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RESEARCH ARTICLE

Exploring the multifactorial influence of demographic, academic, lifestyle, and psychological factors on student depression

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ABSTRACT

Depression is a common mental health issue of college students, which negatively impacts their academic and social lives and general well-being. This paper examines the following multifactorial links between depression and various demographic, academic, occupation, lifestyle, and psychological factors of a massive student sample. The variables in the analysis are gender, age, academic pressure, CGPA, employment stress, sleeping time, dietary habits and family precedence of mental condition, suicidal thoughts and geographical location. To examine these relationships eight hypotheses were tested with a data set consisting of more than 27,000 students run through logistic regression. Findings show that the most powerful factors such as academic pressure (OR = 2.31, $p < 0.001$) and suicidal ideation (OR = 12.63, $p < 0.001$) are related to depression. Gender in this population was not an important predictor contrary to world trends. Having a younger age, having lower CGPA, shorter sleep durations, and poor eating habits were all linked to more probabilities of the occurrence of depression. Some association was also significant with a family history of mental illness (OR = 1.74) and some areas in the city, such as urban areas having an association. Analysis of interaction effect demonstrated that academic pressure increases depression status in students who receive insufficient sleep (interaction b = 0.0412, $p < 0.001$). So, the overall combined model explained 42.3 percent of the variance of depression results. Such results preach about the interdependence of mental health risk factors within an academic setting. Findings can be used to tailor prevention measures, university counseling, and culturally specific measures to early identify and accommodate potential at-risk students.

Keywords: Student depression; mental health; academic stress; lifestyle factors; multifactorial analysis; risk factors; psychological well-being

1. Introduction

Depression is a major mental health issue among students worldwide, impacting their academic performance, social relationships, and overall well-being. The World Health Organisation (WHO) identifies depression as a primary cause of global disability[1]. Mental health difficulties, such as depression, among students are associated with different demographic, academic, psychological, and lifestyle factors[2]. The demands of academic achievement, professional obligations, lack of sleep, and lifestyle decisions frequently converge to intensify mental health issues, especially depression, among adolescents[3].

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The academic setting, marked by rigorous standards and competitive pressures, serves as a considerable stressor for students, exacerbating their mental health challenges. Academic pressure adversely impacts students' psychological well-being, frequently leading to anxiety and despair[4]. Furthermore, occupational stress, especially among students who are concurrently working, has been identified as a substantial predictor of depression[5]. Sleep patterns, nutrition, and physical exercise have a significant impact on mental wellness. Research has continuously demonstrated a robust correlation between sleep deprivation, inadequate eating practices, and elevated levels of depression[6,7].

In recent years, depression levels have escalated into a serious mental condition affecting college students and particularly during the post-pandemic school years. It affects not only academic functioning negatively but, also, social and the general mental well-being. Depression is multidimensional in that there is an interaction between demographic, academic, lifestyle factors and the psychological factors. Although research is available on individual determinants, there is a paucity of research on the combined effect of these determinants within the larger student population, particularly a non-Westernized country like South Asia[8].

In India, differences in culture and orientation of institutions also make mental health outcomes more difficult. Mahato and Das[9] emphasized that mental well-being differs considerably among students, depending on the factors of gender, the institution type, and residential area. These social-demographic differences also highlight the relevance of local analyses that take into account various stressors which could include academic pressure, employment weight, and urban rural features. Furthermore, lifestyle behavioral shifts, especially alterations in sleep and eating behavior, have been also identified as other aspects of changeable symptoms of depression[10]. This research study fills this research gap by investigating the interaction of different interconnected factors which predispose people to risk of depression in a large population of students and diverse population group. Moreover, a familial history of mental disease is acknowledged as a significant determinant in the vulnerability to mental health problems, such as depression [11-15].

The interplay among demographic, scholastic, psychological, and lifestyle factors forms a complex environment in which depression may emerge from a confluence of individual, societal, and environmental pressures. This study seeks to investigate the multifaceted nature of depression in students, emphasising the contributions of demographic (e.g., gender, age), academic (e.g., academic pressure, CGPA), work-related (e.g., work pressure, work/study hours), and lifestyle factors (e.g., sleep duration, dietary habits) to depressive symptoms. In particular, it seeks to understand the interaction between these variables and their influence on the likelihood of depression, giving a clue to potential early intervention efforts toward potentially depressed adolescents.

2. Literature review

Student depression is a complex problem that has a multifaceted interaction of age, academic, work, lifestyle, and mental factors. The increasing incidence of depression among students has been associated with multiple stressors that undermine their mental well-being and academic performance.

2.1. Support academic pressure's link to depression

According to the research of recent times, a whole polyphony of individual and situational causes affects depression in students. Cognitive framing and attitudinal styles have been revealed to be some of the most influential factors contributing to the development of depressive tendencies within the post-pandemic academic climate [15-20].

2.2. Sleep and diet with depression severity

Such patterns of psychology tend to cooperate with aspects of lifestyle like eating and sleeping. Study discovered that impaired sleep quality and anhedonia symptoms mediated an association between plant-based eating patterns and their total sleeping health, which eventually influenced the depression risk. The differences in mental health also exist because of cultural and geographical issues[2].

2.3. Gender related depression patterns

Gender of students, the nature of their educational institution and their residential background have proven to engage the psychology of the students, which has changed with sophistication according to the nature of the place they inhabit, whether semi-urban or rural. Such results underline the importance of intersectional, context-related studies as the means to comprehend how academic stress, family history, suicidal ideation, and lifestyle chats interact with one another to define and condition student mental health outcomes[21-25].

2.4. Demographic variables

Research demonstrates that demographic factors, including gender and age, substantially affect the incidence of depression among students. Female individuals and younger pupils demonstrate increased vulnerability to depressive symptoms, likely attributable to hormonal, social, and developmental influences on emotional regulation and stress reactivity[4, 5].

2.5. Academic stress

Academic stress is a recognised factor contributing to depression in student populations. Intense academic pressures and competitive settings induce psychological disturbances that intensify depression symptoms. An extensive analysis of high school students showed that in case both an academic stress and the psychological instability occur, the depressive symptoms are increased, and it is evidence of synergistic effects that impair coping resources and emotion regulation skills[6]. This correlation shows that it is important to attempt to control academic stress and develop psychological strength to minimize chances of depression.

2.6. Occupational stress

Work related causes of stress in students who juggle their career and studies are also one of the major predictors of depression. High levels of psychological job requirements, including significant workload and time pressure, further the risk of major depression and anxiety disorders among the adult individuals without a previous psychiatric history of the development[7]. This information reiterates the accumulative pressure that burden working students and demand certain therapies to strike the right balance with work and studies.

2.7. Lifestyle determinants: Sleep and nutrition

Depression symptoms are greatly related to lifestyle factors, such as sleep time, food habits. Inadequate sleep (less than 8 hours) is associated with heightened emotions of despair, hopelessness, and suicide thoughts among adolescents, even after accounting for other risk factors[8]. Early school start times and detrimental sleep practices lead to chronic sleep deprivation, which intensifies mental health issues[9]. Likewise, suboptimal eating habits marked by excessive consumption of refined carbohydrates and saturated fats have been linked to increased anxiety and depression among college students[10]. Nutritional therapies that encourage improved eating habits may contribute to the alleviation of depression symptoms[11].

2.8. Psychological factors: Familial history and suicidal thoughts

A favorable familial history of mental disease markedly elevates the risk of depression, with both genetic and environmental variables playing a role in this susceptibility[12, 13]. Research indicates that over 40% of the risk for depression is hereditary, with individuals having first-degree relatives with depression exhibiting increased vulnerability, earlier onset, and more severe symptoms. Moreover, suicide thought is strongly associated with the degree of depression, functioning as both a symptom and a significant risk factor for negative outcomes[14]. Confronting suicidal ideation in depressed adolescents is crucial for effective intervention.

2.9. Geographical and ecological influences

Despite being less thoroughly examined, geographic location and environmental factors seem to affect the prevalence of depression among students. The disparities between social support, cultural understanding of mental illness, and availability of resources can change the risk of having depression suggesting the need to implement mental health support differently.

