthinking from surroundings, experiencing fear of life events, and irritability are key indicators associated with rising anxiety severity among students. In terms of Stress, the highest impact comes from "OverwhelmedByTasks", "LossOfControl", and "Upset on Academic Performance". This highlights that feeling overwhelmed by academic responsibilities, a lack of control over academic matters, and general academic distress are strong contributors to higher stress levels. For Depression, the top three influencing factors are " Low on SelfWorth", "Low Energy", and "Hopeless". These findings emphasize that negative self-perception, fatigue, and hopelessness are the most telling symptoms associated with more severe depression levels. Overall, the top contributing variables for each mental health condition align closely with clinical symptoms and can be valuable for early identification and intervention efforts.

## Heatmap Analysis:



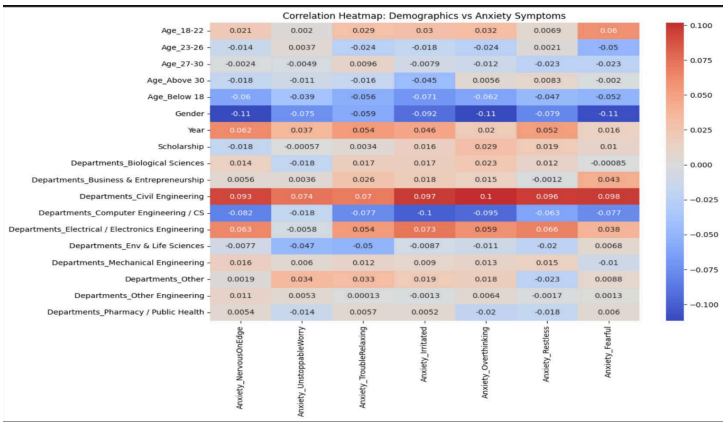
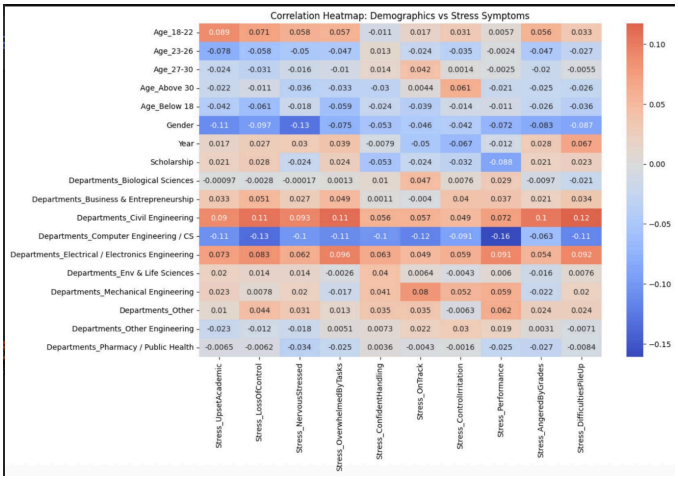
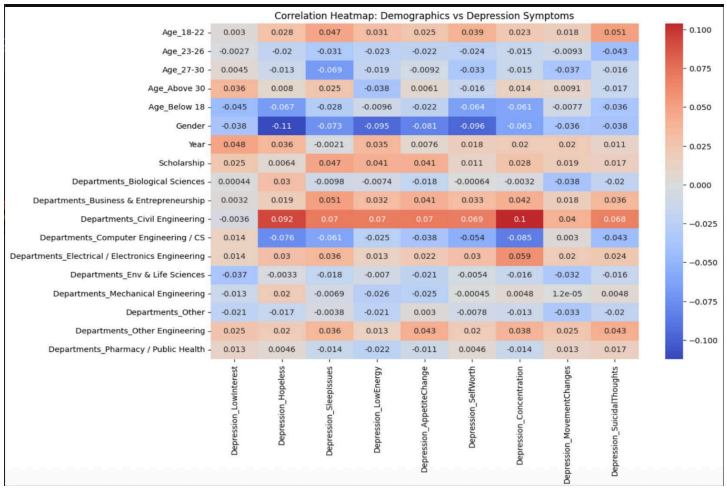



Figure 11: Correlation Heatmap between Demographic factor and Mental State

The correlation analysis between demographic variables and mental health outcomes reveals several insightful patterns (figure 11). Overall, the demographic factors showed relatively weak correlations with mental health labels and symptoms, suggesting that while demographics may influence mental health, they do not strongly determine its severity in this dataset. Among the variables, gender displayed a consistent negative correlation with stress, anxiety, and depression labels and their associated symptoms, indicating potential gender-based differences in self-reporting or experience of mental health. Departmental factors were more prominent, with students in Civil Engineering and Electrical/Electronics Engineering (0.11 and 0.13, respectively) showing small but noticeable positive correlations with higher stress and anxiety labels as well as their symptoms, suggesting academic workload or culture may contribute to elevated mental health challenges in these programs. In contrast,




factors like scholarship status and year of study showed
minimal correlation across all mental health measures, which may be surprising as these factors are often assumed to impact student stress and anxiety. Age groups also did not present strong patterns, apart from slightly elevated stress in the 18–22 age group with a correlation of 0.066 out of 0.1. It is important to note that, due to data encoding (one-hot or categorical conversion), the correlation coefficients range between approximately −0.15 and 0.1 instead of showing higher typical numeric associations, so even small correlations can still be meaningful. Taken together, these results imply that mental health challenges are fairly evenly distributed across student demographics, though specific academic programs may warrant closer monitoring and support intervention.

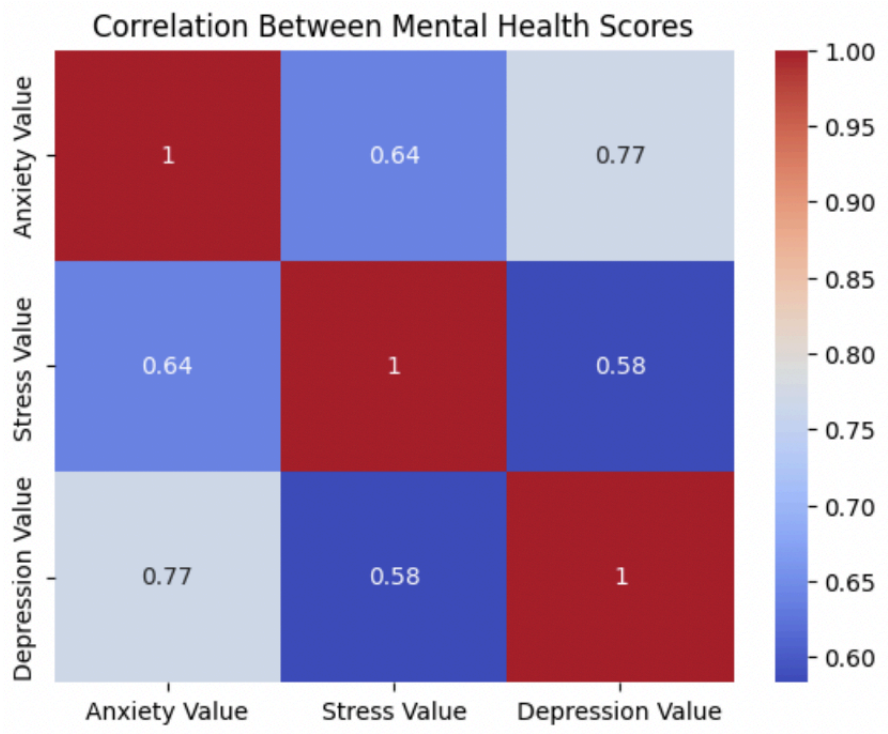



Figure 12: Correlation Heatmap between Mental State

Moreover, the correlation heatmap in Figure 12 provides additional insight by illustrating the relationships between the mental health scores themselves namely anxiety, stress, and depression. The numbers represent Pearson correlation coefficients, with higher values indicating stronger positive associations. The strongest observed correlation is between anxiety and depression (0.77), suggesting that students experiencing higher levels of anxiety are also likely to report more depressive symptoms. A moderately strong correlation of 0.64 exists between anxiety and stress, indicating that these conditions often co-occur. The correlation between stress and depression is slightly weaker at 0.58 but still shows a positive relationship. These findings underscore the interconnected nature of mental health conditions, highlighting anxiety as a particularly central link that may influence both stress and depression levels among students.

# Methodology

### I. Data Collection

The dataset used in this study was obtained from Kaggle [1], titled *"University Student Mental Health."* It contains self-reported data from university students, covering basic demographic variables such as age, gender, university, academic year, CGPA, and scholarship status. In addition, the dataset includes responses to questions aligned with DSM-5 criteria to assess three mental health conditions: 7 items related to Anxiety, 10 items for Stress, and 9 items for Depression. This dataset was selected for its relevance to student well-being, diversity in features, and open accessibility for academic research.

### II. Data Preprocessing

Column names were first renamed for consistency, readability, and to avoid overly long labels. Most features in the dataset were already in numerical format, which facilitated easier processing. For categorical variables, different encoding techniques were applied based on their nature and number of categories:

- One-Hot Encoding was used for variables like Age and Department, which had multiple non-ordinal categories.
- Label Encoding was applied to Gender, Course, Academic Year, Scholarship, CGPA, and the mental health labels (Depression Label, Anxiety Label, and Stress Label) to convert them into numeric format suitable for machine learning models.