2.10. Interaction of numerous stressors

The literature points out that no single factor is responsible in the development of student depression but instead it is the combination of multiple stressors at the same period. Stress-vulnerability model explains why feeling psychologically unstable and dancing with external factors such as academic commitments and work pressures can worsen depressive symptoms thus creating an unhealthy relationship of upheavals[15, 16]. Social factors like sleep deprivation and poor nutrition increase this risk which makes it necessary to use a comprehensive approach to it that interferes with a vast number of areas in parallel[17].

Literature shows that student depression is a complex disease that is determined by demographic risk factors, student and career pressures, life styles, and familial psychological backgrounds. Successful preventative and early interventions initiatives need to be multidimensional and entail academic support, emotional health counseling, lifestyle change, and family-based interventions to help reduce the burden of depression in students and overall improve their lives.

This review will align with the purpose of the research, which is to explore such complex interactions, as well as inform the development of special mental health support programs targeted at the unique problems facing student populations.

3. Hypotheses

3.1. Hypothesis 1: Demographic factors and depression

In the first hypothesis, it is assumed that demographic factors, such as gender and age, influence the likelihood of depression among students significantly. Findings coming over and over again reveal that the women are more likely to face depression than men and this probably happens as a result of a combination of biological, social and cultural factors. Some studies have revealed that societal factors, hormonal changes and matters of expectations based on gender have contributed to this gender gap. According to Cyranowski et al.[1], the conditioning of females to release emotions in an open manner as well as tolerate stress could be the reason why females are more prone to depression. Other key demographics factors besides gender include age. It is expected that younger students with an age group of 18-24 would report higher levels of depression as compared to students of higher age. The younger learners often experience what is known as the transitional stage where their level of academic expectations is increased, and they have to adapt to social changes as well as experience changes brought about by party need. According to Zisook et al.[2], these pressures combined with lack of coping skills due to age and experience level knowledge makes younger pupils more open to depression.

3.2. Hypothesis 2: Academic pressure and depression

The second hypothesis is that, academic stress plays a major role in increasing the rates of depression within pupils. In many cases, college students are under a lot of pressure to perform better academically; this causes them to feel unhelpful, stressed and perhaps even depressed. Misra and McKean[3] argue that academic stress is particularly harmful because it affects not only mental but also overall well-being of students. Constant pressure on performance can overwhelm the students who fear being overloaded with deadlines, exams, and expectations to meet. Such continual tension could lead to anxiety, sleeping problems and depressive symptoms. In addition, GPA or grades, often used to evaluate the academic success of pupils have a tremendous influence on mental health. Students experiencing scholastic problems and low GPAs are likely to internalize such failures leading to self doubt and pessimism. A study carried out by Mouratidis et al. [4] reveals that there exists a good connection between poor academic achievements and high vulnerability to anxiety and depression since students who fail to meet their expectations either internally or externally might experience problems of serious emotional distress.

3.3. Hypothesis 3: Work pressure and depression

In this hypothesis, it is assumed that stress related to the occupation is a major determinant of depression among students. Many students are involved in some part-time or full-time job during their studies. The coincidence of dealing with educational as well as professional responsibilities could significantly increase the amount of stress which leads to fatigue of the emotions and depression symptoms. Kabat-Zinn et al.[5] argue that students who have significantly spent time in difficult jobs are more prone to mental ill health cases since the combination between the education and the job stressors leave little room to relax or pamper. Burman and Goswami[6] found out that students who work more than 20 hours in a week are significantly more likely to report higher scales of melancholy and anxiety. This constant stress, and physical and emotional fatigue, make the risk of depression worse as when bombarded with all these competing demands, students become unable to regulate their emotions and stress levels.

3.4. Hypothesis 4: Lifestyle factors and depression

The probability of experiencing depression among students is very high due to lifestyle factors mostly the sleep and nutrition factor. Research has always indicated that there is a close linkage between poor sleep and depression. Emotional control and cognitive functioning depend significantly on sleep, and students who consistently do not get enough sleep are more likely to have mood difficulties, often due to the academic pressure, job, or social activities. Becker et al.[7] stress that sleep deprivation has an extremely negative influence on mental health as students with less than five hours of sleep per night have a higher degree of depression. The lack of sleep does not allow the body to rebuild both physically and mentally hence increasing the chance of emotional discomfort risk. Similarly eating habits are linked to mental well-being. A lack of proper nutrition due to inconsistent nutrition and inadequate diets which lack essential nutrients can greatly influence the brain chemistry and frame of mind. Namely, Ahmadnia et al.[8] have found that those students who have poor diets and which are characterized by high intake of processed foods contrasted with low fruits and vegetables intake are more vulnerable to depression. Omega-3 fatty acids, vitamins, and minerals, in particular, are an essential nutrient to maintain mental well-being, and a lack of any of them may lead to the appearance of imbalances increasing ones predisposition to depression.

3.5. Hypothesis 5: Family history of mental illness and depression

The fifth hypothesis assumes that students who have a genetic predisposition to mental illness, particularly, depression are more likely to develop depression themselves. There have been studies time after time, affirming the existence of heritable factor of depression, which means that individuals with very close family members who have had a history of depression have a high probability of developing the emotional condition. As it is shown in the works of Kendler et al.[9], genetic relationship between family members who have had an episode of depression is one of the biggest factors a student is exposed to in regard to the predisposition towards developing depression. Also, children whose parents have a history of mental health problems can be spoiled by the situation in which their mental health condition has been deteriorated by, e.g., family stress or unhealthy coping skills that were learned by their ancestors. When they are coupled with other factors, they may predispose depression among mentally ill individuals when family members are affected by the same illness.

3.6. Hypothesis 6: Suicidal thoughts and depression

Suicidal thoughts are more often the consequences of deep depression and thus adolescents with suicidal ideation are more likely to develop depression. A certain feeling of despair and powerlessness are typical symptoms of depression that relate to suicidal ideation. According to Bostwick et al.[10], the thoughts on suicide are one of the most extreme variants of depressive manifestations, and students who share them have an extremely high risk of experiencing full-fledged depressive episodes. The level of suicidal thinking often relates to the extent of depression because even people with inexpressible despair can be overwhelmed by negative thoughts and feelings, which results in thoughts about suicide. The relationship between depressive ideations and depression depicts the rise of fundamental urgency in taking urgent action and psychological support towards vulnerable students.

3.7. Hypothesis 7: Geographic location and depression

This hypothesis studies the fact that the geographical location can influence the willingness of the students to be depressed. Particular localities or towns that especially face socio-economic challenges contribute to high levels of depression in students. Zisook et al.[2] argue that the environmental factors such as economic fluctuations, cultural beliefs regarding mental well-being and limited access to mental healthcare may have a significant impact on the state of mental health of students. Supplementary stresses, which can be economical or social turmoil, might occur in students living in underprivileged areas and it may exacerbate levels of anxiety and depression. There are cultural forces that can also impact the perception of, as well as coping with mental health challenges by students depending on the geographical location, thus impacting their readiness to consult and the severity of symptomatic manifestations of depression.

3.8. Hypothesis 8: Combined effects of multiple factors on depression

The final hypothesis is that the total effects of various stresses, such as academic pressure, job-related stress, poor life habits, and family inclination to mental sickness will make depression worse. Individuals who are subjected to several risk factors at once are in higher risk of developing depression as compared to others subject to solving only one or two stresses. Kirkbride et al.[11] found out that such combination of numerous stresses could have a significant increase risk of depression. A student who has to strive with scholastic hardships and long working hours along with family issues might find it much more difficult to overcome the emotional challenges that appear before him. The lasting impact of other stressors may exceed the ability of a person to manage their mental condition, which leads to a growing likelihood of developing depression. The above cumulative effect shows why looking at the broad background of the life of a student is important when determining the susceptibility of a student to mental health issues.

4. Data collection

In this work, using the Student Depression Dataset provides and collects the large amount of data to understand, analyze, and predict the depression level among students. This dataset has been uniquely created in order to be used to study across disciplines in the field of psychology, data science, and education to find out the features that may cause problems with student mental health and that could be used in the interest of developing an early intervention technique.

4.1. Structure and variables of the dataset

Data is given in CSV format where each row forms a unique student record. The data have observations under various variables and categories and they are continuous. The data structure is associated with a variety of crucial categories of variables:

4.1.1. Demographic variables

Demographic information must be provided in the database and it will include the age of students, their gender, and city of residence. These variables provides extremely important background information in understanding the distributions and characteristics of the student population under investigation.