Additional preprocessing steps included:

- Handling missing values – ensuring completeness and preventing model bias due to null entries
- Feature scaling – standardizing data using techniques such as Min-Max Scaling or Z-score normalization for better model convergence

These preprocessing steps ensured the dataset was clean, consistent, and ready for efficient and accurate model training.

### III. Visualization Data

Graphs and visualizations were utilized to gain deeper insights into the dataset. Various chart types—such as bar charts, pie charts, line graphs, and heatmaps—were employed to explore both univariate distributions and multivariate relationships. These visual tools helped identify patterns, trends, and correlations between variables. All visualizations were created using Python.

### IV. Model Development

To predict and classify mental health conditions—specifically Anxiety, Stress, and Depression, three machine learning models were developed and evaluated: XGBoost, Random Forest, and Support Vector Machine (SVM). These models were chosen for their effectiveness in handling classification tasks and their ability to manage both linear and non-linear relationships in the data. We exclude the Mental Health score as it doesn't fit the classification criteria. The model development process included the following key steps:

- Data Splitting: The dataset was divided into training, validation, and test sets to ensure robust evaluation. Typically, 70% of the data was used for training and the remaining 30 % was reserved for final testing to assess model generalization.
- Hyperparameter Tuning: Each model underwent grid search with cross-validation to find the optimal hyperparameters. For SVM, for example, different combinations of C and gamma values were tested using an RBF kernel. This tuning was performed using 5-fold cross-validation to ensure stability and prevent overfitting.
- Model Training: Once optimal hyperparameters were identified, the models were trained on the full training set. The goal was to accurately classify students into different severity levels of mental health conditions (e.g., minimal, moderate, severe).

## V. Model Evaluation

To assess the performance of the classification models, several evaluation metrics were used. The confusion matrix served as a foundational tool to visualize the model's prediction outcomes. For each mental health classification task (Anxiety, Stress, Depression), the confusion matrix displayed the number of correct and incorrect predictions by comparing the predicted labels against the true labels. In the case of multiclass classification, the confusion matrix helps identify how well the model distinguishes between different severity levels. Each cell in the matrix represents the count of predictions made for a given true label and predicted label combination. The diagonal values indicate correct predictions (True Positives for each class), while off-diagonal values represent misclassifications (i.e., False Positives and False Negatives across classes).
From the confusion matrix, we can derive key performance metrics:

- Precision – the proportion of correct positive predictions relative to total predicted positives
- Recall – the proportion of correct positive predictions relative to total actual positives
- F1-Score – the harmonic mean of precision and recall, useful for imbalanced class evaluation
- Accuracy – the overall percentage of correctly classified instances

These metrics were calculated using sklearn's classification_report, providing a detailed evaluation for each class label. High precision and recall across severity levels indicated the model's effectiveness in minimizing both false positives and false negatives.

## VI. Web-Based Analytics System Implementation

a. Mental Health Risk Prediction:
Predictive models were developed to estimate the likelihood that a student may be experiencing symptoms of anxiety, stress, or depression. These models function as early warning systems, offering a form of pre-diagnosis that enables timely intervention before symptoms progress into a formal mental health condition. Students can choose which mental health category they wish to evaluate themselves on, allowing for a more personalized and targeted risk assessment. By identifying at-risk individuals early, appropriate support and resources can be provided proactively, improving outcomes and reducing the burden on counseling services.

c. Prescriptive Recommendations:
Tailored, actionable interventions are generated immediately after the model predicts a student's mental health risk level. These recommendations are based on the predicted likelihood of experiencing symptoms of anxiety, stress, or depression. Depending on the severity of the predicted risk, students may be guided toward appropriate support options such as counseling services, mental health workshops, or evidence-based self-help resources. This personalized feedback ensures that students receive timely and relevant support aligned with their individual needs, promoting proactive mental health care.

d. Descriptive Analytics Dashboard:
An interactive dashboard was developed using Tableau (or Power BI) to visualize aggregated insights from the mental health prediction models. This dashboard is designed to support university counselors, administrators, and support staff by presenting data in a clear, accessible format for informed decision-making. Key features of the dashboard include:

- Lists of high-risk students, prioritized by their predicted likelihood of anxiety, stress, or depression
- Demographic breakdowns, such as risk levels segmented by gender, age group, academic year, and department or course of study
- Trend analysis, showing changes in mental health risk levels over the academic year
- Filter and drill-down options, allowing users to explore specific student subgroups or mental health conditions
- Exportable reports and alerts, which enable mental health professionals to take timely actions or schedule interventions

By consolidating predictive results with descriptive analytics, the dashboard serves as a centralized decision-support tool, helping institutions proactively monitor and respond to student mental health needs.

e. Student Risk Flagging and Notification Mechanism:

A notification feature was implemented to automatically flag students classified as high-risk based on their most recent mental health assessment. When a student completes the survey or when new data is analyzed, the system identifies those with elevated likelihood scores for anxiety, stress, or depression and places a risk flag on their profile. Rather than triggering real-time alerts, this mechanism is designed to support scheduled, periodic reviews by university mental health professionals. Counselors and support staff can access updated risk lists through the analytics dashboard, allowing them to prioritize outreach and interventions efficiently. This approach ensures that mental health services can respond promptly while avoiding unnecessary alert fatigue. By maintaining an up-to-date record of at-risk individuals, the flagging system enhances institutional readiness and helps ensure that no student in need goes unnoticed.

f. Reporting and Data Export:

A feature for report generation and data export was integrated to support strategic decision-making and institutional mental health planning. The system allows users to generate customizable reports that summarize trends in mental health risk, demographic distributions, and predictive model outputs. Reports can be filtered by variables such as academic year, gender, department, or mental health category, making it easier for stakeholders to tailor insights to specific groups. Exportable formats such as PDF, Excel, or CSV are provided, enabling seamless integration into internal documentation, presentations, or institutional records. These reports equip university administrators, mental health teams, and academic leadership with evidence-based insights to inform policy-making, allocate resources more effectively, and track the impact of mental health initiatives over time.

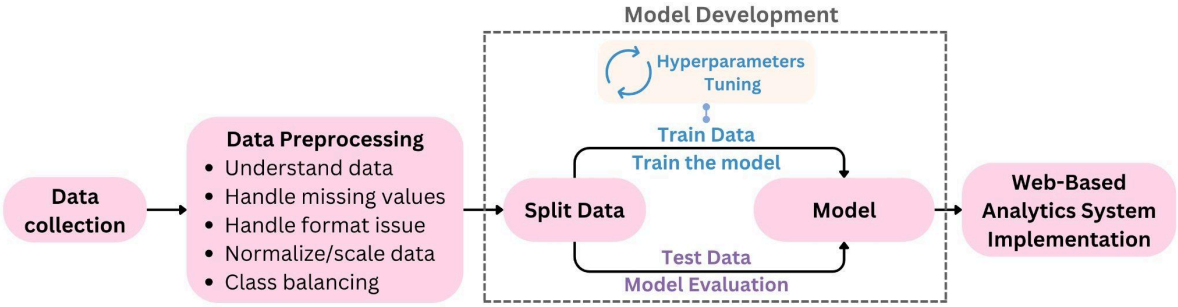



Figure 13: Proposed Methodology for prediction Mental Health

# Model

To classify the severity levels of depression, stress, and anxiety, three machine learning models were selected: Random Forest, XGBoost, and Support Vector Machine (SVM). Random Forest was chosen for its robustness and ability to handle non-linear relationships, as well as its built-in feature importance capabilities, which help interpret the influence of different variables. XGBoost was included due to its strong performance in structured data classification tasks, particularly when dealing with imbalanced classes, thanks to its boosting technique and regularization features. Lastly, SVM was selected for comparison purposes, as it performs well on smaller datasets and is effective in high-dimensional spaces, especially when the classes are not linearly separable. Using these three models allows for a balanced evaluation of both interpretability and predictive performance in detecting mental health risks among students.

**Anxiety** - The best performing model for anxiety classification was the Support Vector Machine (SVM), achieving the highest overall accuracy of 0.95. It also outperformed other models on precision (0.95), recall (0.96), and F1-score (0.96) for both macro and weighted averages. The confusion matrix shows that SVM had minimal misclassification across all four anxiety levels, with perfect prediction for class 0 and no confusion between class extremes. This makes it the most robust and reliable model for distinguishing between different anxiety severity levels in this dataset.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Random Forest | 0.92 | 0.92 | 0.91 | 0.92 |
| XGBoost | 0.92 | 0.93 | 0.91 | 0.92 |
| SVM | 0.95 | 0.95 | 0.96 | 0.96 |

**Stress** - The Support Vector Machine (SVM) was the best performing model for stress classification, achieving the highest accuracy of 0.96 along with precision (0.97), recall (0.96), and F1-score (0.97). It showed strong classification performance across both majority and minority stress levels, particularly excelling in detecting the severe stress group, a common challenge in imbalanced datasets. In comparison, XGBoost and Random Forest performed slightly worse, especially in recall, indicating they missed more true positive cases from the minority classes. SVM's balanced and high scores across all metrics make it the most robust choice for stress-level prediction.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Random Forest | 0.92 | 0.93 | 0.78 | 0.82 |
| XGBoost | 0.94 | 0.92 | 0.85 | 0.88 |
| SVM | 0.96 | 0.97 | 0.96 | 0.97 |

**Depression** - Support Vector Machine (SVM) remained the top-performing model for depression classification, achieving the highest accuracy of 0.95 along with precision, recall, and F1-score all at 0.95. It effectively distinguished between all six depression severity levels, with minimal misclassification between adjacent categories a common pitfall in multi-class classification tasks. In contrast, Random Forest and XGBoost showed greater confusion between neighboring classes and performed less consistently across the full range of severity levels. SVM's balanced performance and superior generalization make it the most reliable model for predicting depression severity.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Random Forest | 0.89 | 0.91 | 0.90 | 0.89 |
| XGBoost | 0.88 | 0.91 | 0.91 | 0.99 |
| SVM | 0.95 | 0.95 | 0.95 | 0.95 |

After training and evaluating all three models—Random Forest, XGBoost, and Support Vector Machine (SVM)—it was found that SVM consistently outperformed the others across all three mental health classification tasks: Anxiety, Stress, and Depression. Based on its superior performance, further optimization was conducted using Grid Search with 5-fold cross-validation to fine-tune SVM's hyperparameters. The parameter grid included different values of `C` (0.1, 1, 10) and `gamma` (1, 0.1, 0.01) with an RBF kernel. The best performing combination identified through this process was `C=10` and `gamma=0.01`, which yielded the highest accuracy and F1-score on the validation sets. This fine-tuned SVM model further improved the classification consistency and minimized misclassifications, making it the optimal choice for predicting severity levels of Anxiety, Stress, and Depression among students.

The results from the fine-tuned SVM models for each mental health condition demonstrate exceptional predictive performance. For the Anxiety classification, the model achieved an overall accuracy of 99%, with macro and weighted F1-scores both close to 0.99. The confusion matrix reveals near-perfect predictions across all four severity levels (labels 0 to 3), with only three instances of misclassification occurring in lModerate Anxiety, where a few samples were misclassified as Minimal Anxiety. This indicates that the model can accurately differentiate between different anxiety severity levels with very high reliability.

Similarly, the Stress classification model also attained a high accuracy of 98%, supported by strong macro and weighted F1-scores of 0.98. The confusion matrix shows minimal errors: one instance from low stress was predicted as moderate stress, and three instances from moderate stress were predicted as high perceived stress. Despite slight overlap in adjacent severity levels, the model shows a strong capacity for distinguishing stress categories, particularly the large class of Moderate Stress (label 1), which was classified correctly 260 out of 264 times.

For Depression, which had six classification levels from no depression to severe depression (abels 0 to 5), the SVM model achieved an outstanding accuracy of 99%. The F1-scores for individual classes ranged from 0.95 to 1.00, with the majority of predictions aligning exactly with the true labels. The confusion matrix shows only a few misclassifications (e.g., one instance of minimal depression misclassified as no depression and two instances of severe depression misclassified as moderate severe depression). Overall, the model successfully handled the increased complexity of multiclass classification, effectively capturing nuanced differences in depression severity.

In summary, the fine-tuned SVM models performed robustly across all three mental health prediction tasks, maintaining high precision, recall, and F1-scores while minimizing misclassification. These results confirm the SVM's reliability for early risk detection and classification of student mental health conditions, making it a valuable tool for pre-diagnostic screening and targeted intervention.

# Website

**Home Page** -
The homepage of the SynapSense website offers a clear introduction to its mission of supporting student mental health through data-driven tools. It highlights key statistics on the prevalence of depression, anxiety, and stress among university students, underscoring the urgency of early intervention. The platform's mission, offerings, and value are summarized through its commitment to predictive analytics, interactive dashboards, and collaborative insights, empowering universities to identify and assist at-risk students. Additionally, the homepage educates visitors on the definitions and symptoms of anxiety, stress, and depression, and presents a "Mental Health at a Glance" table comparing these conditions across triggers, symptoms, duration, and academic impact. Together, these elements create an accessible and professional interface that blends advanced technology with human empathy to promote student well-being.

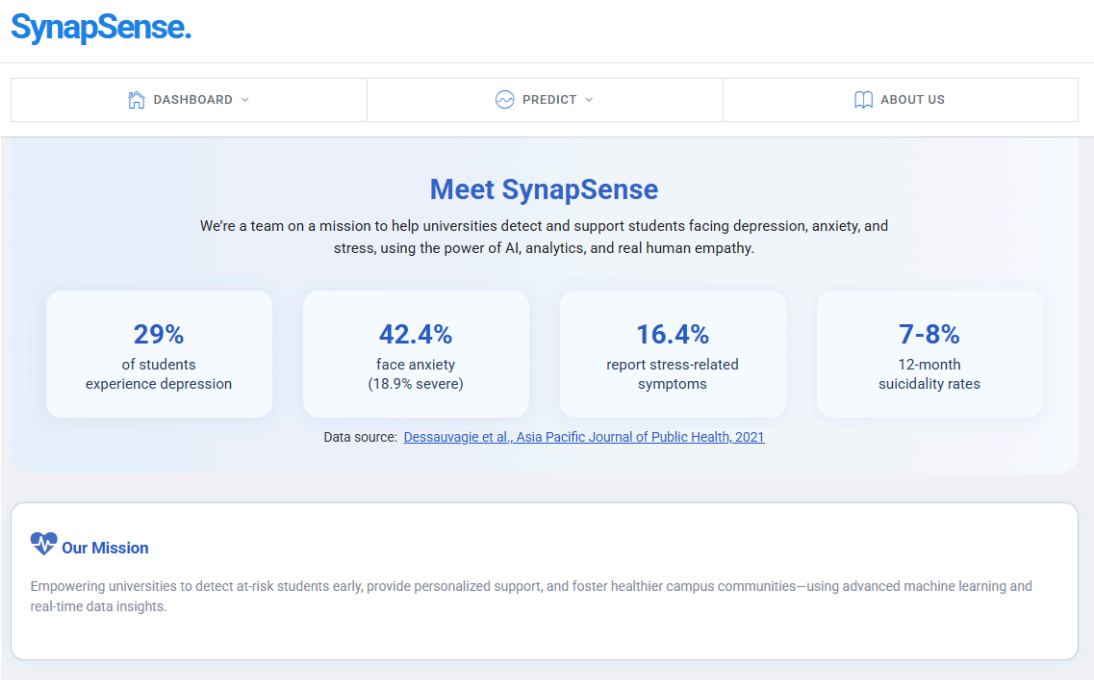
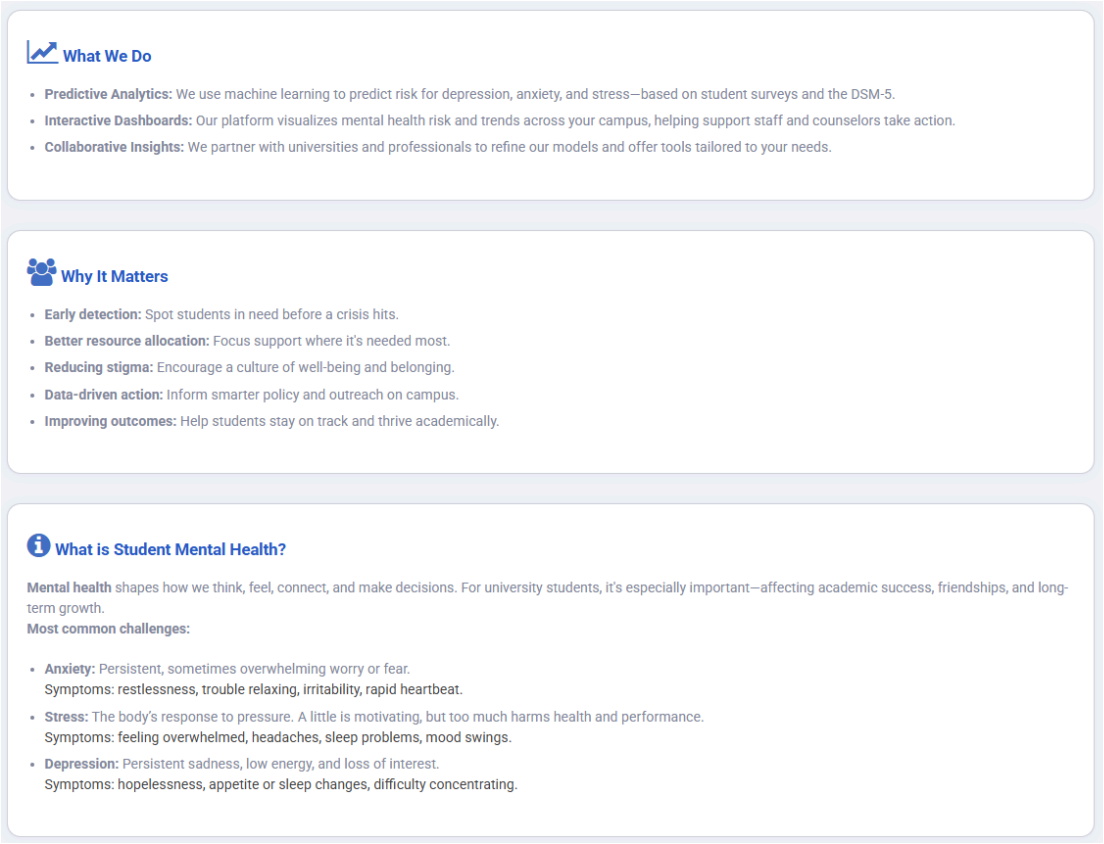



Figure 14: Website Home Page Display

When students or university staff log into the SynapSense platform, they are welcomed with a clear and impactful snapshot of global student mental health trends. The homepage prominently features key statistics drawn from published research, such as the proportion of students experiencing depression (29%), anxiety (42.4%, with 18.9% severe), stress-related symptoms (16.4%), and annual suicidality rates (7 – 8%). These headline figures, supported by a referenced data source, immediately set the context for why proactive mental health screening and support are urgently needed.