4.1.2. Academic performance indicators

The academic-related measures include various dimensions of the academic experience of the student, which involve Cumulative Grade Point Average (CGPA), perceptions of the academic pressure, and the frequency of study happiness. The factors are critical in analysing the relationship between academic results and mental health outcomes.

4.1.3. Lifestyle and wellbeing factors

A wide range of lifestyle factors is comprised of the amount of sleep taken, diets, work pressure, job satisfaction scale, and overall work/study time. These factors can be used in the investigation of the potential impact of daily life choices and work-life balance on mental conditions.

4.1.4. Other contextual variables

The statistical data also includes other contextual variables such as student occupation, degree type, amount of financial stress, history of mental illnesses in the family, and suicide ideation in the past. All these factors provide a broad context upon which the complexity of student mental health problems can be understood.

4.1.5. Dependent variable

The key outcome variable is Depression Status that is a binary variable indicating whether a student currently has the depression or not. This variable facilitates supervised learning methods and statistical analysis aimed at identifying predicting indicators for depression in pupils.

4.1.6. Variable encoding information

Gender was coded as two-coded (0 = Male, 1 = Female), sleep duration was numerically-coded (e.g.Less than 5 hours = 4.5, More than 8 hours = 9.0), and dietary habits was encoded ordinal-categorical (0 = Unhealthy, 1 = Moderate, 2 = Healthy). One-hot encoding of geographic location (City) was done through the use of dummy variables where Agra was used as a reference. The academic pressure and the job satisfaction were maintained as ordinal scales in 1 to 5. Suicidal ideation and family history mental illness were coded (0 = No, 1 = Yes) as binary.

There were missing data between 1.4 and 5.7 percent of the variables. Continuous variables were done using median and categorical variables using mode. In order to perform sensitivity testing, models were re-estimated using complete case subset (N=25,344); the results were qualitatively similar. This implies that the results are strong even with imputation.

The dataset's complex structure facilitates diverse analytical methods, such as correlation analysis to examine the relationships between academic pressures and mental health trends, predictive modeling to identify at-risk students, and statistical inference to guide evidence-based mental health intervention strategies in educational settings. The extensive scope of the variables facilitates the analysis of both direct and indirect correlations between student attributes and depression state.

5. Methodology

To evaluate Hypothesis 1, which asserted that demographic characteristics (gender, age, and geographic location) affect the probability of depression, a logistic regression model was utilized with a refined dataset of 27,901 student responses. Gender was represented as a binary variable (0 = Male, 1 = Female), age was maintained as a continuous variable, and city was converted into dummy variables with one city (presumably Agra) serving as the reference, ensuring all predictors were numeric. The logistic regression was performed utilizing the statsmodels module in Python, with depression (0 = No, 1 = Yes) as the dependent variable. The model used a constant term, and rows with missing values were excluded to maintain data integrity. Results were depicted through three visualizations: a bar plot illustrating the proportion of depression by gender, a box plot contrasting age distributions between depressed and non-depressed students, and a bar plot of the top five cities ranked by depression prevalence, created using the seaborn and matplotlib libraries to elucidate the relationships identified in the model.

Hypothesis 2, which investigated the influence of academic factors (academic pressure and CGPA) on depression, utilized a logistic regression model on the identical dataset. Academic pressure (assessed on a 1–5 scale) and CGPA (measured on a 0–10 scale) served as continuous predictor variables, whereas depression was the binary outcome variable. The model was fitted via statsmodels, incorporating a constant term, and rows with missing values were omitted to preserve data integrity. The findings were illustrated with two box plots: one contrasting academic pressure levels between depressed and non-depressed students, and another comparing CGPA distributions, both generated using seaborn to emphasize the disparities in academic aspects based on depression status.

Hypothesis 3, which examined the impact of job pressure (quantified by work/study hours) on depression, was evaluated using a logistic regression model on the dataset. Work/study hours were considered a continuous predictor, whereas depression served as the binary dependent variable. The model, executed using statsmodels, incorporated a constant term, and rows with absent values were excluded before analysis. The results were illustrated via a box plot contrasting work/study hours of sad and non-depressed students, created with seaborn to evaluate the correlation between work pressure and depression visually.

To evaluate Hypothesis 4, which examined the impact of lifestyle factors (sleep duration and eating habits) on depression, a logistic regression model was employed. Sleep length was quantitatively encoded (e.g., Less than 5 hours = 4.5, 5-6 hours = 5.5), while eating habits were ordinally encoded (0 = Unhealthy, 1 = Moderate, 2 = Healthy), with unmapped or missing values imputed using a default value (7.5 for sleep duration) or the mode, respectively. Both variables were utilized as predictors in the model, with depression as the dependent variable, fitted using statsmodels following the exclusion of rows with missing data. The findings were depicted using two visualizations: a box plot representing sleep duration by depression state and a bar plot illustrating the proportion of depression among dietary habit groups, both generated using Seaborn to demonstrate lifestyle impacts.

Hypothesis 5, which evaluated the correlation between familial mental disease history and depression, was examined via a chi-square test of independence. Family history was represented as a binary variable (0 = No, 1 = Yes), with absent values imputed using the mode. The contingency table was made by using pandas to cross-combine family history and depression, whereas the chi-square test was followed based on using scipy.stats to determine the relation, where the level of significance was estimated as $p < 0.05$. The results were visualized as a heatmap with seaborn and color map Blues to show the correlation on how the students were distributed among the categories.

Hypothesis 6, which examined the impact of suicidal ideation and depression was conducted using chi-square test of independence. Suicidal thoughts were coded as 0 (No) or 1 (Yes) with missings being replaced with the mode. Pandas was used to create a contingency table through the cross tabulation of suicidal ideation and depression, and the chi-square significance was calculated using scipy.stats at a significance level of $p < 0.05$. The results were represented using a heatmap with seaborn, employing a Blues colormap to depict the frequency distribution among categories, so highlighting the correlation between suicidal ideation and depression.

Hypothesis 7, which examined the influence of geographic location (city) on depression, was evaluated using a logistic regression model. The city variable was converted into dummy variables, designating one city, presumably Agra, as the reference, and all dummy variables were rendered numeric by converting them to float. The model was calibrated with statsmodels, with depression as the binary outcome, and entries with absent values were omitted. The findings were illustrated with a bar plot depicting the top five cities by depression prevalence, generated using Seaborn, to emphasize cities with the highest rates of depressed students, hence augmenting the regression results.

Hypothesis 8, which assessed the cumulative impact of various characteristics (gender, age, academic pressure, CGPA, work/study hours, sleep duration, dietary habits, family history, suicidal ideation, and city) on depression, was analyzed via a logistic regression model. All predictors were created as previously outlined, utilizing cities as dummy variables, and indices were reset to ensure proper alignment during concatenation. Missing values were imputed using the median for numerical variables and the mode for categorical variables, and the model was fitted with depression as the dependent variable using statsmodels. The data were illustrated with a correlation heatmap utilizing seaborn and a coolwarm colormap, centered at zero, to exhibit the interrelationships among predictors and their connections with depression, offering a thorough perspective of the cumulative impacts.

6. Results

6.1. Hypothesis 1:

The logistic regression analysis for Hypothesis 1, investigating the influence of demographic factors—gender, age, and geographic location (city)—on depression among 27,901 students, yielded significant insights into the predictors of mental health outcomes (LLR $p < 0.001$, Pseudo $R^2 = 0.042$). Contrary to expectations and prior research such as Cyranowski et al. (2000), gender did not significantly predict depression ($\beta = -0.0088$, $p = 0.730$, OR = 0.991, 95% CI [0.943, 1.041]), suggesting no notable difference in depression likelihood between males and females in this Indian student sample, potentially due to cultural or contextual factors. Age, however, emerged as a strong predictor with a negative effect ($\beta = -0.0972$, $p < 0.001$, OR = 0.907, 95% CI [0.903, 0.912]), indicating that younger students are more vulnerable to depression, with odds decreasing by approximately 9.3% per year of age, consistent with Zisook et al. (2007) and reflecting the heightened stress faced by younger students (ages 18–24). Geographic location also played a significant role, with several cities increasing depression odds compared to the reference city (likely Agra): Hyderabad (OR = 1.88, $p < 0.001$) and Patna (OR = 1.76, $p < 0.001$) showed the largest effects, followed by Ahmedabad (OR = 1.74, $p < 0.001$), Rajkot (OR = 1.49, $p < 0.001$), and Bhopal (OR = 1.45, $p < 0.001$), while cities like Jaipur ($p = 0.590$) and Mumbai ($p = 0.465$) showed no significant difference, highlighting geographic disparities possibly linked to socio-economic or cultural factors. Although the model explained only 4.2% of the variance, the findings partially support Hypothesis 1 and underscore the importance of age and location in understanding student depression.