This overview is designed to build awareness and emphasize the scale of mental health challenges affecting student populations, providing motivation for users to explore the platform's predictive tools and dashboards. By highlighting these evidence-based statistics at the entry point, SynapSense helps create a sense of urgency and empathy, encouraging institutions and individuals to take informed, data-driven action to promote well-being and resilience on campus.



**What We Do**

- **Predictive Analytics:** We use machine learning to predict risk for depression, anxiety, and stress—based on student surveys and the DSM-5.
- **Interactive Dashboards:** Our platform visualizes mental health risk and trends across your campus, helping support staff and counselors take action.
- **Collaborative Insights:** We partner with universities and professionals to refine our models and offer tools tailored to your needs.

**Why It Matters**

- **Early detection:** Spot students in need before a crisis hits.
- **Better resource allocation:** Focus support where it's needed most.
- **Reducing stigma:** Encourage a culture of well-being and belonging.
- **Data-driven action:** Inform smarter policy and outreach on campus.
- **Improving outcomes:** Help students stay on track and thrive academically.

**What is Student Mental Health?**

**Mental health** shapes how we think, feel, connect, and make decisions. For university students, it's especially important—affecting academic success, friendships, and long-term growth.
**Most common challenges:**

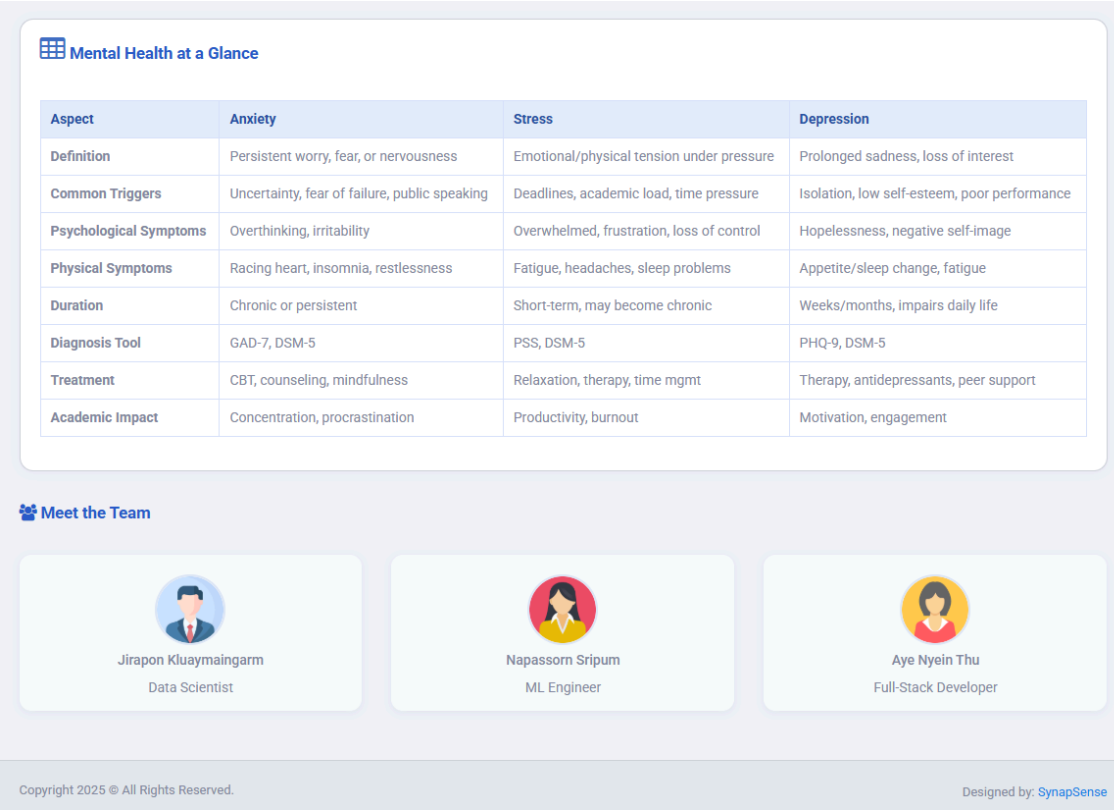
- **Anxiety:** Persistent, sometimes overwhelming worry or fear.
  Symptoms: restlessness, trouble relaxing, irritability, rapid heartbeat.
- **Stress:** The body's response to pressure. A little is motivating, but too much harms health and performance.
  Symptoms: feeling overwhelmed, headaches, sleep problems, mood swings.
- **Depression:** Persistent sadness, low energy, and loss of interest.
  Symptoms: hopelessness, appetite or sleep changes, difficulty concentrating.

Figure 15: Website Home Page Display (What we do)

This section of the SynapSense homepage provides users with a comprehensive introduction to the platform's core mission, features, and the critical importance of mental health support. Under "What We Do," SynapSense describes its commitment to using predictive analytics to estimate student risk for anxiety, stress, and depression based on scientifically grounded criteria (DSM-5), and highlights the use of interactive dashboards to make data-driven decisions accessible to counselors and administrators. The section also emphasizes collaboration with universities to continuously refine models and tailor solutions.

In "Why It Matters," the page explains the platform's real-world impact: early detection of mental health concerns, improved resource allocation, stigma reduction, data-informed decision-making, and ultimately better academic outcomes for students. This motivates both students and universities to engage with the platform's tools proactively.

Finally, under "What is Student Mental Health?", there is an educational explanation of mental health for students, including its influence on thinking, connection, and decision-making. It lists the most common challenges anxiety, stress, and depression with associated symptoms in simple, relatable language. This helps students and staff recognize these mental health issues early and understand why it is worth exploring further predictive assessments offered by SynapSense.



Mental Health at a Glance

| Aspect | Anxiety | Stress | Depression |
|---|---|---|---|
| Definition | Persistent worry, fear, or nervousness | Emotional/physical tension under pressure | Prolonged sadness, loss of interest |
| Common Triggers | Uncertainty, fear of failure, public speaking | Deadlines, academic load, time pressure | Isolation, low self-esteem, poor performance |
| Psychological Symptoms | Overthinking, irritability | Overwhelmed, frustration, loss of control | Hopelessness, negative self-image |
| Physical Symptoms | Racing heart, insomnia, restlessness | Fatigue, headaches, sleep problems | Appetite/sleep change, fatigue |
| Duration | Chronic or persistent | Short-term, may become chronic | Weeks/months, impairs daily life |
| Diagnosis Tool | GAD-7, DSM-5 | PSS, DSM-5 | PHQ-9, DSM-5 |
| Treatment | CBT, counseling, mindfulness | Relaxation, therapy, time mgmt | Therapy, antidepressants, peer support |
| Academic Impact | Concentration, procrastination | Productivity, burnout | Motivation, engagement |

Meet the Team

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Data Scientist

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Designed by: SynapSense

Figure 16: Website Home Page Display (More about us)

This section provides a concise, side-by-side comparison of anxiety, stress, and depression to help both students and university staff quickly understand their key characteristics. Presented in a simple table format, it highlights important aspects such as definitions, common triggers, psychological and physical symptoms, duration, diagnosis tools, recommended treatments, and the academic impact of each condition.

By summarizing these factors clearly, the table equips users with an easy reference to distinguish between these mental health challenges. This helps students choose the correct screening tool when using the predictive assessments, while also supporting counselors and decision-makers in tailoring their interventions and communication.

**Dashboard Page** -

After this overarching snapshot, the system offers individual dashboards dedicated to anxiety, stress, and depression. Each of these dashboards is designed to present in-depth visual insights and interactive features that help users explore specific mental health patterns, risk factors, and demographic trends. These dedicated pages enable counselors, faculty, and students to drill down into the data relevant to each mental health area, supporting more targeted and proactive decision-making. The following sections describe each of these dashboards in greater detail, explaining their graphs, visual elements, and practical applications.