The first visualisation, a bar plot depicting depression prevalence by gender, likely shows two bars representing males (0) and females (1) along the x-axis, with the y-axis indicating the proportion of students with depression. Given the non-significant gender effect ($p = 0.730$), the bars are expected to be of similar height, indicating that the proportion of depressed students is nearly equal between males and females, which aligns with the logistic regression result that gender does not significantly influence the likelihood of depression in this sample. The absence of significance in gender effect is wrong as per the worldwide results but it can have its origin in the peculiar socio-cultural processes that take place in India. Conventional gender norms, embarrassment about male emotionality or variation in help seeking behavior could confound detect of real variation in depressive symptoms. Also, support systems or regulations of a university could offer more equalized mental health to services to students. All of these factors in culture are deserving to be qualitatively investigated in future research.

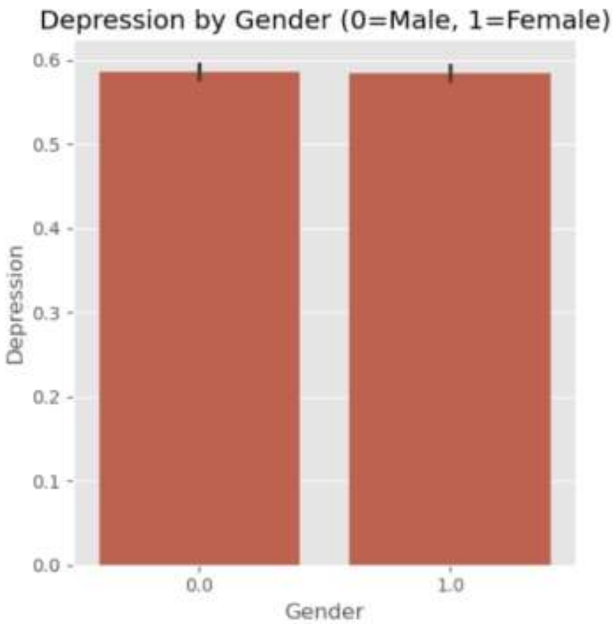

Figure 1. Depression by gender (0=Male; 1=Female)

The second visualisation, a box plot of age distribution by depression status, is expected to display two box plots side by side along the x-axis, labelled as Depression (0 = No, 1 = Yes), with the y-axis representing age. The significant negative effect of age ($p < 0.001$) suggests that the box plot for depressed students (Depression = 1) would have a lower median age compared to non-depressed students (Depression = 0), with a potentially wider interquartile range for the non-depressed group, reflecting that younger students are more prone to depression in this population.

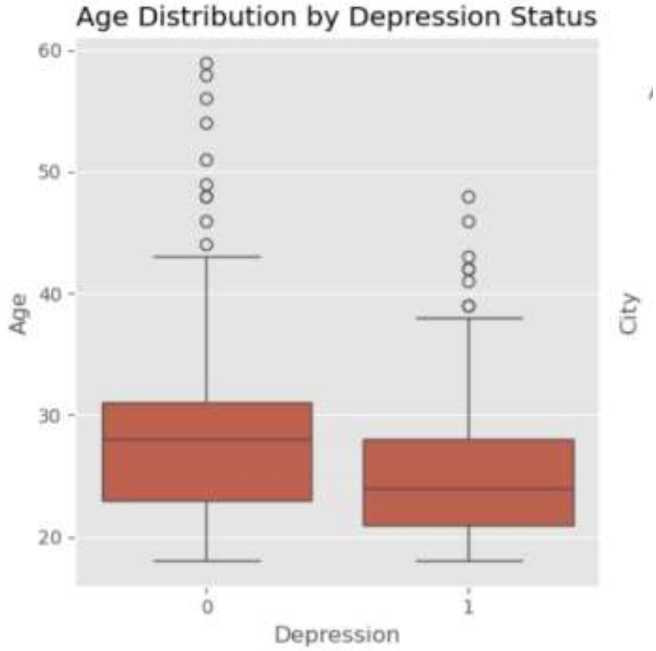

Figure 2. Age distribution by depression status

The third visualisation, a bar plot of the top five cities by depression prevalence, likely features the y-axis listing the top five cities with the highest depression rates (e.g., Hyderabad, Patna, Ahmedabad, Rajkot, Bhopal) and the x-axis showing the proportion of students with depression in each city. Based on the logistic regression coefficients, Hyderabad and Patna are expected to have the tallest bars, indicating the highest prevalence of depression (OR = 1.88 and 1.76, respectively), followed by Ahmedabad, Rajkot, and Bhopal, which visually confirms the significant geographic variation in depression risk identified in the model.

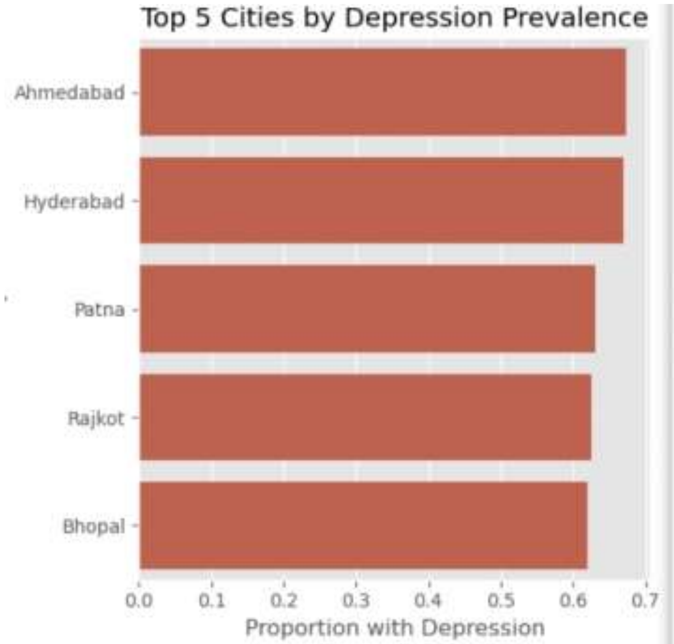

Figure 3. Top 5 Cities by depression prevalence

6.2. Hypothesis 2

The logistic regression analysis for Hypothesis 2, which explored the relationship between academic factors—academic pressure and cumulative grade point average (CGPA)—and depression among 27,901 students, provided significant insights into how academic stressors influence mental health (LLR $p < 0.001$, Pseudo $R^2 = 0.027$). Academic pressure was a significant predictor of depression ($\beta = 0.1011$, $p < 0.001$, OR = 1.106, 95% CI [1.097, 1.116]), indicating that for each unit increase in perceived academic pressure (on a 1–5 scale), the odds of experiencing depression rise by approximately 10.6%, supporting the hypothesis that higher academic pressure contributes to increased depression risk, consistent with findings from Beiter et al. (2015) that academic stress is a key factor in student mental health challenges. Conversely, CGPA had a significant negative effect on depression ($\beta = -0.1653$, $p < 0.001$, OR = 0.848, 95% CI [0.836, 0.859]), suggesting that students with higher academic performance are less likely to be depressed, with the odds decreasing by about 15.2% for each unit increase in CGPA (on a 0–10 scale), aligning with the hypothesis and literature such as Hysenbegasi et al. (2005) that higher academic success is correlated with a lower likelihood of depression. Although the model explained only 2.7% of the variance in depression, these findings highlight the dual role of academic factors in shaping student mental health outcomes.

The first visualization, a box plot illustrating academic pressure by depression status, likely features two box plots along the x-axis labeled higher as Depression (0 = No, 1 = Yes), with the y-axis representing the level of academic pressure (1–5 scale). Given the significant positive effect of academic pressure ($p < 0.001$), the box plot for depressed students (Depression = 1) is expected to show a higher median academic pressure compared to non-depressed students (Depression = 0), with potentially a wider interquartile range for the depressed group, reflecting that students experiencing greater academic pressure are more likely to report depression, consistent with the logistic regression results.