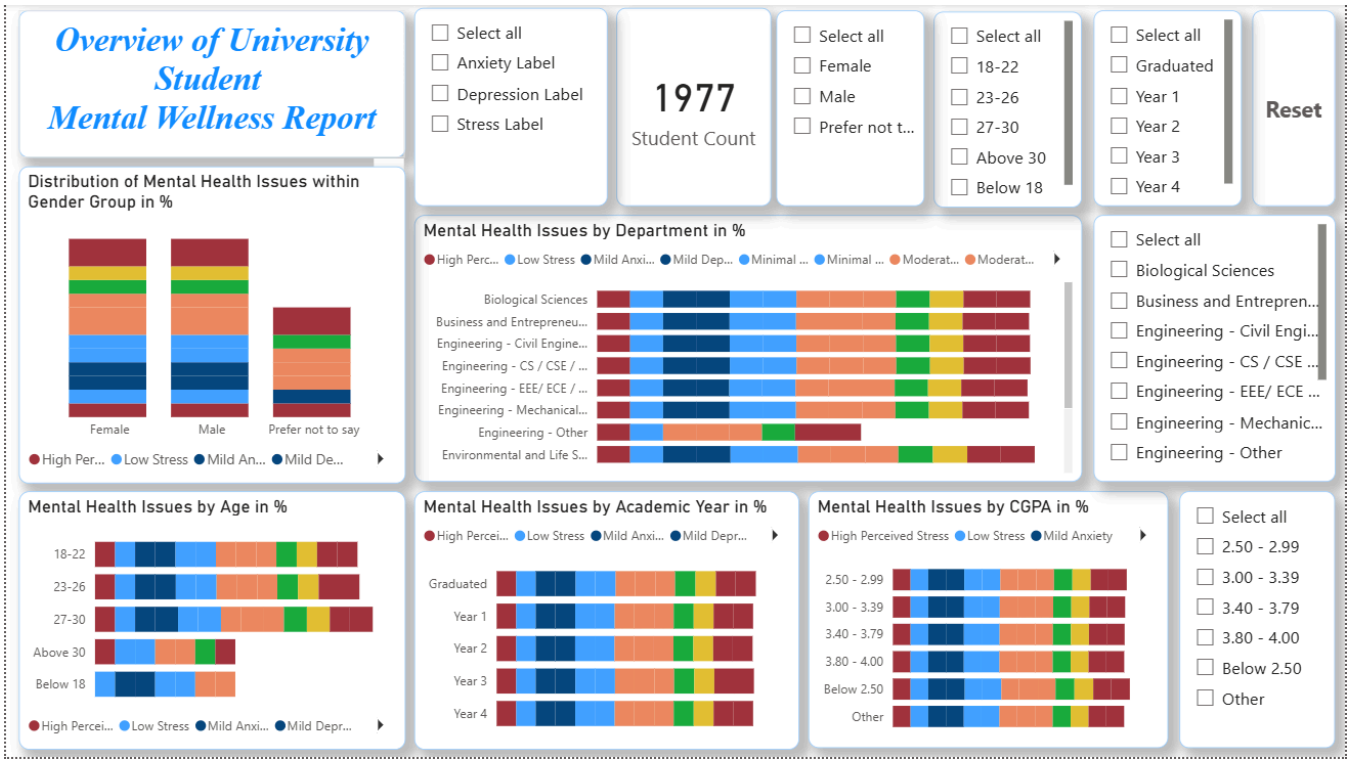


Figure 17: Overall University Mental Health Dashboard

**University Student Mental Wellness Report Overview**

The University Student Mental Wellness Report dashboard provides a comprehensive bird's-eye view of mental health issues—specifically anxiety, depression, and stress—among university students. A total of 1,977 students are presented in this dataset. As key features of the dashboard, the three core mental health issues are tracked using both horizontal and vertical stacked bar charts, which effectively display the proportion of each issue. These visualizations offer clear comparisons across various student attributes such as gender, age group, academic year, current CGPA, and department.

**Mental Health Issue Distribution by Attributes**

The vertical stacked bar chart illustrates the distribution of mental health conditions across gender categories, including female, male, and those who preferred not to disclose their gender. Horizontal bar charts are used to show the prevalence of mental health issues across six age groups: Below 18, 18–22, 23–26, 27–30, and Above 30. The academic year dimension includes first- through fourth-year students as well as graduates, highlighting mental wellness at different stages of university education. Additionally, current CGPA is analyzed across performance ranges (Below 2.50 to 4.00) to examine potential links between academic performance and mental health. The department-wise distribution covers a broad range of academic disciplines, including various engineering branches, biological sciences, liberal arts, and others, revealing department-specific mental health patterns.

**Interactivity and Filters**

The dashboard includes a set of slicers that enable users to filter and explore the data interactively by selecting specific mental health issue types (anxiety, depression, stress), gender, age group, academic year, department, and CGPA range. This interactivity allows for tailored analysis and deeper insight into specific student subgroups. Additionally, a "Reset" button is provided to clear all selections and return the dashboard to its default view, ensuring ease of navigation and exploration.

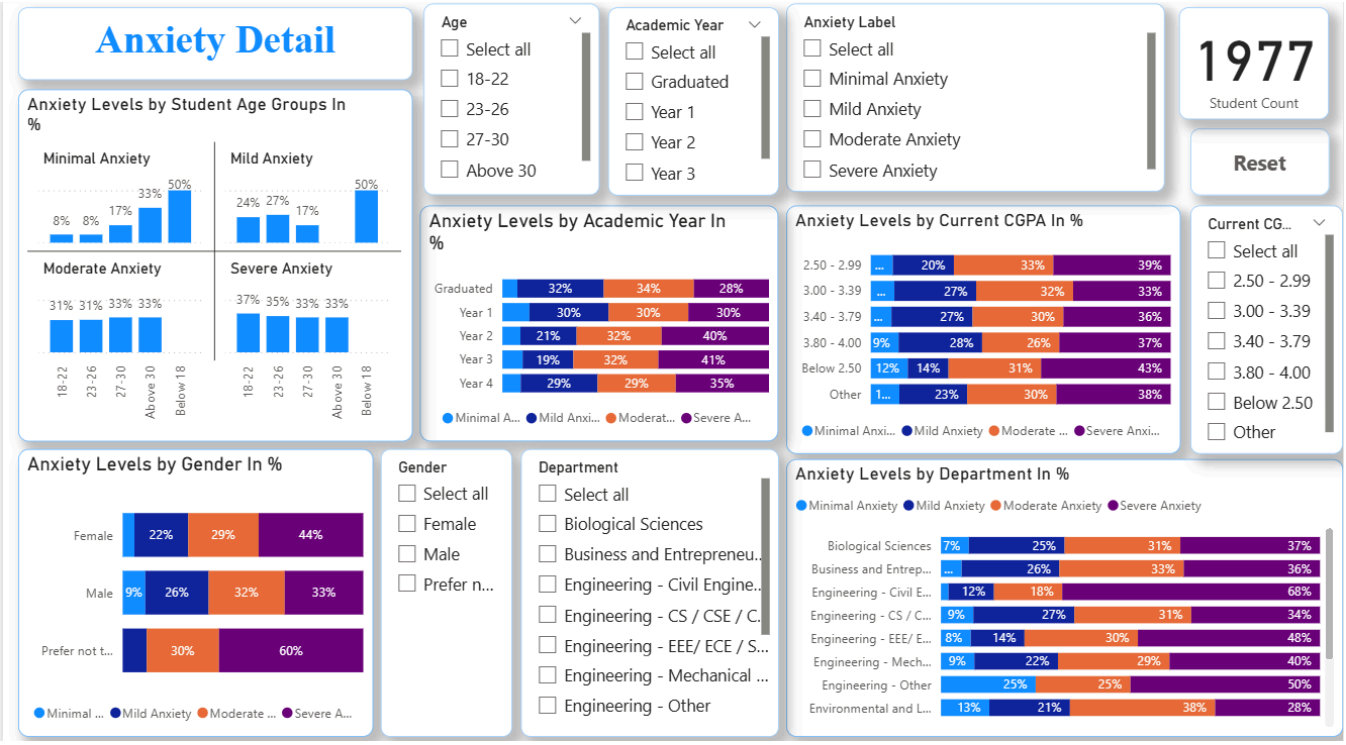


Figure 18: Anxiety Dashboard Overview

## Anxiety Detail Dashboard Summary

The "Anxiety Detail" dashboard provides a visual analysis of four anxiety levels—Minimal, Mild, Moderate, and Severe—among 1,977 students, using percentage distributions within each subgroup to ensure fair comparison across uneven sample sizes (e.g., gender and department).

**Anxiety Level by Age Group:** Displayed as a column chart with four small quadrants representing each anxiety level. About 50% of students below 18 fall into the Minimal and Mild Anxiety categories, indicating lower anxiety levels in younger students. In contrast, students in other age groups consistently show higher proportions of Moderate and Severe Anxiety (ranging from 31% to 37%), suggesting an increase in anxiety severity with age.