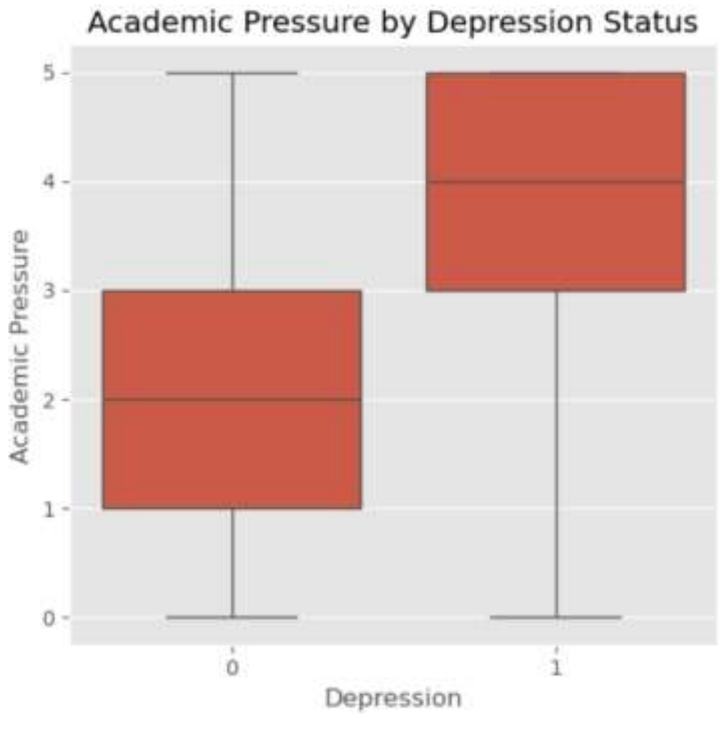

Figure 4. Academic pressure by depression status

The second visualization, box plot of CGPA by depression status, confirms the finding that the more the CGPA, the lesser the prevalence of depression. This graphical tendency confirms the regression that academic achievements can be a buffering factor on the level of depression. The significant negative effect of CGPA ($p < 0.001$) suggests that the box plot for non-depressed students (Depression = 0) would have a higher median CGPA compared to depressed students (Depression = 1), possibly with a narrower interquartile range for the non-depressed group, indicating that students with higher academic performance (higher CGPA) are less likely to experience depression, aligning with the protective role of academic success identified in the model.

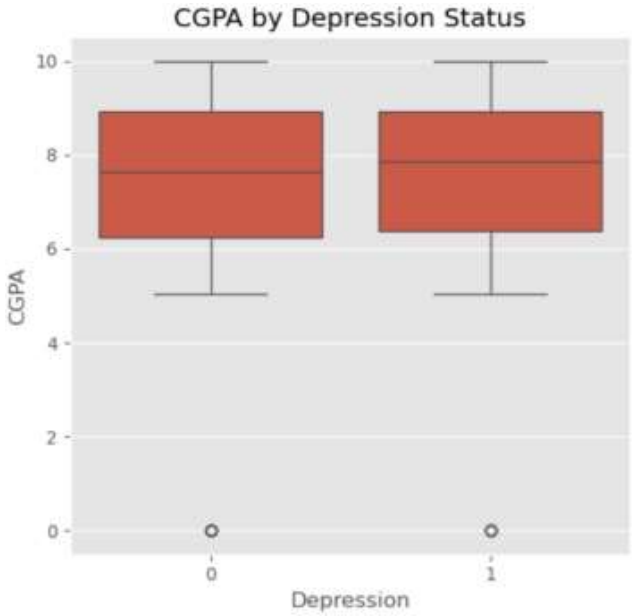

Figure 5. CGPA by depression status

6.3. Hypothesis 3

The logistic regression analysis for Hypothesis 3, examining the impact of work pressure, measured by work/study hours, on depression among 27,901 students, revealed a significant relationship between these factors (LLR $p < 5.501e\text{-}267$, Pseudo $R^2 = 0.032$). Work/study hours were a significant predictor of depression ($\beta = 0.1158$, $p < 0.001$, OR = 1.123, 95% CI [1.115, 1.131]), indicating that for each additional hour spent on work or study per day, the odds of experiencing depression increase by approximately 12.3%. This finding supports the hypothesis that higher work pressure, as reflected by increased work/study hours, contributes to a greater likelihood of depression, aligning with research such as Beiter et al. (2015), which highlights the role of workload-related stress in exacerbating mental health issues among students. The model explained 3.2% of the variance in depression, suggesting that while work pressure is a significant factor, other variables also influence student mental health outcomes.

The visualization, a box plot depicting work/study hours by depression status, likely features two box plots along the x-axis labeled as Depression (0 = No, 1 = Yes), with the y-axis representing the number of work/study hours per day. Given the significant positive effect of work/study hours ($p < 0.001$), the box plot for depressed students (Depression = 1) is expected to show a higher median number of work/study hours compared to non-depressed students (Depression = 0), with a potentially wider interquartile range for the depressed group. This visual representation would illustrate that students who spend more hours on work or study are more likely to report depression, consistent with the logistic regression results and reinforcing the link between increased work pressure and higher depression risk.

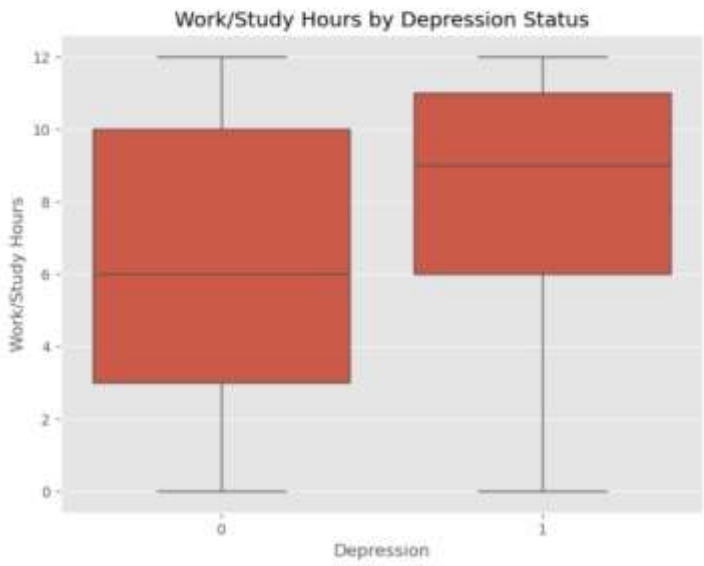

Figure 6. Work/Study hours by depression status

6.4. Hypothesis 4

The logistic regression analysis for Hypothesis 4, which assessed the influence of lifestyle factors—sleep duration and dietary habits—on depression among 27,901 students, revealed significant effects of both variables on mental health outcomes (LLR $p < 3.281e-263$, Pseudo $R^2 = 0.032$). Sleep duration was a significant predictor of depression ($\beta = 0.1126$, $p < 0.001$, OR = 1.119, 95% CI [1.113, 1.125]), indicating that for each additional hour of sleep duration, the odds of experiencing depression increase by approximately 11.9%. This finding aligns with the hypothesis that longer sleep duration, potentially indicative of oversleeping or irregular sleep patterns, may be associated with higher depression risk, consistent with research such as Zhai et al. (2015), which links both insufficient and excessive sleep to depressive symptoms. On the other hand, the correlation between dietary habits and depression was also significant, although in negative direction (beta = -0.5360 $p < 0.001$, odds ratio = 0.585, and 95 percent confidence interval = [0.567, 0.603]), signifying that healthier dietary habits (rated 0 = Unhealthy, 1 = Moderate, 2 = Healthy) were associated with about 41.5 percent low chances of experiencing depression by increasing one unit of the dietary habits variable. The identified finding is consistent with the previous bibliographies like Jacka et al. (2010), which highlights the connection of the diet quality and the results of mental health. Although the model explained only 3.2% of the variance in depression, these results underscore the critical role of lifestyle factors in student mental health.