**Anxiety Levels by Gender:** Visualized as a horizontal stacked bar chart, this illustration shows that 44% of female students experience Severe Anxiety, representing the highest proportion within that group. Among male students, 32% experience Moderate Anxiety and 33% experience Severe Anxiety, while only 9% fall into the Minimal Anxiety category. Notably, 60% of students who prefer not to disclose their gender experience Severe Anxiety, and none fall into the Minimal category (0%). These percentages reflect the distribution within each gender subgroup, not across anxiety levels, highlighting how the severity of anxiety varies by gender identity.

**Anxiety Levels by Academic Year:** Displayed as a horizontal stacked bar chart, the data indicate that 41% of Year 3 students and 40% of Year 2 students experience Severe Anxiety, making them the most affected groups. In contrast, 32% of Graduated students fall into the Minimal Anxiety category, suggesting a potential reduction in stress following graduation. Among Year 1 students, 30% experience Mild Anxiety and another 30% experience Moderate Anxiety, reflecting challenges commonly faced during the early transition into university life. These percentages are based on the distribution within each academic year group, offering insight into how anxiety levels vary throughout the student journey.

**Anxiety Levels by Current CGPA:** Presented as a horizontal stacked bar chart, this section shows that 43% of students with a CGPA below 2.50 experience Severe Anxiety, the highest proportion among all CGPA groups. The same group also reports the lowest share in Minimal Anxiety at 12%, indicating a strong association between low academic performance and heightened anxiety. In comparison, 37% of students with a CGPA between 3.80–4.00 also experience Severe Anxiety, showing that even top-performing students face considerable stress. These percentages represent the distribution within each CGPA group, highlighting that while anxiety exists across performance levels, it is most strongly concentrated among academically underperforming students.

**Anxiety Levels by Department:**This horizontal stacked bar chart illustrates notable differences in anxiety levels across academic departments. Among all groups, 68% of Engineering – Civil students experience Severe Anxiety, the highest proportion observed, while only 12% fall into Minimal Anxiety. Students from Engineering – EEE/EC also show elevated Severe Anxiety at 48%. In contrast, the Environmental and Life Sciences department presents the most favorable distribution, with 13% of students in Minimal Anxiety and just 28% in Severe Anxiety. These percentages are calculated within each department's population, indicating that students in engineering-related programs, particularly Civil and EEE, are more prone to experiencing severe anxiety compared to those in other fields.

## Conclusion

This dashboard provides valuable insights into how anxiety levels differ by age, gender, academic year, performance, and field of study. The findings highlight the importance of targeted mental health support—particularly for students in engineering, those in mid-academic years, low-performing individuals, and students who choose not to disclose their gender.

Figure 19: Depression Dashboard Overview

**Depression Detail Dashboard Summary**

The "Depression Detail" dashboard presents a comprehensive view of six categorized depression levels—No Depression, Minimal Depression, Mild Depression, Moderate Depression, Moderately Severe Depression, and Severe Depression—among 1,977 students. Percentages in the visualizations reflect the proportion within each subgroup (age, gender, academic year, CGPA, and department), allowing for fair comparison across groups of different sizes.The dashboard contains five key visual components:

**Depression Levels by Age Group**

This column chart with six small multiples shows how depression levels vary across five age groups. Among students below 18, half experience Minimal Depression, while the other half are evenly split between Mild and Moderate Depression (25% each), indicating a concentration in lower-level symptoms. Students aged 18–30 display consistent distributions across Mild, Moderate, Moderately Severe, and Severe Depression (ranging from 21% to 26%), suggesting a persistent presence of depressive symptoms. The Above 30 group shows the highest severity, with 67% experiencing Moderate Depression and 33% Moderately Severe Depression. No Depression is rare across all age groups, especially in younger adults (2%–13%), highlighting that most students experience at least some level of depression.

**Depression Levels by Gender**

This horizontal stacked bar chart illustrates the distribution of depression levels within each gender group. Among female students, 30% experience Severe Depression, followed by 28% in Moderately Severe Depression, and 18% each in Moderate Depression and Mild Depression, indicating a significant concentration in higher-level symptoms. For male students, depression levels are more evenly distributed: 25% report Moderate Depression, 24% Moderately Severe, and 22% each in Mild and Severe Depression. Students who prefer not to disclose their gender show the highest proportion (60%) in Severe Depression, with equal shares of 20% in Moderately Severe and Moderate Depression, emphasizing a pronounced mental health concern in this group. All percentages reflect proportions within each gender category.

**Depression Levels by Academic Year**

This vertical stacked bar chart highlights that Severe Depression is most prevalent among Year 2 students (31%), followed by Year 3 (28%) and Graduated students (27%). Additionally, 27% of Year 2 and 26% of Year 3 students experience Moderately Severe Depression, along with 24% of both Year 1 and Year 4 students. In the Moderate Depression category, 26% of Year 4 and 25% of Year 1 students are affected. These patterns suggest that students in Years 2 and 3 are particularly vulnerable to higher levels of depression, likely due to academic pressure and workload, while mental health tends to improve slightly after graduation.

**Depression Levels by Current CGPA**

This horizontal stacked bar chart shows that Severe Depression is highest among students with CGPA 2.50–2.99 (29%), followed by 25% in both the below 2.50 and 3.40–3.79 ranges. Moderately Severe Depression peaks at 31% for students below 2.50 and 27% for those with 3.00–3.39 CGPA. Moderate Depression is most common among students labeled as “Other” (27%) and those with 3.00–3.39 CGPA (24%). Among top performers (CGPA 3.80–4.00), 24% fall into Mild, Moderately Severe, and Severe Depression categories equally. These results indicate that both low and high academic achievers experience significant levels of depression, though students with lower CGPA face a higher risk of more severe depressive symptoms.

**Depression Levels by Department**

This horizontal stacked bar chart shows that Severe Depression affects 44% of Civil Engineering, 50% of Engineering – Other, and 34% of Business & Entrepreneurship students. Notably, 100% of Law and Human Rights and 100% of Liberal Arts and Social Sciences students suffer from Severe Depression, though each has only one student in the sample. Moderately Severe Depression is highest in Civil Engineering (34%), Mechanical Engineering (32%), and Electrical Engineering (30%). 100% of Pharmacy and Public Health students (n=1) report Moderate Depression. In Computer Science, 24% of students fall into each of the Moderate, Moderately Severe, and Severe Depression categories.Depression severity is notably high in engineering and business fields, with

Civil Engineering standing out for both Severe and Moderately Severe Depression. While smaller departments show extreme values due to limited samples, the data overall suggest that students in technical and high-pressure programs face greater mental health challenges.

**Conclusion:**

The dashboard reveals that depression is widespread among students, with the highest severity observed in mid-academic years, lower CGPA ranges, and demanding fields like engineering and business. While some extremes are linked to small sample sizes, the overall trend highlights a clear need for targeted mental health support, particularly for academically pressured and high-risk groups.