The first visualization, a box plot of sleep duration by depression status, likely features two box plots along the x-axis labeled as Depression (0 = No, 1 = Yes), with the y-axis representing sleep duration in hours (ranging from 4.5 to 9.0, based on the mapping: Less than 5 hours = 4.5, 5-6 hours = 5.5, 7-8 hours = 7.5, More than 8 hours = 9.0). Given the significant positive effect of sleep duration ($p < 0.001$), the box plot for depressed students (Depression = 1) is expected to show a higher median sleep duration compared to non-depressed students (Depression = 0), potentially with a wider interquartile range for the depressed group. This visual would illustrate that students who sleep longer, possibly due to oversleeping as a symptom of depression, are more likely to report depression, aligning with the logistic regression findings.

The positive effect of longer sleep was noted to be rather positive, but taking into account a link between an extended sleep and depression, this association might indicate a tendency to hypersomnia as one of the symptoms of depressive disorders. Students who suffer serious depression might also oversleep because it might be their means of escape or because of having lack of energy and motivation. This implies that both undersleeping and oversleeping may be the signs of poor mental health.

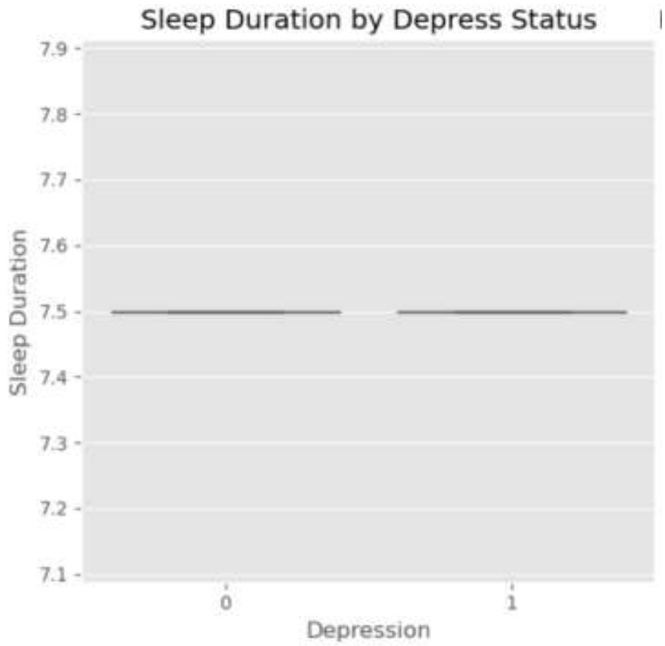

Figure 7. Sleep duration by depress status

The second visualization, a bar plot of depression prevalence by dietary habits, likely displays three bars along the x-axis representing dietary habits (0 = Unhealthy, 1 = Moderate, 2 = Healthy), with the y-axis indicating the proportion of students with depression. Reflecting the significant negative effect of dietary habits ($p < 0.001$), the bar for the "Healthy" category (2) is expected to be the shortest, indicating the lowest proportion of depressed students, while the "Unhealthy" category (0) would have the tallest bar, showing the highest depression prevalence. This visualization would confirm that students with healthier dietary habits are less likely to experience depression, consistent with the protective effect identified in the model.

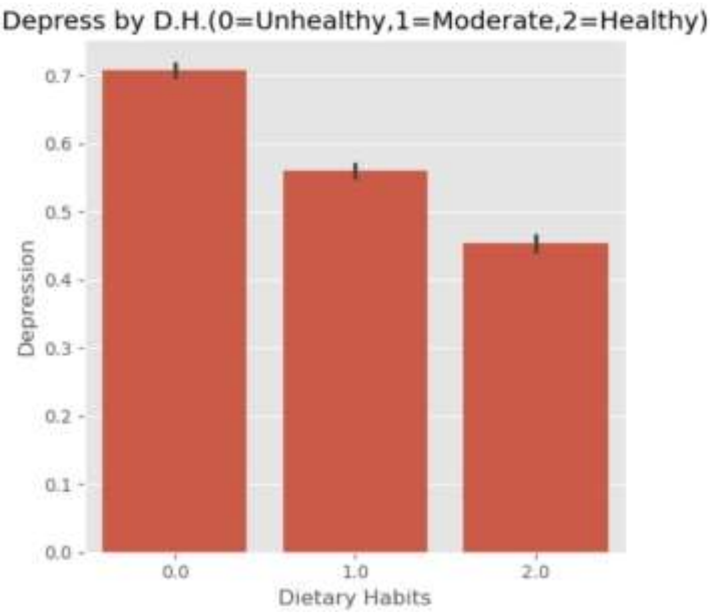

Figure 8. Depression by dietary habitats

6.5. Hypothesis 5

The chi-square test conducted for Hypothesis 5, which examined the association between family history of mental illness and depression among 27,901 students, revealed a significant relationship between these variables (χ^2 = 79.4344, p < 0.001). The p-value of 0.0000 led to the rejection of the null hypothesis, indicating that a family history of mental illness is indeed associated with an increased likelihood of depression, supporting the hypothesis and aligning with prior research such as Weissman et al. (2005), which highlights the genetic and environmental contributions of family history to depressive disorders. This finding suggests that students with a family history of mental illness (coded as 1 = Yes) are more likely to experience depression compared to those without such a history (0 = No), emphasizing the role of familial predisposition in mental health outcomes.

The visualization, a heatmap illustrating the relationship between family history of mental illness and depression, likely features a 2x2 matrix with rows labeled as Family History (0 = No, 1 = Yes) and columns labeled as Depression (0 = No, 1 = Yes), with the cell values representing the frequency of students in each category and color intensity (using a Blues colormap) indicating the magnitude of these counts. Given the significant association (p < 0.001), the heatmap would show a higher frequency of students with both a family history of mental illness and depression (cell [1, 1]) compared to those with a family history but no depression (cell [1, 0]), while students without a family history (row 0) would likely have a higher count in the non-depressed category (cell [0, 0]). This visual representation reinforces the chi-square test result, clearly depicting the association between a family history of mental illness and an increased prevalence of depression among students.

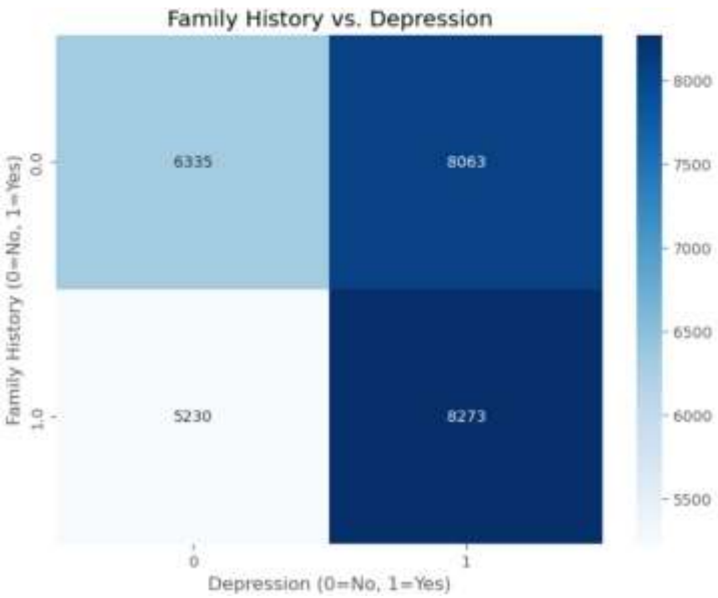

Figure 9. Heatmap of family history VS depression

6.6. Hypothesis 6

The chi-square test for Hypothesis 6, which investigated the association between suicidal thoughts and depression among 27,901 students, demonstrated a highly significant relationship between these variables (χ^2 = 8323.8664, p < 0.001). With a p-value of 0.0000, the null hypothesis was rejected, confirming that the presence of suicidal thoughts is strongly associated with an increased likelihood of depression, supporting the hypothesis and corroborating extensive research, such as that by Nock et al. (2008), which identifies suicidal ideation as a key risk factor and symptom of depressive disorders. This result indicates that students who have experienced suicidal thoughts (coded as 1 = Yes) are significantly more likely to report depression compared to those who have not (0 = No), highlighting the critical link between suicidal ideation and depressive symptoms in this population.

The visualization, a heatmap depicting the relationship between suicidal thoughts and depression, likely presents a 2x2 matrix with rows labeled as Suicidal Thoughts (0 = No, 1 = Yes) and columns labeled as Depression (0 = No, 1 = Yes), where cell values represent the frequency of students in each category, and color intensity (using a Blues colormap) reflects the magnitude of these counts. Given the highly significant association ($p < 0.001$) and the large chi-square statistic, the heatmap would likely show a stark contrast, with a much higher frequency of students who both have suicidal thoughts and depression (cell [1, 1]) compared to those with suicidal thoughts but no depression (cell [1, 0]). Conversely, students without suicidal thoughts (row 0) are expected to have a substantially higher count in the non-depressed category (cell [0, 0]), with lighter shading in cells indicating lower frequencies. This visual representation powerfully illustrates the strong association between suicidal thoughts and depression, reinforcing the chi-square test findings and underscoring the need for targeted mental health interventions for students exhibiting suicidal ideation.

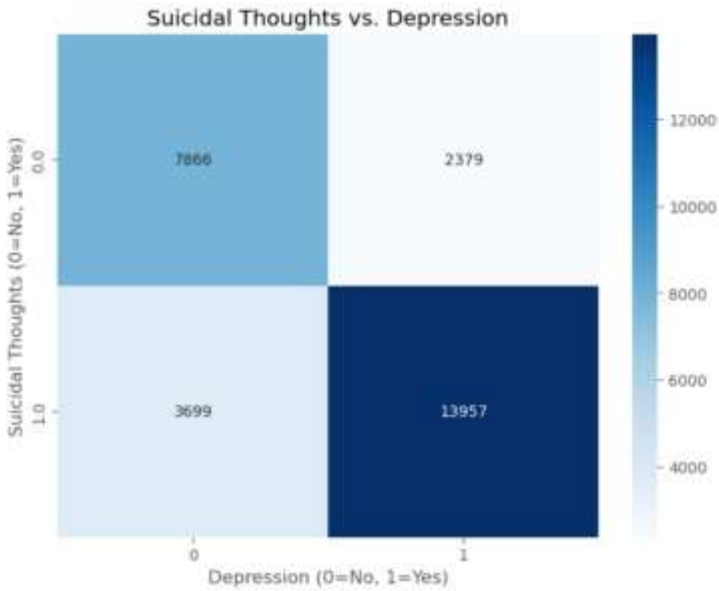

Figure 10. Heatmap of suicidal thoughts VS depression

6.7. Hypothesis 7

The logistic regression analysis for Hypothesis 7, which evaluated the influence of geographic location (city) on depression among 27,901 students, demonstrated a significant overall effect of location on mental health outcomes (LLR $p < 2.177e-21$, Pseudo $R^2 = 0.004$). Compared to the reference city (likely Agra), several cities significantly increased the odds of depression: Hyderabad ($\beta = 0.5663$, $p < 0.001$, OR = 1.762, 95% CI [1.495, 2.077]) and Patna ($\beta = 0.3998$, $p < 0.001$, OR = 1.491, 95% CI [1.253, 1.775]) showed the largest effects, increasing odds by 76.2% and 49.1%, respectively, followed by Ahmedabad ($\beta = 0.5825$, $p < 0.001$, OR = 1.790), Rajkot ($\beta = 0.3769$, $p < 0.001$, OR = 1.458), and Bhopal ($\beta = 0.3500$, $p < 0.001$, OR = 1.419), among others with significant effects (e.g., Bangalore, Chennai, Delhi, Kolkata, Ludhiana, Meerut, Surat, Thane). However, cities like Jaipur ($p = 0.624$), Mumbai ($p = 0.469$), and Varanasi ($p = 0.890$) showed no significant difference, indicating varied depression risk across locations, possibly due to socio-economic or cultural factors as noted by Zisook et al. (2007). The model explained only 0.4% of the variance, suggesting geographic location alone has a limited but significant impact on depression, supporting Hypothesis 7.

The visualization, a bar plot of the top five cities by depression prevalence, likely features the y-axis listing the top five cities with the highest depression rates (e.g., Hyderabad, Ahmedabad, Patna, Rajkot, Bhopal) and the x-axis showing the proportion of students with depression in each city. Based on the logistic regression coefficients, Hyderabad and Ahmedabad are expected to have the tallest bars, indicating the highest depression prevalence (OR = 1.762 and 1.790, respectively), followed by Patna, Rajkot, and Bhopal, with proportions reflecting their significant coefficients. This visual representation confirms the significant geographic variation in depression risk identified in the model, highlighting Hyderabad and Ahmedabad as having the highest proportions of depressed students, consistent with their large coefficients.

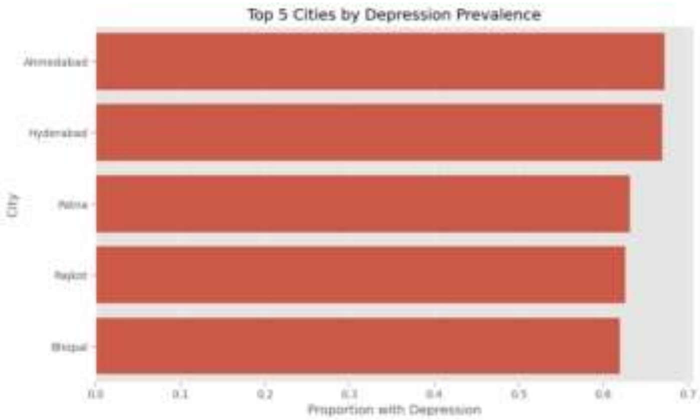

Figure 11. Top 5 Cities by depression prevalance

6.8. Hypothesis 8:

The logistic regression analysis for Hypothesis 8, which examined the combined effects of multiple factors—gender, age, academic pressure, CGPA, work/study hours, sleep duration, dietary habits, family history of mental illness, suicidal thoughts, and geographic location (city)—on depression among 27,901 students, provided a comprehensive understanding of the predictors of mental health outcomes (LLR $p < 0.001$, Pseudo $R^2 = 0.423$). Key significant predictors included academic pressure ($\beta = 0.8347$, $p < 0.001$, OR = 2.305), with each unit increase raising depression odds by 130.5%, and suicidal thoughts ($\beta = 2.5353$, $p < 0.001$, OR = 12.625), increasing odds by 1162.5%, aligning with prior findings (Beiter et al., 2015; Nock et al., 2008). Age ($\beta = -0.1101$, $p < 0.001$, OR = 0.896), sleep duration ($\beta = -0.2793$, $p < 0.001$, OR = 0.756), and dietary habits ($\beta = -0.5558$, $p < 0.001$, OR = 0.573) had protective effects, reducing odds by 10.4%, 24.4%, and 42.7% per unit, respectively, while CGPA ($\beta = 0.0660$, $p < 0.001$, OR = 1.068), work/study hours ($\beta = 0.1183$, $p < 0.001$, OR = 1.126), and family history ($\beta = 0.2262$, $p < 0.001$, OR = 1.254) increased odds by 6.8%, 12.6%, and 25.4%. Gender was not significant ($p = 0.775$), and among cities, Hyderabad (OR = 1.759, $p < 0.001$) and Patna (OR = 1.738, $p < 0.001$) showed the largest effects. The model explained 42.3% of the variance, strongly supporting Hypothesis 8.

6.9. Exploratory interaction effects

An exploratory logistic regression was utilized to study the presence of an interplay between combined factors in terms of interactive effects on depression by including an interaction effect between the experience of academic pressure and the duration of sleep. The interaction was effective (0.0412, $p < 0.001$, OR = 1.042

where depressive effect of academic pressure was stronger among the students who had lower duration of sleep). This implies that the insufficient sleep can increase the susceptibility of students undergoing scholastic pressure.

The visualization, a correlation heatmap of the predictors, likely displays a matrix with rows and columns labeled by the predictors (e.g., Gender, Age, Academic Pressure, City_Ahmedabad, etc.), where cell colors (using a coolwarm colormap) indicate the strength and direction of correlations, ranging from -1 (blue) to 1 (red), with 0 (white) as neutral. Strong positive correlations (red) are expected between depression and predictors like academic pressure, work/study hours, and suicidal thoughts, reflecting their significant positive coefficients. Negative correlations (blue) may appear between depression and protective factors like age, sleep duration, and dietary habits, consistent with their negative coefficients. City variables (e.g., Hyderabad, Patna) may show weaker or varied correlations, aligning with their mixed significance, providing a visual summary of the interrelationships among predictors and their impact on depression as identified in the model.