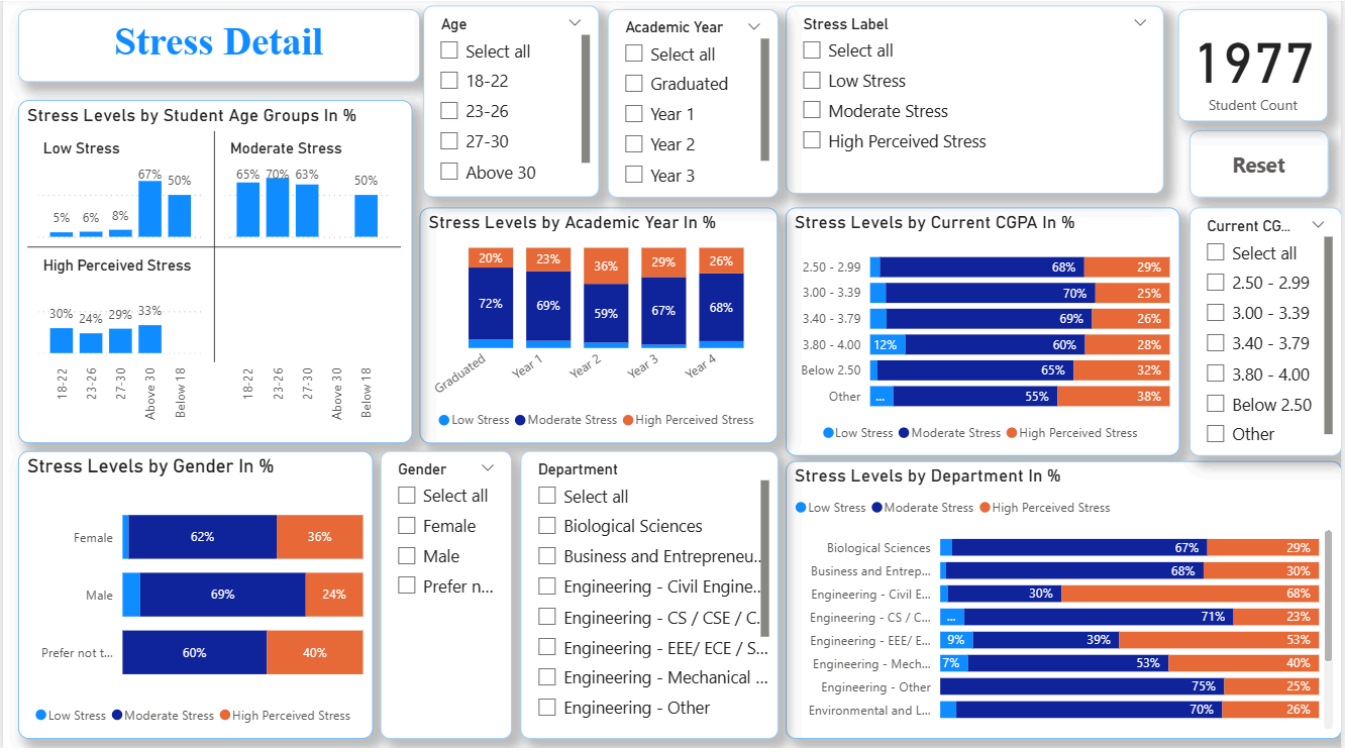


Figure 20: Stress Dashboard Overview

**Stress Detail Dashboard Summary**

The "Stress Detail" dashboard presents a visual breakdown of three stress levels—Low, Moderate, and High Perceived Stress—across 1,977 students. All percentages represent the internal distribution within each subgroup (e.g., gender, academic year, department), enabling fair comparison across varying group sizes.

**Stress Levels by Age Group**

This column chart shows that 70% of students aged 23–26, 65% of those aged 18–22, and 63% of students aged 27–30 experience Moderate Stress. Even among students below 18, 50% report Moderate Stress—an unexpectedly high level for this age. Another 50% of students below 18 are in Low Stress, which appears reasonable. Interestingly, 67% of students above 30 report Low Stress, while 33% face High Perceived Stress. Among 18–22-year-olds, 30% experience High Perceived Stress, with only 5% in Low Stress—highlighting a concerning stress burden on younger adults.

**Stress Levels by Gender**

This horizontal stacked bar chart shows that 69% of male students experience Moderate Stress, with 24% facing High Perceived Stress. Among female students, 62% fall into Moderate Stress, while a higher 36% report High Perceived Stress. For students who prefer not to disclose their gender, 60% are under Moderate Stress and 40% under High Perceived Stress, indicating elevated stress levels in this group.

**Stress Levels by Academic Year**
The chart shows that Moderate Stress is common across all academic years, affecting 72% of Graduated students, 69% of Year 1, 59% of Year 2, 67% of Year 3, and 68% of Year 4 students. High Perceived Stress is highest among Year 2 students at 36%, while it remains below 30% for students in other academic years, suggesting that Year 2 is a particularly stressful stage in the academic journey.

**Stress Levels by Current CGPA**
Moderate Stress is prevalent among students across all CGPA bands, with 70% of those in the 3.00–3.39 range, 69% in 3.40–3.79, 68% in 2.50–2.99, 65% in below 2.50, and 60% in 3.80–4.00 reporting it. High Perceived Stress affects 32% of students with CGPA below 2.50 and peaks at 38% in the "Other" category, while it remains under 30% for students within the 2.50–4.00 CGPA range. These patterns indicate that moderate stress is widespread, while high perceived stress is more common among lower-performing or unclassified students.

**Stress Levels by Department**
The horizontal stacked bar chart presents stress levels across departments. 68% of Civil Engineering students experience High Perceived Stress—the highest among all departments—followed by 53% of EEE/ECE students and 40% of Mechanical Engineering students. In contrast, 71% of Computer Science, 75% of Engineering–Other, and 70% of Environmental and Life Sciences students report Moderate Stress as the dominant level. Notably, 100% of students in Pharmacy and Public Health, Law and Human Rights, and Liberal Arts and Social Sciences fall under High Perceived Stress; however, each of these categories contains only one student. These findings indicate that Civil, EEE, and Mechanical Engineering students are the most affected by intense stress levels among the larger departments.

**Conclusion**
The "Stress Detail" dashboard reveals that Moderate Stress is the most common stress level across age, gender, academic year, CGPA, and department. However, High Perceived Stress is notably elevated among students aged 18–22, those in Year 2, students with low CGPA, and specific departments such as Civil Engineering and EEE/ECE. While older students and those in departments like Computer Science and Environmental Sciences report more moderate stress, the overall data underscores a significant mental health burden, particularly among academically pressured and technically demanding fields. These insights point to the need for targeted stress management interventions for vulnerable student groups.

Overall, the dashboards provide valuable insights into students' mental health, highlighting critical stress, anxiety, and depression patterns across demographic and academic profiles—serving as a vital tool for guiding targeted support and well-being interventions.

**Predictive Page** -
The mental health prediction section of the SynapSense website guides students through an intuitive and supportive workflow designed to prioritize their well-being. Upon accessing this section, students are prompted to select which mental health domain they wish to assess anxiety, stress, or depression. After making a selection, they are directed to a dedicated page for their chosen mental health category, where they will find a clear explanation of the condition along with descriptions of its common symptoms to help build awareness.

Students then proceed to complete a structured assessment form, which gathers essential demographic details (such as age group, gender, academic year, scholarship status, and department) alongside targeted mental health screening questions mapped to DSM-5 criteria. Once responses are submitted, the system generates a prediction indicating the likelihood of experiencing symptoms in the selected mental health category, classifies the severity of the condition, and presents the results in a user-friendly format.

Alongside the prediction, students receive tailored recommendations, including actionable steps, supportive resources, or professional referrals suited to their predicted risk level. This process empowers students to take ownership of their mental health, make informed decisions, and seek timely support if needed all through an accessible and data-driven online platform.

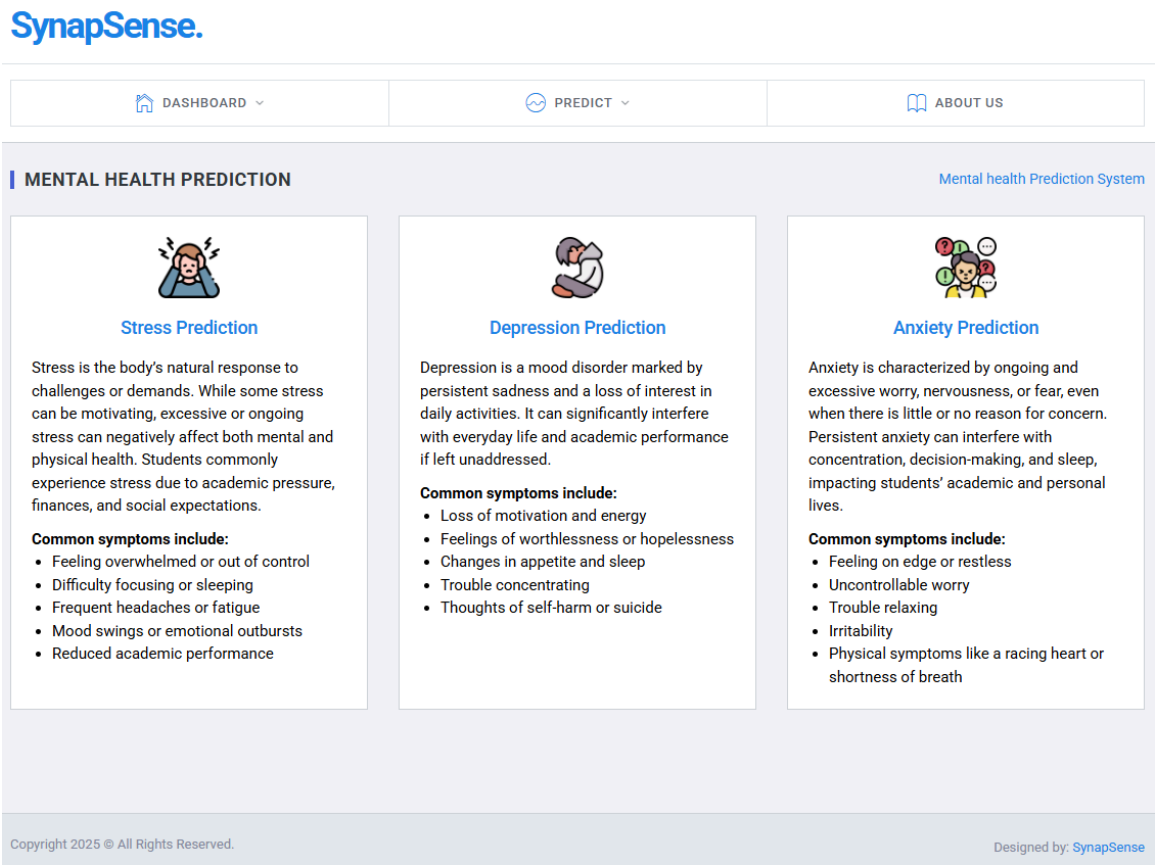


Figure 22: Mental Health Predictive Page

This section serves as a helpful guide for students and university staff to better understand which mental health category may align with their experiences before proceeding to prediction. By providing clear descriptions of stress, depression, and anxiety, along with their common symptoms, students can reflect on their own thoughts, feelings, and behaviors to identify which mental health concern may be most relevant to them. For example, those feeling persistently worried, tense, or restless may consider the anxiety prediction, while students experiencing prolonged sadness and loss of motivation might focus on the depression prediction. Those who feel overwhelmed by academic demands and constant pressure may explore stress prediction. This targeted guidance helps ensure students select the most appropriate mental health assessment, leading to more accurate results and timely recommendations. Universities can also use this information to educate their communities on recognizing early signs and choosing the right self-assessment tool.