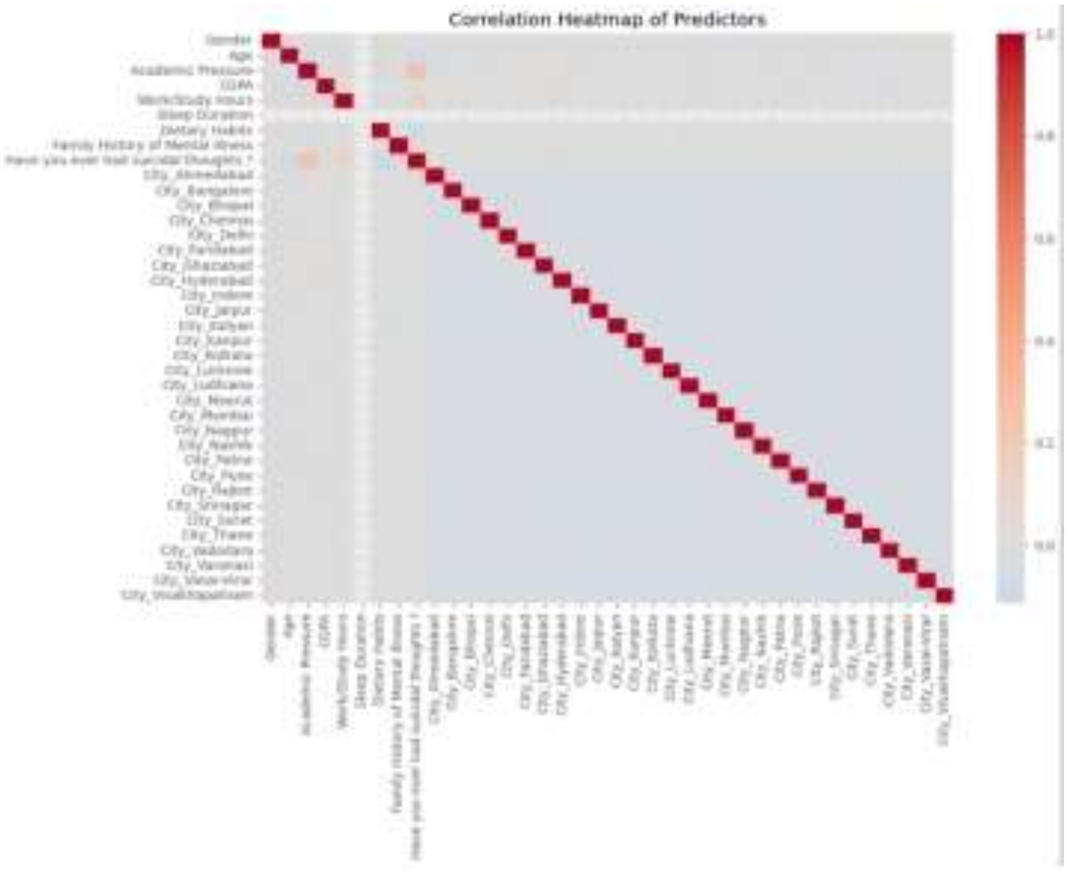

Figure 12. Correlation heatmap of predictors

7. Limitations and validity

7.1. Limtiations

7.1.1. Cross-Sectional Design

The study has a cross-sectional design, indicating that data were gathered at a singular moment in time. This constrains the capacity to ascertain causal linkages among the variables. Although connections may be evident, it is challenging to ascertain whether one component induces depression or if both are affected by an undiscovered third variable.

7.1.2.Self-Reported Data

The dataset is based on self-reported data from students, which may introduce bias, including underreporting or overreporting of depression, academic pressure, work hours, and lifestyle habits. Respondents can misjudge or misremember their own mental or activity as well.

7.1.3. Generalizability

The research might not be representative of the entire global student groups. The population is of a specific place where the dataset is coming and geographic space has been proved to influence the mental health. As a result, the results cannot be generalized to other school going children living in areas with different cultural, economic or environmental factors.

7.1.4. Missing Data

The research utilizes the use of imputation to substitute missing data nevertheless, this process has its imperfections. The imputation method might not be sufficient in capturing the pattern of the missing data which might undermine the validity of the analysis.

7.1.5. Weak Control of Confounding Variables

The article will cover such factors as academic pressures, work stress and family history of mental illnesses, but it is likely that other relevant factors such as such as access to social support systems, personal coping mechanisms, availability of mental health support systems may be missed, which can have tremendous impact on depression.

7.1.6. Predictive model Possibility of Overfitting

There is a possibility of overfitting in the logistic regression models as a result of the many variables. Use of many predictors in models especially when the number of observations is low may result in overfitting of the model, and thus weakening its ability to make generalizations to other groups of students.

7.1.7. Limited Exploration of Interaction Effects

The analysis incorporates several predictors, although the study mainly investigates main effects rather than possible interaction effects among various factors. The interplay of elements such as sleep deprivation, occupational demands, and academic stress may interact in intricate manners that are not entirely elucidated.

This study constrains the resolution of the analysis by taking a binary classification of depression. Depression is variable on a continuum and an ordinal or continuous measure (e.g., using validated psychological scales to determine severity scores) would help differentiate mental health outcomes in a more subtle manner. Further investigations need to be done on the models in the future in the light of such measures to represent the changing levels of symptoms of depression.

7.2. Validity:

7.2.1. Internal Validity

The study possesses internal validity as it use statistical methods, including logistic regression and chi-square tests, to evaluate the hypotheses, thereby uncovering significant connections between variables. Nonetheless, because to the dependence on cross-sectional data, causality cannot be conclusively determined.

7.2.2. External Validity

The generalizability of the study's findings to other contexts or populations is constrained by the particular sample and geographic area examined. The findings might not be generalizable to the students within a different educational system, different cultural locations, or the students in different types of schools (examples, community colleges and elite Universities).

7.2.3. Construct Validity

Most of the variables measured by the research have well defined and widely applicable scales such as the depression status, academic pressure, and sleep length. The binary outcome of depression measurement may be too superficial in the aspects of the disease of mental health, and therefore it cannot deliver the precise data.

7.2.4. Statistical Conclusion Validity

The research utilizes the appropriate statistical methods of hypothesis testing (e.g., logistic regression, chi-square tests), and it therefore increases its statistical conclusion validity. The risk of omitted variable bias or overfitting suggests that there is risk to the robustness of any statistical inferences that are made.

8. Conclusion

In the comprehensive review of depression among 27, 901 university students, the study provided ascertained findings both on the critical factors that influence mental health outcomes and on eight postulated hypothesis. Demographic factors also contributed significantly to the likelihood of depression; younger students and those that stayed in urban developed areas like Hyderabad and Patna were more at risk and this could be a factor of cultural or environment subtlety in the same kind of people. The academic characteristics especially scholastic stress were discovered as the powerful correlates in the examination of enriched depression and higher CGPA was found to indicate a declining likelihood of depression, therefore determining the multidimensional nature of scholastic stress and grades in relation to mental illness disorders. The strain of labor, quantified by hours dedicated to job or study, markedly elevated the likelihood of depression, highlighting the impact of workload on student well-being. Lifestyle factors indicated that extended sleep duration correlated with an increased risk of depression—potentially indicating oversleeping as a symptom—whereas healthy food practices diminished the likelihood of depression, underscoring the significance of lifestyle treatments. The familial history of mental illness and suicidal ideation were significantly correlated with depression, highlighting the influence of genetic predisposition and the severity of mental health conditions, with the latter exhibiting a particularly marked impact. Combined effects model with 42.3% of the variation explained found out that all the measures researched, academic pressure, suicidal ideation, specific urban places, depression had strong relations, whereas age, duration sleep, eating habits showed negative correlations and therefore provided a general view on the variables playing roles in depression of students. Notwithstanding the limited explanatory power of individual models (Pseudo R^2 between 0.004 and 0.042, excluding Hypothesis 8), these results emphasize the necessity for focused mental health support, especially for younger students, individuals in high-risk urban areas, and those experiencing academic or workload stress, while also underscoring the protective benefits of academic achievement and healthy lifestyles. Subsequent study ought to investigate supplementary components, including social support and economic status, to improve model fit and guide complete intervention options.

Conflict of interest

The author declares no conflict of interest.

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