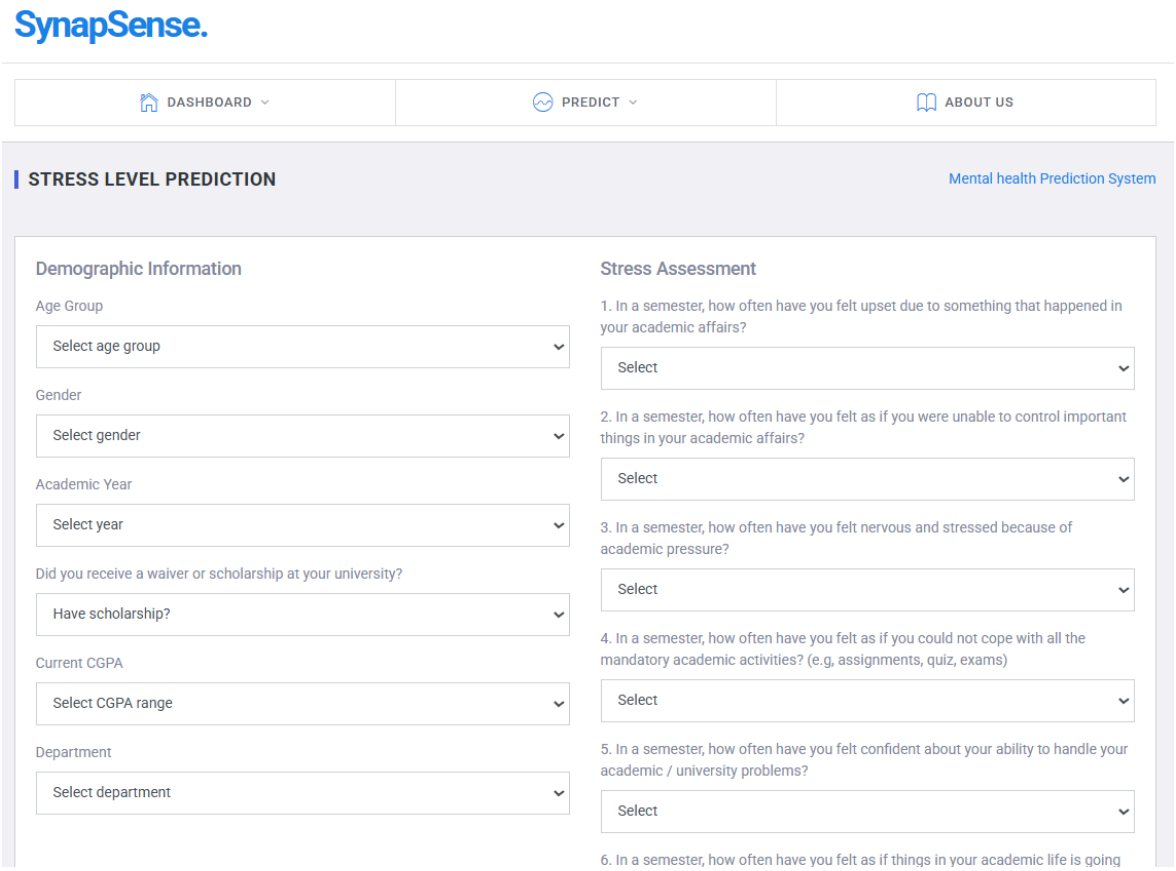


Figure 23: Example of Stress Predictive Page

In this section, users are required to complete all questions in order to generate an accurate prediction of their mental health risk. The form is divided into two parts: demographic information and a mental health assessment aligned with DSM-5 criteria. Demographic details include factors such as age group, gender, academic year, current CGPA, department, and scholarship status. This helps contextualize the results within the student's background. The second part contains targeted questions related to mental health symptoms, for example feelings of academic overwhelm, emotional distress, or loss of control, depending on the mental health category chosen. Completing these questions allows the model to analyze patterns comprehensively and deliver a personalized prediction with recommended next steps. This structured input ensures the system provides meaningful, evidence-based insights to support student well-being and guide potential interventions.

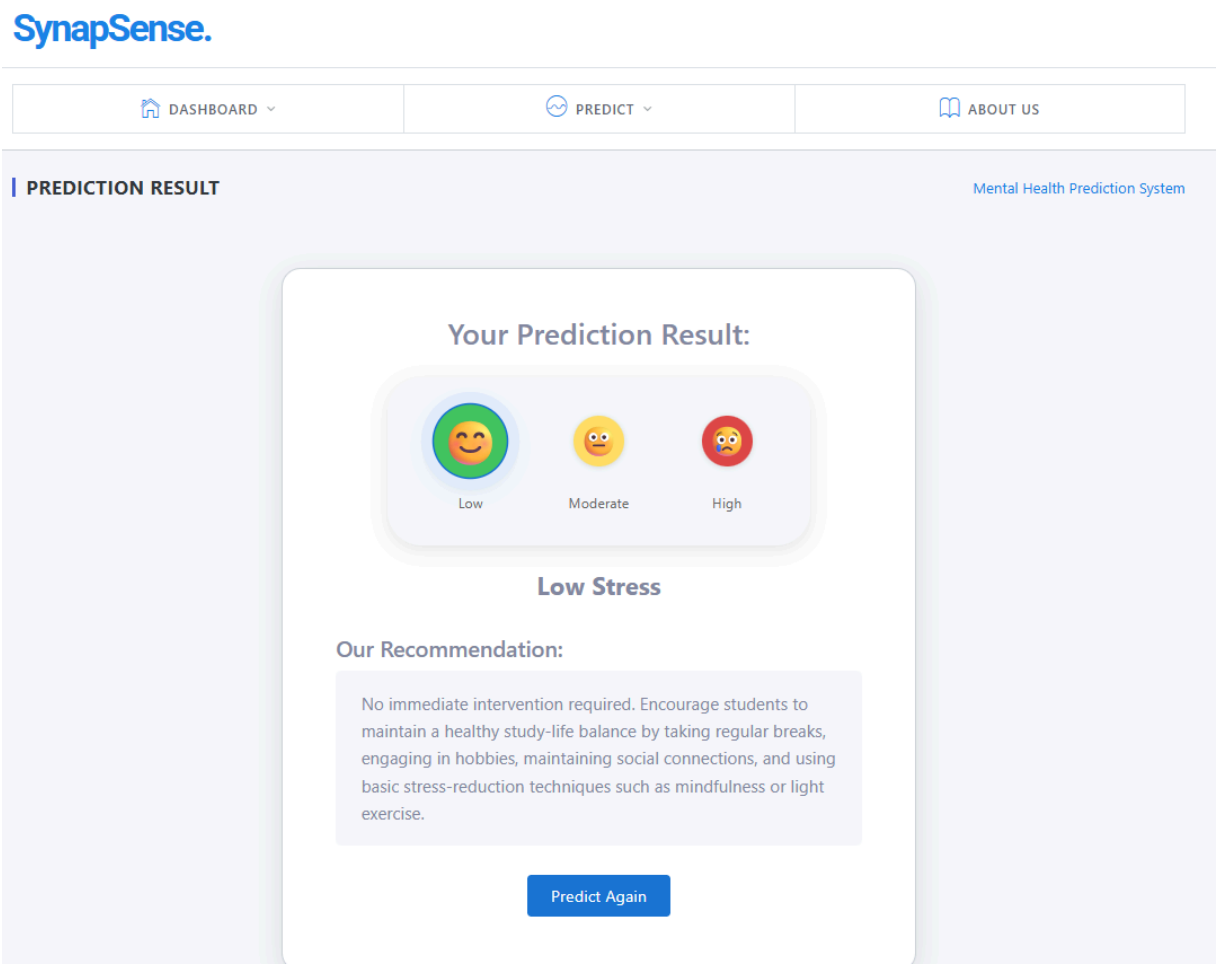


Figure 24: Example of Predictive Result from Mental Health Model

After submitting the assessment, students receive a clear and user-friendly prediction result indicating their mental health risk level  for example, Low, Moderate, or High along with a corresponding icon to aid quick interpretation. Below the risk level, a tailored recommendation is provided based on the student's predicted category. This recommendation suggests actionable next steps, such as maintaining a balanced study-life routine, engaging in hobbies, building social connections, or seeking further professional support if necessary. The system ensures that students are not only informed of their mental health status but are also guided on practical ways to improve their well-being which is crucial to preventing further deterioration of symptoms and fostering a healthier academic and personal life. A "Predict Again" button is available to encourage re-assessment whenever the student feels the need, supporting continuous monitoring and self-awareness.

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